Designing Non-Verbal Expressions for Appearance-Constrained Robots

SONG Sichao

Doctor of Philosophy

Department of Informatics
School of Multidisciplinary Sciences
The Graduate University for Advanced Studies,
SOKENDAI

Designing Non-Verbal Expressions for Appearance-Constrained Robots

by

SONG Sichao

Dissertation

submitted to the Department of Informatics

in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

SOKENDAI (The Graduate University for Advanced Studies)

November 2018

Acknowledgments

First and foremost, I would like to thank my advisor Prof. Seiji Yamada for the continuous support of my Ph.D. study and related research, for his patience, motivation, and immense knowledge. It has been an honor to be his Ph.D. student. I appreciate all his contributions of time and ideas to make my Ph.D. experience productive and stimulating. I could not have imagined having a better advisor and mentor for my Ph.D. study.

Besides my advisor, I would like to thank my thesis committee: Prof. Ryuraro Ichise, Dr. Tetsunari Inamura, Dr. Shingo Murata, and Dr Kazunori Terada, for their insightful comments and encouragement, but also for the hard questions which inspired me to widen my research from various perspectives. Special thank you to Dr Terada, he offered me invaluable suggestions on my Ph.D. research. Also, he taught me, both consciously and unconsciously, how to blend into Japanese culture.

I would also like to thank Prof. Jim Tørresen for his support and advice. Thank you for offering me a chance to revisit the Robotics and Intelligent Systems (ROBIN) group of University of Oslo, the place where I have spent two memorable years of life as a master student.

Thank you to Kazuo Okamura, Tetsuya Matsui, Yasuhisa Kitai, Kayo, Osako and Takato Okudo and the other members of my lab. I appreciate their friendships as well as good advice and comments on my research.

Sincere thanks also goes to my friends Yushan Pan, Lin Sun, Serhat Sama, Arjun Chandra, Tor O Steine, Xuemei Cui, Natthawut Kertkeidkachorn, Tiago Oliveira, Xiangwen Li, Jian Lan, Hongxing Zou and others who were always there listening to me and offering support. Thank you for the wonderful times.

Very special thanks are dedicated to my family members, who have been a constant source of love, concern, encouragement and continuous support throughout my years of studying, researching, and writing this thesis. None of this would have been possible without them. Finally, I would like to thank you, my wife, Ruizhi Ning for the love, patience, and positive outlook.

Abstract

In the last few decades, we have witnessed an enormous increase in social robotics. In addition to industrial robots that work in factories, social robots are expected to be employed in a variety of applications such as education, health care, public service, and domestic uses, where communicating and interacting with humans are a necessary. However, a large number of robots currently in use are neither anthropomorphic nor zoomorphic. When we first encounter such robots, the lack of appropriate mental models and knowledge with regard to these robots can lead to unsmooth or even failed interaction. In addition, such robots are generally constrained in appearance, meaning that they are designed to be functional and lack expressive faces and bodies. Therefore, there is a significant challenge in finding effective ways for these robots to successfully interact with human users.

To design effective expressions for appearance-constrained robots, I probe non-verbal cues include expressive lights, motion, sound, and vibration. I consider the four modalities are particularly suitable for appearance-constrained robot as they do not require human-like features such as face and hand. Besides, because these modalities are neither anthropomorphic nor zoomorphic, they would not cause people's expectations of the appearance-constrained robots to exceed the real capabilities of the robots and result in a negative HRI experience. However, there is much unknown with regard to how the non-verbal expressions can be implemented to facilitate interactions between robots and humans. Theories and knowledge are needed to form valid assumptions for establishing and formalizing effective designs.

Therefore, to address the challenges mentioned above, I perform a series of studies with a focus on three key research questions: (1) How do people perceive and interpret non-verbal expressions from a robot and what are the influences of the

expressions on people's decision-making and behavior? (2) How to design non-verbal expressions for an appearance-constrained robot to show affect? (3) How to design non-verbal expressions for an appearance-constrained robot to communicate its intent? By answering the three questions, this dissertation contributes to providing fundamental knowledge and building blocks to the design of non-verbal expressions for appearance-constrained robots and opening up possibilities for future related research in HRI.

Contents

List of Figures

List of Tables

1 Introduction

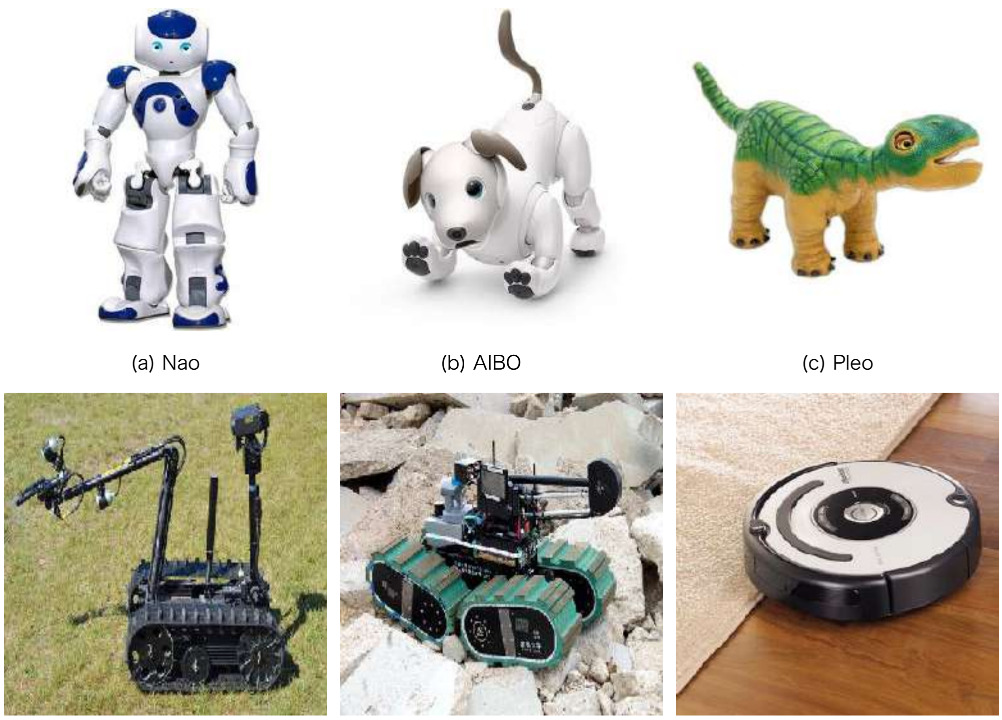
This chapter introduces the topic of this doctoral dissertation and provides an overview of it. Section 1.1 introduces the research background and section 1.2 describes the motivation and research questions of the study. Section 1.3 presents the research approach. Section 1.4 discusses some important experimental and data analysis methods and techniques used in this dissertation. Section 1.5 reviews existing literatures that relevant to the general topic of human-robot interaction, particularly with a focus on appearance-constrained robots. Section 1.6 summarizes the contributions of the study, and section 1.7 gives the structure of the dissertation.

1.1 Background

In the last few years, we have witnessed an enormous increase in social robots. Differing from industrial robots, social robots are expected to be employed in a variety of applications, e.g. education [2, 3], health care [4, 5], public service [6, 7], and domestic uses[8, 9], where communicating and interacting with humans are a necessity. For instance, regarding education, social robots may assist with teaching classes or motivating students to achieve better learning performance; regarding health care, social robots may monitor patients' health conditions, companion them and remind them of taking medicines; regarding public service, social robots may provide information to travelers, guide people in shopping malls or assist with check in/out services in hotels; regarding domestic uses, social robots may assist with human daily lives or secure the house. In such application scenarios, it is necessarily important for the robots to communicate affect and intent to achieve natural and smooth interaction experiences.

As Donald Norman said, "People are explanatory creatures." Due to our tendency to form explanations of things, we build mental models, our conceptual models of the ways objects work or people behave, of those things and use the models to help us understand our experiences and handle unexpected occurrences [10]. Therefore, we naturally adapt our social skills and perform similar social behavior when we first meet a human-shaped robot, e.g., Aldebaran's Nao (Figure 1.1(a)). Similarly, we assume an animal-shaped robot will behave like a real animal, e.g., Sony's robot dog AIBO (Figure 1.1(b)) and Ugobe's robot dinosaur Pleo (Figure 1.1(c)). Social robot designers, thus, tend to add anthropomorphic or zoomorphic features to the robots, aiming at achieving natural and believable human-robot interaction experiences. They consider morphology factors, facial expressions, natural languages, eye gaze, and body gestures essential [11].

Unfortunately, a large number of robots currently in use for applications such as law enforcement (e.g. Figure 1.1(d)), search are rescue (e.g. Figure 1.1(e)), and domestic uses (such as cleaning robots; Figure 1.1(f)) are neither anthropomorphic nor zoomorphic. Such robots are generally constrained in appearance, meaning that they are designed to be functional and lack expressive faces and bodies. Therefore, when we first encounter these robots, the lack of appropriate mental models and



(a) Nao (b) AIBO (c) Pleo

(d) Law enforcement robot (e) Rescue robot (KOHGA3) (f) Cleaning robot (Roomba)

Figure 1.1: Examples of existing robots

knowledge with regard to the robots can lead to unsmooth or even failed interaction. In other words, it is particularly difficult for naïve users to correctly interpret these robots' behaviors due to the lack of natural and informative communication cues from the robots. Thus, there is an eager need for effective methods for such robots to successfully communicate and interact with humans.

However, finding such methods is not easy. Due to their lack of natural and expressive interaction methods, robots that constrained in appearance have to make use of their physical bodies and mobility to communicate with people. Existing approaches focus mainly on motion cues [12, 13] or body posture [14, 15, 16]. For instance, previous work found evidence of relationship between motion parameters (acceleration and curvature) and attribution of affect [13]. Specifically, it was discovered that the level of acceleration can be associated with perceived arousal and that valence information is partly encoded in combinations of acceleration and curvature. Unfortunately, such approaches suffer from low expressibility and are hard, if not impossible, to apply in many application scenarios. For example, in a scenario where space is limited, e.g., a crowded room or a narrow corridor, big movements such as those made through accelerating and moving in an arc can be impossible to employ. Therefore, there remains significant challenges with regard to such topics.

To face these challenges, I explore the design of effective expressions for appearance-constrained robots to communicate affect and intent. Basically, appearance-constrained robots are generally functional robots that are not engineered to be anthropomorphic or zoomorphic and do not have the ability to exhibit facial expressions, make eye contact, or perform gestures. Thus, this dissertation is titled, *Designing non-verbal Expressions for Appearance-Constrained Robots.* The dissertation particularly focuses on non-verbal expressions which include expressive lights, sound, motion, and vibration. For the robots that are equipped with mechanical arms, the effects of motions or gestures of such arms are not considered in this thesis research.

1.2 Motivation

The above challenges attracted me when I had read through a number of literatures related to social interactions in human-robot interaction (HRI). Many studies seemed to rely on human-like features for their robots to communicate and interact with humans. Such a way of thinking made sense because social cues in humans are indeed powerful. However, human-like features can hardly be applied to and may be inappropriate for appearance-constrained robots. Firstly, most appearance-constrained robots have limited ways of social communication. They are not able to show facial expressions and perform body gestures. Secondly, because of an adaptation gap [17], it is considered that applying human-like features, including natural language communication, would cause humans' expectations of the appearance-constrained robots to exceed the real capabilities of the robots and result in a negative HRI experience. For instance, a person may expect a cleaning robot, which can only perform cleaning tasks, to behave intelligently and perform more complex tasks if the robot is programmed to communicate to its users using natural languages.

Therefore, I considered non-verbal expressions suitable for appearance-constrained robots, and importantly, such non-verbal expressions shall not introduce unnecessarily high level of anthropomorphism to the robots. I, then, asked myself the following question: If I focused on non-verbal expressions, what could I do with them? In other words, what were the purposes of using non-verbal expressions for an appearance-constrained robot? Indeed, it is particularly important for a robot to communicate its internal states to avoid confusion and misunderstanding of humans [18]. However, internal states could refer to different categories of information, including function-related states, affect or emotion, intent and so on. I realized that I was not able to cover all the internal states in my research. Instead, I shall address the essential points which were particularly important for appearance-constrained robots with regard to social communication and interaction with humans. Thus, I decided to concentrate on affect and intent.

I started to look for theories and methods that could be used to design effective non-verbal expressions which could be appropriate for appearance-constrained robots to communicate affect and intent. Unfortunately, there were only a handful of literatures addressed on such topics. At that time, HRI researchers just began to realize the importance for functional robots (appearance-constrained robots) to communicate affect. Due to practical reasons, designing new robots or making physical modifications on the robots were not preferred [19]. Therefore, researchers tried to find effective non-verbal modalities which could be easily implemented to the appearance-constrained robots, that were currently-in-use, without physical modifications. With such considerations, previous work remained in the exploratory stage of investigating relationship between non-verbal expressions and perceived emotions [20]. Thus, I wished my research could deepen our understandings on the design of non-verbal expressions and push the research to a next stage in which we could use a systematic framework to study the effects of the non-verbal expressions on humans' behavior.

1.2.1 Research Question

Therefore, I decided the following primary research question:

How to design effective non-verbal expressions which allow an appearance-constrained robot to communicate affect and intent to humans?

This research question is broad. It could cover a range of challenges within HRI. Basically, there was yet no established ground knowledge with regard to the relationship between non-verbal expressions of a robot and human perception and interpretation. Besides, there lacked knowledge on the topic of communicating affect and intent using non-verbal modalities (other than facial expression and gesture). Thus, to address different aspects of the general research question, three specific questions were decided as follows:

- **RQ1**: How do people perceive and interpret non-verbal expressions from a robot and what are the influences of the expressions on people's decision-making and behavior?
  Because humans are social beings, we are good at interpreting others' behaviors. For instance, we can understand what others said and read their facial expressions and gestures. HRI researchers have been making use of such capabilities of humans to design natural interaction experiences for human-shaped robots. However, with regard to appearance-constrained robots, we, as naïve users, do not know how to interact with them since we do not have mental models and knowledge of such robots. Therefore, the non-verbal expressions shown from these robots are not intuitive and can be very difficult to understand. Hence, to design effective non-verbal expressions for appearance-constrained robots, I need to first understand how do people perceive and interpret the non-verbal expressions from appearance-constrained robots.

  Besides, a further question that closely related is asked: what are the influences of the expressions on people's decision-making and behavior? Basically, people make decisions on the basis of their knowledge and understanding of what is happening at the time and what may be the consequences of the decision in the future. Therefore, their perception and interpretation of a robot's expression and behavior can influence their decisions of interaction behavior e.g. response behavior to the robot. Hence, findings from this research question can provide HRI researchers with important knowledge of how to design robot expressions and behaviors to affect human decision-making and behavior and thus achieve desired interaction goals.

- **RQ2**: How to design non-verbal expressions for an appearance-constrained

robot to show affect?
To achieve certain level of social interaction to humans, robots need to express their affect to their interlocutors. Such a task is much easier for a robot if it has the ability to communicate human-like expressions, e.g. facial expression, as such human-like expressions are intuitive to us and can be well understood. However, affective expression can be a very difficult task for appearance-constrained robot since such robots lack methods of social interaction. Therefore, an appearance-constrained robot has to consider alternative non-verbal modalities, e.g. light, sound, and motion. With such constrains, it is challenging to find effective designs for appearance-constrained robots to communicate affect using these modalities. A difficult point is that there is yet no established theories with regard to people's attribution of affect of the non-verbal expressions using light, sound, or motion. Hence, I hope that findings observed from this research question would offer useful knowledge as building blocks and contribute to future research in affective HRI.

- **RQ3**: How to design non-verbal expressions for an appearance-constrained robot to communicate its intent?
In addition to emotions, it is also important for appearance-constrained robots to communicate their intent. It is because that humans are able to better coordinate their behavior and response to the robot if they understand what it is doing and what it wants to do. Particularly, in contexts such as human-robot co-work, it can significantly improve task performance if a robot is able to communicate its intent to its partners. However, similar as affective HRI, it is challenging for appearance-constrained robots to convey intent as such robots lack effective communication methods. Therefore, in this dissertation, I explore alternative ways that I make use of lights for a robot to show gaze information. Findings from this research question provide design implications that can be beneficial to HRI researchers.

Particularly, I consider RQ1 an essential question since understandings of people's perception and interpretation of the non-verbal expressions could be served as ground knowledge for further investigation on RQ2 and RQ3.

1.3 Research Approach

There was huge design space to explore with regard to finding good designs of non-verbal expressions. For each non-verbal modality, it was essential to reduce the parameter space by focusing on a set of core parameters instead of trying to touch each possible parameter. I referred to the typical design thinking approach which suggests a five-stage model: emphasis, define, ideate, prototype, and test [1]. To me, I did not need to strictly follow this five-stage model since my work was not positioned as application-oriented and my experimental participants were not necessarily to be actual users. However, the design thinking approach offered me a powerful guide to efficiently explore and reduce the parameter spaces so that I could find good designs of non-verbal expressions without spending much time on testing out too many unnecessary design alternatives.

In general, I began with reading through related literatures. Such literatures came from multiple disciplines, including human-computer interaction (HRI), psychology, social science, cognitive science, affective computing, HRI, and so on. The reason for this was simple: HRI, as a general field, was multi-disciplinary and lacking of fundamental theories and methods. Theories and knowledge were needed to form valid assumptions for establishing and formalizing efficient design spaces. Other methods, in addition, were also considered at this stage such as performing brainstorms and discussions among group of designers. When design space was decided, I started to build (robotic) systems with prototypic non-verbal expressions, followed with an evaluation stage in which human participants were recruited and tested on with the prototypic expressions. On the basis of the observations and analyses from the evaluation tests, I further improved my designs and/or reported my findings.

[1] Five Stages in the Design Thinking Process. https://www.interaction-design.org/literature/article/5-stages-in-the-design-thinking-process, (Accessed November 5, 2018).

1.4 Research Methods and Techniques

1.4.1 Live vs. Video-Based HRI

User test is considered an essential part of a typical HRI study. Because most HRI research aims at practical applications, it is particularly important for researchers to test their hypotheses and systems on potential human users. Hence, user study is used as an experimental method in this dissertation. However, with regard to user study in HRI, it can be categorized into two different approaches: live HRI and video-based HRI [21].

Live HRI refers to the HRI studies in which a human participant is actually interacting with a robot, meaning that both the participant and the robot are spatially located at a same place. In a video-based HRI study, however, a participant does not spatially share a same place with a robot. The robot's behavior and actions are pre-recoded and saved as video files. The participant is, thus, usually required to watch the videos and give his or her impressions of the robot. Both of the two approaches are considered having their own merits. A Live HRI test can well simulate a practical HRI scenario and allows its participants to interact with the robot via different means such as verbal communication and physical contact. However, such experiment settings require the development of reliable and safe robot systems, which can cost much time and money. With regard to this point, video-based HRI is considered a methodology in place where low cost trial studies could be piloted and tested.

Therefore, here comes a question: Is findings from studies that results obtained from the same HRI scenarios in trials using live and video-based HRI approaches comparable? If the answer is yes, then I can use video-based HRI method to conduct low cost and fast trail tests without the need of developing and executing full live experiments. Fortunately, Woods et al., [21] provided the answer, showing that video-based methods can provide comparable results, compared to live HRI, in contexts such as a robot approaches a person. They suggested that HRI studies could use videotaped scenarios as opposed to live interactions for new exploratory studies.

In accordance to such findings, I often prefer to rely on video-based HRI and use it as an exploratory approach to investigate research problems in which physical contact with robots are not necessary. To conduct a video-based HRI study, there are two ways of choice: offline and online. An offline study refers to a traditional HRI experiment where human participants are recruited and invited to visit the research lab. This approach allows researchers to supervise and observe the participants' behaviors and reactions, leading to more reliable experimental results. However, this approach is not appropriate if researchers wish to obtain data from a large sample pool in a short time period with low cost. In such situations, researchers, instead, can employ online approaches such as crowdsourcing. Although data obtained from online studies lack reliability, low reliable results could be screened using several reliability-check methods [22, 23].

1.4.2 Quantitative vs. Qualitative Approaches

There exists two types if data that fundamentally distinct from each other: qualitative and quantitative. With regard to data analysis approaches in HRI (as well as in other fields, e.g. HCI and psychology), qualitative and quantitative methods are often discussed and both their advantaged and disadvantages are compared. Basically, quantitative data refers to numbers (data in numerical form) whereas qualitative data refers to the data in other forms, such as words, text, photographs, and sound recordings. It is generally considered that quantitative data is hard, rigorous, credible, and scientific, whereas qualitative data is sensitive, nuanced, detailed, and contextual [2].

It is suggested that a number of important questions should be considered before making decision of choosing between quantitative and qualitative approaches [24]:

- Do you want to generate new theories or hypotheses?
  By doing qualitative research, researchers are able to become more experienced and obtain more knowledge and understandings with the research problem. With regard to the research problems in which ground theories and knowledge are not well established, qualitative approach can help a researcher with jumping into the real phenomenon and getting direct experience. By doing so, the researcher is able to formulate his or her own perspectives on the research questions. This, hence, contributes to the originate of new theories and hypotheses. However,

[2] Qualitative vs. quantitative research. https://www.simplypsychology.org/qualitative-quantitative.html, (Accessed November 5, 2018).

when tentative theories and hypotheses are formulated, quantitative approach can be then applied to test on them.

- Do you need to achieve a deep understanding of the issues?
  It is suggested that qualitative research is particularly important for investigating complex problems. Qualitative approach allows a researcher to deeply understand how people think about these issues because qualitative methods such as interview and dairy are able to acquire detailed information with regard to people's subjective opinions and experience.

- Are you willing to trade detail for generalizability?
  As discussed above, qualitative research helps a researcher to get detailed information with regard to a research problem. However, such data is raw and seldom pre-categorized. Particularly, the data obtained from qualitative approaches is very subjective, meaning that findings from the results can highly depend on the participants recruited for the experiment. Since the sample size of a qualitative research is usually small, the experimental findings are not very reliable and can hardly be generalized to common cases. To the contrary, quantitative research can be used to obtain general findings, although it has to trade detail for generalizability.

In this dissertation, I applied both of the two analysis methods. In some cases, my hypotheses are formalized on the basis of previous literatures and existing theories. Hence, quantitative research is used to test the hypotheses as well as check whether the hypotheses can be generalized to common cases in HRI. However, in some other cases where ground knowledge is lacked, qualitative research is applied to explore the research problems and seek deep understandings of the phenomenons. Besides, in some studies, both quantitative and qualitative approaches are combined. This allows me to take advantage of the both methods and obtain a holistic understandings of the research issues.

1.5 Related Work

1.5.1 Human-Robot Interaction (HRI)

The word of “robot" originates from the Czechoslovakian word *robota* which has the meaning of work [25]. In early history of human beings, such as ancient Egypt, Greece, and China, people made automatic mechanical creatures to assist in wars and manufacturing [26]. More recently, Azimov’s *Laws of Robotics*, mentioned in his science fiction literature, has been considered as the first design guidelines for HRI. Basically, early robot implementations were aimed at replacing human works to perform tasks in dangerous scenarios. Till now, most robots exist are deployed in industries to improve production efficiency and reduce labor cost.

However, in the last decade, we have witnessed an enormous increase in social robots. Differing from those industry robots, social robots are expected to be used in applications, such as education, health care, public service, and domestic uses, in which humans will have direct contact with the robots. Therefore, it is becoming important to understand how do people perceive and interact with robots and how can we design effective methods of communication to facilitate the interaction between humans and robots. According to Goodrich et al., [26], human-robot interaction is:

> ... a field of study dedicated to understanding, designing, and evaluating robotic systems for use by or with humans.

As defined by the authors, the HRI problem is to *understand and shape the interactions between one or more humans and one or more robots*. Particularly, evaluating the capabilities of humans and robots and designing the technologies which lead to desirable interactions are essential. With regard to problem domains in HRI, Goodrich et al. [26] summarized six major application areas [see Figure 1.2(a)–(f)]:

1 Search and rescue.
  A search as rescue robot is a robot that has been designed for the purpose of rescuing people in situations such as mining accidents, urban disasters, hostage situations, and explosions. The benefits of such robots include reduced personnel requirements, reduced fatigue, and access to otherwise unreachable areas. Example literatures can be referred to [27, 20, 19, 28].

2 Assistive and educational robotics.
This application domain often places the robot in a peer-like or mentoring role with the human in practice. The robots are designed and used to assist in human's daily lives, such as taking care of elder people or patients, or applied in schools to assist teachers with lectures and programming practices. Related studies can be referred to [29, 30, 31, 32, 33].

3 Entertainment.
There have been many examples of entertainment robots such as Sony's AIBO [34] and Ugobe's robot dinosaur Pleo [35]. Such robots are expected to play the role of pets to accompany humans. Other HRI-related studies in the use of robots for entertainment include robot dance partners [36] and robot story tellers [37, 38].

4 Military and police.
Robots belong to this category are autonomous robots or remote-controlled mobile robots particularly designed for military and police applications. Example application scenarios include transport, detect, and attack. These robots can be used to improve the efficiency of task execution and reduce casualties. Some relevant literatures can be referred to [39, 40, 41, 42].

5 Space exploration.
Space exploration is also considered a promising research topic for HRI. We have seen highly intelligent robots (such as popular robots R2D2 and WALL-E) that used in space travels in various science fiction literature and movies. In practice, robots are expected to have certain communication and social interaction capabilities to assist astronauts with space exploration tasks and accompany them during the long and boring period of space flight. Related work can be referred to [43, 44, 45].

6 UAV Reconnaissance and UUV Application.
Unmanned Air Vehicles (UAV) and Unmanned Underwater Vehicles (UUV) are becoming to attract attention for HRI applications. They can be employed to public uses or assist in underwater construction and maintenance [12, 46, 47].

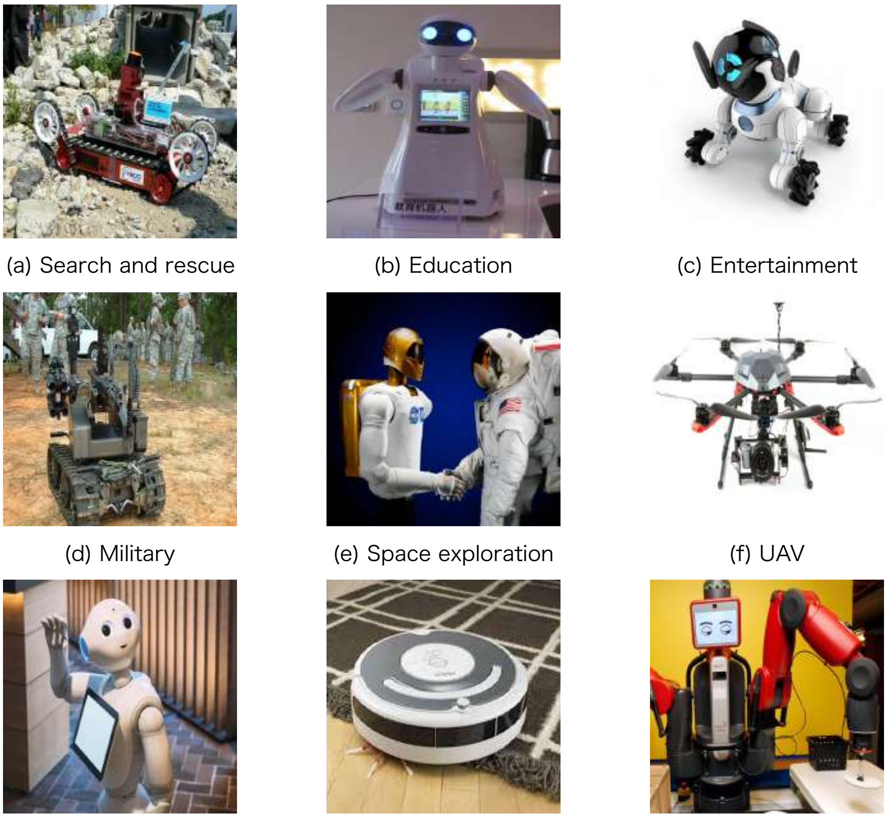
Besides the six domains discussed by Goodrich, there are recently other promising applications that rapidly attracting attention from HRI researchers and practitioners [see Figure 1.2(g)–(i)]:

7 Public service.
One of a highest profile HRI research recently is employing social robots to public uses. Specifically, social robots are expected to be deployed to public areas, such as shopping malls, transportation stations (e.g. train stations and airports), and hotels, to provide information or guidance services. Previous work also suggested that robot can attract people's attention and curiosity [48, 32]. Many studies can be found with regard to this research domain [33, 49, 50, 51].

8 Domestic use.
A domestic robot is a type of autonomous service robot that is particularly used for household chores as well as health care and security. Typical examples of such robots are Roomba (a series of cleaning robots) and Jibo (a prototype robot which can talk with people, deliver forecasts and emails, manage calendar, and do many things else). This is a promising application domain with a lot of challenges as domestic robots need to share the same living space with people and direct contact with them. Therefore, safety and privacy problems have to be carefully addressed. Example literatures can be referred to [52, 53, 54, 55].

9 Co-working.
Differing from traditional industrial robots that repeatedly performing the same programmed tasks, emerging co-working robots need to co-operate with human workers. Hence, communication and interaction capabilities become essential. Baxter provided an inspiring way of thinking with regard to how to design social cues for the co-working robots [56]. Existing studies investigated how do human workers perceive such robots and how to improve task efficiency by shaping social behaviors of the robots [57, 58, 59, 60].

Nonetheless, HRI, as a multi-disciplinary field, is still in its infancy. Ground knowledge, including theories, empirical experience, and research methods, are lacked. Therefore, HRI researchers are looking for theories and methodologies from neighboring fields such as HCI, psychology, artificial intelligence, cognitive science,



(a) Search and rescue (b) Education (c) Entertainment

(d) Military (e) Space exploration (f) UAV

(g) Public service (h) Domestic (i) Co-working

Figure 1.2: Application areas of HRI

and social science. It may be potentially dangerous to directly apply other fields' method to HRI research as HRI studies focus on robots which are essentially different from a computer, a machine, or a person. People's perception and attitude towards robots can differ, depending on their experience, culture, and beliefs. Hence, HRI researchers have to face unique challenges like "Shall we design the robots to be human-like or not?", "Will people treat robots as alive or just pure machinery?" and "Can robots achieve natural communication and interaction with people?"

1.5.2 Non-verbal expressions in HRI

Nonverbal communication between people is communication through sending and receiving wordless cues. Previous research suggested that about 80% of human communication is encoded in facial expressions and body movements [61]. With regard to HRI research, many studies explored the role of non-verbal cues for a robot to communicate internal states (e.g. intent or affect). As natural language processing and related technologies are still not reliable in practical uses, non-verbal methods are becoming to attract attention for HRI projects. Major non-verbal modalities used in HRI (and HCI) related literatures can be summarized in the following:

- Facial expression
  Facial expression is essential to social communication between humans. It plays an vital role in interpersonal relationships as it puts verbal utterances in context and also tells a lot about how the interlocutors feel about each other [62]. With regard to HRI, facial expression is important for a social robot to express emotions. Emotion recognition, expression, and emotionally enriched communication have been intensively discussed in HRI research. Researchers often build human-like robot faces or use embedded screens to display animated face expressions. Related studies can be referred to [63, 64, 65, 66].

- Gesture
  Gesture has been studied throughout centuries from different perspectives such as culture communication and performance studies. Basically, gestures allow humans to communicate of a variety of feelings and thoughts, from contempt and hostility to approval and affection. Therefore, gesture expressions for human-shaped robots have received a considerable amount of attention in HRI research. According to previous research [67], gestures can be categorized into four kinds: iconic, metaphoric, deictic, and beat gestures. Particularly in HRI, deictic gestures, also referred to as “pointing gestures", have been used to shape referential communication and improve task performance [68, 60, 69]. Other work applied gestures for their robots to communicate affect or achieve believable social interaction [70, 71, 72].

- Eye gaze
  Eye gaze is considered a particularly important non-verbal signal, compared with pointing, body posture, and other behaviors, because evidence from psychology suggests that eyes are a cognitively special stimulus, with unique “hard-wired"

pathways in the brain dedicated to their interpretation [73]. Research on gaze in HRI generally focuses on four types of gaze behavior: mutual gaze, referential (deictic) gaze, joint attention and gaze aversions [73]. Example literatures can be referred to [74, 75, 76, 77].

- Expressive lights
  Expressive lights, as an explicit way of communication, have been discussed in studies across various fields such as psychology [78, 79], human-computer interaction (HCI) [22, 80, 81, 82], and human-robot interaction [83, 84, 85]. With regard to HRI scenarios, a majority of work focuses on human-oriented applications because one fundamental goal of social robots is to serve people. Expressive lights have been considered as an effective approach for non-verbal communication, and such an approach is considered to be particularly useful for appearance-constrained robots, as such robots generally have very low social expressivity [27]. Several studies have investigated potential functional uses of lights for robots. Related work can be referred to [83, 18, 85, 86, 87].

- Motion
  Motion is considered a powerful non-verbal behavior as it can reveal details on a person's current physical and mental state [13]. With regard to HRI research, motion cues are widely investigated for a robot to communicate affect and intent [13, 88, 89]. In addition, motions are suggested particularly effective for appearance-constrained robots to communicate social cues as such robots lack expressive faces and bodies [27]. Other related literatures can be referred to [90, 91, 92].

- Artificial sound
  Depending on the differences in the underlying nature and the usage in HRI research, artificial sounds, or semantic-free utterances, can be categorized into four types: gibberish speech (GS), non-linguistic utterances (NLU), musical utterances (MU), and paralinguistic utterances (PU) [93]. Artificial sounds can be applied for social robots to facilitate rich communication and expression during HRI. Example studies with regard to the use of artificial sound for HRI can be referred to [94, 95, 96, 14].

- Vibration
  Vibration is mostly investigated in CHI related studies. For instance, it can be used to convey level of confidence of a system [97] or embedded into wearable devices as part of navigation systems [98] or as an auxiliary modality for communicating affect [99, 100]. To our knowledge, no study uses vibration as a single modality to express emotions. The use of vibration in HRI research has received very little attention in comparison to other modalities. Some other related literatures can be referred to [101, 102, 103].

In this dissertation, I particularly investigate four non-verbal modalities, expressive lights (color), motion, sound, and vibration, with a focus on expressive lights. Because my research questions address design issues with regard to effective expressions for appearance-constrained robots, anthropomorphic methods, such as facial expression and gesture, are inappropriate. Besides, I consider the four modalities intuitive, expressive, and could be easily implemented to most robots regardless of the shape of the robot.

1.5.3 Interact with Appearance-Constrained Robots

Although affective interaction has become an active research topic in social robotics and human-robot interaction (HRI) [15], major studies on it have been focused on human- and animal-like robots [15, 11]. Such anthropomorphic or zoomorphic robots are considered to have natural advantages in interacting with humans since human users can intuitively form conceptual (or mental) models of these robots and thus easily adapt their interactive behaviors. As a result, plenty of literature can be found on investigating affective interaction modalities such as facial expressions [62, 64]), gestures [70, 104], posture [15, 16], and gaze [105, 106].

However, there is a lack of methods that can enable appearance-constrained robots to express affect and intent. Such methods are in eager need, as many currently-in-use robots are restricted in appearance, while there is a need for them to be capable of affective interaction [19]. C. Bethel et al. [19, 28, 27, 20] have been very active regarding this issue and performed a series studies regarding non-facial/non-verbal affective expressions for appearance-constrained robots. They claimed that appearance-constrained robots are not engineered to be anthropomorphic and do not have the ability to exhibit facial expressions or make eye contact. It is either the limitation of the application or cost-saving reasons that lead to such appearance constraints. They documented the need for affective interaction abilities for such robots across many different fields. For instance, [107] describe how rescue workers expected a small tank-like robot to follow social conventions. Work by [108] provide an example of using man-packable robots to act as a surrogate presence for doctors tending to trapped victims. They found that the robots were perceived as "creepy" and not reassuring when they were operated close to simulated victims. To address such issues, [20] investigated five methods of non-facial and non-verbal affective expression: body movement, posture, orientation, color, and sound. As evidenced by their results, they claimed that humans were calmer with robots that exhibited non-facial and non-verbal affective expressions for social human-robot interaction in urban search and rescue applications.

Although C. Bethel et al.'s studies provide insights and a valuable mechanism for naturalistic social interaction between humans and appearance-constrained robots, there are several limitations, and therefore, a huge amount of work remains to be carried out by researchers in HRI and related fields. Their focus was mainly restricted to application scenarios of victim assessment in the aftermath of a disaster. Accordingly, their experimental findings are majorly based on human simulated victims interacting with two types of search and rescue robots: the Inuktun Extreme-VGTV and the iRobot Packet Scout [20]. Robots such as these two share similar features, and thus, it is hard to say that their affective interaction methods can be generalized to other types of robots such as the domestic-use cleaning robot, the Roomba. Since appearance-constrained robots are varied in embodiment, some of the interaction methods, such as body movement and posture, may not be applicable to some of these robots. In addition, C. Bethel et al. did not investigate the use of color and sound to express affect in depth. In their experiments, they used only blue light as an auxiliary expression to elicit a calming response. They therefore indicated several open research questions including "Can illuminated colored lighting effects be used effectively to convey affect and for naturalistic social human-robot interactions" and "Can the use of non-verbal sounds, tones, and/or music be used as an effective method of affect expression for a naturalistic human-robot social interaction" [20]. These questions are explored in this dissertation.

In addition to C. Bethel et al.'s work, a handful of other literature has explored the use of color and/or sound stimuli as affective interaction methods for different kinds of robots. [109] used colored lights for their robot WAMOEBA-1R to express affect. However, no statistical data is presented in their report. [110] utilized a red LED screen for their Sony AIBO to display affective expressions. [86] investigated a novel method of expressing emotions for a simply shaped robot by dynamically changing the color luminosity of its body. Their work addressed the effect of both color and its temporal change on the emotion expression of a robot. A special example is Kismet, developed by Breazeal [15]. Although Kismet is an anthropomorphic robot, it employs non-facial/non-verbal affective expression methods for redundancy in social interactions. For instance, it uses a vocal response to reinforce its emotional display, such as surprise.

1.6 Contribution

Most approaches in HRI focus on anthropomorphic or zoomorphic features. It is yet unclear how can an appearance-constrained robot communicate and interact with humans in a social manner. Because communication cues, such as natural language an facial expression, are considered not appropriate for appearance-constrained robots, a handful of studies explored alternative non-verbal expressions such as expressive light, motion, and sound. However, their findings remain at an exploratory stage. Hence, this work focuses on a systematic investigation on designing and evaluating non-verbal expressions for appearance-constrained robots. The dissertation can be served as important groundwork for designing communicative non-verbal expressions especially for (but not limited to) appearance-constrained robots which lack expressivity.

Many other studies only investigated effects of single modality, whereas I assume that better performance might be achieved if multiple modalities are used. In this work, I investigate four different communication cues, light, motion, sound, and vibration, among which I consider expressive lights is a preliminary one. However, particularly with regard to affective HRI, I decide to evaluate and compare the performance among different combinations of multiple modalities. Findings from the experiments offer evidence that multi-modal expressions could achieve an overall better performance of communicating emotions, and this contribution could provide flexibility with regard to choosing appropriate non-verbal cues in accordance with the hardware configuration of a robot.

Besides, it is suggested that the goals of using non-verbal expressions on social robots can be summarized by the three I's: Inform, Influence, and Interact [18]. However, existing literatures mainly touched on the first component only, and the other two components, influence and interact, have seldom been investigated. Therefore, I found it important to investigate how do humans perceive and interpret different non-verbal expressions from an appearance-constrained robot, and moreover, how will the expressions influence people's decision-making and behavior. This dissertation, hence, provides both theoretical and empirical knowledge as building blocks for more sophisticated and interaction-oriented HRI.

1.6.1 Papers Included in the Dissertation

Below is a list of articles that jointly answer the research questions. I have marked which papers refer to research questions RQ1, RQ2 and RQ3.

- **Paper 1:** Sichao Song and Seiji Yamada. Ambient Lights Influence Perception and Decision-Making. (RQ1)
- **Paper 2:** Sichao Song and Seiji Yamada. 2018. Bioluminescence-Inspired Human-Robot Interaction: Designing Expressive Lights that Affect Human's Willingness to Interact with a Robot. In Proceedings of the 2018 ACM/IEEE International Conference on Human-Robot Interaction (HRI '18). ACM, New York, NY, USA, 224-232. (RQ1)
- **Paper 3:** Sichao Song and Seiji Yamada. Narrative Frame Impacts Perception and Interpretation of Expressive Lights Shown By a Robot. (RQ1)
- **Paper 4:** Sichao Song and Seiji Yamada. 2017. Expressing Emotions through Color, Sound, and Vibration with an Appearance-Constrained Social Robot. In Proceedings of the 2017 ACM/IEEE International Conference on Human-Robot Interaction (HRI '17). ACM, New York, NY, USA, 2–11. (RQ2)
- **Paper 5:** Sichao Song and Seiji Yamada. 2018. Designing Expressive Lights and In-Situ Motions for Robots to Express Emotions. In 6th International Conference

on Human-Agent Interaction (HAI '18), December 15–18, 2018, Southampton, United Kingdom. ACM, New York, NY, USA, 7 pages. (RQ2)

- **Paper 6:** Sichao Song and Seiji Yamada. 2018. Designing LED Lights for a Robot to Communicate Gaze. (RQ3)

1.7 Outline

This dissertation is organized as follows:

Chapter 2: Perception, interpretation and decision-making. This chapter presents three studies that investigate human perception and interpretation of non-verbal expressions as well as how will these expressions influence people's behavior and decision-making.

Chapter 3: Communicating affect. This chapter describes two studies that explore how to design non-verbal expressions for an appearance-constrained robot to communicate affect. The two studies, together, cover four non-verbal modalities, including light, sound, vibration, and motion. Both single- and multi-modal expressions are evaluated and discussed.

Chapter 4: Designing communication cues. This chapter presents one study that investigates the design of communication cues, with a focus on LED-based gaze behavior design.

Chapter 5: Conclusion. This chapter discusses the studies presented in previous chapters, highlights the contributions of this dissertation and recommends areas for future research.

2
Perception, Interpretation and Decision-Making

This chapter reports how non-verbal expressions, particularly expressive lights, influence people's perception and behavior. Section 4.1 gives an overview of the studies reported in this chapter. In section 2.2, I performed three experiments using a ping-pong game, Ultimatum game, and Give-Some game. Evaluation of the results suggested that expressive lights do affect human perception and decision-making. Section 2.3 introduces a study in which I work through a structured approach to determine the best light expression designs for a Roomba robot to show attractiveness and hostility. In section 2.4, I conduct a mixed-methods exploration into the research question: how naïve users perceive and interpret the meaning of expressive lights in various scenarios? A thematic analysis reveals important findings that people's perception and interpretation of a robot's behavior are influenced by three factors: design of light expression, type of robot, and context. Section 4.3 summaries this chapter.

2.1 Overview

This chapter reports findings from three studies related to the research question that how do expressive lights influence people's perception, interpretation, and decision-making.

The first study shows evidence that ambient lights influences people's perception and decision-making. Previous studies explored the design of ambient light displays and suggested that such systems can convey information to people in the periphery of their attention without distracting them from their primary work. However, they mainly focused on using ambient lights to convey certain information. It is still unclear whether and how the lights can influence people's perception and decision-making. To explore this, I perform three experiments using a ping-pong game, Ultimatum game, and Give-Some game, in which I attach an LED strip to the front-bottom of a computer monitor and had it display a set of light expressions. Evaluation of the results suggests that expressive lights do affect human perception and decision-making. Participants liked and anthropomorphized the computer more when it displayed light animations. Particularly, they perceived the computer as positive and friendlier when it displayed green and low intensity light animation, while red and high intensity light animation was perceived as negative and more hostile. They consequently behaved with more tolerance and cooperation to the computer when it was positive compared with when it was negative. The findings can open up possibilities for the design of ambient light systems for various applications where human-machine interaction is needed.

The second study discusses the idea of bioluminescence-inspired human-robot interaction. Bioluminescence is the production and emission of light by a living organism. It, as a means of communication, is of importance for the survival of various creatures. Inspired by bioluminescent light behaviors, I explore the design of expressive lights and evaluate the effect of such expressions on a human's perception of and attitude toward an appearance-constrained robot. Such robots are in urgent need of finding effective ways to present themselves and communicate their intentions due to a lack of social expressivity. I particularly focus on the expression of attractiveness and hostility because a robot would need to be able to attract or keep away human users in practical human-robot interaction (HRI) scenarios. In this study, I install an LED lighting system on a Roomba robot and conducted a series of two experiments. I first work through a structured approach to determine the best light expression designs for the robot to show attractiveness and hostility. This results in four recommended light expressions. Further, I perform a verification study to examine the effectiveness of such light expressions in a typical HRI context. On the basis of the findings, I offer design guidelines for expressive lights that HRI researchers and practitioners could readily employ.

Findings of the third study reveal deep understandings and indicate that narrative frame do impact people's perception and interpretation. Previous studies suggested that expressive lights, as a dynamic vision cue, can be used for appearance-constrained robots to communicate their intent and make their behaviors explainable. However, they focused on specific tasks and goals, leaving it still unknown with regard to how naïve users perceive and interpret the meaning of expressive lights in various scenarios. In this work, I conduct a mixed-methods exploration into this research question. The initial exploration study suggests effects of light expressions on people's valence perception of a robot's behavior. The results also provide empirical evidence on the impact of narrative frame on people's behavior interpretations. By applying a thematic analysis, the second experiment reveals important findings that people's perception and interpretation of a robot's behavior are influenced by three factors: design of light expression, type of robot, and context. In particular, design of light expression significantly impacts valence perception while context has a powerful influence on the diversity of behavior interpretation. On the basis of the findings, I offer design implications on expressive lights for HRI researchers and designers.

2.2 Ambient Lights Influences Perception and Decision-Making

2.2.1 Introduction

Electronic devices such as computers are widely used in our daily lives, either personally or publicly. They are used in various applications such as education, entertainment, and information services. In all cases, it is important for such devices to guarantee their users a pleasant and natural interaction experience. Such an objective has become an important research topic in human-computer interaction (HCI) and human-machine interaction (HMI) in general.

Many factors are related to this goal. Among them, anthropomorphism has been considered as one key factor for interaction design as it can influence a user's perception of a device substantially. According to [111], people interact with new media in much the same way as they interact with other people. Moreover, [112] and [113] well demonstrated the intrinsic mechanism of humans to anthropomorphize objects. For this reason, various studies tried to reach a more natural interaction design by using anthropomorphism methods such as adding human-like eyes and body parts to a device [114] or providing human-like body movements [115].

Unfortunately, these methods are not applicable to many currently-in-use devices such as personal computers as most PCs at present use a keyboard, a mouse, and/or a touchpad as input modalities and a display (monitor) and/or a speaker as output modalities. It can be complex or even impractical to apply human-like design methods to such PCs. Thus, it is important to investigate new methods that can improve a user's interaction experience while being simple and adequate to apply.

To address this problem, we probe an alternative modality: expressive light. Light, as an interaction modality, has been widely studied in different fields. Many previous studies in fields such as psychology, HCI, and human-robot interaction (HRI) have investigated the effect of light and color on human perception. For instance, a number of researchers used expressive lights for their systems to either express affect [116, 117, 118] or convey certain information [22, 18, 85]; a handful of papers discussed affective modulation using light and color [117, 119].

Particularly with regard to HRI related studies, expressive lights have been considered as effective dynamic vision cues for appearance-constrained robots to communicate internal states and intent. Similar to a computer, such robots are neither anthropomorphic nor zoomorphic. The lack of expressiveness makes these robots' behaviors hard for people to understand. Therefore, HRI researchers explored the use of expressive lights in various contexts to indicate internal states [18], communicate intent [85], and express emotion [120].

In addition, expressive lights can be seen as a calming technology [121]. Systems that use light to convey information on the periphery of human vision are defined as ambient light systems [81]. Users of such systems can perceive information encoded

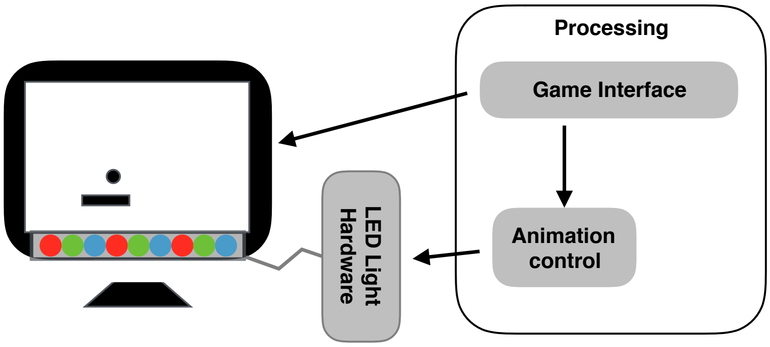


Figure 2.1: System overview

in the lights while maintaining focus on main tasks. Basically, it is suggested that expressive lights can be used to convey the information of four classes: progress, status, spatial, and notification [81]. In particular, [122] designed an ambient light display system named "Lighten Up." They built a four-side frame equipped with individually controllable LEDs and mounted it to the back of a computer monitor. Further, they explored the design space with 42 light patterns and found that users prefer their ambient light system over an on-screen display.

Despite the promising results, previous work mainly focused on informing users of certain information, e.g., progress on tasks or notifications. It is still unclear whether and how expressive lights can influence people's perception, behavior, and decision-making. This is important as today's computers are becoming more versatile in various applications, such as for entertainment, education, business, and even social interactions. As a result, ambient light display systems used for different applications may have the potential to affect their users' psychological functioning and behaviors, either explicitly or implicitly. This will push forward the design of the systems toward a more ambitious goal: interacting with users.

To explore this, in this work, we attached a programmable LED strip to the front-bottom of a monitor [123]. On the basis of previous work [124], we assumed that such a monitor placement is within a user's peripheral visual field and thus will not distract him or her. Figure 2.1 shows an overview of our system. We worked through a structured process to investigate our research question: whether and how expressive lights can affect people's perception and behavior towards a computer.

We divided our approach into two parts. In study 1, we developed a PingPong game for carrying out an experiment. We designed a set of LED light animations for various events that happen during the game, e.g., the racket hitting the ball, the racket hitting the walls, and game over. We collected experiment data by using a post-game questionnaire and game log data. The goal of this study was to observe whether adding expressive lights to game playing can influence people's attitude and performance of the game. Moreover, we were interested in whether such lights can further impact people's perception of the computer itself. Results of study 1 was reported in [123].

To further investigate effects of expressive lights on people's perception and decision-making, we performed a series of two more studies. In study 2, we introduced two games, the Ultimatum game and Give-Some game. Differing from the PingPong game, these two games require people to make economic decisions and thus can be used to measure human altruistic behavior [125]. During each game, the LED strip displayed pre-designed light animations together with the proposals offered by the computer. We collected experiment data by using post-game questionnaires and game logs. The goal of this study was to explore whether and how expressive lights can influence people's decision making toward the computer.

Findings from both studies together will contribute to deeper understanding of the effects that expressive lights have on humans and further open up possibilities for the design of ambient light systems for various applications.

2.2.2 LED Strip Light Animation

[18] used expressive lights to reveal their mobile service robot's states. As we used the same LED strip, an Adafruit NeoPixel strip with 144 programmable LED pixels per meter, we adapted the light animation pattern definitions from their work. In order to fit the width restriction of our monitor, we used a half meter of the LED strip (72 pixels) [123].

We define an animation A(t) of 72 pixels as a time-varying 72×3 matrix of color intensities:

$$A(t) = \begin{pmatrix} i_{1r} & i_{1g} & i_{1b} \\ i_{2r} & i_{2g} & i_{2b} \\ \vdots & \vdots & \vdots \\ i_{72r} & i_{72g} & i_{72b} \end{pmatrix} \tag{2.1}$$

,

where the rows represent the indices of pixels and the columns represent the three color channels r, g, and b. The intensity values are the values of the three channels, respectively:

$$\forall : 0 \leq i_{jc_k} \leq 255 j = 1, \cdots, 72; c_k = r, g, b \tag{2.2}$$

2.2.3 Study 1

Method

Experiment Design We developed the ping-pong game using Processing. Figure 2.2 shows different game screens: an initial screen, ready-to-start screen, in-game screen, and game-over screen. We set the goal of the game as to bounce the ball (moving the racket by mouse) to reach a high score. Four difficulty levels were designed by setting different racket lengths and horizontal forces on the ball when it hits the racket to meet the participants' different gaming abilities. Basically, we designed different scoring metrics with regard to the difficulty levels, where a player get 1 point each time the ball hits the racket in the easy mode, 2 points in the medium mode, 5 in the hard mode, and 10 in the hell mode. We observed five events in the ping-pong game: waiting for game to start, ball hits racket, ball hits wall, playing, and game over. Each event was coded uniquely, and the corresponding code was sent to an Arduino board to control the LED strip to display event-triggered light animations on-the-fly.

Figure 2.3 illustrates the setting of the experiment environment. Basically, a notebook PC was used to run the ping-pong game software developed in Processing. A monitor was connected to the notebook PC to display the game. During the experiment, the notebook PC's cover was kept closed, and the game was played via the monitor in full-screen mode. A NeoPixel LED strip was attached to the bottom side of the monitor. The LED strip was controlled by an Arduino UNO board and powered by a 5-V, 10-A

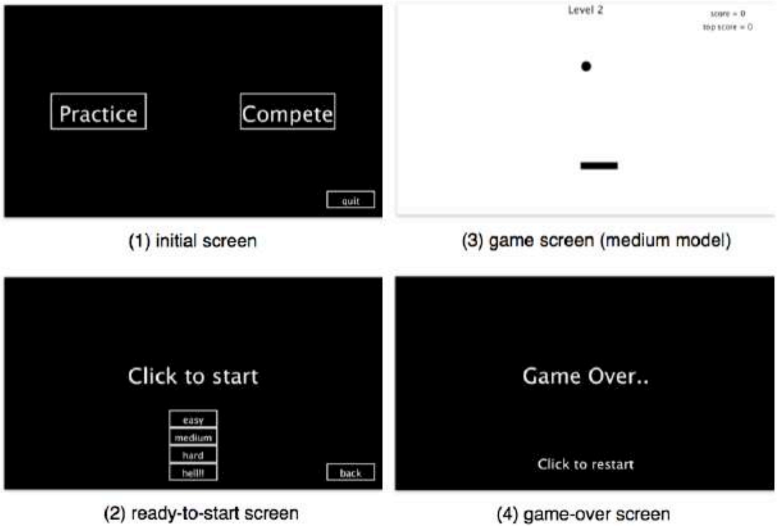


Figure 2.2: Four screen shots of ping pong game

AC adaptor. It needs to be clarified that the image in Figure 2.3 was taken in a dark environment for the purpose of showing the light effect clearly. The actual experiment was done in a bright environment.

Design of Light Expressions On the basis of the defined animation space 2.1, we designed a set of four parameterized light animation patterns: sinusoidal, triangle, swipe, and random (see Figure 2.4). Patterns (a)(b) consist of two basic periodic waveforms, sinusoidal and triangle, and (c)(d) are patterns based on the whole LED strip. The parameters I_{min} and I_{max} are the minimum and maximum intensity values for the RGB color channels, and duty ratio D is the ratio of the rise time to period T. Table 2.1 demonstrates the set of light animations for each game event. Particularly, the light animation for the game-over event consists of both a sinusoidal pattern (first) and random pattern (after).

We tried to design the light animations to match with their corresponding events. For instance, we assumed that people would be calm when they were waiting for the game to start. Therefore, we chose a sinusoidal waveform with low intensity (2-second period) to match with this event. Oppositely, we presumed that people would be aroused and probably be upset and annoyed when they missed the ball (the goal was to bounce the ball by moving the racket). We thus used high intensity lights (0.2-second

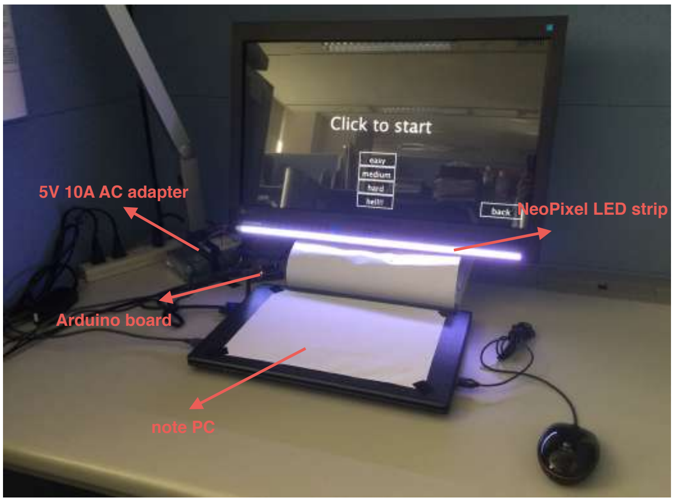


Figure 2.3: Setting of experiment environment

Table 2.1: Set of light animations for each game event

Light Animation	Period (T, second)	Duty Ratio (D)	I_{min}	I_{max}	Event
sinusoidal	2	–	RGB: 0,0,0	RGB: 255,255,255	waiting for game to start
	0.2	–	RGB: 0,0,0	RGB: 255,0,0	game over
triangle	0.6	60%	RGB: 0,0,0	RGB: 0,255,0	ball hits racket
	0.6	60%	RGB: 0,0,0	RGB: 0,0,255	ball hits wall
swipe	–	–	RGB: 255,255,255	RGB: 255,255,255	playing
random	–	–	RGB: 100,100,100	RGB: 255,255,255	game over

period) to match with this event.

Procedure We recruited twenty-two Japanese in total (9 males) for the experiment. Their ages ranged from 20 to 38 years old (M = 28.09, SD = 6.23). We designed two between-subject conditions: one with light animation and one without light animation.

Basically, the experiment was designed in two phases: a practice phase and a compete phase. In the practice phase, each participant practiced the game freely with access to all four difficulty levels. No time limit was given, so they were able to end the practice phase at any time when they felt comfortable with playing the game. In the compete phase, each participant selected one difficulty level only and played three

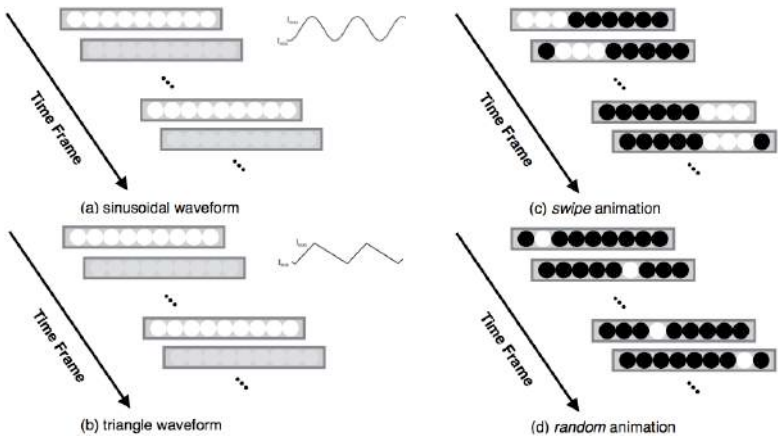


Figure 2.4: Set of light patterns we designed for ping pong game

rounds with regard to this difficulty level. His or her final score was decided as the highest score among the three rounds.

The participants were first welcomed by an experimenter and asked to sign some administrative documents. After this, the experimenter explained the ping pong game to the participants. They were asked to practice the game freely with no time limit before they were ready to "compete" with the others. When the participants thought that they had sufficient practice, they were then required to choose one difficulty mode and play three rounds in the same mode.

Measurement We carefully designed our post-questionnaire on the basis of [60, 126, 127]. It consisted of 22/21 items in total regarding the two experiment conditions with/without LED light animation. The questionnaire used for the with-LED condition contained one more question, "Did you notice the LED light animation?", to check for manipulation. Each questionnaire had three types of items: yes/no questions, 7-point Likert-scale questions, and open questions, where 7-point Likert-scale questions were used the most (18 items). The yes/no questions were used to check for manipulation and for participant-related information.

In particular, the 7-point Likert-scale questions were designed with four main categories: Participant's

- **perception of game** - included questions such as "Do you like this game?" and "Have you enjoyed playing the game?"

- **perception of computer** - included questions such as “How much fun did you have using this computer?", “Do you feel close to the computer?", and “Do you think the computer is alive?"
- **rate of his or her gaming performance** - included questions such as “Do you think you are good at this game?" and “How competitive do you think your score is compared with others?"
- **rate of his or her perceived workload** - included questions such as “Did you feel tired when playing the game?" and “Did you feel pressure during the game?"

Results

We checked if the participants were familiar with the game. Half of the participants (11 out of 22) answered that they had played similar games before the experiment. However, this would not affect the experiment results as we asked the participants to freely practice the game with no time limit before the formal test. We also checked if the participants perceived the game to be difficult by using a Mann-Whitney U test. No significant difference was found between the two experiment conditions with/without LED light animation (with light animation: 5.45; without light animation: 5; $Z = 0.37$; n.s.). Besides, we checked if the selected difficulty level of game impacted the results. Most of the participants chose easy and medium mode and only 3 of them chose hard and hell mode. No evidence was found that selected difficulty level affected the experiment results. In addition, no significant difference was found between the two conditions with regard to average practice time (with light animation: 1m 46.5 s; without light animation: 1m 39.5 s; $Z = 0.24$; n.s.).

Table 2.2 summarizes the evaluation results. The participants in the with-light-animation condition liked playing the game significantly more than those in the without-light-animation condition. They also liked and anthropomorphized the computer more. However, there was no significant difference between the two experiment conditions in terms of subjectively rated performance and perceived workload. Therefore, there is no evidence suggesting that using light animation would affect the participants' subjective ratings of their gaming performance and cause them extra frustration and stress. The final score also shows no significant difference between the two conditions.

Table 2.2: Summary of evaluation results

Category	Sub-category	With light animation	Without light animation	Z	p value	η^2
		Median	Median			
perception of game	–	5.67	4.33	3.21	$p < 0.001$	0.47
perception of computer	likeness	5	3.25	3.26	$p < 0.001$	0.48
	anthropomorphism	2.83	2	2.69	$p < 0.01$	0.33
rate of gaming performance	capability	3	2	0.84	n.s.	0.03
	competitiveness	2.5	2.5	−0.23	n.s.	0.00
rate of perceived workload	frustration	2.5	2	1.61	n.s.	0.12
	stress	5	5	−0.07	n.s.	0.00
final score	–	60	30	1.42	n.s.	0.09

Discussion

The results suggest that using light animations to improve a user's experience with using a computer is promising. Specifically, we show that light animations can have a positive effect on a user's perception of a computer. This method is simple and therefore can be readily used to currently-in-use devices, e.g., computers, as lighting components such as LEDs can be easily embedded to them.

Our results reveal the interesting phenomenon that people anthropomorphize devices more when they include light animations. Although the link between light animation and anthropomorphism is unclear, we envision that expressive lights can be applied to intelligent devices and machines that require affective interaction abilities. This would not only improve the user experience with such devices but also facilitate in achieving more harmonious interactions with people.

In this work, we mounted an LED strip to the front-bottom of a monitor on the basis of previous studies on peripheral cognition technology [124]. Our results indicate that setting an LED strip in such a way may not have a negative effect on a user's task performance and lead to an increase in workload. Thus, such a setting is recommended. However, other settings such as the positions and number of LED strips used to display light animations need to be further explored.

2.2.4 Study 2

Design of Light Expressions

Previous research [128] claimed that color meanings can be grounded in two sources: learned associations that develop from repeated pairings of colors with particular concepts or experiences and biologically based proclivities to respond to particular colors in particular ways in particular situations. For instance, a specific red-danger association can be generated from experiences with regard to (life-threatening) situations such as viewing blood, an angry face, traffic lights, and/or warning signals and sirens [129]. Similarly, green can be associated with positive meanings, e.g., approach and pleasure, due to experiences with green traffic lights and the general image of being the color of the natural. Besides, [86] studied color and dynamic parameters for representing emotions. They found that a rectangular waveform with a high frequency represents intense emotions, while a sinusoidal waveform with a low frequency represents weak (low intensity) emotions.

In this study, we chose two colors: green and red. They are able to produce opposite effects on human psychological functioning. In general, green can be associated with positive perception, while red can be associated with negative perception. Further, we combined a sinusoidal waveform and a low frequency with green to enhance the effect of the color green. Similarly, we combined a rectangular waveform and a high frequency with red to enhance the effect of the color red. As a result, we design two light expressions: *GL* (green, low frequency, and sinusoidal waveform) and *RH* (red, high frequency, and rectangular waveform). Table 2.3 lists the two expressive lights.

Method: Ultimatum Game

Experiment Design There are two players in the Ultimatum game [130, 131]: a proposer and a receiver. They are given the opportunity to split an amount of money. The proposer makes an offer as to how this money should be divided. The receiver can choose to either accept or reject this offer. If the receiver accepts the offer, the money is split according to the proposal. If the receiver rejects, neither player receives any money. In either case, the game is over.

Conventional human decision-making theories suggest that most humans, as rational agents, would accept any non-zero offer to maximize the benefit. However, recent research has revealed that people tend to reject lower offers (p<30% of the amount of money) [130, 131]. It appears that people perceive such offers as unfair, and the negative emotions evoked by the unfair offers can lead people to sacrifice financial gain in order to punish their partner. In this work, we applied the Ultimatum game to observe the behavior of human players towards non-human–i.e., computer–opponents. Specifically, we wanted to see how their tolerance to unfair offers changed when the computer showed different light animations.

Procedure Twenty Japanese individuals (10 males, 10 females) ranging from 21 to 38 years old (M = 28.9, SD = 4.66) were recruited for the experiment. The experiment had a 3 (Light Animation: GL vs. RH vs. without light animation) × 4 (Offer: 50%50% vs. 70%30% vs. 80%20% vs. 90%10%) within-participant design.

Table 2.3: Set of light animations for each game event

Light Animation	Period (T, second)	Duty Ratio (D)	I_{min}	I_{max}	Expected Effect
sinusoidal	1	–	RGB: 0,0,0	RGB: 0,255,0	induce positive perception
rectangle	0.2	50%	RGB: 0,0,0	RGB: 255,0,0	induce negative perception

The experimenter welcomed the participants, explained the game, and gave instructions. Each participant completed a total of 36 rounds (each combination of the levels of the two factors was repeatedly shown three times within the 36 rounds). Since the rounds were presented randomly, there was almost no learning effect. The computer showed a black screen for four seconds after each round, and the participants were asked to treat each round as an independent game. The total amount of money was set to 1000 Japanese yen, which is roughly equal to 10 US dollars.

Results We checked if the participants were familiar with the game. None of the participants answered that they had played similar games before the experiment.

An aligned rank transform (ART) for nonparametric factorial data analysis was conducted to determine the effect of two independent factors (light animation vs. offer) on the acceptance rate as a dependent factor. Significant difference was found in the main effect of the type of offer [F(3, 209) = 128.25, p<0.001, $\eta_p^2 = 0.57$]; see Fig. 2.5(b). This is expected, as previous studies have indicated that the lower the offer, the lower the acceptance rate [130]. Significant difference was also found in the main effect of type of light animation [F(2, 209) = 4.57, p<0.05, $\eta_p^2 = 0.02$]; see Fig. 2.5(a). The Tukey least-squares-means test showed that participants accepted offers made when the computer displayed GL more than when it displayed RH (p=0.0623, marginally significant) or no light animation (p<0.05), but no significant difference was found between when the computer displayed RH and no light animation. No significant difference was found in the interaction effect.

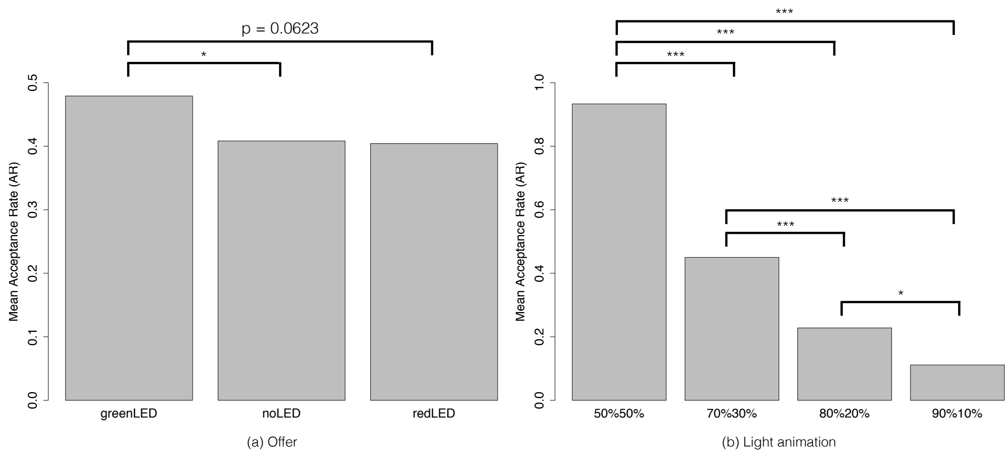


Figure 2.5: Results of the Ultimatum game

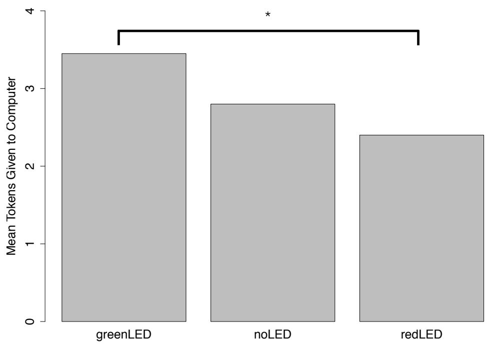
Method: Give-Some Game

Experiment Design In the Give-Some game, each participant is given four tokens, each worth a certain amount of money to the participant if he or she keeps it, but more if given to the partner. Therefore, maximal cooperation and communal gain occur if each participant gives all four tokens to his or her partner, while maximal individual gain accrues to someone who keeps all four tokens to him- or herself and receives all four tokens from his or her partner [132].

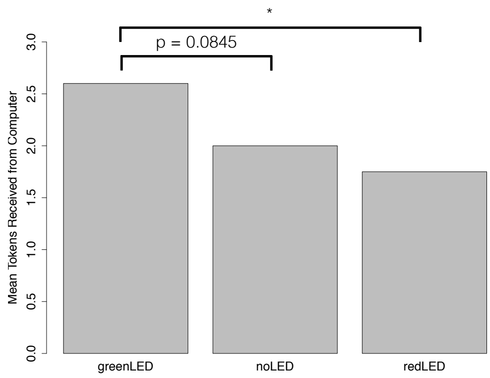
In this work, we applied the Give-Some game to observe the behavior of human players towards non-human opponents (i.e., computers). We adapted the original game to our study. Specifically, maximal cooperation (i.e., trustworthy) behavior is observed if a participant gives all four tokens to the computer, while maximal selfish (i.e., untrustworthy) behavior is observed if a participant keeps all four tokens to his- or herself [132].

Procedure The same twenty Japanese who were recruited for the Ultimatum game experiment also participated in this experiment (after a short break). The experiment had a 3 (Light Animation: GL vs. RH vs. without light animation) within-participant design.

Each participant completed three rounds (each level of the light animation factor), and the rounds were presented randomly. The computer showed a black screen for four seconds after each round, and the participants were asked to treat each round as



(a) Mean tokens given to computer.



(b) Mean tokens expected from computer.

Figure 2.6: Results of Give-Some game

an independent game. Each token was set to be worth 100 Japanese yen, which is roughly equal to 1 US dollar.

We also designed a post-game questionnaire to investigate the subjective perception of the participants on the LED light animations. The questionnaire contained both yes/no questions and open questions. The yes/no questions, such as "Have you played this kind of games before?", were mainly used to find out about the manipulation. The open questions include questions such as "How did you think of the computer when it showed green/red light?" and "Please write down your comments on this game."

Results We checked if the participants were familiar with the game. None of the participants answered that they had played similar games before the experiment.

Non-parametric Friedman tests were conducted to determine the effect of the independent factors (light animation) on the two dependent factors (number of tokens given to the computer and number of tokens expected from the computer). Light animation had a significant effect on the number of tokens given to the computer (Chi-square = 16.21, $p<0.001$, $\eta_p^2 = 0.11$); see Fig. 2.6(a). Wilcoxon signed-rank test with Holm's correction posthoc analysis showed that participants gave tokens to the computer when it displayed GL more than when it displayed RH ($p<0.05$). We also found that light animation had a significant effect on the number of tokens expected from the computer (Chi-square = 7.32, $p<0.05$, $\eta_p^2 = 0.07$); see Fig. 2.6(b). Wilcoxon signed-rank test with Holm's correction posthoc analysis also showed that the participants expected more tokens from the computer when it displayed GL than

Table 2.4: List of adjectives used by participants to describe the light animations. Numbers in parenthesis indicate number of participants who gave comments.

	Green & low intensive	Red & high intensive	No light animation
Description	friendly (12), calm (9), gentle (6), smiling (1), beautiful (1), kind (5), alive (2)	angry (14), oppressive (6), feeling of tension (2), warning (7), challenging (3), dangerous (3)	normal (20)

when it displayed RH ($p<0.05$) or no light animation ($p=0.0845$, marginally significant).

Post-Game Questionnaire

Analysis of the post-game questionnaire showed that 17 out of 20 participants used contrasting descriptions for the two light animations, as listed in Table 2.4. Two participants said that they did not notice any difference and one indicated that the LED lights reminded him of gambling machines.

Discussion

The results indicate that the participants anthropomorphized the computer and treated it as a social agent, although such a process may be unconscious. They used adjectives such as “friendly" and “angry" to describe the computer, where such descriptions are generally applied to humans. Interestingly, the participants were more willing to accept unfair offers (the Ultimatum game) and were more cooperative (the Give-Some game) when they formed positive impressions of the computer compared with negative ones. This shows strong evidence that expressive lights affected the participants' perception of the computer and, more importantly, influenced their decision-making towards the computer's offers.

2.2.5 Discussion

The two studies reveal significant results regarding the effect of expressive lights on human perception and behavior. The results of the PingPong game experiment showed that the participants preferred the computer displaying event-driven light animations and anthropomorphized it more, although the light animations were not exactly designed to express affect. However, it was not clear whether and how such a variation in perception can actually change people's attitude and behavior towards the computer. Therefore, we performed two more experiments, the Ultimatum game and the Give-Some game (both widely used in many fields to study human decision-making mechanisms). We found that the participants had positive impressions of the computer when it displayed green and low intensity light animation but negative impressions when it displayed red and high intensity light animation. Specifically, the participants were more willing to accept unfair offers (the Ultimatum game) and were more cooperative (the Give-Some game) when they formed positive impressions of the computer compared with negative ones. Our analysis of the post-experiment questionnaires confirmed these findings, as indicated by the participants using positive adjectives such as "friendly" and "kind" to describe the computer when it displayed GL and negative adjectives such as "angry" and "oppressive" when it displayed RH. We conclude that expressive lights can be an effective modality that facilitates human-machine interaction.

Our results suggest that color has strong effect on people's perception and decision-making. Basically, color psychologists have being focusing on red and green since such colors have been considered to be special and have positive links in the natural realm. [128] claimed that each color activities associations that contain psychologically relevant messages. Therefore, viewing a color can influence psychological functioning and foster motivational and behavioral process such as approach and avoidance. Red can be associated with danger and anger and further induce avoidance-like behavior in people, whereas green carries positive meanings and can further induce approach-like behaviors.

We summarize our findings as three general design implications:

I. Event-driven light displays can increase people's experience of using a computer.

II. People have positive impressions of and further act approach-like behavior to a computer when it shows green light (combined with a sinusoidal waveform and a low frequency).

III. People have negative impressions of and further act avoidance-like behavior to a computer when it shows red light (combined with a rectangular waveform and a high frequency).

It should be noted, however, that such design implications, especially II and III, may depend on people's attribution of a computer. Although most participants in our experiments attributed agency to the computer when it showed light displays, a few of them did not perceive any differences. Effect sizes of significant results of study 1 are fairly large, suggesting that event-driven light animations can have strong and positive influence to people's experience of using a computer. However, effect sizes of significant results of study 2 are overall small, indicating that effects of light animations on people's decision-making may not be very strong and reliable. Therefore, future research and applications may take user's personality into account.

The findings can open up possibilities for the design of ambient light systems for various applications. Previous studies with regard to ambient light displays mainly focused on informing users of certain information, e.g., progress on tasks and notifications. In this work, we show that LED lights can be applied to influence people's perception and decision-making. This effect can be used to support the design of ambient light systems for different applications. An ambient light system mounted to a computer monitor can be effective in scenarios such as entertainment, education, and social interaction. For instance, light animations can be designed to improve gaming experiences and make the computer more attractive, help people to relax and concentrate on study-related tasks, support in communicating social cues, and influence people's behavior and decision-making.

To achieve such goals, it is thus important to design appropriate expressive lights for specific applications and purposes. We, in this work, mainly focused on the exploration of the effects that expressive lights have on people. Therefore, we pre-designed our light animations on the basis of the findings from previous work [18, 86]. We did not intend to treat the parameters, e.g., color, waveform, and intensity, as independent factors as this would unnecessarily increase the complexity of our studies and make experimental results hard to explain. However, there may inevitably be concerns about an interaction effect among the factors, making it difficult to understand if the effects of expressive lights are to be attributed more to a particular parameter. Thus, future work can investigate the effects of individual parameters to contribute to better understanding of the design of effective light expressions.

Besides the design of expressive lights, further exploration into other factors, e.g., where and how to mount the LEDs, can reveal interesting findings and practical design implications of ambient light systems. In this work, we mounted a programmable LED strip to the front-bottom of a computer monitor as we assumed that such a place was within a user's peripheral visual field and thus would not distract him or her. However, other places of the monitor and more LED strips can be investigated as well. Such findings can be obtained to support the general design of ambient light systems for various other devices such as smart home devices and robots.

Compared with on-screen displays, ambient light systems have advantages in that they communicate in the periphery of people's attention without distracting them from their primary task. Previous work [122] also suggested that people would prefer ambient light systems over on-screen displays. [81] described four information classes, progress, status, spatial, and notification, that an ambient light system can convey. However, our findings show evidence that expressive light animations can be designed to achieve more functionalities, e.g., influencing people's perception and decision-making. Therefore, future work should explore more application scenarios for the use of ambient light systems.

2.3 Bioluminescence-Inspired Human-Robot Interaction

2.3.1 Introduction

Bioluminescence is the production and emission of light by a living organism [133]. The majority of bioluminescent organisms reside in the ocean as about 80% of the genera known to contain luminous species are marine, including, for instance, luminescent fish, e.g., mycophids and hatchetfish, and crustaceans, e.g., copepods and krill) [134]. In addition, bioluminescence occurs in some fungi and terrestrial invertebrates, such as fireflies, as well (Figure 2.7). A large number of organisms retain functional eyes to detect bioluminescence in dark environments, which suggests the importance of bioluminescence as a means of communication for the survival of a vast variety of creatures [134].

Appearance-constrained robots, in comparison, reside in a similar situation as bioluminescent organisms. These robots are designed to be functional and lack expressive faces [27]. Although they primarily work in bright places, their lack of social expressivity makes it hard for them to be perceived and understood by humans. As a result, people are in a way "blind" to appearance-constrained robots. In human-robot interaction (HRI) scenarios, this can lead to unsmooth or even failed interaction [20]. As if they were bioluminescent organisms in the dark, appearance-constrained robots are in urgent need of finding effective ways to present themselves and communicate their intentions.

Because of the restricted interaction modality of appearance-constrained robots, current approaches rely mainly on motion cues [13, 12, 135, 88, 8]. Unfortunately, these approaches are limited in expressivity and are hard to apply in many practical scenarios. For instance, it can be impossible for a robot to use big movements, e.g., acceleration and moving in an arc, to interact with human users when situated in a crowded room. To address such limitations, we investigate expressive lights as an alternative interaction modality. By using expressive lights, we are enabling a robot to modify its appearance as a means of communicating with humans.

Expressive lights as a dynamic visual cue have been explored for HRI applications. For instance, Sony's robot dog AIBO and Aldebaran's NAO use LED lights to assist in affective expression. In general, expressive lights have been shown to be effective in various HRI contexts such as indicating internal states [84], communicating intent [85], and expressing emotion [120]. The goals of using expressive lights on a social robot could be summarized by the three I's: Inform, Influence, and Interact [84]. Specifically, *Inform* is about showing a robot's internal state, *Influence* is about changing human behavior to a robot's advantage, and *Interact* is about affective communication and interaction. Most current research has mainly been relevant to *Inform*, and the other two components, *Influence* and *Interact*, have seldom been touched upon. It is therefore important to encourage further exploration on the use of expressive lights.

Bioluminescence provides good inspiration. Basically, luminescence can serve three purposes within a single organism: offense, e.g., attracting prey, defense, e.g., warning a predator, and mate attraction [1]. With regard to HRI, we think that a robot may need to possess two general social abilities: initialize or escape from an interaction.

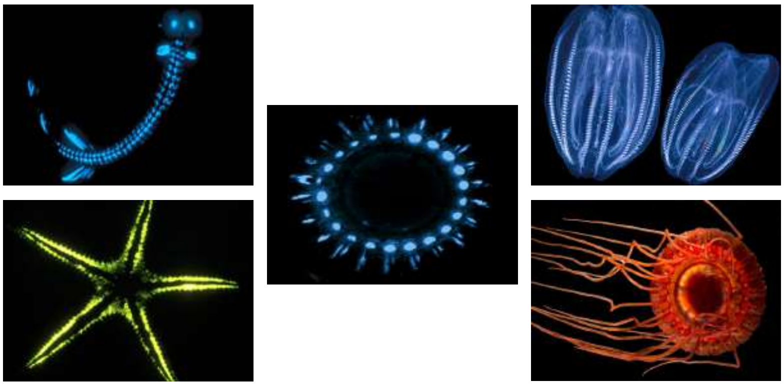


Figure 2.7: Examples of bioluminescent organisms

The importance of a robot initializing an interaction is evident in the vast applications of social robots. For instance, a service/guide robot needs to proactively approach customers/visitors to promote successful interactions as previous research suggests that potential interaction opportunities, e.g., with people that hesitate about whether or not they will engage a robot, may be missed if the robot is inactive [136, 49]. In addition, a robot needs to escape from a potentially harmful interaction as well. As reported by a few pieces of literature, robots may physically get abused by humans [137, 138, 139]. In such cases, we compare a potential target human to prey when a robot approaches him or her proactively. Similarly, we compare a potentially dangerous human to a predator when he or she approaches the robot. Inspired by the functions of bioluminescence, we accordingly consider that such a robot needs to either attract its target humans (offense) or warn the dangerous ones to keep their distance (defense).

In this work, we primarily explore the design of expressive lights to achieve such goals. Specifically, we aim at designing expressive lights that are either perceived as **attractive** or **hostile**. We presume that a robot that is perceived as attractive may do a better job at initializing an interaction, whereas a robot that is perceived as hostile may reduce a human's willingness to interact with it. On the basis of inspiration from bioluminescence and color psychology theories, we work through a structured process to determine a set of effective light expressions. A follow-up video-based validation study is then performed to verify the effectiveness of the light expressions in practical HRI scenarios. Our work can serve as an extension of [85, 84] and suggests potential effects of expressive lights on influencing people's perception and behavior, therefore increasing exploration on the use of expressive lights in HRI.

2.3.2 Background

Appearance-Constrained Robot

Affective interaction has become an active topic in social robotics and HRI [14]. However, major studies on it have been focused on human- and animal-like robots [14, 11]. There is a lack of methods that appearance-constrained robots can use to express affect. Such methods are in eager need, as many currently-in-use robots are restricted in appearance, while there is a need for them to be capable of affective interaction [19].

A number of studies have been carried out to explore the design of non-facial/non-verbal affective expressions [28, 27, 19, 20]. The authors claimed that appearance-constrained robots are not engineered to be anthropomorphic due to either there being limited applications or for cost-saving reasons. They highlighted the importance for such robots to express emotions. For instance, rescue workers were found to expect a small tank-like robot to follow social conventions [107]; man-packable robots were observed to be perceived as “creepy” and not reassuring when they were operated close to simulated victims [108].

Although these pieces of work provide insights into affective social interaction between humans and appearance-constrained robots, there are several limitations with regard to the generality of their findings. As they focused on application scenarios involving assessing victims in the aftermath of a disaster, their results were majorly based on simulated human victims interacting with two types of search and rescue robots [20]. Therefore, their methods can be hard to generalize to other types of robots, e.g., Roomba, and practical scenarios. In addition, since they used only blue light as an auxiliary expression to elicit a calming response, they thus offered open research questions such as “Can illuminated colored lighting effects be used effectively to convey affect and for naturalistic social human robot interactions?” [20]. These questions are ones that we try to solve.

Initialize or Escape from Interaction

We think that a social robot needs to have two basic social abilities: to initialize or escape from a potential interaction. How a robot should approach humans and try to successfully establish an interaction has been an active topic. Scenarios involving public service, e.g., an information center in a shopping mall, have been particularly researched [136, 49]. In many cases, if a robot only passively waits for a human user to initiate an interaction with it, people who are hesitating or unsure of how to interact would be not served [136]. Thus, it is of importance to allow a robot to proactively approach target humans. To achieve such a goal, the robot needs methods to attract target people so as to increase the possibility of successfully establishing interactions with them.

In addition, a handful of studies have investigated robot abuse [137, 138, 139]. It is reported that people, children in particular, tend to react to robots with high curiosity and often treat them aggressively [137, 138]. Abuse behaviors include saying bad things to the robots and sometimes even kicking or punching them [137]. Therefore, robots in such situations need to be able to escape from human abuse.

Bioluminescence Functions

The many functions of bioluminescence reflect the unique nature of the environment in which a vast variety of bioluminescent organisms have evolved [134]. Basically, luminescence can serve three purposes within a single organism: offense, e.g., attract prey, defense, e.g., warning predators, and mate attraction [1]. For example, bioluminescent creatures, e.g., dinoflagellates and squid, use light to startle a predator in order to defend themselves from being preyed upon. Some predators, e.g., anglerfish, use light to lure their prey. Many creatures, e.g., ostracodes and flashlight fish, rely on bioluminescent light to attract and recognize their mates [1]. In general, bioluminescence functions can be summarized into two kinds: those that attract or keep others away (Figure 2.8).

With regard to the two HRI scenarios we focus on in this work, that is, initialize and escape from an interaction, we think that a robot, similarly, should be able to attract or keep humans away. To be specific, a robot needs to attract human users to successfully establish an interaction, whereas it needs to keep unfriendly people away to escape from abuse.

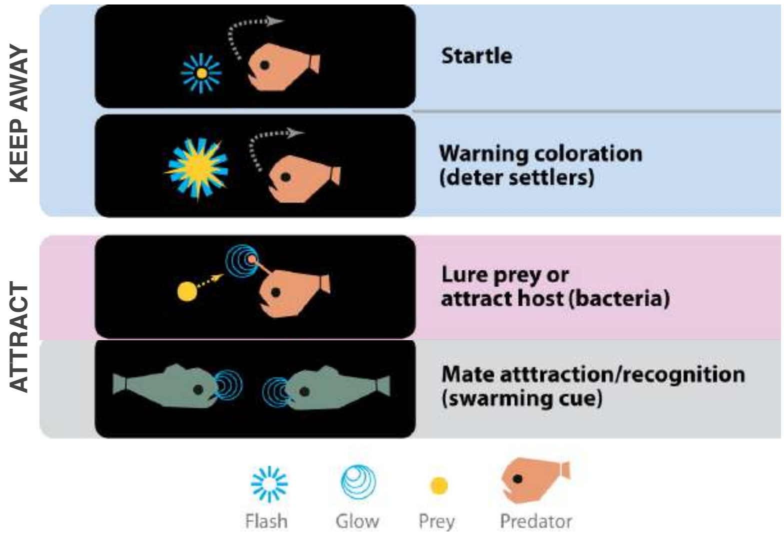


Figure 2.8: Two general functions of bioluminescence: attraction and keeping away (adapted from [1])

Expressive Lights for Robots

Expressive lights, as an explicit way of communication, have been discussed in studies across various fields such as psychology [78, 79], human-computer interaction (HCI) [22, 80, 81, 82], and human-robot interaction [83, 84, 85]. To be specific, it is suggested that even simple light expressions can be highly expressive [22] and are able to evoke high-level social and emotional content [80, 82]. Such artificial lights in different colors can implicitly affect human perception and psychological functioning and therefore may influence human behavior [78, 79].

With regard to HRI scenarios, a majority of work focuses on human-oriented applications because one fundamental goal of social robots is to serve people. Expressive lights have been considered as an effective approach for non-verbal communication, and such an approach is considered to be particularly useful for appearance-constrained robots, as such robots generally have very low social expressivity [27]. Several studies have investigated potential functional uses of lights for robots. For instance, expressive light animations were applied to visualize a mobile service robot's internal state [84]. The authors designed different light patterns to indicate that the robot is waiting for human input, is being blocked by a human, or is showing task progress. Another work [85] explored design constrains to robot flight behaviors. Their designed light expressions were able to significantly improve people's response time and accuracy for predicting the flying direction of the robot.

Research on expressive lights for HRI is still in its infancy. It is suggested that the goals of using expressive lights on social robots can be summarized by the three I's: Inform, Influence, and Interact [84]. Despite the many promising studies that have been done in this area, they mainly touched on the first component only. Therefore, both theoretical and empirical work regarding the design of expressive lights are needed to provide building blocks for more sophisticated and interaction-oriented HRI.

2.3.3 Expressive Light Design

Exploring Design Space

Color Although the RGB color space contains tens of thousands of colors, we only consider categorical colors, e.g., green and red, due to their simplicity and representativeness. In addition, this is valid as the human color vision system processes color signals in a categorically driven manner [140]. Color psychologists have intensively investigated various aspects of color, including color vision, color symbolism and association, and the effects of color on psychological and biological functioning [140]. Basically, their work primarily focuses on red, blue, and green since such colors (especially red) have been considered to be special and have positive links to the natural realm.

On one hand, *associative learning theory* provides a promising explanation of color-emotion associations [128]. According to this theory, color meanings are grounded in two basic sources: learned associations that develop from repeated pairings of colors with particular messages, concepts, or experiences and biologically based proclivities to respond to particular colors in particular ways in particular situations [128]. For example, red carries the meaning of danger and anger in life-threatening situations, such as when viewing blood, an angry face, traffic lights, and/or warning signals and sirens [129]. Similarly, green can be associated with positive meanings due to traffic lights (green light indicates "go") and an image of being the color of nature. Blue can be associated with sadness due to the saying "I feel blue" [129].

On the other hand, *mental alertness theory* suggests that color can affect a person's level of mental alertness and therefore influence his or her psychological functioning

Figure 2.9: Demonstrations of candidate expressive light patterns. All, except static, were periodic. Each periodic expressive light pattern consisted of five periods. For random pattern, singular random pixels in the LED strip were turned on and off throughout the given time period

[141]. Previous work indicates that red makes people more alert and risk averse, whereas blue encourages people to take risks and perform exploratory behaviors [78]. In addition, blue light is able to elicit pleasure [79] and creativity [142]. These findings indicate that the color blue can be attractive to humans.

In addition, previous studies observed that exposure to green and blue evokes lower feelings of anxiety and greater feelings of calmness [143]. It has long been proposed that being exposed to colors with longer wavelengths such as red and yellow is stimulating and arousing, whereas shorter wavelength colors, such as green and blue, tend to evoke feelings of calmness and tranquility [143].

Patterns Due to the shape of the LED strip, the design space of a light expression pattern is restricted to one dimension. However, because each LED pixel can be individually controlled, finding desirable designs is still challenging. To cover a wide range of possible light expressions, we primarily investigated two types of patterns: strip-based patterns and pixel-based ones. The former includes light expressions that make use of all LED pixels as a whole (the entire LED strip), whereas the latter consists of light expressions that take advantage of individual LED pixel expressions.

During her speech at TED2011[1], Edith Widder demonstrated plenty of bioluminescent light behaviors performed by sea creatures. Inspired by such natural bioluminescent lights, we designed a set of representative light patterns. To be specific, a pattern can have two parameters: waveform and intensity (frequency). Existing findings suggest that a rectangular waveform and high intensity represent intense emotions, while a sinusoidal waveform and low intensity represent weak emotions [86]. Therefore, with regard to strip-based patterns, we explored both rectangular (named *blinking*) and sinusoidal (named *breathing*) waveforms with low and high frequencies, respectively. In addition, a *static* pattern, in which the entire LED strip is always lit, was also chosen. With regard to pixel-based patterns, the waveform parameters for individual LED pixels were not considered. We chose three patterns: *circle*, *split*, and *random*. It is notable that, for the random pattern, singular random pixels in the LED strip were turned on and off throughout the given time period.

Candidate Expressive Lights

We decided on 44 light expressions in total as our expressive light candidates (Figure 2.9). In summary, they made use of four colors (red, green, blue, white), five patterns (blinking, breathing, circle, split, random) with two intensities (low, high), and one special pattern (static). All light expressions, except static, were periodic, and each corresponding expressive light contained five periods. We designed a large number of expressive light patterns in the hope of covering a wide range of potential light expressions.

Roomba Lighting System

We installed an LED lighting system on an iRobot Create 2 robot. Roomba is a series of indoor autonomous robotic vacuum cleaners. All Roomba robots are disc-shaped,

[1]The Weird and Wonderful World of Bioluminescence. https://www.ted.com/talks/edith_widder_the_weird_and_wonderful_world_of_bioluminescence#t-112245, (Accessed November 5, 2018).

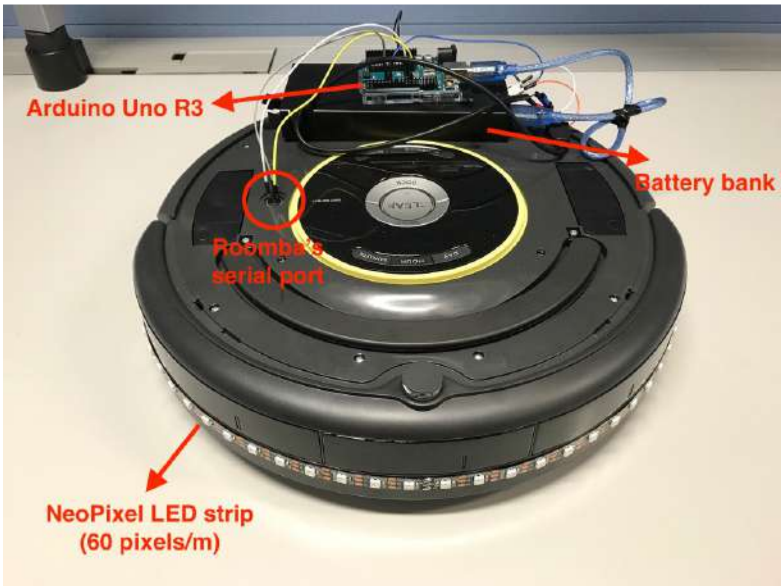


Figure 2.10: Configuration of Roomba robot with LED lighting system

34 cm in diameter, and less than 9 cm in height. iRobot Create 2 is a programmable Roomba robot for educators, students, and developers. Therefore, it allows for a variety of programming methods and can be connected to a microcontroller. We think that such a robot perfectly meets the definition of an appearance-constrained robot, and in addition, has limited methods of expressing affect, e.g., moving forward/backward and spinning.

Figure 3.10 illustrates the configuration of the Roomba robot with the LED strip. Following the design of [85], we attached a NeoPixel LED strip (1 meter, 60 pixels) to the body of the robot in a ring. The strip was controlled by an Arduino Uno R3 board, where the data pin of the strip was connected to the digital output pin of the Arduino board. Both the strip and board were powered by a 5-V, 3-A portable powerbank. In addition, the same board was used to control the movements of the Roomba robot as well. iRobot Create 2 provides the Roomba Open Interface (OI) which is a software interface for controlling and manipulating Roomba's behavior.

2.3.4 Experiment

Procedure

We aimed at finding a set of appropriate expressive lights that can allow the Roomba robot to be perceived as either attractive or hostile by humans. To ensure the generality of the experimental results, having a large and diverse set of participants was important. Therefore, we employed a Japanese online crowdsourcing platform Fastask to recruit participants for the experiment. Recent studies, e.g., [22, 23], have shown the validity and power of crowd-sourced approaches. It allowed us to rapidly and inexpensively gather data from many more participants than would have been practical with other approaches. Data integrity was guaranteed by dropping participants whose answers had near-zero variances, e.g., all 3's. As a result, a total of 27 of them were discarded, leaving data from 73 participants (23 females, M_{age} =48.04, SD_{age} =14.12). All participants were native Japanese speakers.

We used video recordings to demonstrate all the candidate expressive lights. For each video, we provided two statements to evaluate the participants' perception of the robot: "This robot looks attractive" and "This robot looks hostile." A five-point Likert scale was used for the statements (ranging from 1, strongly disagree, up to 5, strongly agree). Each participant in the study viewed all 44 videos and rated them one at a time (within-participant design), and the order of the videos was randomized.

Criteria

We analyzed the candidate expressive lights with regard to the two perceptions, attractive and hostile, separately. For the evaluation, we introduced two criteria (adapted from [22]) to select good light expressions: 1) an expression must have a strong interpretation with regard to a perception (mean Likert rating in the top quartile) and 2) an expression must be iconic, meaning that it has only one dominant perception among the two (an expression should not be perceived as both attractive and hostile). We assessed the iconic-ness of each candidate expression that meets criteria 1.

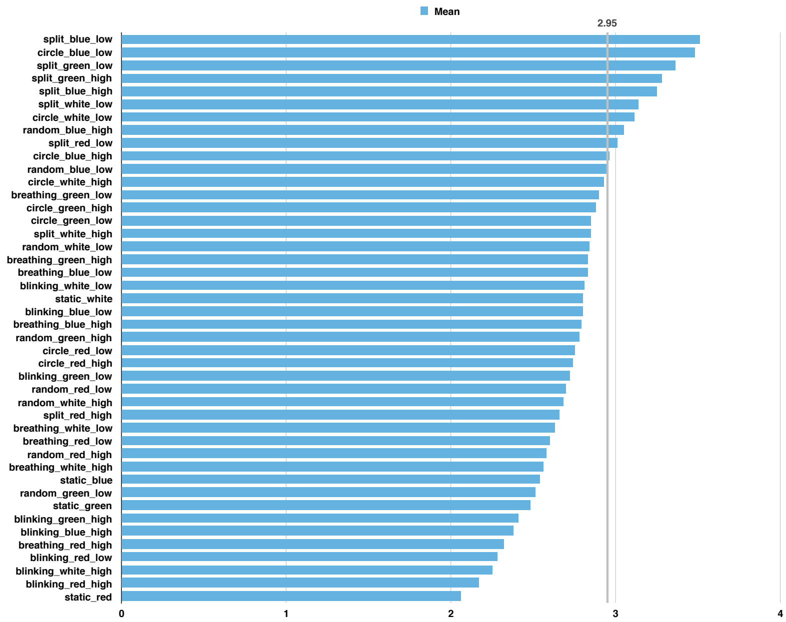


Figure 2.11: Mean Likert ratings for attractive perception.

Results

We summarized the ratings from all 73 participants. Figures 2.11 and 2.12 show the mean Likert ratings for attractive and hostile, respectively. Because we used a single Likert term rather than constructed scales to assess human perception, statistic measures, such as ANOVA, were not appropriate. Instead, we characterized the main trends observed in the data and reported on them with regard to each perception.

Attractive: We recommend *split_blue_low* (a low-intensity blue split pattern) and *circle_blue_low* (a low-intensity blue circle pattern) for showing attractiveness. These are iconic and the top two highest-rated light expressions (see Fig. 2.11). The commonality between the two light expressions is straightforward in that they both feature the color blue and have a low intensity. In general, it can be observed that expressive lights with one or more of the following three features received high ratings from the participants: 1) blue, 2) low intensity, 3) pixel-based patterns (particularly split and circle ones). On the other hand, expressive lights with one or more of the following three features received low ratings for attractiveness: 1) red, 2) high intensity, 3) strip-based patterns.

Hostile: We recommend *blinking_red_high* (a high-intensity red blinking pattern)

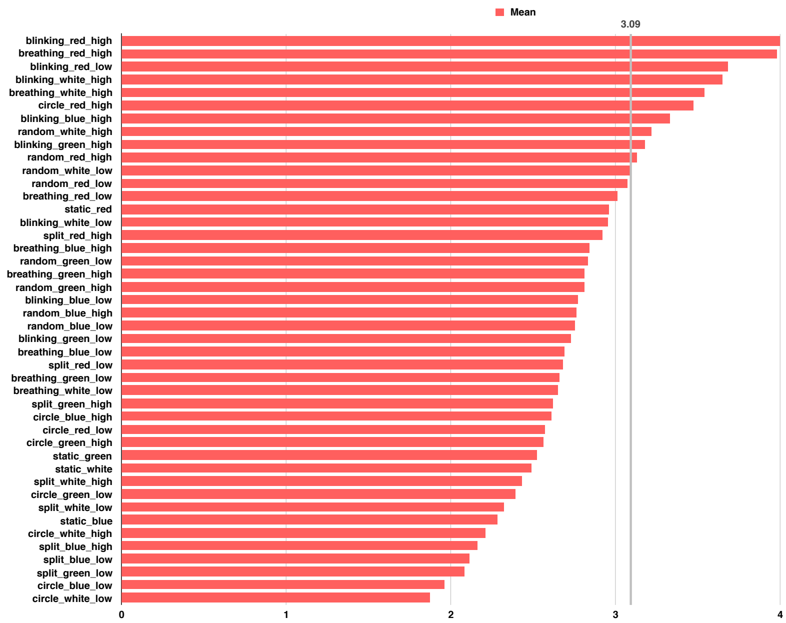


Figure 2.12: Mean Likert ratings for hostile perception.

and *breathing_red_high* (a high-intensity red breathing pattern) for showing hostility. These are iconic and the top two highest-rated light expressions (see Fig. 2.12). The commonality between the two light expressions is clear in that they both feature the color red and have a high intensity. In general, several trends can be observed that show that expressive lights with one or more of the following features received high ratings: 1) red, 2) high intensity, 3) strip-based patterns (particularly blinking and breathing). Oppositely, expressive lights with one or more of the following features received low ratings for hostility: 1) low intensity, 2) pixel-based patterns (particularly split and circle ones).

Discussion

Four expressive lights were selected as effective expressions for the Roomba robot to show either attractiveness or hostility. The results offer strong evidence, indicating that expressive lights can effectively affect a human's perception of a robot. To be specific, we found that the robot was particularly attractive when showing blue light at a low intensity. In addition, the split and circle patterns turned out to be more absorbing compared with the other patterns. We also found that the robot was perceived as particularly hostile when showing red light at a high intensity. Both blinking (rectangular) and breathing (sinusoidal) patterns were selected, suggesting that waveform was a less important factor compared with color and intensity (frequency). However, it is noticeable that the two patterns are strip-based patterns. This indicates that high luminance may be of importance for showing hostility as well.

Interestingly, features of these four expressive lights can be observed in a variety of bioluminescent ocean creatures. Edith Widder demonstrated plenty of bioluminescent light behaviors performed by sea creatures, where many of them showed similar patterns. This indicates that bioluminescent lights used by natural creatures may have analogous effects on human perception and psychological functioning. In addition, the results are in line with color psychology theories. As suggested by color psychology literature [78, 142], red carries the meaning of danger and hostility and moreover makes people more alert and risk averse, whereas blue elicits pleasure and encourages people to take risks. Therefore, it can be presumed that blue light, in many situations, is more attractive than other colors, while red light conveys a negative effect.

2.3.5 Follow-Up Verification Study

As we worked through a structured process for designing affective expressive lights, we were able to offer a set of four light expressions that can well show attractiveness and hostility. However, the effectiveness of such lights had not yet been examined in practical HRI scenarios. Therefore, we further conducted a verification experiment in which the same Roomba robot with LED lighting system was employed. In the follow-up study, we evaluated the effectiveness of the recommended light expressions by observing whether people would be willing to approach and interact with the robot when it showed attractiveness and whether they would consider keeping away from it when it showed hostility.

Procedure

We designed two HRI scenarios: *robot approaches human (RH)* and *human approaches robot (HR)*. To be specific, in RH, the Roomba robot moved toward a person (experimenter) proactively, whereas, in HR, the person moved toward the robot. Particularly in HR, the robot started to show expressive lights when the person was within about

(a) RH_none (b) RH_split (c) RH_blinking

(d) HR_none (e) HR_split (f) HR_blinking

Figure 2.13: Screenshots of each video clip (condition)

2 m. RH was designed to simulate a scenario in which a robot tries to initiate an interaction with a person, and HR was to simulate a scenario in which a robot is approached by an unwanted person.

We employed the same Japanese online crowdsourcing platform to recruit participants for this study. Video recordings were used to demonstrate the two HRI scenarios via an online survey. For each scenario, we provided one synthetic video involving three conditions: the robot showing attractiveness, the robot showing hostility, and the robot not showing any expressive light. With regard to the attractiveness condition, we picked *split_blue_low* as the representative light expression. Similarly, we chose *blinking_red_high* as the representative light expression for the hostility condition.

Figure 2.13 shows screenshots of each video clip. It is notable that although the screenshots show a large difference in distance between the camera and the robot regarding the two scenarios (RH and HR), this was due to the different timings of taking these screenshots. In RH, the robot is close to the person, which shows the effect of the robot's approach behavior (the robot has moved a long distance from its original position). Similarly in HR, the person is seen standing close to the robot, which indicates the person's approach behavior (the person has moved a long distance from his original position). The order of the three clips for each scenario was randomized. Participants whose responses had near-zero variances were removed from the results evaluation. In total, 16 of them were discarded, leaving data from 205 participants (68 female, M_{age} =50.97, SD_{age} =13.03). All the participants were Japanese.

With regard to each synthetic video, we prepared four statements to evaluate the participants' perception of and attitude toward the robot: 1) "This robot looks attractive," 2) "This robot looks hostile," 3) "I like this robot," 4a) "I want to play with this robot" (RH scenario), and 4b) "I want to keep away from this robot" (HR scenario). For each statement, the participants were asked to choose the robot presented in one of the three conditions that best fit the statements. The selection rate (SR) was counted for each condition. The SR number, ranging from 0 to 205 (total amount of participants), indicated how many participants chose a robot for a particular statement. Similar approaches were used in other studies, e.g., [84].

Results

We applied Pearson's chi-square test to evaluate the effect of the independent factor (expressive light) on the five statements as dependent factors. A post-hoc binomial test with Holm's correction was further applied if a significant difference was found. Because of the three conditions, the hypothesized probability that each condition would be chosen at random with regard to a statement was set to one-third (33.33%, which is the probability of a random guess).

Figure 2.14 shows the selection rates with regard to the participants' perception of the robot. For each statement, a significant difference was found for both the RH scenario (attractive: $\chi^2(2) = 157.09, p < 0.001$; hostile: $\chi^2(2) = 203.01, p < 0.001$; likeable: $\chi^2(2) = 123.11, p < 0.001$; want-to-interact: $\chi^2(2) = 113.98, p < 0.001$) and

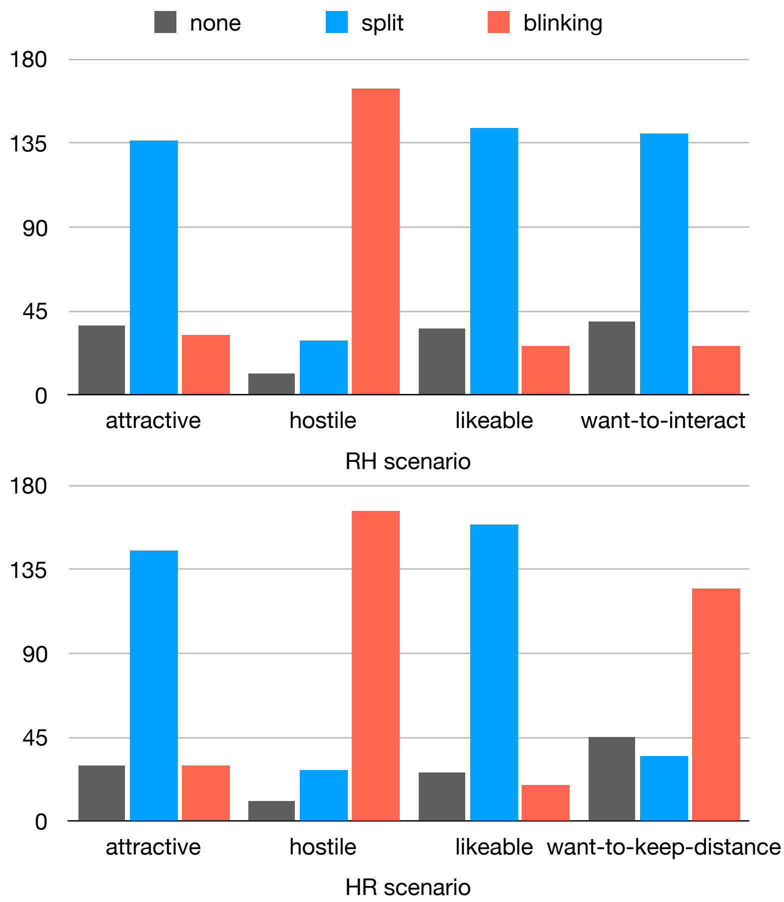


Figure 2.14: Selection rates for each statement for RH scenario (above) and HR scenario (below)

the HR scenario (attractive: $\chi^2(2) = 129.02, p < 0.001$; hostile: $\chi^2(2) = 211.5, p < 0.001$; likeable: $\chi^2(2) = 180.71, p < 0.001$; want-to-interact: $\chi^2(2) = 71.22, p < 0.001$). The post-hoc tests suggest that the conditions with the top SR, e.g., split_blue_low for *attractive* and blinking_red_high for *hostile*, were selected as the ones that most fit the corresponding statements (significantly above 33.33%, $p < 0.001$), while the SRs for the other conditions were all significantly below 33.33% ($p < 0.001$).

Discussion

The results verify the effectiveness of our recommended expressive lights on people's perception of a robot. The robot showed that split_blue_low was particularly perceived as attractive and preferred by the participants, while it was perceived as hostile when showing blinking_red_high. This meets our expectation as expressive light split_blue_low was recommended to show attractiveness and blinking_red_high was recommended to show hostility. Moreover, the participants' attitudes toward the robot was influenced as they preferred to play/interact with the robot when it showed split_blue_low, whereas they considered keeping their distance from the robot when it showed blinking_red_high.

2.3.6 Discussion

This work explored the design of expressive lights for a Roomba robot to influence humans' willingness to interact with it. The goal was to allow robots to either attract people so that they can more easily initialize an interaction with them, or keep people away so that they can escape from a potentially harmful interaction. Our work expands on previous studies [85, 84] in terms of the following three points. First, we took inspiration from bioluminescence and showed that LED lights that simulate communication cues used by living creatures may have analogous effects on human perception and psychological functioning. Second, we proved that findings from color science and color psychology can be referred to as theoretical groundings by HRI researchers to design effective light expressions. Third, we tested a large design space that contained 44 candidate light expression combinations from a possibility of four colors, six patterns, and two levels of intensity. This allowed us to observe common trends for the effects of the features of expressive lights (color, pattern, and intensity) regarding two perceptions: attractiveness and hostility. To summarize, our findings suggest that there are potential effects of expressive lights on influencing people's perception and behavior, therefore we intend to delve further into the exploration of the use of expressive lights in HRI.

On the basis of the results, we offer five design guidelines for the design of affective expressive lights:

I. Blue light is recommended to show attractiveness in a robot;

II. Red light is recommended to show hostility in a robot;

III. Patterns such as split and circle can be attractive to humans;

IV. A low intensity (frequency) can be used to support the expression of attractiveness, while a high one can be used to support the expression of hostility;

V. With regard to expressing strong or weak emotions, the type of waveform, e.g. rectangular or sinusoidal, is less important compared with color and intensity.

2.3.7 Limitations and Future Work

Several limitations of this work should be recognized. First of all, the effects of expressive lights on human behavior (in practical HRI contexts) remain purely potential as we did not explicitly investigate dynamic human interaction behavior. In this study, we employed a video-based HRI method because such a crowd-sourcing-based approach enabled us to access a large and diverse set of participants. Compared with a live HRI method, previous studies (e.g., [21]) have shown that a video-based method can provide comparable results in certain contexts, such as when a robot approaches a person (similar contexts are used in this work). However, people's perception and especially their behavior would possibly differ in contexts where s/he were a participant of an interaction or were simply an onlooker. Therefore, future work needs to apply live HRI to reveal direct evidence for the influence of expressive lights on human behavior.

It should also be noted that the results of the first experiment seemed to have fairly small effect sizes. With regard to the analyses of both attractive and hostile perceptions, the majority of ratings were given within the range of two to four. Therefore, the fact that the effect on people was not so large means that this work may not be able to support strong recommendations for using the four expressive lights. However, since both the trends observed in the first experiment and the results of the validation study support our findings, we consider our proposed general design guidelines to be valid and useful.

Besides, due to the fact that color carries different meanings in different contexts [140], the generality of this work may be limited. Therefore, research on expressive lights needs to be explored with various HRI contexts. Moreover, since the effects of color on humans may depend on culture (in particular cases, for example, red has positive meanings in Chinese culture) [140], it is also of importance to test our findings (obtained with Japanese participants) on people with different cultural backgrounds.

This work can be further explored. We decided upon our 44 candidate expressive light patterns by referring to color psychology theories and bioluminescent light patterns in nature. Different design approaches (e.g., [8, 86, 144, 145]) can be applied to the early design stage to guarantee that a set of highly representative candidate light patterns are prepared for the later experiments and analysis. With regard to evaluation, interaction attributes [144, 145], as a set of vocabulary for describing interaction experience, may be useful for investigating people's subjective experience of perceiving and interacting with the robot. We also suggest applying constructed scales rather than single terms (attractiveness and hostility) to investigate people's perception. In addition, future work is required to investigate more design factors (e.g., a robot's shape and arrangement of LEDs). Results from such studies would provide further insights and be more generalized to various types of robots.

2.4 Narrative Frame Impacts Perception and Interpretation

2.4.1 Introduction

Recently, robots are becoming a part of human society. As a consequence, these robots need to be capable of interacting with people. This requires an adequate level of transparency of the robots' internal state and ease of understanding of their intent and behavior for naïve users [11].

Because people are explanatory creatures, we build mental models, our conceptual models of the way objects work or people behave, of things and use the models to help us understand our experiences and handle unexpected occurrences [10]. Therefore, when we encounter a human-shaped robot, we naturally adapt our knowledge and social skills and form mental models in order to facilitate our interaction with it [11]. Similar process happens when we meet an animal-shaped robot.

However, a large number of robots currently in use for applications such as search and rescue and domestic cleaning which are neither anthropomorphic nor zoomorphic. When we first encounter such robots, the lack of appropriate knowledge and mental models with regard to these robots can lead to unsmooth or even failed interaction

[19]. Bethel et al. [20] indicated that these appearance-constrained robots do have an urgent need for certain social abilities. Therefore, there is a significant challenge in finding effective ways for these robots to successfully interact with humans.

Due to the effect of adaptation gap [17], interaction modalities such as natural language are not appropriate for the appearance-constrained robots as they may unnecessarily raise the expectations of these robots' functional and social capabilities from the users. Existing approaches, therefore, mainly focus on nonverbal cues such as motion [88, 12, 13, 8]. Unfortunately, such methods suffer from low expressibility and are hard, if not impossible, to be applied in many scenarios such as places that have restricted space.

Alternatively, previous research showed that expressive lights, as a dynamic vision cue, can be used for robots to communicate their intent and make explainable behavior. For instance, Sony's robot dog AIBO and Aldebaran's NAO use LED lights to assist in affective social interaction. Basically, expressive lights has been shown to be effective in various human-robot interaction (HRI) contexts such as indicating internal states [18], communicating intent [85], and expressing emotion [120]. The goals of using expressive lights on a social robot can be summarized by the three I's: inform, Influence, and Interact [84].

To be specific, several studies have explored various functional uses of lights for robots. For instance, Baraka et at. [18] applied expressive lights to visualize their mobile service robot's internal state. They designed different light expressions to indicate that the robot is waiting for human input, is being blocked by a human, or is showing task progress. Szafir et al. [85] investigated design constrains to robot flight behaviors. They demonstrated that their designed light patterns were able to greatly improve people's response time and accuracy for predicting the flying direction of the robot. Song and Yamada [146] explored the design of affective light expressions inspired by bioluminescent light behaviors. Their robot was able to show either attractiveness or hostility by displaying particular light expressions.

Despite the many promising results, a commonality with regard to the previous studies is that they focused on specific tasks or goals, such as conveying internal states of a service robot or expression emotions. An essential limitation of their methodologies is that assumptions were made, either consciously or unconsciously, with regard to the functionality and meaning of the lights shown by their robots. To be specific, expressive lights were pre-assumed to be with the functionality of convey information of internal state, intent, or pure emotion, where such assumptions were formed to serve the researchers' objectives. These assumptions were further delivered to the participants, either explicitly or implicitly, during the experiment stage.

We argue that such limitation of methodology is essentially dangerous as naïve users would not be able to identify the particular functionality of a light expression shown by a robot (Is the robot unhappy or is it just needed to be charged?). They, instead, would make subjective interpretations with regard to the meaning of the light expression on the basis of their knowledge of the light expression itself (e.g. color and pattern), their knowledge of the robot (e.g. type and embodiment), and the context they are in. And in particular, they build up narratives and make interpretations accordingly.

In this work, we conducted a mixed-methods exploration into our hypothesis and argument on how naïve users perceive and interpret the meanings of expressive lights shown by a robot, appearance-constrained robot in particular. To be specific, we hypothesize that people build narratives of the robot and their perception and interpretation of the robot's behavior are heavily impacted by their narrative framing. In other words, we argue that people's perception and interpretation of the robot's behavior are influenced by mainly three factors: *design of light expression*, *type of robot*, and *context* (e.g. when and where). We prepared in total 20 scenarios (2 expressive lights $\times$ 10 contexts) and listened to participants' free descriptions of what they thought the robot was doing. Further using both quantitative (independent samples t-test) and qualitative (thematic analysis [147]) analysis, we confirmed that the narrative frame that participants built into the robot heavily impacted valence perception (positive vs. negative) and interpretation of the robot's behaviors. In particular, design of light expression significantly impacted valence perception while context has a powerful influence on behavior interpretation. In general, all the three factors contribute to the perception and interpretation of the robot's behavior.

Rational and Contributions

Bucci et al. [148] has shown the powerful impact of narrative frame on people's perception of a simple furry robot's emotion. In their work, they designed eighteen breathing behaviors, differing in complexity of patterns, for a furry robot toy. Their objective was to investigate into how the complexity and variability of a simple robot's breathing behaviors impact its perception as emotionally valenced (positive vs. negative). A key finding reveals that participants formed various stories of the robot's behaviors and the narrative frame that they built into the robot heavily impacted valence perception.

An important point of such methodology is to ensure participants' freedom of imagination. In practical HRI scenarios, a naïve user normally possesses little knowledge of the robot he or she is interacting with. This is particularly true if the robot is constrained in appearance. Therefore, any assumption that be delivered to participants (e.g. the expressive lights shown by the robot are expressions of emotions) may lead to biased experimental results.

Therefore, similar as Bucci et al's approach, we, in this work, did not control narrative frame as an experimental variable. We let participants freely imagine what was happening in a scenario and what the robot was doing in the scenario, and we listened to their descriptions of their imagination. We believe that this is an adequate approach to discover what and how are naïve users perceive and interpret a robot's behavior in an interaction.

Other than Bucci et al's approach, we controlled context as a main variable. The control of context can inevitably constrain participants' narrative framing. However, we consider this is necessary. Due to the nature of HRI, context is indispensable to any practical interaction. In other words, every HRI takes place in some kind of context. This promotes context as an important factor in many HRI studies [149, 34]. Consequently, by controlling the context of interaction, we are able to achieve deep understandings of whether and how people's perception and interpretation of a robot's behavior are context-depended, and such findings can offer significant contributions to HRI and related research.

Our main contribution is that we show people's narrative framing has powerful influence on both valence perception and interpretation of a robot's behaviors. Particularly, we suggest design of light expression (e.g. color and intensity) strongly impact valence perception and context has a powerful influence on the diversity of behavior interpretation.

2.4.2 Expressive Lights Design and Robot System

Design Expressive Lights

Color is one of the most ubiquitous phenomena in human experience as it is perceived on essentially every object that we view. Although research on color psychology is still at a nascent stage, color psychologists have intensively investigated various aspects of color, including color vision, color symbolism and association, and color effects on psychological and biological functioning [140]. Elliot and Maier [129] reviewed both theoretical and empirical work that investigated the effects of perceiving color on psychological functioning in humans. Their work clearly shows that color can carry important meaning and can have a significant impact on people's affect, cognition, and behavior.

Red has been shown to be critical color and has thus garnered the majority of research attention. Many things in biology, culture, and language point to the poignancy and prominence of red [129]. Red is the color of blood, and dynamic variations in visible blood flow on the face and body can indicate fear, arousal, anger, and aggression [150]. Red is used in aposematic (warning) signals by many poisonous insects and reptiles [151]. Red is also a term that appears in almost all lexicons and, moreover, in many sayings such as "in the red." Besides red, a few other colors, particularly green and blue, have been intensively studied as well. They both have positive links in the natural realm, for example, green foliage and vegetation and blue sky and ocean [129].

Hue emotion associations have been an active research topic in psychology [140]. The associative learning theory suggests that the formation and activation of color associations can be understood through models of semantic memory, and a number of previous studies have provided empirical evidence of color-emotion associations and psychological functioning [152]. Specifically, color meanings can be grounded in two basic sources: learned associations that develop from repeated pairings of colors with particular concepts or experiences and biologically based proclivities to respond to particular colors in particular ways in particular situations [128]. For instance, a specific red-danger association can be generated from experiences with regard to (life-threatening) situations such as viewing blood, an angry face, traffic lights, and/or warning signals and sirens [129]. Similarly, green can be associated with positive meanings, e.g., approach and pleasure, due to experiences with green traffic lights

Table 2.5: Two expressive lights designed in this work

Light	Color	Waveform	Period (ms)	Expected Effect
GL	RGB: 0,255,0	sinusoid	1000	induce positive perception
RH	RGB: 255,0,0	rectangle	200	induce negative perception

and the general image of being the color of natural, and blue can be associated with sadness due to the say "I feel blue."

On the basis of the above short survey on color psychology and related work, we decided to focus mainly on two colors: green and red. They are two intensively studied colors and, moreover, they produce opposite effects on human psychological functioning. In general, green can be associated with positive perception, while red can be associated with negative perception.

Besides color, two more parameters, waveform and intensity (frequency), needed to be decided to design expressive light patterns. In particular, Terada et al. [86] studied color and dynamic parameters for representing emotions. They found that a rectangular waveform with a high frequency represents intense emotions, while a sinusoidal waveform with a low frequency represents weak (low intensity) emotion. On the basis of their work, we decided to combine a sinusoidal waveform and a low frequency with green to enhance the effect of the color green. Similarly, we combined a rectangular waveform and a high frequency with red to enhance the effect of the color red. Table 2.5 lists the two expressive lights.

Design Rational We did not treat expressive lights parameters (color, waveform, and intensity) independently. Instead, we referred to related literatures and theories and pre-assigned typical values to them. This resulted in two light expressions, GL and RH, which could be associated with opposite valence perceptions. We consider this approach is valid due to the objective of this study. There may be concerns about an interaction effect among color, waveform, and intensity, making it difficult to understand if the perceptions of the robot's behavior are to be attributed more to which parameter. However, since we set our focus on the impact of narrative frame on people's perception and interpretation of expressive lights of a robot, we mainly controlled context as an important variable to the building of narrative frame of the participants. Therefore, we wanted to reduce the complexity of the other variables so that we could reach a clear and deep understanding of our research question, although such understanding may hardly be complete. We were afraid that introducing too many variables (including levels of a variable) would make the analysis hard and unreliable.

The designed two light expressions were used as a manipulation of the participants' valence perception of the robot's behavior because valence can contribute to the building of narrative frame. By investigating on two expressive lights that had opposite psychological effects, we were able to discover how the participants' narratives were related to their valence perceptions. Such findings can contribute to design implications for the design of effective light expressions for robots.

Roomba Lighting System

We installed an LED lighting system on an iRobot Create 2 robot, which is a Roomba robot. Roomba is a series of autonomous robotic vacuum cleaners used in in door environments. It perfectly fits the definition of an appearance-constrained robot and has very limited ways to express itself, e.g., moving forward/backward and spinning. Figure 2.15 shows the configuration of the robot with LED lighting. We used one meter of a NeoPixel LED strip (60 pixels). The LED strip was controlled by an Arduino Uno R3 board, and both the strip and the board were powered by a 5-V, 3-A portable powerbank. The same board was also used to control the movements of the robot.

By using expressive lights, we are effectively enabling the robot to modify its appearance as a method of communicating with humans. It provides additional cues to assist in interpreting the robot's behavior and intent. We expect that the expressive lights can facilitate people to construct rich and complex interpretations.

2.4.3 Exploration

We worked through a structured process to investigate how do people perceive and interpret expressive lights shown by a robot. To explore this question, we first took advantage of the knowledge and opinions of groups of people to ground and enrich our understanding from a naïve user's angle of view. By using online crowdsourcing, we were able to rapidly and inexpensively gather information from many more participants

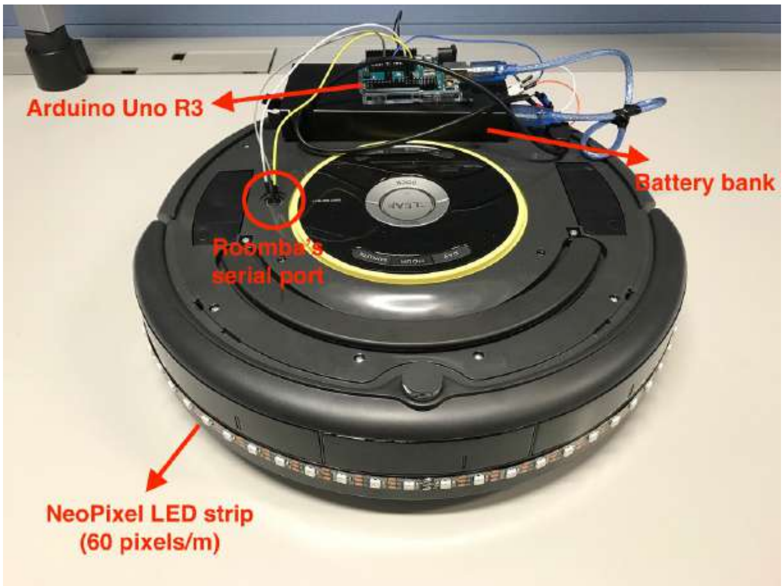


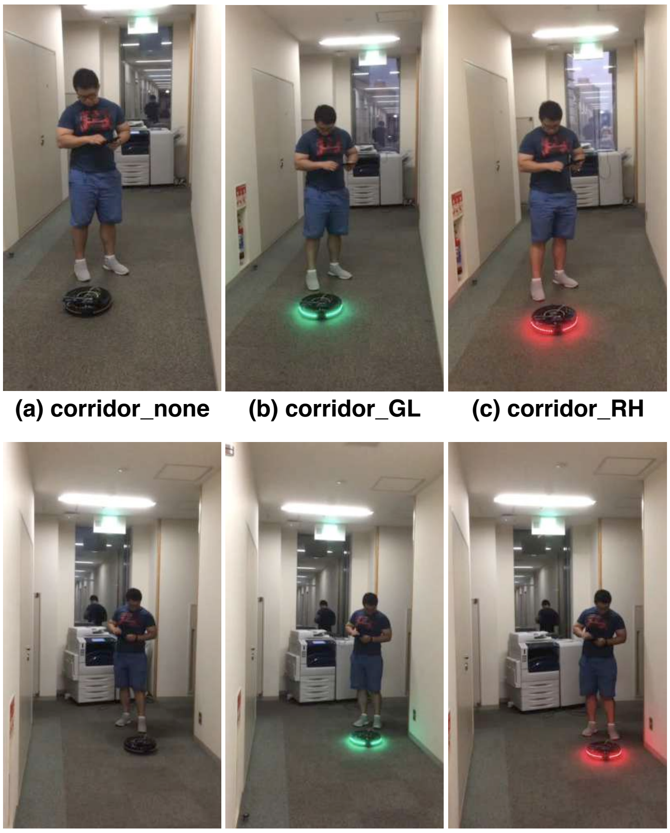
Figure 2.15: Configuration of Roomba robot with LED lighting system

than would have been practical using other approaches [22]. The crowded-sourced approach has been shown effective and powerful by previous studies [153, 23].

We first performed an initial exploration to uncover people's perception of a robot showing expressive lights when they were not informed with the functionality of the lights. We asked the participants simple open-ended questions such as "What was the robot doing?" to avoid delivering implicit assumptions (e.g. the robot is showing an emotion or a task-related state) to them. We then worked on establishing a list of contexts that are most familiar to naïve people. An example of such context can be *home*. Finally, we consolidate the findings from the two exploration studies and decided upon a set of scenarios in which expressive lights were used by a robot as a method of communication to humans in different contexts.

Initial Exploration

The initial exploration mainly serves as two purposes. Firstly, we wanted to affirm the effects of our designed light expressions, GL and RH. We would like to see if they indeed had positive (for GL) or negative (for RH) bias on the participants' valence perception. Secondly, we wished to investigate if the participants indeed made various interpretations of the robot's behavior. In other words, we wanted to have a preliminary



(a) corridor_none (b) corridor_GL (c) corridor_RH

(d) corner_none (e) corner_GL (f) corner_RH

Figure 2.16: Screenshots of each video clip (condition)

understanding on whether narrative frame has impact on the participants' valence perception and behavior interpretation of the robot.

The findings can be then used as empirical evidence and theoretical groundings for our formative exploration study. It can help us to achieve a more focused thematic analysis.

Procedure We considered two similar practical HRI contexts, *corridor* and *corner*, which are common for indoor autonomous robot [84]. Specifically, the Roomba robot moved along a narrow corridor (corridor context) or approached a corner of the corridor (corner scenario). In the two cases, the robot encountered a person and stopped before it ran into the person. While stopped, the robot further showed GL, RH, or simply no lights (see Figure 2.16). We presumed that the robot's intent, i.e., what it wanted to do, in such contexts would be ambiguous and thus could be interpreted in various ways. We presumed that the added expressive lights could significantly affect and bias people's perception and interpretation of the robot's behavior.

The experiment had a between-participant design, where each person viewed two videos belonging to the same condition (GL, RH, or None). A Japanese online crowdsourcing platform (Fastask) was employed to recruit participants. We initially hired 180 participants, 60 for each condition. In a questionnaire, we asked three open-ended questions: 1) What was the robot doing? 2) Did the robot want to communicate something to the person? If yes, what information did the robot want to communicate? 3) Do you think that the robot was friendly?

Results After filtering out unreliable data, we had 40 participants from the None condition (11 females, M_{age} = 39.9, SD_{age} = 7.6), 40 participants from the GL condition (14 females, M_{age} = 42.3, SD_{age} = 9.3), and 40 participants from the RH condition (14 females, M_{age} = 43.6, SD_{age} = 8.6). We analyzed all their answers and observed interesting findings. We summarize the key findings below.

I In the RH condition, 15 out of 37 participants (41%) used negative words, such as warning or hostile, to describe the robot and its behavior. No participants (0 out of 40, 0%) in the None condition and only 1 participant (1 out of 42, 2%) in the GL condition used such descriptions.

II In the RH condition, only 8 out of 37 (22%) participants described the robot as a cleaning robot. However, half of the participants (20 out of 40, 50%) in the None condition and almost the same number of participants (20 out of 42, 48%) in the GL condition explicitly described the robot as a cleaning robot.

III In the GL condition, a majority of the participants (32 out of 42, 76%) perceived the robot as friendly. In comparison, half of the participants (19 out of 40, 48%) in the None condition, and, in particular, only 12 participants (12 out of 37, 32%) in the RH condition perceived the robot in the same way.

IV Participants showed different levels of imagination when explaining what was happening in the videos. Specifically, participants in the None condition showed a low level of imagination. They generally described the robot's behavior in three different ways: the robot was cleaning, moving (tele-operated), and approaching the person (intended). However, participants in both the GL and RH conditions showed a high level of imagination (described the robot's behavior in 5 and 6 ways, respectively). People in the GL condition described the robot as cleaning, moving (tele-operated), approaching the person (intended), communicating to the person, and playing; people in the RH condition thought the robot was cleaning, moving (tele-operated), approaching the person (intended), warning the person, patrolling, and malfunctioning.

V On average, participants used less words to answer the three open-ended questions in the None condition (83.9 words/person). In comparison, participants in the GL and RH conditions used 91.7 w/p and 90.9 w/p, respectively.

Preliminary Findings The findings show that RH expressive lights can have a particularly strong negative bias on people's perception of a robot. People tend to interpret the robot's behavior in a negative way. In comparison, GL expressive lights can have a positive bias on people's perception of a robot. Interestingly, in general, people tended to interpret the robot's behavior as goal-directed when it showed either GL or RH. This indicates that they perceived the robot as having intent (beliefs and desires). As summarized in finding II, far fewer participants, especially in the RH condition, described the Roomba robot as a cleaning robot, suggesting that they anthropomorphized the robot in both the GL and RH conditions more than in the None condition. Therefore, we infer that social HRI is more likely to be established when a robot shows expressive lights as a means of communication.

Further, we found that expressive lights can affect how a person perceives the friendliness of a robot. Summarized in finding III, most participants perceived the Roomba robot as friendly in the GL condition, and on the contrary, the lowest number of participants thought so in the RH condition. This can be explained by referring to findings I and IV. Finding IV particularly lists how participants imagined and interpreted the scenarios in the videos. Besides the common interpretation that the robot was cleaning, moving (tele-operated), and approaching the person (intended), participants in the GL condition additionally imagined that the robot was either trying to communicate to the person or playing. These interpretations are positive in general, which is probably why people interpreted the robot as friendly. On the contrary, both findings I and IV clearly suggest that participants in the RH condition thought that the robot was giving warnings and was hostile. It is thus not surprising that they treated the robot as less friendly.

Contexts: Where Could This Take Place?

Next, we created a second online survey to gather information on where HRI scenes (e.g. a robot approach a person and shows an expressive light) could take place.

Procedure A Japanese online crowdsourcing platform (Yahoo crowdsourcing) was employed to recruit participants. We initially hired 50 participants. In the survey, we provided a figure of example HRI scene to help the participants frame their ideas with constrains such as robot type (disc-shaped robot) and robot's behavior (showing an expressive light). This was necessary as we did not want the participants to provide ideas that were our of the focus of this work. Besides the figure, we provided a brief explanation of the scene, saying that "In a *corridor of a research institute*, a robot approaches a person and tries to communicate via LED lights." We instructed the participants to imagine how could a similar interaction take place in other contexts. Each participant was asked to list 3 contexts.

Results Due to technical issues, we had the participants who viewed the survey on mobile phones reported that the example image could not be displayed. Therefore, their responses were not included in the analysis. In addition, we filtered out unreliable responses that were clearly inappropriate (e.g. meaningless numbers). We eventually had 21 participants (16 females, $M_{age} = 42.7$, $SD_{age} = 11.6$).

We then coded their responses and grouped the similar codes into same contexts. For instance, codes such as"living room", "bath", and "kitchen" were grouped into the context *home*. As a result, we grouped in total 109 codes into 23 distinct contexts. A summarization of the contexts is shown in Figure 2.17.

Findings The results demonstrated the breath of possible HRI contexts. However, some of the contexts showed higher popularity than the others. The top 10 most

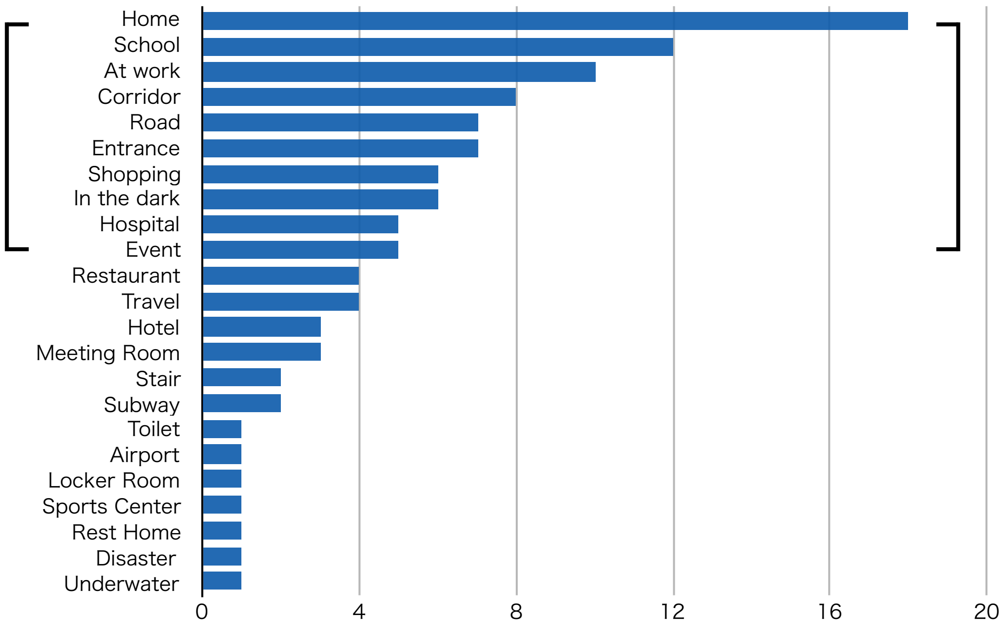


Figure 2.17: Summary of contexts collected

mentioned contexts were home (18), school (12), at work (10), corridor (8), road (7), entrance (7), shopping (7), in the dark (6), hospital (5), and event (5).

Consolidation

The initial exploration revealed the effects of our designed expressive lights (GL and RH) on people's valence perception, and the second survey demonstrated a list of most popular contexts at where HRI scenes could take place. Using data from the two studies, we formulated a vocabulary of HRI scenarios on the basis of the three factors: design of light expression, type of robot, and context.

Particularly, we manipulated the values of each factor and created in total 20 scenarios (2 design of light expression $\times$ 1 type of robot $\times$ 10 contexts):

1a/b: The robot approaches a person and shows GL/RH when at home.

2a/b: The robot approaches a person and shows GL/RH when at school.

3a/b: The robot approaches a person and shows GL/RH when at work.

4a/b: The robot approaches a person and shows GL/RH when in a corridor.

5a/b: The robot approaches a person and shows GL/RH when along a road.

6a/b: The robot approaches a person and shows GL/RH when at an entrance.

7a/b: The robot approaches a person and shows GL/RH when at a shopping center.

8a/b: The robot approaches a person and shows GL/RH when in a building at night.

9a/b: The robot approaches a person and shows GL/RH when in a hospital

10a/b: The robot approaches a person and shows GL/RH when at an exhibition.

Note that we used concrete contexts to replace the ones that were too abstract (e.g. event were replaced by exhibition).

2.4.4 Experiment: Narrative Framing

The explorations provided a list of 20 HRI scenarios. What was unknown was how people perceive and interpret the robot's behavior with regard to each scenario. As findings from the initial exploration provided empirical evidence on the impact of narrative frame, we, in this study, sought for deeper understandings with regard to the research question. Therefore, we listened to the participants' free descriptions of what they thought the robot was doing and further applied thematic analysis in a deductive way. This means that the coding of the data from the experiment was driven by our analytic interest (e.g. hypothesizes).

Procedure

The experiment had a within-participant design, where we conducted a mixed-methods study to evaluate the participants perception and behavior interpretation of the robot with regard to the 20 HRI scenarios. Ten Japanese (3 females, $M_{age} = 25.9$, $SD_{age} = 8.7$) were recruited from the University of Tokyo. We considered the participants as naïve users as none of them had experience in using or working with a robot before the experiment.

The participants were first greeted and explained about the general instructions of the experiment. Then, they were asked to get ready for the main tasks. In this study, the main tasks were divided into 10 sections, each section represented a context. Moreover, each section consisted of two subsections, each subsection represented one expressive light (GL or RH). For each subsection, participants were asked to watch a short video clip (screenshots see Figure 2.18) demonstrating a HRI scenario in which a same robot approached a same person and displayed one expressive light (GL or RH). After watching the video, participants were instructed to think about what if such a scenario took plade in the context which represented the current subsection. They were then asked to rate the valence of their perception of the robot's behavior using a five-point Likert scale (ranging from 1, negative, to 5, positive) and to provided a brief description of the robot's behavior. This was iterated until all sections were finished. To summarize, the flow of performing the entire main tasks can be considered as *1a (home, GL) -> 1b (home, RH) -> 2a (school, GL) -> 2b (school, RH) -> ... -> 10a (exhibition, GL) -> 10b (exhibition, RH)*. After then main tasks, participants were presented a post-questionnaire in which they had to give free comments to questions such as "What kind of activity was the robot doing and why?" Finally, participants were thanked and compensated 1500 Japanese yen (about 14 dollar).

Measurement

To investigate the participants' perceived valence of the robot's behavior, we used a five-point Likert scale (ranging from 1, negative, to 5, positive) and asked the question "Please rate how positive or negative the robot's behavior seemed to you." To uncover their narratives on the robot's behavior, we used open-ended question such as "Please briefly describe the robot's behavior."

2.4.5 Experiment Design Rationale

In the experiment, we instructed the participants to imagine about the robot's behavior in different contexts. We did not provide them video clips of real contexts as we were afraid such videos would suppress the participants' power of free imagination. For instance, we would only be able to demonstrate concrete instances, such as a living room, to represent the home concept. This would inevitably set constrains to the

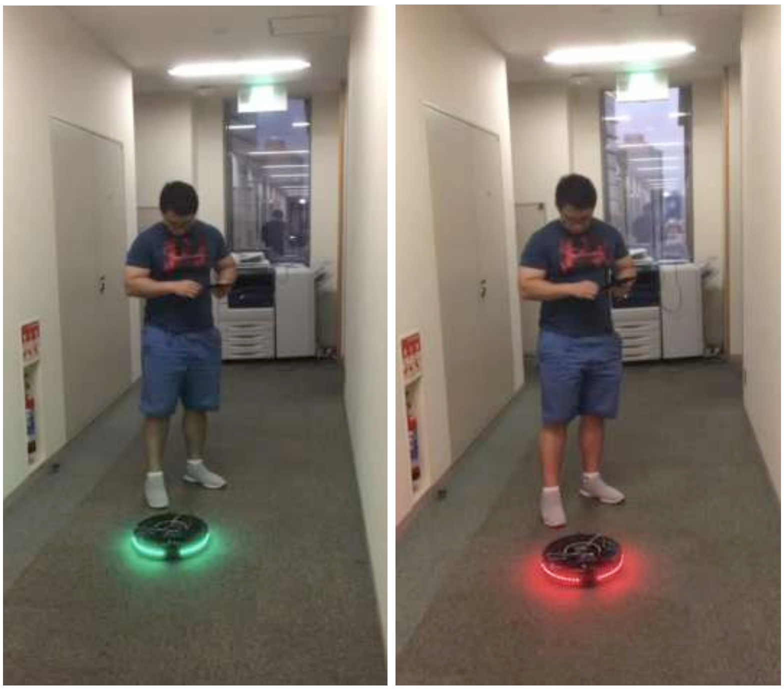


Figure 2.18: Screenshots of each video clip: GL (left) and RH (right)

generality of the concepts. Instead, by showing the participants video clips with sufficient information of robot's behavior but minimum information of context, we allowed them to build opinions and narratives largely on the basis of their experience, knowledge, and understanding. Therefore, we were more likely to uncover the true mechanism behind the participants' perception and interpretation of the expressive lights shown by the robot.

2.4.6 Results

We first describe the results of the participants' valence ratings on the robot's behavior. In general, we found they perceived the robot's behavior positive when it showed GL and negative when it showed RH. Then, we report the qualitative results, which were obtained from a thematic analysis, and highlight the influence of narrative frame on valence perception and behavior interpretation.

Table 2.6: Summary of results of hypothesis tests on valence rating

Context	GL		RH		df	t	p
	Mean	SD	Mean	SD			
home	4.2	0.63	1.7	0.48	18	9.93	<0.001
school	3.9	0.57	1.1	0.32	18	13.63	
work	3.3	0.67	1.5	0.97	18	4.81	
corridor	3.6	0.97	1.6	0.97	18	4.63	
road	4	0.67	1.5	0.97	18	6.71	
entrance	4.3	0.82	1.2	0.42	18	10.6	
shopping center	4.4	0.52	1.6	0.97	18	8.08	
building at night	4.3	0.48	1.3	0.95	18	8.91	
hospital	4	0.47	1.7	0.95	18	6.87	
exhibition	4.5	0.53	1.4	0.97	18	8.91	

Valence Rating

Inter-rater reliability Because we used an ordinal scale for the valence rating, we applied Krippendorf's alpha [154] to determine inter-rater reliability. The Krippendorf's alpha is a rater-reliability measure that accounts for the order of the scale items.

We computed the Krippendorf's alpha for ratings with regard to expressive lights GL (contexts from 1a to 10a) and RH (contexts from 1b to 10b), respectively. It produced $\alpha = 0.15$ for GL and $\alpha = 0.03$ for RH, both indicating slight agreement. Particularly, the valence ratings of RH showed less consistency among the participants compared to the ratings of GL.

Hypothesis test For each context, we applied independent samples t-test to evaluate the effect of the independent factor (expressive light) on the participants' valence ratings. We summarize the analysis results in Table 2.6. Basically, significant differences were found with regard to all the ten contexts. The results suggested a strong fact that the participants perceived the robot's behavior significantly more positive when it showed GL than RH.

A Special Participant The hypothesis tests suggested that the participants, in general, had positive perceptions of the robot's behavior when it showed GL and negative perceptions when it showed RH. However, interestingly, we found one participant (female, 50 years old) attributed overall positive perceptions when the robot showed RH (average rating over 3). A close examination on her comments to the open-ended questions revealed that she had a special angle of view when judging on the robot's behavior. For instance, she had a similar opinion on the robot's behavior in context 5b (RH, road) as some other participants that the robot was sort of *informing of danger to pedestrians*. While the others showed negative perception due to the relationship with danger, she interpreted this positively as she thought that such a robot's behavior actually contributed to the safety of the pedestrians.

Narrative Analysis

We performed a thematic analysis on the participants' descriptions of the robot's behavior. This allowed us to analyze their experience (although imagined) and understand their thinkings. The participants' comments were open-coded and themes were developed. Basically, we discovered four themes which demonstrated the powerful impact of narrative frame on people's perception and behavior interpretation of a robot.

In general, the participants described the robot as having agency and was performing tasks. The tasks they thought the robot was doing were highly related to the contexts. Universally, they considered the robot as something other than a cleaning robot. This was true even for the participants who recognized that it was a Roomba robot demonstrated in the video clips. However, the participants in this experiment seemed to attribute less anthropomorphism to the robot compared to the participants who attended the initial exploration study.

Theme 1: The robot has agency Most participants described the robot as it had certain levels of agency, and their perceptions of agency were framed by the scenarios. For instance, the robot was described as *welcoming and greeting at people* in the home context (Participant 1, Scenario 1a) but as *warning people for danger or accidents* in the road context (P4-S5b). For many scenarios, the participants perceived the robot as having power and authority. For example, they described the robot as *it recognizes relevant people and give them permissions for entering the building* (P4-S6a) and *it requires people to leave the place* (P2-S10b). This was true particularly for the scenarios in which the robot showed RH. Such a bias was expect as the findings from the initial exploration suggested strong negative perception bias of the RH expressive light. In addition, some participants interpreted the robot as having desires and goals as well such as *it demands for friendship* (P2-S1a).

Theme 2: Narrative frame influenced behavior interpretation The participants' interpretations of the robot's behavior highly depended on their narratives of the robot, and such narratives were strongly linked to the contexts. Context played an essential role in creating stories and opinions of the robot by offering groundings of where the scenes took place, what were happening, who were involved and when (e.g. at daytime or night). By combining this process with their own knowledge and experience, the participants were then able to make inferences on explanations of what the robot was likely doing. As a consequence, the descriptions of the robot's behavior were diverse as different people had different stories. For instance, a same participant (P7) made different interpretations of the robot's behavior with regard to different scenarios: *the robot informs a person that another person is looking for him* (S3a) and *the robot gives permission to a person for entering a shop* (S6a). Moreover, different participants made different descriptions of the robot's behavior with regard to a same scenario (9b): *the robot informs a patient about abnormal status of his body* (P6) and *the robot patrols the hospital and warns people for suspicious behaviors* (P7).

Theme 3: Robot type influenced behavior interpretation A cleaning robot Roomba was used in the study. It was disc-shaped, 34 cm in diameter, and less than 9 cm in height. Such features with regard to the type of robot showed impact on the participants' behavior interpretation of the robot. Due to its shape and small size, one participant described the robot as it *warn people not to tread on itself* (P5-1b). Besides, we found that participants' generally saw the robot as it was performing tasks, although in some scenarios the robot was described as *greeting to people* (e.g. P4-1a and P6-2a). The robot was often described as informing or warning people about something or patrolling. For example, the robot's behavior was interpreted as *informing about someone is visiting the house* (P1-1a) or *warning about forbidding entry* (P9-8b).

Theme 4: Valence rating depended on subjective angle of view In general, the participants showed agreement on perceived valence with regard to the expressive lights shown by the robot. However, their individual angle of view influenced their interpretations of the robot’s behavior, which lead to different levels of perceived valence. For instance, with regard to a same scenario (4a), P4 described the robot as *guiding people to their destinations* and rated it highly positive (rating of 5) while P7 interpreted it as *informing people to step aside* and rated it somewhat negative (rating of 2). Particularly, one participant, P2, demonstrated unique valence perceptions with regard to the scenarios in which the robot showed RH. For example (5b), differing from the other participants, she rated the robot’s behavior as positive even if she described the robot as *informing of danger to pedestrians*. While the others showed negative perception due to the negative meaning of danger, she explained this positively as she saw the robot as caring about people’s safety.

Post-Questionnaire

The participants were asked to answer a post-questionnaire after the main session of the experiment. We wanted to have a deeper understanding of how they built their narratives. Specifically, we sought for detailed information behind the narratives. Such information of interest included what did the participants actually recognize the robot as, what and why they thought the robot was doing in general, and particularly, how did they make judgements on whether the robot’s behavior was positive or negative.

Basically, the participants reported that they thought the robot was a cleaning robot or a guard robot. Three participants (P1, P8, and P10) even recognized the robot was a Roomba robot. Two participant (P3 and P6) associated the robot to either a cleaning robot or a guard robot in accordance with the contexts: “I think it depends on contexts. In most contexts I imagined the robot as a guard robot. However, in the home context, I saw it as a cleaning robot" (P3).

The participants described the robot’s behavior as patrolling, guarding, monitoring, or cleaning, in general. They seemed to judged the robot’s behaviors by relying on its movements and light expressions. Some participants reported that they thought the robot was patrolling or guarding as the robot was approaching people and communicating by lights (P1, P3, P4, and P10).

With regard to valence perception, all the participants explained that they judged the valence of the robot’s behavior on the basis of the color of lights shown by the robot. Besides, five of them (P3, P4, P6, P9, and P10) mentioned one more factor of intensity (frequency), for instance "I judged [the valence of the robot's behavior] by the color of the lights and their blinking speed. Green indicated normal situations while red indicated emergent events. Besides, the lights with high blinking speed also reminded me about emergent events" (P4). These results are in consistent with the findings of the initial exploration.

2.4.7 Discussion

Narrative Frame Matters

The findings of this work suggest strong impact of narrative frame on people's valence perception and interpretation of expressive lights shown by a robot. Despite of the non-anthropomorphic shape of the robot and the simple light expressions it displayed, people are able to build rich narratives of the robot on the basis of their knowledge and experience. Such narratives play an important role in forming subjective interpretations. Therefore, different people make different explanations, even for the same expressive light shown by the robot.

We observed that the participants of the second experiment seemed to attribute less anthropomorphism to the robot compared to the ones of the initial exploration study. In the initial exploration, some participants interpreted the robot as *seeking to play with the person* (in GL condition) or *hostile* (in RH condition), indicating that they responded highly emotionally to the robot's behavior. However, we did not observe similar interpretations from the participants of the second experiment. We speculate that concrete contexts that introduced to the second study imposed restrictions on the participants' imaginations of the robot's behaviors. These concrete contexts facilitated the participants to build their narratives within the frame of their knowledge and past experience of such contexts. As a consequence, the participants of the second study probably created less imaginative but more practical points of views of the robot's behaviors, which leaded them to attribute less anthropomorphism to the robot.

Bias of Robot Type

Previous work in HRI (e.g. [155, 156]) has stressed the impact of embodiment and shape of a robot. In this work, we show evidence that such factors, with regard to the type of a robot, have influences on how people build narratives of the robot. When people first encounter a robot, we build mental models of the robot to facilitate us in interacting with it. Such mental models are our conceptual models of the way objects work. We use our knowledge and experience as theoretic groundings to build the models, and the particular knowledge and experience related to the interaction of the robot can be retrieved according to the explicit information provided by the robot, for instance its embodiment and shape. Therefore, when people build narratives of the robot, they likely to consider the type of the robot as an important cue. In other words, they would make stories that are appropriate to the practical applications of the robot. For example, people may be more likely to interpret a Nao robot (human-like robot) as expressing emotions when its eyes display lights compared to a Roomba robot (disc-shaped robot) that shows similar light expressions.

Design Implication

There are mainly three factors, design of light expression, type of robot, and context, that contribute to the processing of building narratives. Therefore, we suggest design implications with regard to each factor, respectively.

Design of Light Expression We found that people mainly rely on color to judge of a light expression. As claimed by previous studies in color psychology (e.g. [140]), color can carry important meaning and show a significant impact on people's affect, psychological functioning, and behavior. Especially, theories and empirical findings on hue emotion associations can offer useful basis for expressive light designers to assign meanings to their lights via color. Besides, intensity of a light expression affects people's perception of lights as well, and such impact seems to be more related to arousal perception. For example, one participants of the second experiment commented on intensity of the expressive lights: "... the lights with high blinking speed also reminded me about emergent events." Therefore, we, as designers, need to carefully manipulate the factors, such as color and intensity, so as to design the light expressions that are appropriate to the application purposes.

Type of Robot Results from the second experiment suggest an interesting fact that while they had practical knowledge on the robot itself (many of them recognized the robot as a cleaning robot), the participants made out-of-the-box imaginations of the robot's behaviors and responded emotionally to them. Bucci et al. [148] reported similar findings in their work. Their participants acted and responded emotionally to their simple fairy robot as it was alive in spite of the fact that no one ever believed it was. Therefore, they suggested that, instead of attempting to make robots more biomimetic, we may act more like writers and design the robots to perform in their narratives so that we can leverage the power of human imagination. We believe that such a design idea can be introduced to interaction design for functional robots as well, especially since biomimicry in robot bodies and behaviors is considered inappropriate [19].

Context Compared to the other factors, context has strong impact on the diversity of people's behavior interpretation of a robot. It frames people's narratives by defining key story elements such as when and where, and such narratives play an essential role in forming subjective interpretations. Therefore, with regard to the meaning of a same expressive light shown by a same robot, even a same person would give distinct explanations in accordance with the context he or she is in. We, thus, need to fully take the application contexts into account when we design expressive lights for robots as the robots can be applied for entirely different purposes, for example search and rescue, public use, or cleaning at home. Behaviors of these robots, such as light expressions to be displayed, should ideally be context-adaptable so that the possibilities of miss interpreting and understanding their meanings could be minimized.

Limitations and Future Work

Several limitations of this work should be recognized. To explore the participants narratives, we relied on their imaginations of the robot's behaviors. We chose this method instead of providing them video clips of real contexts as we wanted to ensure the participants' power of free imagination. However, the quality of stories received from the participants inevitably lied on their capability of imagination. Besides, we only prepared two expressive lights and did not treat their parameters, such as color and intensity, independently. Interaction effects among the parameters may existed, making it hard to understand if the participants' perceptions were to be attributed more to which parameter.

Therefore, future work should investigate expressive lights in real HRI scenarios, and more complex behaviors from robots, compared to the simple approaching behavior used in this work, can be considered. With regard to the design of expressive lights, the parameters should be evaluated independently. It will also be interesting if we can explore more light expressions with different patterns. Besides, since color perception can be culture-dependent, it is important to study narratives of expressive lights of people from different countries and with different culture backgrounds.

2.5 Summary

This chapter discusses how do expressive lights influence people's perception and interpretation of a robot's behavior and further affect the people's behavior and decision-making. Findings from the three studies can open up possibilities for future HRI research. Researchers may pay attention to designing effective non-verbal cues for social robots, especially appearance-constrained robots, to influence people's behavior, either explicitly or implicitly. Such designs can be used in applications such as sales, education, and persuasive robots.

3 Communicating Affect

This chapter introduces two studies which investigate how an appearance-constrained robot could communicate affect using non-verbal cues such as color (light), sound, vibration, and motion. Section 4.1 provides an overview of the studies. In section 3.2, I probe three modalities, color, sound, and vibration, for a simple-shaped robot “Maru" to express emotions. The result suggests nine best expressions that can well convey relaxed, sad, and angry emotions but not happy. Section 3.3 presents a series of three studies to explore how a utility robot might express emotions via expressive lights and in-situ motions. Section 4.3 summaries the studies.

3.1 Overview

This chapter discusses findings from two studies related to the research question that how an appearance-constrained robot could communicate affect using non-verbal cues.

The first study explores effective designs to express emotions through color (light), sound, and vibration. Many researchers are now dedicating their efforts to studying human-like interactive modalities such as facial expressions, gestures, and gaze. Unfortunately, many robots currently in use are restricted in appearance and therefore not able to perform such interaction methods. There are significant challenges in finding effective emotional expressions for appearance-constrained robots. To address this, I probe three alternative modalities, namely, color, sound, and vibration. I conduct a well-structured approach to evaluate the effects of the three modalities on a human's emotional perception towards our simple-shaped robot "Maru." Twenty-four native Japanese participants were recruited in the experiment. They were asked to match Maru's expressions with a particular emotion. The result suggests, in total, nine best expressions that can well convey relaxed, sad, and angry emotions; however, no expression can be recommended for the happy emotion. The findings offer insights into human-robot affective interaction, which can be particularly beneficial for appearance-constrained robots.

In the second study, I explore how a utility robot might express emotions via expressive lights and in-situ motions. In most previous work, methods for either modality were investigated alone, leaving a huge potential to improve the expression of emotions by combining the two modalities. I present a series of three studies, one for investigating how well people might recognize emotions on the basis of expressive light cues alone, one for exploring how people might perceive affect towards in-situ motion characteristics, and one for further combining the two modalities and studying whether multi-modal expressions could be better recognized by people. Results from the first study show participants were not able to recognize target emotions with high accuracy. Results from the second suggest a relationship between the in-situ motion characteristics of a robot and perceived affect. Results from the third suggest that expressions that combine in-situ motions with expressive lights were better able to convey many emotions but not all. I conclude that adding in-situ motions to affective expressive lights appears to be better able to help convey emotions. These findings are important for designing affective behaviors for future utility robots that need to possess certain social abilities.

3.2 Expressing Emotions through Color, Sound, and Vibration

3.2.1 Introduction

In the last few decades, we have witnessed an enormous increase in social robotics [14]. In addition to industrial robots that work in factories, social robots are expected to be employed in a variety of applications, for instance, education [2, 3], health care [4, 5], public service [6, 7], and domestic uses [8, 9], where communicating and interacting with humans are a necessity. Therefore, it is increasingly important for such robots to be able to express affect.

As Cynthia Breazeal [1] claimed, robots are actually a really intriguing social technology and have the ability to "push our social buttons." People respond to social media, robots in particular, similar to how they respond to people, especially if the robots communicate with people using the same body language and other nonverbal cues that people use. As a result, more and more researchers are now dedicating their efforts to studying human-like robots. Some famous examples of such robots are Aldebaran's NAO, MIT Media Lab's Nexi, and Hiroshi Ishiguro's androids and geminoids [157]. Accordingly, the research themes on affective expression and social interaction are mainly focused on facial expressions, gestures, and gaze.

Unfortunately, a large number of robots currently in use for applications such as law enforcement, search and rescue, and domestic uses (such as cleaning robots) are not anthropomorphic, do not have any way of showing facial expressions and are basically designed not to support affective expression, e.g., [19, 28]. In other words, the abilities of these appearance-constrained [designed to be functional and lack expressive faces [19] robots in affective expression are highly restricted. In addition, although such robots may not require rich expressivity, they do need to have certain abilities to show affect. For example, [108] found that victims may perceive a rescue robot as

[1] The Rise of Personal Robots. https://www.ted.com/talks/cynthia_breazeal_the_rise_of_personal_robots, (Accessed November 5, 2018).

“creepy" and not reassuring. They thus suggested that such a robot needs to convey a certain affect to reduce intense emotions in victims.

There is a significant challenge in finding effective emotional interaction modalities for appearance-constrained robots. Basically, they lack natural interaction methods, so they have to make use of their physical bodies and mobility. Existing approaches mainly focus on motion cues [13, 12], or body posture [15, 14, 16]. However, such approaches lack expressibility and are hard, if not impossible, to apply in many application scenarios. For instance, in a scenario where space is limited (a crowded room), big movements such as those made through accelerating and moving in an arc can be impossible to apply.

To address this issue and make interaction design simple and intuitive, we probe three alternative modalities: color, sound, and vibration. Specifically, we treat color as the primary modality and sound and vibration as auxiliary modalities. This is because color, among the three modalities, has been widely studied in various fields and centuries since long ago [140]. Color psychologists and scientists intensively investigated various aspects of color, including color vision, color emotion, and color effects on psychological and biological functioning [140]. Their work primarily focused on categorical colors, for instance, red, blue, and green. Unfortunately, their research has not yet established a rigid framework for color design, and many research subfields are still in the nascent stages. Nonetheless, we are able to take advantage of their findings and make reasonable assumptions on color-emotion associations.

Fewer studies have been carried out to examine sound and vibration cues and their associated emotional expressions, so it is hard to make sound assumptions for sound- and vibration-emotion associations. However, there is a handful of literature in human-computer interaction (HCI) and related fields that explored and employed sound and vibration cues for affective and/or cognitive interaction design [96, 158, 159, 93, 160, 99, 100]. According to their findings, humans have different perceptions, such as positive/negative and high/low arousal, with regard to different sound and vibration stimuli. Therefore, sound and vibration can be utilized as auxiliary modalities to improve multi-model emotional expression as a whole.

However, it is notable that such a three-modality approach may have practical limitations. Although using more modalities may lead to higher reliability, it is unfortunately easier to meet the physical constraints of many appearance-constrained robots currently in for the reason that many of the robots have been designed not to be capable of using all three modalities. They cannot be equipped with LED lights, speakers, and/or vibration motors. As a result, it is also essential to explore both two-modality and single-modality expressions in addition to three-modality expressions.

On the basis of the above discussion, in this work, we work through a structured process to reach our design of emotional expressions for appearance-constrained robots through three modalities: color, sound, and vibration. [22] reported exploring various light behaviors, for a single LED, as a means of expressing a mobile phone system's states (such as incoming call and low battery) to a user. Our approach is adapted and improved from their well-structured design process. Specifically, we begin with a survey of a number of pieces of literature to form our fundamental assumptions on expression-emotion associations, and we further build our prototypical social robot, "Maru," to test our designs. We present both quantitative and qualitative results of our experiment and provide preliminary design guidelines. On the basis of the results, we recommend a set of nine expressions that can well express affect.

3.2.2 Color-, Sound-, and Vibration-Emotion Associations

Color-, sound-, and vibration-emotion associations have been widely investigated in many fields, particularly in psychology and HCI. We survey a number of related pieces of literature to gain insight into basic mappings between each single modality and emotions. In particular, we see color as the primary modality and sound and vibration as the auxiliary modalities.

Color

Color is one of the most ubiquitous, and often least-well-understood, phenomena in human experience. Nonetheless, color psychologists have intensively investigated various aspects of color, including color vision, color symbolism and association, and color effects on psychological and biological functioning [140]. Basically, their work primarily focuses on red, blue, and green since such colors (especially red) have been considered to be special and have positive links in the natural realm. [128] claim that each color activates associations that contain psychologically relevant messages. Therefore, viewing a color can influence psychological functioning and foster motivational and behavioral processes such as approach and avoidance.

Although the effects of colors on motivational and behavioral processes are not evaluated in this paper, *associative learning theory* [128, 161] is closely related to and well explains color-emotion associations. To be specific, color meanings are grounded in two basic sources: learned associations that develop from repeated pairings of colors with particular messages, concepts, or experiences, and biologically based proclivities to respond to particular colors in particular ways in particular situations [128]. For example, red can be associated with danger and anger. One possible source is biological in nature, such as gelada baboons and mandrills displaying red on the body to indicate dominance, aggressiveness, or attack readiness toward an opponent. In addition and more generally, red carries the meaning of danger and anger in life-threatening situations, such as when viewing blood, an angry face, traffic lights, and/or warning signals and sirens [161]. Similarly, blue can be associated with sadness due to the English idiom "I feel blue." Green can be associated with positive meanings due to traffic lights and a general image of being natural.

More explicit studies on color-emotion mappings have been carried out by a number of researchers. [162] indicate that green is perceived as the most positive emotion. [163] claim that a strong color (especially red) puts the brain into a highly excited state and might induce a bad mood. In addition, [117] discuss various studies on color-emotion mapping. The authors suggest that white means peaceful, blue means depressed, and red means angry.

It is notable that there are yet no exact color-emotion mappings. This is probably due to context and culture factors as [128] claim that the same color can carry different meanings with regard to different contexts. Nevertheless, we select color-emotion mappings that are supported by the literature in general.

Sound

Sound stimuli, compared with color, are considered to have vague associations with emotions [10] and thus can be associated with positive/negative states in general. A handful of studies have explored using artificial sounds, especially non-linguistic utterances (NLUs), to express affect. In particular, [96] suggests that, when beep sounds with upward slopes (increasing intonation) are presented from a computer, people perceive the computer's attitude as showing "disagreement" regardless of the duration of the beeps and that, when slower downward slopes (decreasing intonation) with a longer duration are presented, the computer's attitude is interpreted as "hesitation." We think that "disagreement" can be interpreted as an emotion consisting of a negative affect and a high level of arousal, while "hesitation" consists of a negative emotion with a low level of arousal. Therefore, we believe that both suggestions also hold if "disagreement" and "hesitation" are replaced by the emotions "angry" and "sad."

Vibration

Vibration stimuli are mostly investigated as an auxiliary modality for conveying affect in many HCI related studies. To our knowledge, no study uses vibration as a single modality to express emotions. [99, 100] explored vibration cues in their series of studies with regard to vibrotactile emotions on mobile phones. They suggest that levels of vibration intensity are associated with different emotions, particularly the arousal levels of the emotions.

3.2.3 Expression Design

Circumplex Model of Affect

In accordance with most related literature, we focus on categorical emotions, such as happy and angry. We use the *circumplex model of affect* [164] as a two-dimensional model of emotion to map categorical emotions onto a valence-arousal space (see Figure 3.1). This model can offer benefits to maximize diversity if four particular emotions are to be evaluated: relaxed, happy, sad, and angry. This is because each of the emotions can be mapped onto a different quadrant of the valence-arousal space. To be specific, relaxed is of positive and low arousal, happy is of positive and high arousal, sad is of negative and low arousal, and angry is of negative and high arousal. Although one can argue about the selection of these four emotions, we believe that such a choice is valid. Basically, most emotions belonging to the same quadrant of the valence-arousal space are similar to each other but quite different from emotions belonging to the other quadrants. For instance, calm and serene are close to relaxed

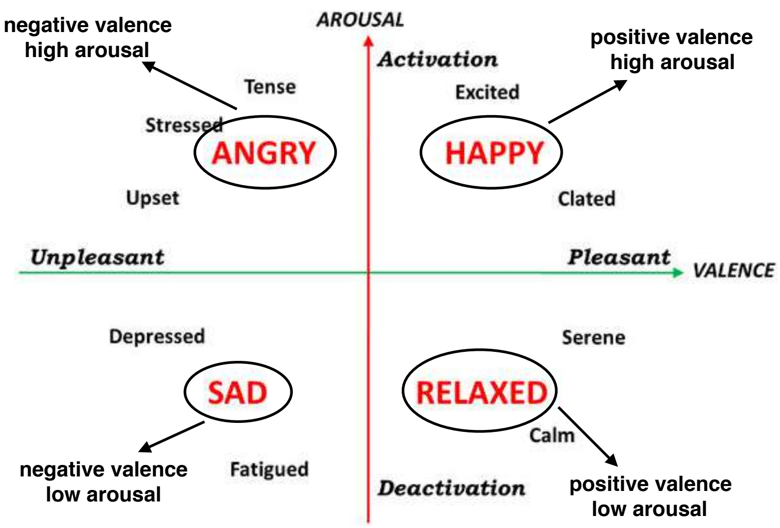


Figure 3.1: Circumplex model of affect

but distinct from happy. Therefore, we claim that the four emotions we chose can represent people's perceptions to the greatest extent without introducing additional complexity if more emotions are introduced.

Candidate Expressions

We designed a set of candidate expressions that consisted of both *basic expressions* (expressions through one single modality) and *mixed-modality expressions* (expressions through multiple modalities). We first decided on a set of basic expressions that represent the mappings between each single modality and the emotions. Further, mixed-modality expressions were built upon these basic expressions.

On the basis of the survey in section 3.2.2, we determined our assumptions on single modality-emotion mappings. Specifically, for the color modality, we associated relaxed with white, happy with green, sad with blue, and angry with red. For the sound modality, we associated a falling beep sound with sad and a rising beep sound with angry. For the vibration modality, we associated relaxed with a mildly intense vibration, happy with highly intense vibration (lower than that for angry), sad with a low intense vibration, and angry with a highly intense vibration. However, the mappings between sound stimuli and relaxed and happy emotions remained unclear. Therefore, we further organized a pre-design session to particularly address this issue. We would like to note

Table 3.1: Assumptions of mappings between single modality and emotion, forming 12 basic expressions.

Emotion	Color (c)		Sound (s)		Vibration (v)	
relaxed	white	c1	flat beep sound	s1	mildly intense vibration	v1
happy	green	c2	flat beep sound (louder than s1)	s2	highly intense vibration (lower than v4)	v2
sad	blue	c3	falling beep sound	s3	low intense vibration	v3
angry	red	c4	rising beep sound	s4	highly intense vibration	v4

that we are aware of the bias we introduce when such modality-emotion associations are made. However, since we do not take them as a ground truth for participants, we believe that such a bias is insignificant as the validity of our assumed modality-emotion associations will be evaluated in a participant experiment.

We asked a panel of five researchers (members of our research group; one female) to discuss the so-far decided candidate expressions. None of them were familiar with our project before joining the session. The pre-design session lasted for about 30 minutes. We asked them to comment on the expressions we currently decided on and give suggestions on expressing relaxed and happy through sound modality. Basically, they all agreed with the expression designs. In addition, they suggested using a flat beep sound to express both relaxed and happy emotions. To differentiate between the two, the beep sound associated with happy was made louder since happy is of higher arousal than relaxation.

All of the basic expressions were thus determined. Table 3.1 shows 12 basic expressions. Basically, each of them was assigned with a unique code, for example, a white color expression was assigned with "c1," and a falling beep sound was assigned with "s3." On the basis of them, we further designed 16 mixed-modality expressions. Specifically, each mixed-modality expression was a combination of two or three basic expressions from the same emotion category. Their names were decided by mixing codes of combined modalities followed by a number indicating which emotion category

Table 3.2: List of all 28 candidate expressions; 1 - 12 are basic expressions, 13 - 28 are mixed-modality expressions.

1	c1	15	cs3
2	c2	16	cs4
3	c3	17	cv1
4	c4	18	cv2
5	s1	19	cv3
6	s2	20	cv4
7	s3	21	vs1
8	s4	22	vs2
9	v1	23	vs3
10	v2	24	vs4
11	v3	25	cvs1
12	v4	26	cvs2
13	cs1	27	cvs3
14	cs2	28	cvs4

of the basic expressions they belonged to. For instance, “cvs1" is a mixed-modality expression that consists of three basic expressions, “c1," “s1," and “v1." Table 3.2 demonstrates all of the candidate expressions, where Nos. 1 to 12 are basic expressions, and Nos. 13 to 18 are mixed-modality expressions.

Maru the Robot

We built Maru 3.2 as a prototypical social robot to carry out the participant experiment. We applied a minimum design and intentionally made Maru’s embodiment and appearance simple while still having the attribute of anthropomorphism. This is important as we wanted to reduce the bias caused by Maru’s appearance while appropriately using a certain amount of anthropomorphism to facilitate social interaction between Maru and the participants.

Maru is made of two pieces of hollow, semi-spherical Styrofoam (diameter= 15cm). Four LEDs (white, green, blue, and red) are assembled behind each of its eyes. In addition, a speaker is used to generate beep sound stimuli, and a vibration motor is attached to the inner body to produce vibration stimuli. An Arduino Uno R3 board is

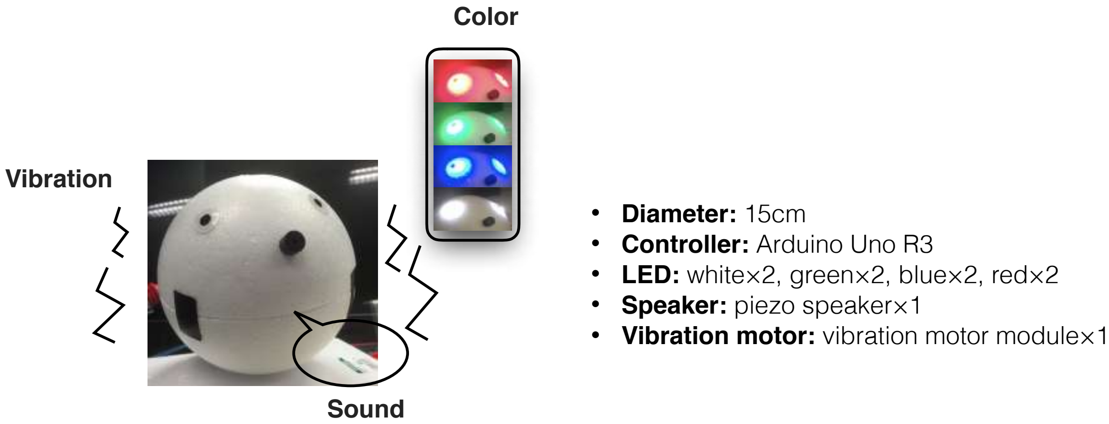


Figure 3.2: Maru and its expressions made through color, sound, and vibration.

programmed to control the robot. Figure 3.2 shows Maru and how it expresses emotions through the three modalities of color, sound, and vibration and their combinations. Information regarding Maru's hardware is also listed.

3.2.4 Experiment

Participant

Twenty-four Japanese in total (12 males, 12 females) ranging from 20 to 39 years old (M = 29.09, SD = 5.90) were recruited for the experiment. All of them were native Japanese speakers with a certain amount of knowledge on English. In addition, none of them had experience in using or working with a robot.

Procedure

Maru was placed in front of the participants at a distance of about 50 cm. Figure 3.3 shows both the experiment setting and a real scene of a participant experiment. The Arduino UNO board inside its body controlled all of its expressions. Before the experiment started, the experimenter welcomed the participants and briefly explained the purpose and setting of the study. The participants were required to complete a short pre-questionnaire consisting of demographic information and questions regarding experience with robots. After finishing the pre-questionnaire, the experimenter started the experiment and left the room. In total, 28 trials were conducted for each participant,

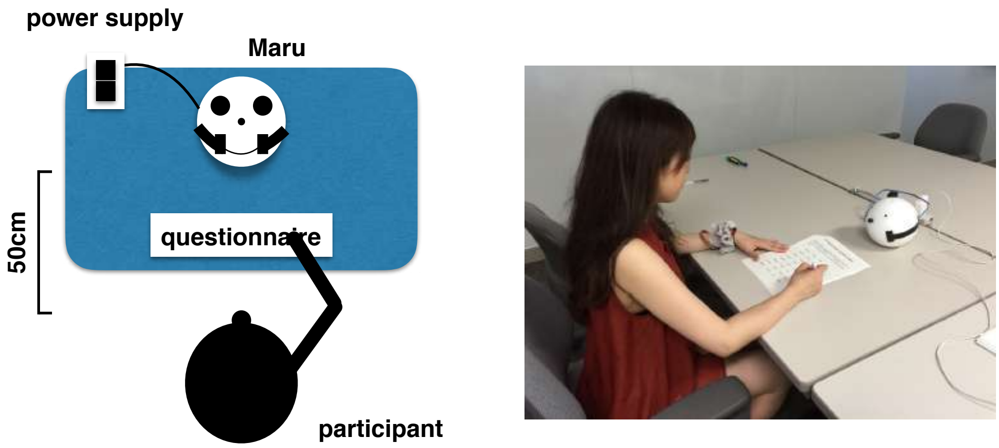


Figure 3.3: Experimental setting. Wires shown in right figure were hidden during actual experiment.

where in each trial, Maru repeatedly performed a single expression (1-second-long expression followed by a 1-second pause; all modalities were synchronized) from the candidate set.

The expressions were randomized across participants. Each trial lasted for 10 seconds, and between each of two trials, the participants had a 20-second pause to select one emotion out of the four (relaxed, happy, sad, and angry) that they believed Maru had just expressed. After all of the trials were completed, the participants were asked to give free comments on Maru's expressions. Last, the experimenter ended the experiment and thanked the participants. All of the participants received five thousand Japanese yen (about 45 dollars) as a reward.

3.2.5 Results

Figure 3.4 gives an overview of the experimental results. For each candidate expression, the selection rate (SR), indicating how many participants perceived an expression as a particular emotion, was counted with regard to each of the four emotions. Because the total number of participants was 24 in this experiment, the value of the selection rate ranged from 0 to 24. For instance, c2 has a SR of 0 regarding the emotion of anger as no participant perceived c2 as angry when Maru expressed it, but it has SRs of 11, 11, and 2 with regard to relaxed, happy, and sad, respectively.

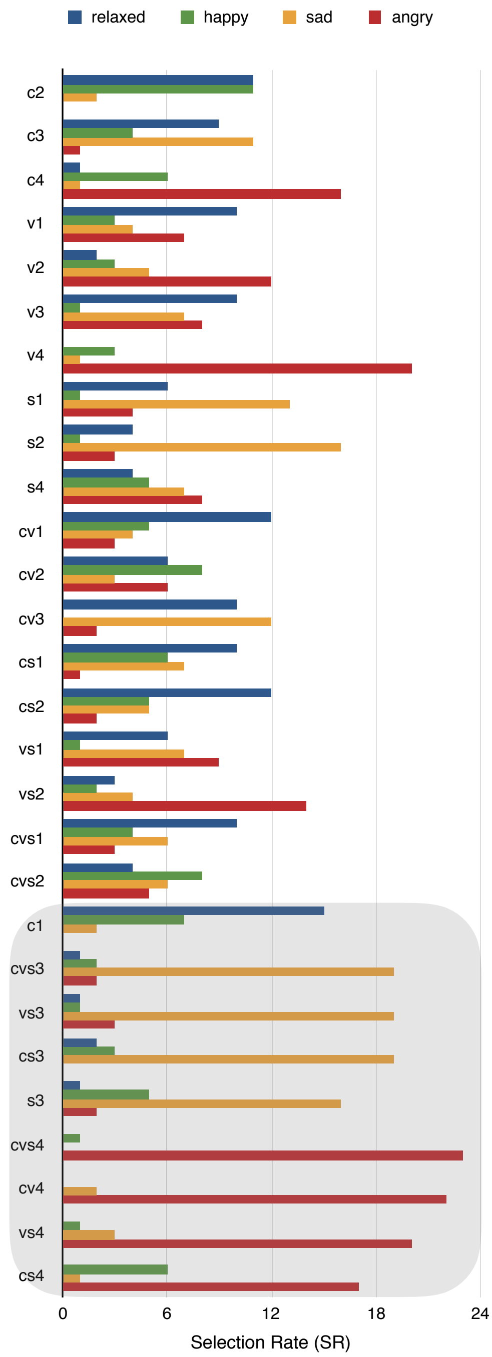


Figure 3.4: Overview of our results. Selection rate (SR), ranging from 0 to 24, indicates how many participants mapped expressions onto emotions; shaded area shows nine recommended expressions.

Table 3.3: Summary of representative comments from participants. Numbers in parenthesis indicate number of participants who gave comments.

(a)	It was difficult to recognize the happy emotion. (7)
(b)	Color is the most important modality for expressing affection. (8)
(c)	Using vibration alone was confusing. (4)
(d)	Vibration conveys negative emotions, and a highly intense vibration especially conveys angry. (6)
(e)	Rising/falling sounds were easily recognized as angry/sad, but flat sounds were difficult to interpret. (7)
(f)	It was difficult to recognize the relaxed emotion when sound was used. (3)
(g)	Using multiple modalities is more understandable than using a single modality alone. (6)

Criteria for Selecting Expressions

[22] presented their study on single LED light behaviors as a means of expressing a mobile phone system's states, such as incoming call and low battery. Our approach is adapted and improved from their well-structured design process. In this experiment, we analyzed the candidate expressions with regard to the four emotions separately. For the evaluation, we first introduced two criteria for selecting good expressions: (1) an expression must have a strong interpretation regarding an emotion (selection rate in the top quartile, or in other words, above the third quartile), and (2) an expression must be iconic, meaning that it has only one dominant perception among the four emotions. For instance, an expression is ambiguous and not desirable if the participants perceive it as more than one emotion. We assessed the iconic-ness for each candidate expression that meets criteria (1). For evaluation, we used one-sample tests of proportions with a multinomial test. For each test that was significant, we further conducted post-hoc multinomial tests with Bonferroni correction for multiple comparisons. Because of the four emotion categories, the hypothesized probability that each emotion would be chosen at random regarding an expression was set to one-fourth (25%, which is the probability of a random guess).

In addition to the selection rates, we also gathered the participants' subjective comments on our expression design through open questions in post-questionnaires. We believed that linguistic feedback from users would be essential to the selection of expressions as such qualitative information can provide more detailed understandings with regards to the participants' subjective perceptions and can be used to validate the quantitative findings. Table 3.3 summarizes the representative viewpoints that were given by at least three participants. Basically, after a selection based on the above-mentioned two criteria, we further discarded expressions that were not in line with the comments since we believed that the collected comments revealed the participants' perceptions and interpretations of our design.

Recommended Expressions

Nine expressions (Figure 3.4, shaded area) were selected as our recommended set of emotional expressions made through color, sound, and vibration. We now describe them with regard to each emotion category.

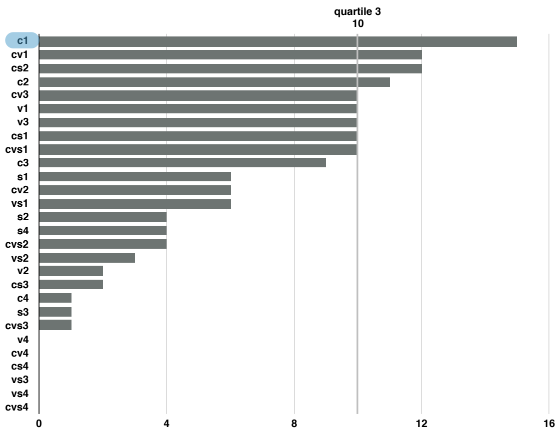


Figure 3.5: Selection rates (SR) for relaxed emotion category

Relaxed We recommend c1 for expressing a relaxed emotion. It also has the highest selection rate with regard to relaxed emotion (see Figure 3.5). Although both cv1 and cs2 also met criteria (1) and (2), they were discarded because of the participants' comments [(d) and (f)] (see Table 3.3).

A multinomial test indicated a significant difference in c1 ($p < 0.01$). Post-hoc tests with Bonferroni correction suggest that the result for relaxed was significant [see Figure 3.9(a), significantly above 25%, $p < 0.001$], while results for the other three emotions were not (happy: n.s.; sad: n.s.; angry: significantly under 25%, $p < 0.01$). In addition, the selection of c1 met our assumptions as we assumed the mapping between the color white and relaxed emotion.

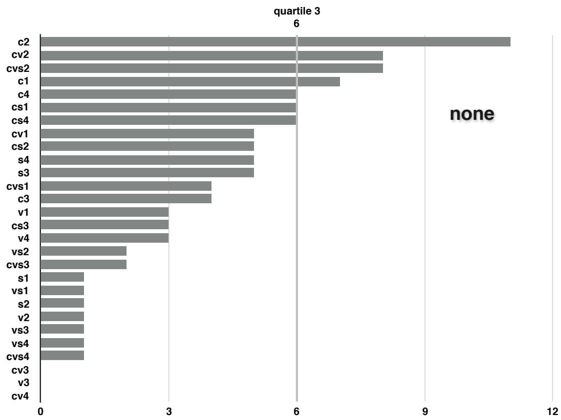


Figure 3.6: Selection rates for happy emotion category

Happy No expressions met our selection criteria with regard to the happy emotion (see Figure 3.6). Although the four expressions had SRs above the third quartile, post-hoc tests showed that none of the four expressions were iconic. This meets comment (a) suggesting the difficulty of recognizing the happy emotion.

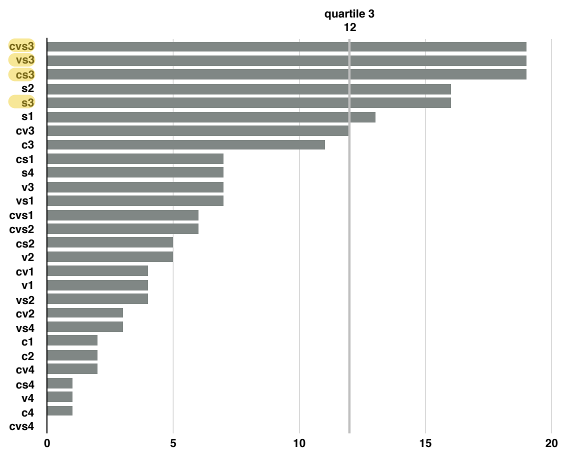


Figure 3.7: Selection rates for sad emotion category

Sad We recommend cvs3, vs3, cs3, and s3 for expressing a sad emotion. They had the top five selection rates with regard to the sad emotion except for s2 (see Figure 3.7). We conducted multinomial tests for the top six expressions that met criteria (1). Post-hoc tests with Bonferroni correction indicates that all six expressions also met criteria (2) [see Figure 3.9(c)].

We further discarded s2 and s1 due to comment (e). All of the remaining four expressions formed our recommended expressions for sad, which consist of basic expressions that are mapped to the sad emotion (c3: blue color; v3: low intense vibration; s3: falling beep sound). This also met our assumptions.

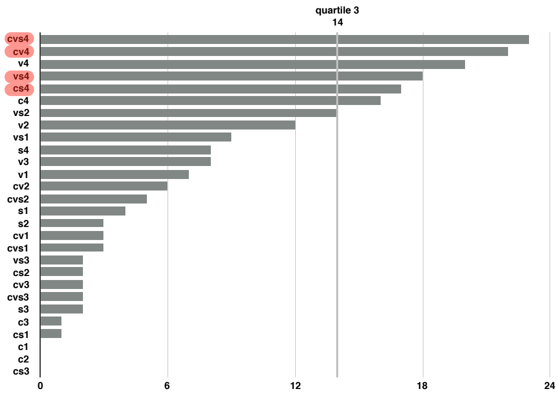


Figure 3.8: Selection rates for angry emotion category

Angry Four expressions, cvs4, cv4, vs4, and cs4, are recommended for expressing an angry emotion. They had the top five scores with regard to the angry emotion except for v4 (see Figure 3.8). Similar with the sad emotion, all of the top six expressions were iconic in the angry category [see Figure 3.9(d)].

Further, we discarded v4 and c4 because of comments (c) and (g). All of the four recommended expressions consisted of basic expressions that were mapped to the angry emotion (c4: red color; v4: highly intense vibration; s4: rising beep sound), which again met our assumptions.

3.2.6 Discussion

As we worked through a well-structured process for designing affective expressions through color, sound, and vibration modalities, we were able to offer a set of nine expressions that can well convey affect. Specifically, for a relaxed emotion (or in

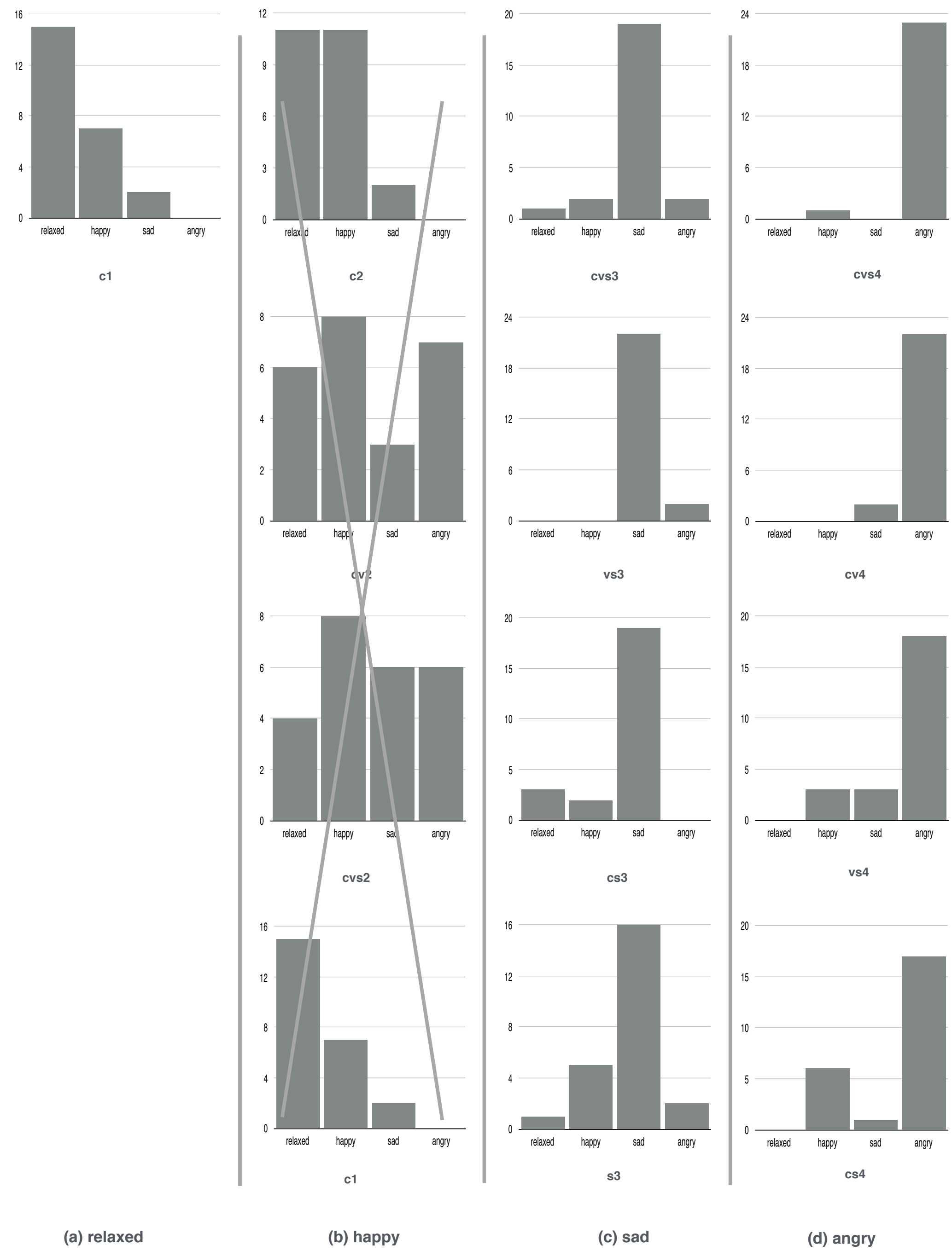


Figure 3.9: Selection rates vs. emotions regarding each expression. All expressions except for four under happy emotion category are recommended.

general, a positive-valence-low-arousal emotion), we recommend c1. For sad (a negative-valence-low-arousal emotion), we recommend four expressions, cvs3, vs3, cs3, and s3. For angry (a negative-valence-high-arousal emotion), we suggest four expressions, cvs4, cv4, vs4, and cs4.

On Expression for Happy

Unfortunately, we are not able to offer any good expressions for happy (a positive-valence-high-arousal emotion). One plausible explanation is that humans tend to perceive a highly intense expression as a negative emotion rather than a positive one. In particular, negative emotions are key to our wellbeing and are more noticeable than positive ones since attending to negative events can be more important for survival than attending to positive events ([165]). Accordingly, the participants might have had a bias toward perceiving and interpreting an expression as a negative emotion, especially for highly intense expressions, since they can be considered as being linked to highly dynamic activities that may be associated with danger. Evidence can be found in the experimental results, where the expressions for negative emotions (sad and angry), compared with positive emotions (relaxed and happy), were well recognized with much less ambiguity (see Figure 3.9). Another possible reason is that the number of participants recruited in our experiment may have been relatively small. Although we conducted the within-participant experiment with 24 people, a larger number of participants may be able to reveal a more powerful statistical significance. To be able to conduct experiments with a large number of participants, we had to use online crowdsourcing as an economical means to get experimental data. However, the expressions we studied, especially those that contained the vibration modality, were not able to be explicitly conveyed through an online investigation. Thus, as a compromise, we recruited a relatively small but reasonably sufficient number of participants.

Importance of Each Modality

On the basis of the participants' comments, we confirmed that color is the most important modality for expressing emotions among the three. Color is one of the most ubiquitous phenomena in human experience and has been intensively explored by psychologists and designers. In addition to the wide use of color among animals and plants, humans have made use of it throughout a long part of history. We associate color with symbolic meanings and emotions. Just as Don Norman put it, color offers good natural mappings [see [10]. This is why we employed color as the primary modality for expressing affect.

In contrast, sound- and vibration-emotion associations are in general considered to be more vague. Expressions through either modality alone may probably not be able to convey explicit emotions. However, these modalities are expressive with regard to particular emotions. Sound stimuli can well convey sad and angry emotions, while vibration stimuli can convey different levels of arousal. According to our experimental results, most of the recommended expressions for a sad emotion consist of a falling beep sound and/or low intense vibration, while most of the expressions for an angry emotion consist of a rising beep sound and/or highly intense vibration. Therefore, we considered utilizing sound and vibration as auxiliary modalities. In addition, the results also indicate that flat beep sounds (regardless of volume) can be too ambiguous to be interpreted as a particular emotion.

A few more implications can also be drawn from the experimental results. Since the participants were strongly biased toward negative emotions when perceiving expressions that consisted of sound and/or vibration modalities, the consideration of involving such modalities in designing positive expressions needs to be made with caution. In addition, if applicable, using multi-modality expressions can reduce ambiguity in recognizing certain emotions (such as sad and angry) compared with using single-modality expressions.

Design Guideline

On the basis of our findings, we offer six suggestions as general design guidelines:

I. It is suggested to use expressions that contain the color modality;

II. When expressing sadness, a falling sound is strongly recommended;

III. When expressing anger, a rising sound and highly intense vibration are strongly recommended;

IV. Use multiple modalities rather than a single modality, if applicable;

V. It is better not to use vibrations for positive emotions.

VI. It is much easier to express negative expressions rather than positive expressions.

We note that we selected all of the expressions that met our criteria rather than pick only the best one. This is because there might not be one best expression that holds for everyone. Instead, we offer a set of good expressions so that variety and flexibility are promised. Basically, a practical issue could be the various designs of robotic platforms. A robot may not be able to perform expressions through all of the three modalities, especially vibration. Therefore, for designers who would apply our findings to their projects, we suggest that they start with choosing the expressions that have the highest selection rates while meeting their hardware configurations and that they further adjust their choices on the basis of the performance.

Inevitably, this work has certain flaws. The generality of our findings may be restricted due to the appearance of our robot Maru. Maru was built to have two eyes to gain the attribute of anthropomorphism, and LEDs are attached behind the eyes. As a result, expression through color modality is achieved by Maru "blinking" in the eyes. There is thus the possibility that our results depend on the face-like appearance of the robot. However, as [112] claim that humans' have an intrinsic mechanism for anthropomorphizing things, we argue that the generality of our findings is minimally affected.

Future Work

Future work can further explore certain directions. For example, we restricted our set of candidate expressions to avoid too large a design space. To be specific, we first made our assumptions on single modality-emotion mappings, and we further designed mixed-modality expressions on the basis of these assumptions. As a result, we intentionally discarded many other combinations that we considered not valid (we successfully cut down the number of candidate expressions from 124 to 28). Nevertheless, further investigation on those conflicting mixed-modality expressions may reveal interesting findings.

We did not consider many parameters that can be important for designing expressions through the three modalities, such as duration, brightness of colored LED lights, and volume of sound. Therefore, it is important to carry out follow-up studies to explore the setting of those parameters that may affect emotional expression and perception.

In addition, further tests on different robotic platforms (such as the iRobot cleaning robot, the Roomba) are needed to evaluate the generality of the findings reported in this work.

3.3 Designing Expressive Lights and In-Situ Motions for Robots to Express Emotions

3.3.1 Introduction

There is an increasing need for utility robots to express emotions. People often expect such robots to act socially [19]. For instance, in previous work, it was found that rescue workers expect a small tank-like robot to follow social conventions [107]; man-packable robots were perceived as “creepy" and not reassuring when they were operated close to simulated victims [108]. However, because utility robots are, in general, restricted in appearance, there is a lack of methods that can be used for these robots to express affect and intent.

Due to the restricted interaction methods available to utility robots, human-robot interaction (HRI) approaches rely mainly on motion cues [13, 166, 88, 113]. Strong relationships between motion parameters, e.g., acceleration, curvature, and trajectory, were found, and the type of body that a robot has did not seem to affect such relationships [13]. Nevertheless, motion alone was not able to convey emotions precisely, although motion parameters might be used to predict the perceived arousal and valence. Moreover, current methods regarding robot motion can be hard to apply in many practical scenarios. For instance, it can be impossible for a robot to use big movements to interact with people when situated in a narrow corridor or a crowded room. In addition, making big movements takes a rather long time, which would likely result in users becoming frustrated as it would take a long time to understand what a robot is expressing.

In addition to motion, using expressive lights as dynamic visual cues has been explored for designing affective HRI as well [86, 116]. Researchers found that a robot is able to convey emotions by showing expressive lights that dynamically change in color luminosity [86]. Parameters such as color, period, and waveform contribute to the perception of emotions. In particular, color is considered to be a strong cue for predicting perceived affect. Color psychologists have intensively investigated various aspects of color, including the effects of color on psychological and biological functioning [140]. However, using expressive lights alone did not increase the recognition accuracy as well, although doing so seemed to lead to better performance than using robot motion alone. In addition, approaches using expressive lights are inappropriate if a user has a color-vision disorder.

Contribution

In this work, we explore whether multi-model expressions that combine motion and expressive light cues might better convey target emotions. Particularly, we investigate and apply *in-situ* motions, rather than the motion patterns studied in previous work, in the hope of allowing a robot to express affect in a rather short time frame without making big movements. Our first experiment was performed to evaluate how well a robot might convey emotions on the basis of expressive lights alone. The design of the lights was adapted from previous work [86]. A second experiment was performed to explore how people might perceive affect towards in-situ motions since this was not clear due to lack of related literature. On the basis of the results of the two studies, a third experiment was performed to further investigate whether combining motion and expressive lights modalities might better convey emotions. In this paper, we use the Circumplex Model [167], a two-dimensional space, to investigate the design space. On the basis of participants' ratings of perceived emotions using the Self-Assessment Mannequin (SAM) method [168], we found that adding in-situ motions to expressive light cues helped with more precisely expressing emotions for *happiness*, *sadness*, *disgust*, and *surprise*. With this work, we hope to suggest an effective method for evaluating and comparing the emotional responses of users to robot expressions via different modalities and to further provide insights into designing affective expressions for utility robots.

3.3.2 Related Work

Emotional expressions based on motion cues have been investigated in many studies. Tremoulet and Feldman [113] demonstrated that even a single moving object can be perceived as alive. They discovered that people's ratings of animacy were heavily influenced by the changes in speed and direction of an object. Particularly, in HRI, Saerbeck and Bartneck [13] explored the relationship between the motion features of a robot and the attribution of affect. They found a strong relationship between motion parameters and perceived affect, while the type of body that a robot has had no effect. Specifically, their results indicated that the level of acceleration can be used to predict the perceived arousal and that an interaction effect between acceleration and curvature existed with regards to valence information. Syrdal et al. [169] performed a video human-robot interaction study in which participants viewed a video in which an appearance-constrained robot used dog-inspired affective cues to communicate affinity. They suggested that such cues be effective for non-verbal affective communication. Cauchard et al. [88] explored how personality traits and emotional attributes can be encoded in drones via their flight paths. They found that drone movements, such as speed, altitude, and orientation, were important for designing affective expressions.

Expressive lights used as dynamic visual cues have also been explored for HRI research and applications. For instance, both Sony's robot dog AIBO and Aldebaran's Nao use LED lights to assist in affective expression. Terada et al. [86] studied how a robot might convey emotions by dynamically changing the color luminosity of its body. Their findings suggest a relationship between hue value and basic types of emotion and that duration and waveform represent the intensity of emotion. Rea et al. [87] mounted multi-color LEDs on an iRobot Roomba robot to broadcast ambient information in the form of a colored halo. They investigated how a robot with an ambient light display may integrate into a daily environment. Song and Yamada [116] evaluated the effects of three modalities, color, sound, and vibration, on a human's emotional perception of a simple-shaped robot. Their results indicate that color can be an important cue for people to recognize emotions.

Besides, few studies explored design for multi-modal emotion expression for social robots in which both color and motion cues were employed. Häring et al. [170] designed eight expressions for a Nao robot for the emotions anger, sadness, fear, and joy, consisting of body movements, Sounds and Eye Colors. Their analysis suggested that body movements were appropriate for their target emotion but colors were unreliable. Löffler et al. [94] built a simple movable robot and designed a set of 28 uni- and multi- modal expressions for conveying four basic emotions joy, sadness, fear, and anger. They found that planar motions were the most effective uni-modal expressions but multi-modal expressions that used both color and motion offered overall best performance.

3.3.3 Methodology

3.3.4 Emotional Model

Among a number of proposed psychological models for the cognitive structure of emotions, two of them are widely accepted and supported by empirical evidence. Ekman and Friesen [171] suggested a set of basic emotions based on human facial expressions. Their set consists of anger, disgust, fear, joy, sadness, and surprise. Others evaluated facial expressions for the mental states of boredom, confusion, happiness, interest, and surprise [172] or anger, fear, happiness, sadness, and surprise [173]. To not view emotions as categories, Russell [167] introduced the Circumplex Model of Affect, in which emotions are mapped to a two-dimensional space: the arousal of an emotion and the valence of an experience. In previous studies [166] in which this emotional model was applied, it was found that the model was useful with regards to designing affective expressions, and it was suggested that it a more precise tool for evaluating the accuracy of emotion perception.

3.3.5 Robot Configuration

We used an iRobot Create 2 robot. Roomba is a series of autonomous robotic vacuum cleaners used in indoor environments. All Roomba robots are disc-shaped, 34 cm in diameter, and less than 9 cm in height. This robot perfectly fits the definition of a utility robot and, due to its constrained appearance, has very limited ways of expressing affect, e.g., moving forward/backward and spinning.

Figure 3.10 shows the configuration of the Roomba robot with an LED lighting system installed on it. We used one meter of a NeoPixel LED strip (60 pixels). The LED

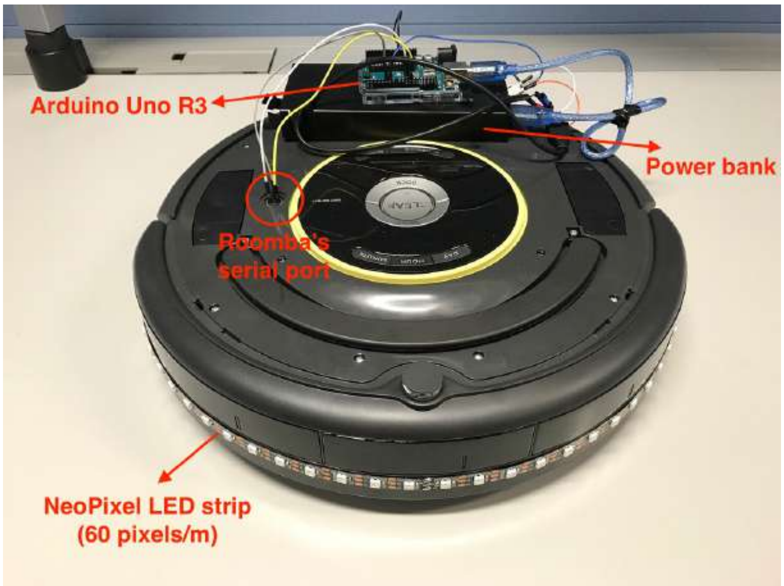


Figure 3.10: Configuration of Roomba robot with LED lighting system.

strip was controlled by an Arduino Uno R3 board, and both the strip and board were powered by a 5-V, 3-A portable power-bank. The same board was also used to control the movements of the robot. iRobot Create 2 robot provides the Roomba Open Interface (OI), which is a software interface for controlling and manipulating Roomba's behavior.

Procedure

In this work, we evaluated the effectiveness of expressions for seven emotions: anger, surprise, disgust, sadness, happiness, fear, and calm. These emotions were chosen on the basis of a model by Ekman and Friesen [171] and from similar studies [86]. To investigate how well these emotions might be recognized, we used the Circumplex Model. Basically, all seven emotions are featured in the model, covering the whole two-dimensional space (a broad spectrum of valence and arousal levels). For evaluation, we applied the SAM method. Participants rated emotions on a five-point valence scale (from very negative to very positive) as well as a five-point arousal scale (from very low to very high). The validity of using SAM scales to rate perceived emotions has already been shown in previous work [166, 168].

We performed three studies, where we designed the third study on the basis of the findings from the first two. Particularly, in study I, we asked participants to rate the seven emotions by using the SAM scales. This procedure was also taken by Strohmeier et al. [166] to account for potential individual variance in the interpretation of emotions. We used the results from this test as referential ratings of the seven emotions and to further obtain distance measures between the reference points and other ratings of perceived emotions. To be specific, with regards to each emotion, we obtained a referential (X, Y) coordinate on the Circumplex Model. For further evaluations, e.g., emotional perception towards expressions based on expressive lights alone and expressions that combined in-situ motions and expressive lights, we then calculated the Euclidian distance between the response emotion and the references. Note that all distances were measured on a five-point SAM scale.

Hypothesis

We hypothesized that emotional expressions based on expressive lights alone would not able to be recognized with high accuracy. This would be revealed in study I by obtaining distance measures between ratings of such expressions and corresponding referential ratings. We also hypothesized that a strong relationship between in-situ motion parameters, e.g., speed and pattern, and participants' ratings of perceived emotions would be observed. This would be evaluated in study 2. Further, we hypothesized that multi-modal expressions that appropriately combine in-situ motions and expressive lights were better able to be recognized. Study III would test such a hypothesis.

3.3.6 Study 1: Emotional Expression via Expressive Lights

In this study, we evaluated how well our Roomba robot might convey emotions on the basis of expressive lights alone. We also asked participants to rate the seven emotions by using the SAM scales, where the results were used as referential ratings of the emotions in both studies I and III.

Method

Our design of expressive lights was mainly adapted from Terada et al. [86]. Table 3.4 demonstrates the parameter settings used in our experiment. Note that we converted their hue values to RGB values to fit our LED lighting system. In addition, we also converted their mixed waveforms by simply applying the following rules; if the mix

Table 3.4: Parameter settings for design of expressive light expressions.

Emotion	RGB	Period[ms]	Waveform
Anger	255, 17, 0	896	square
Surprise	255, 132, 0	747	square
Disgust	255, 0, 179	1645	square
Sadness	21, 0, 255	3310	sinusoid
Happiness	255, 157, 0	1123	square
Fear	166, 0, 255	1377	square
Calm	255, 255, 255	2000	sinusoid

ratio is less than 0.5, use a square waveform; if the mix ratio is greater than 0.5, use a sinusoidal waveform.

Participants

Eighteen Japanese in total (12 males and 6 females) ranging from 22 to 50 years old ($M = 29.44, SD = 9.31$) were recruited for the experiment. None of them had any color-vision disorders. Participants rated the seven emotions (used as referential ratings) before they rated the perceived emotions of expressions based on expressive lights. The order in which the seven expressions were shown was randomized.

Results

Figure 3.11(a) shows the referential ratings of the seven emotions. ◦ indicates the mean valence and arousal values for the emotions, where ellipses represent the standard deviation. In general, our results had a similar distribution to that reported by Russell [167] and Strohmeier et al. [166]. However, our participants rated happy, fear, and anger to be more positive (greater valence value). This might be due to cultural factors as participants from both of their two studies were from Western countries, while our participants were from Eastern countries (Japan).

Figure 3.11(b) shows the ratings of the expressions based on expressive lights. Mean distances between response emotions (◦) and referential emotions (+) are illustrated as line segments. It is clearly revealed that participants perceived emotions with quite different levels of valence and arousal compared with the corresponding referential emotions shown in Fig. 3.11(a). Such results were expected since previous studies

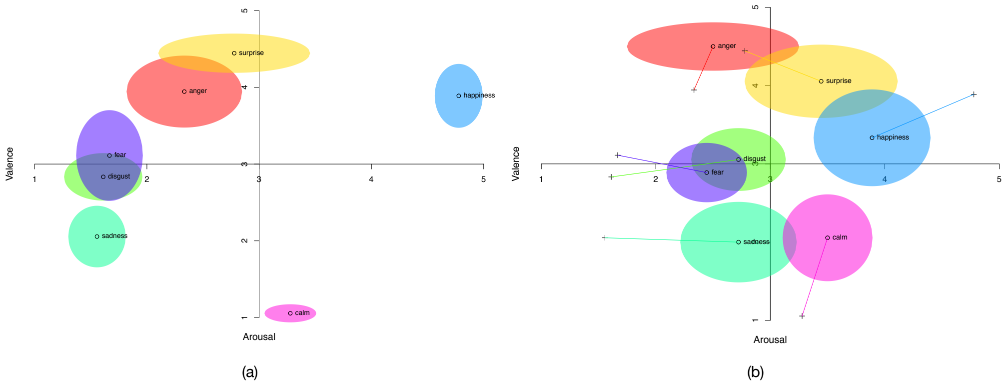


Figure 3.11: Circumplex Model of Affect. ∘ shows mean valence and arousal ratings of emotions, where ellipses show area encompassing one standard deviation. Figure (a) shows referential ratings of seven emotions. Figure (b) shows ratings of expressions based on expressive lights. Particularly, with regards to Figure (b), line segments show mean distances between response emotions (∘) and referential emotions (+).

suggested that correctly conveying emotions via expressive light cues alone is difficult.

3.3.7 Study 2: Emotional Expression via Motion

In this study, we explored how people might perceive affect towards in-situ motions.

Method

Due to the nature of the Roomba robot, we found two parameters that can well represent the characteristics of its in-situ motions: pattern and speed. To be specific, we designed two in-situ motion patterns, *circle* and *shake*, to fit the mobility of the Roomba. For the circle pattern, the robot simply spins 360 degrees clockwise and stops at the initial orientation. For the shake pattern, the robot first turns 45 degrees clockwise and then turns 90 degrees counterclockwise. It then turns 90 degrees clockwise and 90 degrees counterclockwise. Last, it turns 45 degrees clockwise to return to the initial orientation. This pattern design was inspired by both human and animal behaviors. Many people and animals, e.g., dogs, might move similarly in a circle when they have positive feelings and might shake their heads (similar to *shake*) when they have negative feelings, e.g., expressing disagreement.

We also designed three levels of speed for the robot's in-situ motion: low, medium,

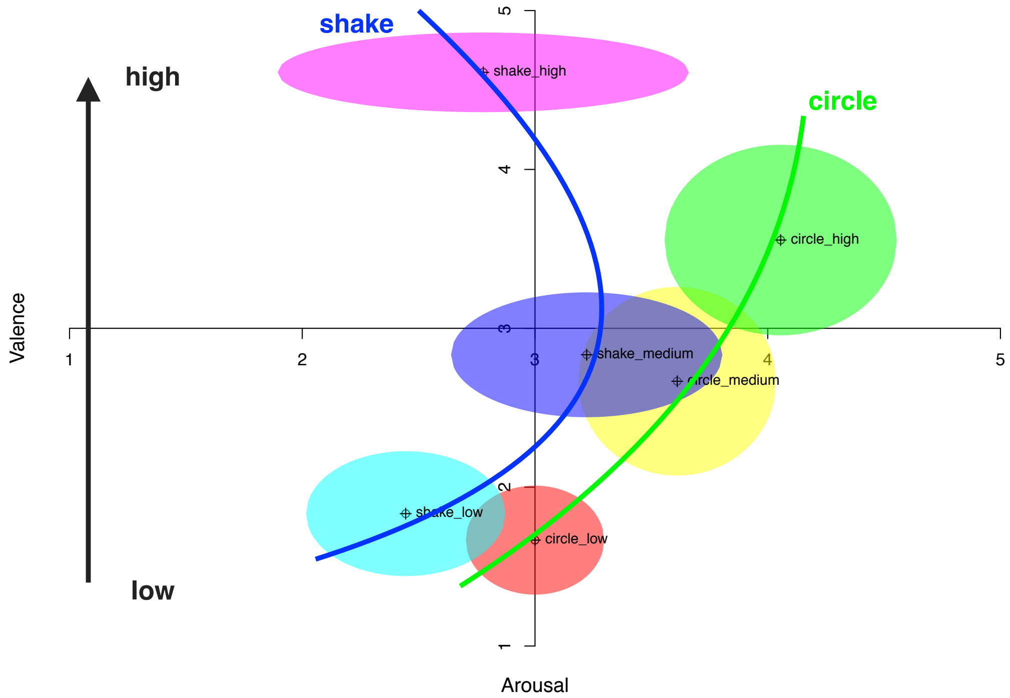


Figure 3.12: Ratings of expressions based on in-situ motions.

and high. According to previous work [13], the use of three levels can sufficiently represent the design space of speed.

Participants

The same eighteen Japanese participants took part in the experiment. They were asked to rate the perceived emotions of expressions based on in-situ motions. The order in which the six expressions were shown was randomized. The experiment had a 2 (pattern: circle vs. shake) × 3 (speed: low, medium, high) within-participant design.

Results

Figure 3.12 shows the ratings of the expressions based on in-situ motions. The results indicate an interesting relationship between in-situ motion parameters and attribution of affect.

We ran a factorial repeated measures ANOVA to test the ratings for valence and arousal separately. With regards to valence, it showed a significant main effect for both pattern $[F(1,17) = 7.59, p < 0.05]$ and speed $[F(2,34) = 5.72, p < 0.05]$. No interaction effect was found. We further conducted post-hoc tests with Holm's correction. The analysis revealed two important points. One, when speed was high, the circle pattern was perceived as significantly more positive than the shake pattern ($p < 0.05$). Two, when the pattern was the circle, the high speed was perceived as significantly more positive than the low speed. Such findings are in line with our hypothesis that humans and animals perform movements similar to the circle pattern to express positive feelings.

With regards to arousal, we found both a significant main effect for pattern $[F(1,17) = 5.35, p < 0.05]$ and speed $[F(2,34) = 76.24, p < 0.001]$ and a significant interaction effect $[F(2,34) = 5.52, p < 0.05]$. This effect might indicate that the shake pattern, compared with the circle one, was particularly strong in conveying emotions with high arousal levels. We conducted post-hoc tests with Holm's correction as well. The findings suggested that, one, when the speed was high, the shake pattern was perceived as significantly more intense than the circle pattern ($p < 0.05$), and, two, for both patterns, a higher level of speed was perceived as significantly more intense than a lower level of speed.

3.3.8 Combining Expressive Lights and Motion

On the basis of the findings from studies I and II, in this study, we investigated whether the robot could better convey emotions by combining in-situ motions and expressive lights.

Method

To evaluate how precisely an expression conveyed a target emotion, we calculated the Euclidian distance between the rating of an expression and its corresponding referential rating. By doing this, we were able to obtain two sets of distances: mean distances between ratings of expressions based on expressive lights alone and the referential ratings and mean distances between ratings of multi-modal expressions and the referential ratings.

The results of study II provided insights into the relationship between in-situ motion characteristics and the attribution of affect. Basically, the speed of motion had a

Table 3.5: Parameter settings for design of multi-modal expressions.

Emotion	RGB	Period[ms]	Waveform	Pattern	Speed
Anger	255, 17, 0	896	square	shake	high
Surprise	255, 132, 0	747	square	shake	high
Disgust	255, 0, 179	1645	square	shake	low
Sadness	21, 0, 255	3310	sinusoid	shake	low
Happiness	255, 157, 0	1123	square	circle	high
Fear	166, 0, 255	1377	square	shake	high
Calm	255, 255, 255	2000	sinusoid	circle	low

strong and positive relationship with the perceived arousal level. Moreover, the shake pattern was overall perceived to be more negative than the circle pattern, especially when the speed level was high. On the basis of these findings, we hypothesized that multi-modal expressions that appropriately combine in-situ motions and expressive lights were better able to be recognized. In other words, we intuitively assumed that adding appropriate in-situ motions might help to decrease the distances between the ratings of expressions based on expressive lights alone and their corresponding referential ratings. For instance, since the rating for happiness (shown in Figure 3.11) had both lower valence and arousal levels compared with its referential rating, a reasonable combination was to add in-situ motion with the circle pattern and the high speed level to the corresponding expressive light expressions. Table 3.5 shows all the combinations for the seven emotions.

Participants

Eleven Japanese in total (8 males and 3 females) ranging from 22 to 50 years old ($M = 27.91, SD = 8.14$) were recruited for the experiment. None of them had any color-vision disorders. Participants were asked to rate the perceived emotions of expressions based on multi-modal expressions that combine in-situ motions and expressive lights. The order in which six expressions were shown was randomized (due to technical problems during the experiment, we failed to show the expression for fear).

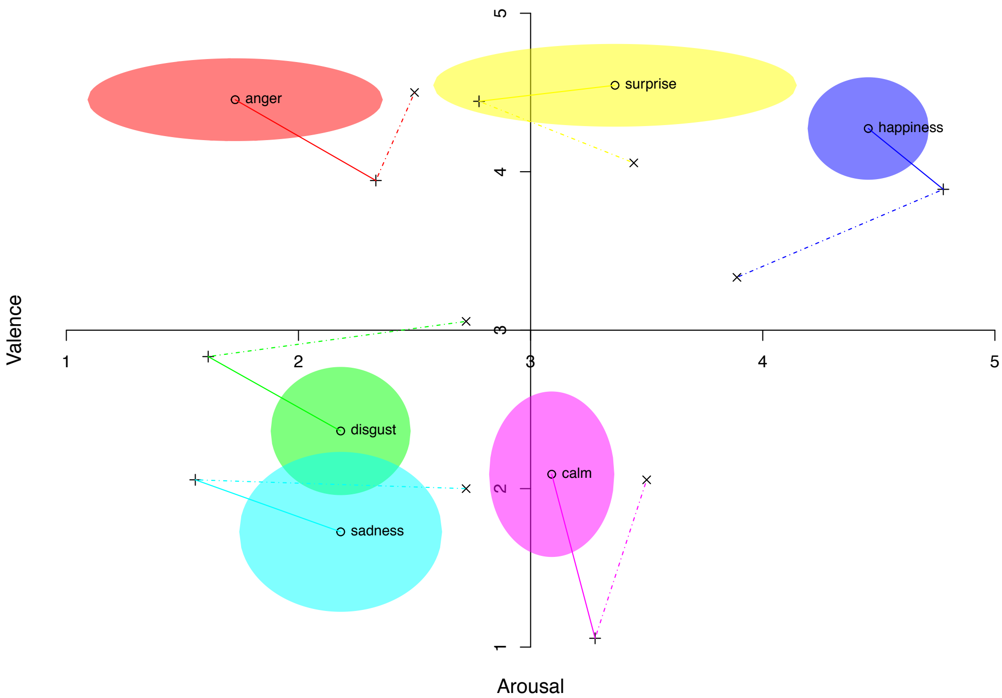


Figure 3.13: Ratings of multi-modal expressions that combine in-situ motions and expressive lights. ∘ indicates mean valence and arousal values for ratings of multi-modal expressions, × indicates mean valence and arousal values for ratings of expressions based on expressive lights alone, and + indicates referential ratings.

Results

Figure 3.13 shows the ratings of the expressions. ∘ indicates the mean valence and arousal values for the ratings of the multi-modal expressions, × indicates the mean valence and arousal values for the ratings of the expressions based on expressive lights alone, and + indicates referential ratings. Mean distances between response emotions (∘) and referential emotions (+) are illustrated as line segments, and mean distances between response emotions (×) and referential emotions (+) are shown as dashed line segments.

Table 3.6 shows the mean distances (computed in the Circumplex Model) of emotion attributes in studies I and study III. The column *Distance_I* represents the mean distances between the referential ratings of emotions and the ratings of the expressions based on expressive lights alone. *Distance_III* represents the mean distances between the referential ratings and the ratings of the multi-modal expressions that combine

Table 3.6: Mean distances in Circumplex Model of emotion attributes in studies I and III.

Emotion	Distance_I	Distance_III	Difference
Anger	0.58	0.79	0.21
Surprise	0.77	0.59	**-0.18**
Disgust	1.13	0.74	**-0.39**
Sadness	1.17	0.71	**-0.46**
Happiness	1.05	0.50	**-0.54**
Calm	1.02	1.05	0.03

in-situ motions and expressive lights. *Difference* demonstrates the differences between Distance_I and Distance_III ($Distance\_I - Distance\_III$). Each difference reflects how much an added in-situ motion helped a corresponding expressive light expression with conveying a target emotion. A minus value of difference indicates that the in-situ motion had a positive contribution to the expression of a target emotion, and a larger value suggests a greater amount of contribution.

3.3.9 Discussion

In general, the experimental results show strong support for our three hypotheses (see 3.3.5). Study I was done to re-examine designs for emotions expressed via expressive lights. The findings reveal that expressions based on expressive lights alone are not able to convey target emotions precisely. The distances between the ratings of response emotions (expressed via expressive lights) and ratings of referential emotions were quite large. Study II was done to explore emotions expressed via in-situ motions. The results suggest a strong relationship between in-situ motion parameters, pattern and speed, and perceived affect. Specifically, the speed factor contributed heavily to the intensity (arousal level) of an emotion, while the pattern factor contributed to the perceived valence level of an emotion. Study III was done to investigate multi-modal expressions that combine in-situ motions and expressive lights. The results show that adding in-situ motion to expressive lights improves affective expression for some emotions but not all.

We found that an in-situ motion seems to act as an “amplifier" to its corresponding expressive lights. For instance, when an in-situ motion with the circle pattern and high level of speed was added to the expressive light expression for happiness (see Table 3.5), the ratings for this emotion had both higher levels of valence and arousal, and the mean distance between the response emotion and referential emotion was decreased by 0.54 (see Figure 3.13 and Table 3.6). Similarly, when an in-situ motion with the shake pattern and low level of speed was added to the expressive light expression for sadness (see Table 3.5), the ratings for this emotion had both lower levels of valence and arousal, and the mean distance was decreased by 0.46 (see Figure 3.13 and Table 3.6). However, the amplifier effect might have negatively influenced the emotional expression for some emotions. For instance, when an in-situ motion with the shake pattern and high level of speed was added to the expressive light expression for anger (see Table 3.5), the ratings for this emotion had a lower valence and higher arousal, but the mean distance was increased by 0.21 (see Figure 3.13 and Table 3.6). In other words, the in-situ motion with the shake pattern and high level of speed made the perceived anger emotion too negative.

Limitations

Our findings were mainly limited in terms of three points. To combine in-situ motions with expressive lights, we assumed that these two modalities were independent of each other. In other words, we ignored that there might be interaction effects between the two modalities. Although our results suggest an improvement in emotion recognition for most emotions, future work still needs to be done to carefully investigate such interaction effects. A second limitation is that we designed only six expressions (2 patterns $\times$ 3 speed levels) for testing the in-situ motions. In study II, we successfully discovered the relationship between in-situ motion characteristics and attribution of affect based on the six expressions. However, the findings were not sufficient enough to give any suggestion on how to fine-tune the in-situ motions (speed in particular) to make optimal multi-modal expressions. A third limitation is that, in this work, we did not test gender effects since people of different sexes might have different levels of sensitivity with regards to emotional perception. In their work, Saerbeck and Bartneck [13] found no significant effects or significant interactions for gender on any combination of their motion characteristics. Therefore, we might assume that there is also no significant effects for gender on any combination of our in-situ motion characteristics. However, there might still be gender effects on the perception of expressive lights, especially on the color factor. We suggest that future work need to take the three limitations into account to achieve more precise design guidelines for designing emotional expressions via in-situ motion cues and expressive light cues.

3.4 Summary

This chapter discusses how to design non-verbal expressions for an appearance-constrained robot to communicate affect. Findings from the two studies give evidence that multi-modal expressions may achieve better performance compared to single-modal expressions. Therefore, further research may investigate effective combinations of different non-verbal cues. However, good balance needs to be considered between number of modalities and availability of a robotic system. In addition, since it is becoming more and more important for functional robots, in many application scenarios, to communicate affect and other social cues, future studies in HRI may explore more effective modalities.

4
Designing Communication Cues

This chapter discusses how to design LED-based gaze behavior for an appearance-constrained robot to communicate intent. Section 4.1 gives an overview of the study presented in this chapter. Section 4.2 reports a study which investigates how to implement gaze behavior in functional robots to assist humans in reading their intent. Section 4.3 summaries this work.

4.1 Overview

Eye gaze is considered to be a particularly important non-verbal communication cue. Gaze research is also becoming a hot topic in human-robot interaction (HRI). However, research on social eye gaze for HRI focuses mainly on human-like robots. There remains a lack of methods for functional robots, which are constrained in appearance, to show gaze-like behavior. In this chapter, I investigate how to implement gaze behavior in functional robots to assist humans in reading their intent. I explore design implications based on LED lights as I consider LEDs to be easily installed in most robots while not introducing features that are too human-like (to prevent users from having high expectations towards the robots). In this study, I first develop a design interface that allows designers to freely test different parameter settings for an LED-based gaze display for a Roomba robot. I summary design principles for well simulating LED-based gazes. The suggested design is further evaluated by a large group of participants with regard to their perception and interpretation of the robot's behaviors. On the basis of the findings, I offer a set of design implications that can be beneficial to HRI and CHI researchers.

4.2 Designing LED Lights for Communicating Gaze

4.2.1 Introduction

Functional robots are becoming more involved in our society. A real live example is the Roomba robot, a series of autonomous robotic vacuum cleaners that are becoming increasingly popular nowadays. However, due to the nature of the tasks such robots perform, they are generally restricted in appearance, making it hard for them to express their intent [20]. With regard to the Roomba robot, while it uses an LED display and beep sounds to indicate some of its internal states, e.g., cleaning or charging, its behavior can still be mysterious to many users. Since more and more functional robots are required to interact with, communicate to, and/or cooperate with human users, it is essential for such appearance-constrained robots to explicitly express their intent [85].

Unfortunately, there is a lack of methods that can enable appearance-constrained robots to express intent. C. Bethel et al. [28, 27, 19] have been very active regarding this issue and have performed a series of studies regarding non-facial/non-verbal affective expressions for appearance-constrained robots. They claim that functional robots are not engineered to be anthropomorphic and do not have the ability to exhibit facial expressions or make eye contact. It is either the limitation of the application or cost-saving reasons that lead to such appearance constraints. They documented the need for such robots to have affective interaction abilities across many different fields. For example, Fincannon et al. [107] described how rescue workers expected a small tank-like robot to follow social conventions. Work by Murphy et al. [108] provided an example of using man-packable robots to act as a surrogate presence for doctors tending to trapped victims. They found that the robots were perceived as “creepy" and not reassuring when they were operated close to simulated victims. To address such issues, Bethel [20] investigated five methods of non-facial and non-verbal affective expression: body movement, posture, orientation, color, and sound. As evidenced by their results, they claimed that humans were calmer with robots that exhibited non-facial and non-verbal affective expressions for social human-robot interaction in urban search and rescue applications.

Although C. Bethel et al.'s studies provide insights and a valuable mechanism for naturalistic social interaction between humans and appearance-constrained robots, there are several limitations, and therefore, a huge amount of work remains to be carried out by researchers in human-robot interaction (HRI) and related fields. The focus of these studies was restricted mainly to application scenarios involving victim assessment in the aftermath of a disaster. Accordingly, the experimental findings of the studies are majorly based on humans who are simulating victims interacting with two types of search and rescue robots: the Inuktun Extreme-VGTV and iRobot Packet Scout [20]. Robots such as these two share similar features, and thus, it is hard to say that their methods can be generalized to other types of robots such as the domestic-use cleaning robot, the Roomba. Since appearance-constrained robots are varied in embodiment, some interaction methods, such as body movement and posture, may not be applicable to some of these robots.

Besides body movement and posture, eye gaze is considered to be a particularly important non-verbal communication cue. Findings from psychology suggest that eyes are a cognitively special stimulus. There are special “hard-wired" pathways in the brain dedicated to vision interpretation [174]. In HRI, many researchers are trying to incorporate gaze into human-robot interactions. Admoni and Scassellati [73] provided an extensive review on social eye gaze in human-robot interaction. Basically, they summarized four types of eye gaze by using established terminology: *mutual gaze*, *referential gaze* or *deictic gaze*, *joint attention*, and *gaze aversion*. To be specific, mutual gaze can be referred to as “eye contact," referential or deictic gaze is gaze directed at an object or location in space, joint attention is two or more people (agents) sharing attentional focus on a common object, and gaze aversion refers to behaviors that shift gaze away from the main direction of gaze.

In human-human interaction, gaze has been suggested as important for providing information, expressing intimacy, and regulating interaction [75]. Due to its effectiveness, many researchers have tried to employ gaze as an interaction modality for social robots. Plenty of research has been done to evaluate the functionality and design principles of gaze behavior for HRI [175, 176, 177]. However, most of it focused on human-like robots or virtual human agents. Because of an adaptation gap [178], applying human-like eye gaze to functional robots, which are constrained in appearance, may cause users’ expectations of such robots to exceed the real capabilities of the robots and result in a negative HRI experience. Therefore, the appropriateness of applying anthropomorphic eyes to functional robots is questionable. There is a lack of knowledge with regard to how we can design eye gaze for appearance-constrained robots.

To address this question, light-based methods were investigated in a handful of previous work [85, 18]. Lights, as an explicit way of communication, have been studied in various fields such as psychology [78, 79] and human-computer interaction (HCI) [22, 82, 81, 81]. With regard to HRI, some researchers have explored the use of lights for their robots to show internal states [18], express affect [116], or communicate intent [85]. Particularly, Szafir et al. [85] explored the design space regarding robots explicitly communicating their flight intentions with LED lights. They tested their four signal designs (blinker, thruster, beacon, and gaze) and found that three of them (blinker, thruster, and gaze) were effective. In particular, they reported that their participants appreciated the greater precision offered by the gaze design. Therefore, their work showed that it can be potentially effective and precise to simulate gaze communication with LED lights.

However, their work leads to several unsolved design issues. Because they did not focus on gaze signals alone, the design principles regarding how "eyes" can be simulated by LED lights were not discussed in detail. As they mentioned in the paper, they designed the signals by using measurements of the human eye. However, due to the huge difference in shape and the many other features between human eyes and LEDs, the appropriateness of such an approach can be questioned. A better method could be offering a design interface to allow designers to freely explore a design space (different combinations of parameters). In addition, color, as a key feature, can be better investigated. To be specific, different colors can be used for different parts of the eye (pupil and sclera). This allows the pupil part to be made prominent, which could lead to a better resolution regarding the recognition of directionality.

In this work, we first examined parameter settings for simulating a gaze signal. We first developed an interface that allows designers to freely investigate different gaze designs. On the basis of the data and comments from volunteer designers, we summarized a set of design recommendations that can be employed as a reference for both HRI and HCI researchers. Then, we further hired a large sample of participants via an online survey platform to evaluate our gaze design. The participants' comments to open-ended questions offered valuable insights into how our designed gaze signal can be perceived and interpreted by humans. We suggest that, particularly for functional robots, LED-based eye gaze can be effective when applied as referential (or deictic) gaze or joint attention but less effective when applied as mutual gaze or gaze aversion.

4.2.2 Robot System

Our study is aimed at exploring the design space with regard to simulating gaze by using LED lights. We installed an LED lighting system (NeoPixel LED strip) on an iRobot Create 2 robot, which is a Roomba robot. In consideration of the disc-shaped embodiment of the Roomba robot, we attached the LED strip to the body of the robot in a ring [87, 146]. Figure 4.1 shows the front side of the robot and the configuration of its LED lighting. To be specific, we used one meter of a NeoPixel LED strip (60 pixels). The LED strip was controlled by an Arduino Uno R3 board, and both the strip and the board were powered by a 5-V, 3-A portable battery bank. The same board was also used to control the movements of the robot.

By employing LED lights, we enable the Roomba robot to modify its appearance as

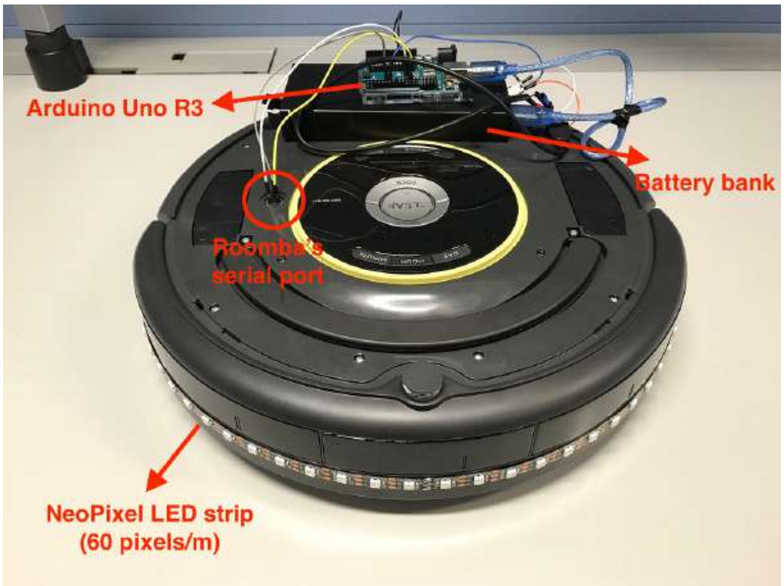


Figure 4.1: Configuration of Roomba robot with LED lighting system

a way of communicating with people. This provides an additional communication cue that can assist in interpreting the robot's behavior and intent.

4.2.3 Gaze Design

Design Interface

We developed a design interface by using Processing. As shown in Figure 4.2, the interface allows designers to explore a set of parameters regarding gaze simulation. Specifically, the associated parameters include *color of pupil*, *width of pupil*, *color of sclera*, *width of sclera*, and *interocular distance*.

The image in the upper left shows the front side of the Roomba robot with LED lighting. It provides an intuitive idea of what the robot looks like and can, explicitly or implicitly, help designers keep a correct mental model of the robot while setting parameters. The right hand side panel allows designers to interact with the interface. Designers can freely try out different combinations of parameter values by setting the corresponding parameters. Particularly, the interface provides a candidate set of basic colors in the lower right side for the designers to select. The design interface can be connected to our Roomba robot equipped with an LED lighting system. By clicking on

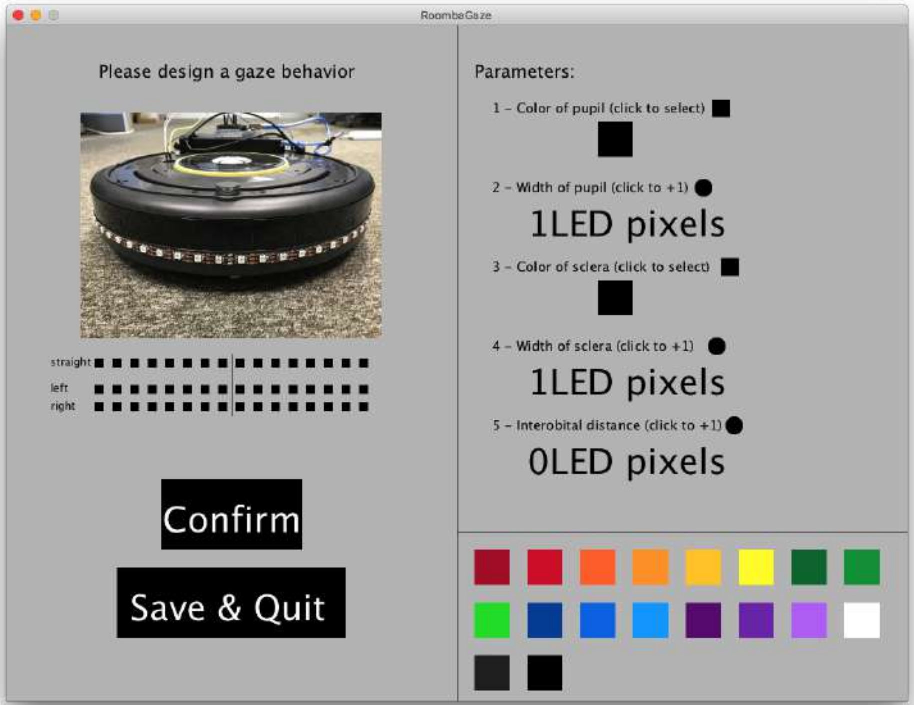


Figure 4.2: Screenshot of design interface

the “Confirm" button, the interface sends the current parameter values to the Roomba (to the Arduino Uno board attached to it), which then displays the corresponding gaze signal. Designers can iterate over and optimize their gaze designs. If they finally decide on a set of parameters, they can click on the “Save & Quit" button to quit the design interface. The final parameter values will be saved to a local file, allowing for later analysis.

Design Rationale Although the appropriateness of applying anthropomorphic gaze design to appearance-constrained robots can be questioned, we still used human eyes as a fundamental design reference for designing LED-based gaze behavior. Specifically, we borrowed the basic features, e.g., two eye balls and concepts of pupil and sclera, from human eyes to guide people with their design. There are several reasons for doing so. Firstly, our design interface was applied as a method to explore the potential designs for LED-based gaze behavior. Almost no existing findings can be used as ground knowledge. Therefore, features from human eyes can be treated as a starting point of the exploration study. Besides, features from human eyes can be intuitive to the designers as they may probably no familiar with designing gaze-like behavior using LEDs. Secondly, some features from human eyes, e.g., the form of pupil and sclera and the distribution of two eye balls, have the advantage of clearly indicating gaze direction and focus compared to other types of gaze such as using only one eye ball. In addition, it should be realized that the design of LED-based gaze depends on the embodiment of a robot since the robot's shape decides the distribution of LED pixels. Since a LED strip was attached to the Roomba robot in a ring, we were able to apply human eye features to our design. However, such design may be not applicable for some other types of robot.

Procedure

We organized a design session in which we invited six designers (one female) to join an experiment. At the beginning of the session, we showed a demo video as a tutorial regarding how to use the design interface. Later, the participants were assigned to individual design trials without any time restriction. At the end of the trials, they were asked to provide comments and opinions in a free manner.

Results

We recorded the designers' choices of parameter values during the design session. Table 4.1 shows these values ("Black" means an LED pixel does not display any light; "gray" refers to white light in low brightness). For color of pupil, we found that the choices of color varied from each other. Colors, such as blue, yellow, and green, were selected. For width of pupil, the choices were consistent with each other. Four of the designers selected 4 LED pixels as the most appropriate, while two of them preferred 3 LED pixels. The median value of their choices was 2. For color of sclera, we also found an overall agreement of choices of color among the designers. Most of them agreed that white (or white light in low brightness) was the most suitable for the color of the sclera. For width of sclera, we saw some divergence among the designers. However, their choices were mostly around the median values, which were 2 or 3 LED pixels. For interorbital distance, a half of the designers chose 4 LED pixels as the most appropriate

Table 4.1: Parameter values chosen by six designers

	P1	P2	P3	P4	P5	P6	Median
Color of pupil	blue	green	yellow	dark blue	orange	green	-
Width of pupil	2	2	2	3	2	3	2
Color of sclera	black	white	gray	white	white	blue	-
Width of sclera	0	3	2	2	3	3	2 or 3
Interorbital distance	4	4	2	4	6	6	4

setting, while two of them selected 6 and one selected 2. The median value was 4.

We also gathered free comments from the designers with regard to their choices of parameter settings by using open-ended questions. In general, the designers seemed to refer to the human eye at the beginning stage of the design session. This was not surprising as eye gaze is a very important non-verbal signal with regard to human-human communication. However, after some trials, they found that it might be inappropriate to use human eye gaze as a reference to design LED-based gaze behavior, e.g., “Mimicking the human eye looked weird" (P3) and “I found it hard to figure out an adequate pattern when I tried to imagine human eye gaze" (P5). Therefore, the designers then tried different parameter settings to make the pupil part stand out, e.g., “... it looked better if only the pupil part was lighted up" (P1) and “It was better if the pupil part could be seen clearly" (P2), or just make the lights look beautiful [“I just tried different combinations of colors that seemed beautiful to me" (P6)]. An important point was pointed out by the designers that the brightness of the sclera part should be much lower than the pupil part, e.g., “It looked weird if the sclera part was set to be too bright" (P3) and “It would look closer to an eye if the sclera part were set to low brightness and the pupil part were set to high brightness" (P4). In addition, one designer particularly mentioned that red was not an adequate color for the pupil [“Red may be inappropriate for the pupil part" (P1)].

Design Principle

We summarized a set of design principles based on the findings from this design session:

I The pupil part should be clearly identifiable. To ensure this, it is suggested that the width of the pupil be more than 1 LED pixel. In addition, the color of the pupil should contrast highly with the color of the sclera.

II The brightness of the sclera part should be much lower than the pupil part to look natural[1]. This also helps the pupil to stand out.

III The width of the sclera should be sufficiently long so that the directionality of gaze, e.g., left, normal, and right, can be well recognized.

IV The interocular distance should be sufficiently long so that the two eyes can be well distinguished.

Particularly, principle II provides partial evidence of the inappropriateness of using measurements of the human eye in gaze signal design because the sclera of a human eye is, in general, much brighter than the pupil. The description of “look natural" means something different, depending on the design space to be referred to. If the task is to design an anthropomorphic eye, it could be preferable to imitate a human eye. However, with regard to designing a gaze signal with LED lights, different design principles should be relied on.

4.2.4 Evaluation

On the basis of the findings from the design session, we decided on an example of a gaze signal that well followed the five principles. Specifically, we set the color of the pupil to bright green and the color of the sclera to dim gray. We set the width of the pupil to 2 LED pixels and the width of the sclera to 3 LED pixels. In addition, we set the interocular distance to 4 LED pixels.

We prepared two demo videos in which the Roomba robot was displaying a “scan" behavior (gazing from left to right regularly in two cycles). In one demo (a screenshot is shown in Figure 4.3, demo 1), the robot was the only object in the video. There was nothing in front of it while it was scanning. However, in the other demo (a screenshot is shown in Figure 4.3, demo 2), three objects were put in front of the robot. The goal of the evaluation was to find out how people would perceive and interpret our designed

[1]The meaning of “look natural" does not suggest that it looks more similar to the human eye. We prefer to interpret this as a lower brightness of the sclera part that makes people more easily perceive LED lights as a gaze signal.

(a) Demo1: without object.

(b) Demo2: with object.

Figure 4.3: Screenshots of two demos: without and with object.

gaze signal that uses LED lights. Due to the mechanic embodiment of the Roomba robot and neutral shape of the LED strip, we hypothesized that people's perception of the robot would be that it is hardly anthropomorphic. As a result, it would be hard for them to interpret the light expressions as gaze signals in general. However, we hypothesized that when reference objects, or additional cues, are provided (the three objects in the second demo), people would then understand the gaze signals and attribute more agency to the robot. This actually meets a key design goal; gaze design should not introduce too much anthropomorphism as it otherwise could cause human's expectations of a robot to exceed its real capabilities.

Procedure

We performed the evaluation by using online surveys. A Japanese online crowdsourcing platform, Fastask (https://www.fast-ask.com), was employed to recruit participants. We hired 120 participants, 60 of them for each condition (demo video). In a questionnaire, we asked two open-ended questions: 1) “What was the robot doing?" and 2) “Is it easy to understand the robot's intent?"

Results

Participants' comments to the open-ended questions were coded into two categories: gaze-related perception and gaze-unrelated perception:

- Gaze-related perception: A participant's descriptions of the robot's behavior were coded into this category if he or she used indicator words such as *detect*,

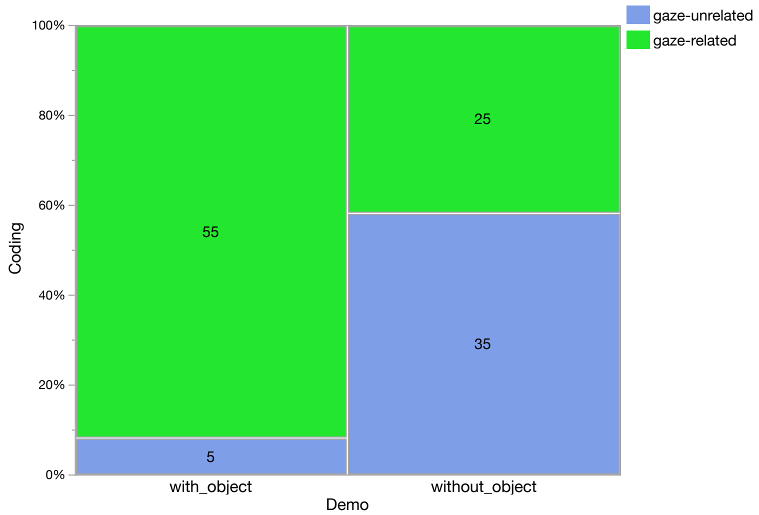


Figure 4.4: Coding results with regard to two demos: with and without object.

perceive, *judge*, *recognize*, *observe*, and *confirm*. These words give the impression that the robot might have been perceived as seeing things, therefore suggesting that the LED light displayed by the robot was interpreted as gaze.

- Gaze-unrelated perception: A participant's descriptions of the robot's behavior were coded into this category if he or she did not use the indicator words mentioned above. Examples of descriptions are "The robot is charging" or "The robot is currently cleaning the floor." Such descriptions suggest that the LED light displayed by the robot was not interpreted as gaze.

Figure 4.4 shows the result. Basically, most participants (55 out of 60) that watched demo 1 interpreted the LED light displayed by the robot as gaze-related behavior, whereas only less than a half of the participants (25 out of 60) that watched demo 2 made similar interpretations. A Mann-Whitney U test was conducted to determine the effect of the independent factor (demo: without object vs. with object) on the dependent factor (coding: gaze-related perception vs. gaze-unrelated perception). Demo had a significant effect on coding (z = 5.7852, p<0.001, η^2 = 0.28).

Interestingly, some of the participants (8 out of 60) that watched demo 1 described the robot as standing by and charging.

Discussion

The results confirmed our hypotheses. In general, participants who viewed the demo showing the robot alone found it hard to understand the robot's intent. Their perceptions and interpretations regarding the robot's behavior were highly biased by the type of robot: cleaning robot. To be specific, many participants described the robot as "searching for garbage" or "cleaning (its current place)." Other participants thought that the robot was charging or waiting for commands. Such descriptions indicate that participants did not attribute agency to the robot. This suggests that, without hints regarding the functionality of the light expressions, it can be difficult for people to perceive them as gaze signals.

However, participants who viewed the demo showing objects in front of the robot found it easy to understand the robot's intent. This is not surprising since the provided objects, as an additional cue, allowed them to dramatically reduce the number of potential scenarios for guessing. An analysis on the participants' descriptions of the robot's behavior clearly showed that they attributed a certain level of agency to the robot. Specifically, many participants used anthropomorphic descriptions such as "observing the objects" or "choosing among the objects." Such descriptions suggest that they interpreted the light expressions as gaze signals (scanning the objects). Importantly, almost none of the participants explicitly described the light expressions as eye-like or gaze-like, suggesting that they did not attribute too high a level of agency to the robot.

In addition, we found that some participants described the robot as standing by and charging. Since conveying a robot's internal states is becoming an important research topic in HRI, this finding may provide inspiration to researchers and designers who aim at designing effective light displays for robots to communicate their states.

4.2.5 Design Implications

On the basis of our findings with regard to both light expression design and light-based gaze evaluation, we offer several important design implications that can be beneficial to HRI and CHI researchers:

- Light-based gaze signals may not be explicit cues that indicate directionality.

However, when a reference (object) is provided, people can easily learn or recognize the functionality of the light expressions, similar to gaze. To be general, such reference information does not necessarily need to be an object. A robot's motion, for instance, that is coordinated to light expressions could probably help people to recognize a gaze signal too.

- Light-based gaze signals should be designed by using measurements of the human eye with caution. Some features (parameter settings) that fit the design of anthropomorphic gaze may not be appropriate for light-based gaze signals.
- Light-based gaze signals can be suitable for functional robots as they will not introduce too much anthropomorphism, which biases people to have expectations that exceed a robot's real capabilities.

4.3 Summary

This chapter reports design implications for well simulating LED-based gaze behavior. Future work may be to evaluate the effect of light-based gaze signals in real HRI contexts. Because gaze can be used to indicate a robot's intent and direct people's attention [75], it is important to examine whether light-based gaze signals possess such functionality. I would consider several evaluation methods to be applied for this purpose. Typical human-robot cooperation contexts can be designed in which task performance can be improved if a human is able to read a robot's intent (next move). Video-recorded data is needed to analyze how humans behave when reacting to a robot's gaze signals. Importantly, I may consider using a wearable eye-tracker device (Tobii Pro Glasses 2) to track people's corresponding gaze behavior on-the-fly. This would allow me to easily identify the joint-attention behavior of a person. In addition, future work could also involve gaze animation design. Gaze animations may cause people to attribute more agency to a robot. In addition, other robot shapes and arrangements of LEDs should be investigated.

5
Conclusion

This chapter concludes this dissertation. Section 5.1 provides a general discussion on the findings presented in this dissertation. Section 5.2 summarizes this thesis work and section 5.3 recommends future research directions.

5.1 Discussion

5.1.1 The Power of Color

With regard to the non-verbal expressions studied in this work, I particularly treat expressive lights as a primary modality. This is because that color, as a core element of expressive lights, has been widely studied in various fields and centuries since long ago. Color psychologists and scientists intensively investigated different aspects of color, including color vision, color emotion, and color effects on psychological and biological functioning. Their work primarily focused on categorical colors such as red, blue, and green.

Specifically, red has been shown to be a critical color and has thus garnered the majority of research attention. Many things in biology, culture, and language points to the poignancy and prominence of red. Red is the color of blood, and dynamic variations in visible blood flow on the face and body can indicate fear, arousal, anger and aggression. Red is used in warning signals by many poisonous insects and reptiles. Red is also a term that appears in almost all lexicons and, moreover, in many sayings such as "in the red."

Besides red, green and blue have been intensively studied as well. They both have positive links in the natural realm, for instance, green foliage and vegetation and blue sky and ocean. In general, although existing research on color has not yet formalized a rigid framework for color related design and many research subfields are still in the nascent stages, we are still able to use the findings as theoretical groundings and application guidelines to explore effective designs in HRI scenarios.

On the basis of the findings presented in this thesis, I summarize three merits of expressive lights as a powerful non-verbal modality:

1 Intuitive
The perception and interpretation of expressive lights can be intuitive as color is one of the most ubiquitous phenomena in human experience. Interpretation of the meanings of different colors are most learnt implicitly from repeated pairings of colors with particular concepts or experiences and biologically based proclivities to respond to particular colors in particular ways in particular situations. Therefore, expressive lights, as a non-verbal communication cue,

would not cost much cognitive load from humans.

2 Effective

Expressive lights, as a dynamic vision cue, can be effective to communicate various information, including affect and intent. Besides, it has the potential to influence a person's behavior and decision-making, either explicitly or implicitly. For instance, findings presented in section 2.2 reveal that red can be associated with danger and anger and further induce avoidance-like behavior in people, whereas green carries positive meanings and can further induce approach-like behaviors.

3 Simple

It only needs programmable RGB LEDs to display various patterns of expressive lights. Such LEDs are easy to control, cheap, and most importantly, simple to be embedded to most robot systems. In other words, it would not cost much effort and money to enable a functional robot, which is constrained in appearance, to communicate in LED lights. Therefore, this makes expressive lights a promising approach that can be applied to most currently-in-use robots.

5.1.2 Single Modality vs. Multiple Modality

Particularly in chapter 3, I discussed about how to design effective non-verbal expressions via modalities–expressive lights (color), sound, vibration, and motion–for an appearance-constrained robot to communicate affect. Findings from a series of two studies reveal that non-verbal expressions using multiple modalities may perform better than those using only one modality. People often feel confused and lack of confidence when they are asked to guess a robot's emotion when single-modal expressions are used. For instance, participants from the first study (section 3.2) gave comments like "Using multiple modalities is more understandable than using a single modality alone." The use of multiple modalities offer redundant information on the affect-expression associations so that people can cross-confirm their perception and interpretation over different modalities. This is particularly useful as existing research lack theoretical groundings with regard to the design of affective communications via expressive lights, sound, vibration, and motion.

Besides, it gives flexibility with regard to choosing appropriate non-verbal cues in accordance with the hardware configuration of a robot. Because different robot systems probably have different physical configurations, the four non-verbal cues investigated in this work, especially vibration, may be not applicable to each of the robots. Therefore, for designers who would apply the design implications to their projects, I suggest that they start with choosing the expressions that have the highest recognition rate while meeting their hardware configurations and that they further adjust their choices on the basis of the performance.

5.1.3 From Inform to Interact

In this thesis, I work through structured processes to explore the effects and design of non-verbal expressions. Till now, research on designing effective non-verbal expressions for appearance-constrained robots is still in its infancy. A systematic exploration in this area seems to be missing. It is mentioned that the goals of using expressive lights on social robots can be summarized by the three I's: Inform, Influence, and Interact [84]. However, I suggest that this three I's approach can be extended to the design of non-verbal expressions in general. I propose that:

- *Inform:* is about conveying certain information to humans. It is uni-directional (from a robot to a person) and mainly explicit.
- *Influence:* is about changing certain behaviors of humans. it is uni-directional (from a robot to a person) and mainly implicit.
- *Interact:* is about communicating with humans. It is bi-directional.

Each component can be particularly important for certain applications. Hence, it may not be appropriate to identify Interact as an ultimate goal. However, Interact can be the most complex component which requires contributions from the other two, Inform and Influence, as interactions between robots and humans can be long-term and require mutual adaption between both parties. The three I's approach is useful as it can help researchers and practitioners to focus on application scenarios and design non-verbal expressions in a goal-driven way. For instance, an autonomous task robot may mainly need to inform its task-related states (e.g. in progress or low battery) to its users whereas a personal training couch robot shall influence its users' behavior and habit.

Most of the studies presented in this dissertation only focus on the first component, Inform, by investigating effective expressions for a robot to communicate affect or intent. Other studies (see sections 2.2 and 2.3) touch on the Influence component, in which potential influence of non-verbal expressions on people's perception and behavior are discussed. Unfortunately, effects of the proposed designs of non-verbal expressions have not yet been evaluated in a bi-directional human-robot interaction fashion. Therefore, future research can follow this direction on the basis of the theoretic groundings and empirical knowledge provided by this work.

5.1.4 Generalization of Findings

Most studies discussed in this dissertation focus on simply shaped robots like a Roomba. A Roomba robot is disc-shaped, without additional features such as a mechanical arm. In addition, it only has limited methods of action such as moving forward/backward and spinning. These simply shaped robots perfectly meet the definition of appearance-constrained robots. Hence, findings from the studies could be generalized to many other functional robots which are constrained in appearance.

With regard to interaction methods, the non-verbal modalities, including LED light, artificial sound, and motion, could be easily applied to most embodied robots. For instance, it only needs programmable LEDs and speakers to display LED light animations and sounds. Many functional robots used in applications, such as search and rescue and cleaning, are autonomous robots, meaning that they already equipped with wheels or tracks to perform motions. Saerbeck and Bartneck [13] suggested that effects of motion seem not depend on the shape of robots. Besides, this work also investigate non-verbal expressions on different platforms, including a monitor, the Maru robot, and a Roomba. Therefore, I would suggest that the designs of non-verbal expressions recommended in this thesis could be also applied to other robotic platforms. However, I would like to say that findings from this work may not be applicable for human-like robots. Basically, humanoid robots can use more anthropomorphic interaction method such as natural languages, facial expressions, or gestures. Such interaction modalities are more human-like, and thus, more natural to humans.

Culture difference should be considered as a potentially important factor which may restrict the generalization of the findings. To be specific, culture difference refers to the fact that people from different regions with different culture backgrounds may have different understanding and interpretation of a same phenomenon. Particularly with regard to HRI, people from different cultures may differ in the perception and interpretation of a same behavior shown by a robot. In this thesis, I investigated non-verbal expressions using light, sound, motion, and vibration. People's perception and interpretation of non-verbal features, e.g., color, tune, pitch, and motion, may be influenced by their cultures. For instance, people from many regions interpret red as dangerous and aggressive whereas Chinese people treat red as a color of luck and happiness. The findings presented in this dissertation were observed only from Japanese participants. Therefore, I would suggest that such findings shall be applied to people from other countries with caution.

Another potentially important factor is gender difference since males and females may have different interpretation and level of sensitivity of a same affective expression. For instance, females may be considered as more sensitive to emotional cues compared to males, and both males and females may show different attitudes toward their interlocutors, depending on the sexes of the interlocutors. According to previous work [13], the authors did not find significant effects for gender on any combination of their motion characteristics. However, I would say that there may still be gender effects on the perception of lights and sound, especially of color.

5.2 Conclusion

Because a large number of robots currently in use are neither anthropomorphic nor zoomorphic, the lack of appropriate mental models and knowledge with regard to these robots can lead to unsmooth or even failed interaction. Besides, such robots are generally constrained in appearance, meaning that they are designed to be functional and lack expressive faces and bodies. Therefore, there is a significant challenge in finding ways for the appearance-constrained robots to successfully interact with people. To address the challenge, this dissertation aims at finding effective designs of expressions that allow an appearance-constrained robot to communicate affect and intent.

To design effective expressions for appearance-constrained robots, I probe non-verbal modalities include expressive lights (color), motion, sound, and vibration. These modalities have been explored by researchers from different fields such as human-computer interaction, psychology, and cognitive science. However, there is still much unknown with regard to how the non-verbal expressions can be implemented to facilitate interactions between robots and humans.

In this thesis, I particularly treat expressive lights as a primary modality and the others, motion, sound, and vibration, as auxiliary ones. It is because that color, as a core element of expressive lights, has been widely studied in various fields. Although existing research has not yet established a rigid framework for expressive lights design, I am still able to use the findings as theoretical groundings and application guidelines to explore their validity and effectiveness in the HRI scenarios. On the other hand, due to the lack of theoretical groundings with regard to the other three modalities, it is hard to make valid assumptions for motion-, sound-, and vibration-affect associations. However, such modalities can be used as auxiliary modalities to form multi-modal expressions so that performance and effectiveness may be improved.

Specifically, this work focuses on three aspects of the research challenge on designing effective non-verbal expressions for appearance-constrained robots: (1) influence of non-verbal expressions on people's perception, interpretation, and decision-making, (2) communicating affect via non-verbal expressions, and (3) communicating intent via non-verbal expressions. Findings from this thesis work, with regard to the first research question, suggest that non-verbal expressions, especially expressive lights, can influence a person's perception and interpretation of a robot's behavior and further change his or her behavior (decision-making). With regard to the second question, a series of two studies reveal evidence that multi-modal expressions may achieve better performance on affect communication compared to single-modal ones. For the third question, a study particularly investigates the design of LED-based gaze behaviors for an appearance-constrained robot to express intent. Detailed design implications are provided which can be beneficial to HRI and CHI researchers.

5.3 Future Work

This dissertation can open up possibilities for future research. Research on the design of effective HRI for appearance-constrained robots is still in its infancy. It is because that researchers are focusing too much on anthropomorphic or zoomorphic robots, neglecting the importance for functional robots to communicate social cues. Therefore, this work offers both theoretical findings and empirical knowledge as building blocks for further investigation on the design of effective non-verbal expressions for functional robots, which are constrained in appearance, to communicate affect and intent and influence people's behavior.

Future work can test the effect of the suggested design implications on other robot platforms because the embodiment (e.g. shape) of a robot may have strong influence to the effect of non-verbal expressions. Therefore, such studies can reveal important findings which can be applied to wider range of robots. Future research shall also test the designs in live HRI scenarios. By doing so, researchers are able to observe direct responses from participants that can well simulate real HRI applications. In addition, culture factors need to be considered in future investigations. People from different regions and with different culture background may have diverse perception and interpretations of a same non-verbal expression.

Bibliography

[1] Haddock Steven HD, Mark A. Moline, and James F. Case. Bioluminescence in the sea. *Annual Review of Marine Science*, 2(1):443–493, 2010. PMID: 21141672.

[2] Fumihide Tanaka and Shizuko Matsuzoe. Children teach a care-receiving robot to promote their learning: Field experiments in a classroom for vocabulary learning. *Journal of Human-Robot Interaction*, 1(1), 2012.

[3] Deanna Hood, Séverin Lemaignan, and Pierre Dillenbourg. When children teach a robot to write: An autonomous teachable humanoid which uses simulated handwriting. In *Proceedings of the 10th Annual ACM/IEEE International Conference on Human-Robot Interaction*, pages 83–90, New York, NY, USA, 2015. ACM.

[4] Angelica Lim and Hiroshi G. Okuno. A recipe for empathy. *International Journal of Social Robotics*, 7(1):35–49, Feb 2015.

[5] Priscilla Briggs, Matthias Scheutz, and Linda Tickle-Degnen. Are robots ready for administering health status surveys': First results from an hri study with subjects with parkinson's disease. In *Proceedings of the 10th Annual ACM/IEEE International Conference on Human-Robot Interaction*, pages 327–334, New York, NY, USA, 2015. ACM.

[6] Maha Salem, Micheline Ziadee, and Majd Sakr. Marhaba, how may i help you?: Effects of politeness and culture on robot acceptance and anthropomorphization. In *Proceedings of the 9th ACM/IEEE International Conference on Human-robot Interaction*, pages 74–81, New York, NY, USA, 2014. ACM.

[7] Astrid Weiss, Nicole Mirnig, Ulrike Bruckenberger, Ewald Strasser, Manfred Tscheligi, Barbara Kühnlenz, Dirk Wollherr, and Bartlomiej Stanczyk. The interactive urban robot: user-centered development and final field trial of a direction requesting robot. *Paladyn J. Behav. Rob*, 6:42–56, 2015.

[8] David Sirkin, Brian Mok, Stephen Yang, and Wendy Ju. Mechanical ottoman: How robotic furniture offers and withdraws support. In *Proceedings of the Tenth Annual ACM/IEEE International Conference on Human-Robot Interaction*, pages 11–18, New York, NY, USA, 2015. ACM.

[9] Jodi Forlizzi. How robotic products become social products: An ethnographic study of cleaning in the home. In *Proceedings of the 2nd ACM/IEEE International Conference on Human-robot Interaction*, pages 129–136, New York, NY, USA, 2007. ACM.

[10] Don Norman. *The design of everyday things.* The MIT Press, London, 1998.

[11] Terrence Fong, Illah Nourbakhsh, and Kerstin Dautenhahn. A survey of socially interactive robots. *Robotics and Autonomous Systems*, 42(3):143–166, 2003. Socially Interactive Robots.

[12] Szafir Daniel, Bilge Mutlu, and Terrence Fong. Communication of intent in assistive free flyers. In *Proceedings of the 9th ACM/IEEE International Conference on Human-robot Interaction*, pages 358–365, New York, NY, USA, 2014. ACM.

[13] Saerbeck Martin and Christoph Bartneck. Perception of affect elicited by robot motion. In *Proceedings of the 5th ACM/IEEE International Conference on Human-Robot Interaction*, pages 53–60, March 2010.

[14] Cynthia Breazeal. *Designing Sociable Robots.* MIT Press, Cambridge, MA, USA, 2002.

[15] Cynthia. Social interactions in hri: the robot view. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, 34(2):181–186, May 2004.

[16] Mark Scheeff, John Pinto, Kris Rahardja, Scott Snibbe, and Robert Tow. Experiences with sparky, a social robot. In *Socially Intelligent Agents*, pages 173–180. Springer, 2002.

[17] Takanori Komatsu, R Kurosowa, and Seiji Yamada. How does difference between users? expectations and perceptions about a robotic agent (adaptation gap) affect their behaviors. In *Proc. of HRI2011 Workshop on The role of expectations in intuitive human-robot interaction*, 2010.

[18] Kim Baraka and Manuela M. Veloso. Mobile service robot state revealing through expressive lights: Formalism, design, and evaluation. *International Journal of Social Robotics*, 10(1):65–92, Jan 2018.

[19] Bethel Cindy L. and Robin R. Murphy. Survey of non-facial/non-verbal affective expressions for appearance-constrained robots. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, 38(1):83–92, Jan 2008.

[20] Bethel Cindy L. *Robots without faces: non-verbal social human-robot interaction.* [dissertation/Ph.D.'s thesis]. University of South Florida, 2009.

[21] Sarah N Woods, Michael L Walters, Kheng Lee Koay, and Kerstin Dautenhahn. Methodological issues in hri: A comparison of live and video-based methods in robot to human approach direction trials. In *ROMAN 2006-The 15th IEEE International Symposium on Robot and Human Interactive Communication*, pages 51–58. IEEE, 2006.

[22] Chris Harrison, John Horstman, Gary Hsieh, and Scott Hudson. Unlocking the expressivity of point lights. In *Proceedings of the 2012 SIGCHI Conference on Human Factors in Computing Systems*, pages 1683–1692, New York, NY, USA, 2012. ACM.

[23] Steven Komarov, Katharina Reinecke, and Krzysztof Z. Gajos. Crowdsourcing performance evaluations of user interfaces. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '13, pages 207–216, New York, NY, USA, 2013. ACM.

[24] Types of data. http://socialscientist.us/nphs/psychIB/IBReview/Quantitative_Qualitative.pdf, (accessed november 5, 2018).

[25] Philip B Gove. *Webster's seventh new collegiate dictionary.* Allen, 1963.

[26] Michael A Goodrich and Alan C Schultz. Human–robot interaction: a survey. *Foundations and Trends® in Human–Computer Interaction*, 1(3):203–275, 2008.

[27] Bethel Cindy L. and Robin R. Murphy. Non-facial/non-verbal methods of affective expression as applied to robot-assisted victim assessment. In *Proceedings of the 2nd ACM/IEEE International Conference on Human-robot Interaction*, pages 287–294, New York, NY, USA, 2007. ACM.

[28] Bethel Cindy L. and Robin R. Murphy. Affective expression in appearance constrained robots. In *Proceedings of the 1st ACM SIGCHI/SIGART Conference on Human-robot Interaction*, pages 327–328, New York, NY, USA, 2006. ACM.

[29] Vladimir Kulyukin, Chaitanya Gharpure, John Nicholson, and Grayson Osborne. Robot-assisted wayfinding for the visually impaired in structured indoor environments. *Autonomous Robots*, 21(1):29–41, 2006.

[30] Michael Montemerlo, Joelle Pineau, Nicholas Roy, Sebastian Thrun, and Vandi Verma. Experiences with a mobile robotic guide for the elderly. *AAAI/IAAI*, 2002:587–592, 2002.

[31] Henry Kautz, Larry Arnstein, Gaetano Borriello, Oren Etzioni, and Dieter Fox. An overview of the assisted cognition project. In *AAAI-2002 Workshop on Automation as Caregiver: The Role of Intelligent Technology in Elder Care*, number 2002, page 6065, 2002.

[32] Goren Gordon, Cynthia Breazeal, and Susan Engel. Can children catch curiosity from a social robot? In *Proceedings of the Tenth Annual ACM/IEEE International Conference on Human-Robot Interaction*, pages 91–98. ACM, 2015.

[33] Iris Howley, Takayuki Kanda, Kotaro Hayashi, and Carolyn Rosé. Effects of social presence and social role on help-seeking and learning. In *Proceedings of the 2014 ACM/IEEE international conference on Human-robot interaction*, pages 415–422. ACM, 2014.

[34] Fujita Masahiro. On activating human communications with pet-type robot aibo. *Proceedings of the IEEE*, 92(11):1804–1813, Nov 2004.

[35] Steffi Paepcke and Leila Takayama. Judging a bot by its cover: an experiment on expectation setting for personal robots. In *Proceedings of the 5th ACM/IEEE international conference on Human-robot interaction*, pages 45–52. IEEE Press, 2010.

[36] Marek P Michalowski, Selma Sabanovic, and Hideki Kozima. A dancing robot for rhythmic social interaction. In *Human-Robot Interaction (HRI), 2007 2nd ACM/IEEE International Conference on*, pages 89–96. IEEE, 2007.

[37] Jaap Ham, Raymond H Cuijpers, and John-John Cabibihan. Combining robotic persuasive strategies: the persuasive power of a storytelling robot that uses gazing and gestures. *International Journal of Social Robotics*, 7(4):479–487, 2015.

[38] Jaime Montemayor, Houman Alborzi, Allison Druin, Jim Hendler, Deborah Pollack, Jessica Porteous, Lisa Sherman, Asmara Afework, Jack Best, Joe Hammer, et al. From pets to storykit: Creating new technology with an intergenerational design team. In *Institute Carnegie Mellon University Pittsburgh*. Citeseer, 2000.

[39] Matthew Gillen, Joseph Loyall, Kyle Usbeck, Kelly Hanlon, Andrew Scally, Joshua Sterling, Richard Newkirk, and Ralph Kohler. Beyond line-of-sight information dissemination for force protection. In *MILITARY COMMUNICATIONS CONFERENCE, 2012-MILCOM 2012*, pages 1–6. IEEE, 2012.

[40] William G Kennedy, Magdalena D Bugajska, Matthew Marge, William Adams, Benjamin R Fransen, Dennis Perzanowski, Alan C Schultz, and J Gregory Trafton. Spatial representation and reasoning for human-robot collaboration. In *AAAI*, volume 7, pages 1554–1559, 2007.

[41] Peter Wells and Dan Deguire. Talon: A universal unmanned ground vehicle platform, enabling the mission to be the focus. In *Unmanned Ground Vehicle Technology VII*, volume 5804, pages 747–758. International Society for Optics and Photonics, 2005.

[42] Jennifer M Riley, David B Kaber, and John V Draper. Situation awareness and attention allocation measures for quantifying telepresence experiences in teleoperation. *Human Factors and Ergonomics in Manufacturing & Service Industries*, 14(1):51–67, 2004.

[43] Terrence Fong, Mark J Micire, Ted Morse, Eric Park, Chris Provencher, Vinh To, DW Wheeler, David Mittman, R Jay Torres, and Ernest Smith. Smart spheres: a telerobotic free-flyer for intravehicular activities in space. 2013.

[44] Terrence Fong and Charles Thorpe. Vehicle teleoperation interfaces. *Autonomous robots*, 11(1):9–18, 2001.

[45] Terry Huntsberger, Guillermo Rodriguez, and Paul S Schenker. Robotics challenges for robotic and human mars exploration. In *Robotics 2000*, pages 340–346, 2000.

[46] Sarita Thakoor. A new approach to future mars missions using bioinspired technology innovations. *Journal of Aerospace Computing, Information, and Communication*, 2(1):65–91, 2005.

[47] Rafael Garcia, J Batlle, Xavier Cufi, and Josep Amat. Positioning an underwater vehicle through image mosaicking. In *Robotics and Automation, 2001. Proceedings 2001 ICRA. IEEE International Conference on*, volume 3, pages 2779–2784. IEEE, 2001.

[48] Peter H Kahn Jr, Takayuki Kanda, Hiroshi Ishiguro, Brian T Gill, Solace Shen, Jolina H Ruckert, and Heather E Gary. Human creativity can be facilitated through interacting with a social robot. In *The Eleventh ACM/IEEE International Conference on Human Robot Interaction*, pages 173–180. IEEE Press, 2016.

[49] Satoru Satake., Takayuki Kanda, Dylan F. Glas, Michita Imai, Hiroshi Ishiguro, and Norihiro Hagita. How to approach humans?-strategies for social robots to initiate interaction. In *2009 4th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*, pages 109–116, March 2009.

[50] Ryo Murakami, Luis Yoichi Morales Saiki, Satoru Satake, Takayuki Kanda, and Hiroshi Ishiguro. Destination unknown: walking side-by-side without knowing the goal. In *Proceedings of the 2014 ACM/IEEE international conference on Human-robot interaction*, pages 471–478. ACM, 2014.

[51] Takayuki Kanda and Hiroshi Ishiguro. *Human-robot interaction in social robotics.* CRC Press, 2016.

[52] Elizabeth Cha, Jodi Forlizzi, and Siddhartha S Srinivasa. Robots in the home: Qualitative and quantitative insights into kitchen organization. In *Proceedings of the Tenth Annual ACM/IEEE International Conference on Human-Robot Interaction*, pages 319–326. ACM, 2015.

[53] Maartje De Graaf, Somaya Ben Allouch, and Jan Van Dijk. Why do they refuse to use my robot?: Reasons for non-use derived from a long-term home study. In *Proceedings of the 2017 ACM/IEEE International Conference on Human-Robot Interaction*, pages 224–233. ACM, 2017.

[54] Michal Luria, Guy Hoffman, and Oren Zuckerman. Comparing social robot, screen and voice interfaces for smart-home control. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, pages 580–628. ACM, 2017.

[55] Wan-Ling Chang and Selma Šabanović. Interaction expands function: Social shaping of the therapeutic robot paro in a nursing home. In *Proceedings of the Tenth Annual ACM/IEEE International Conference on Human-Robot Interaction*, pages 343–350. ACM, 2015.

[56] Allison Sauppé and Bilge Mutlu. The social impact of a robot co-worker in industrial settings. In *Proceedings of the 33rd annual ACM conference on human factors in computing systems*, pages 3613–3622. ACM, 2015.

[57] Maha Salem, Gabriella Lakatos, Farshid Amirabdollahian, and Kerstin Dautenhahn. Would you trust a (faulty) robot?: Effects of error, task type and personality on human-robot cooperation and trust. In *Proceedings of the Tenth Annual ACM/IEEE International Conference on Human-Robot Interaction*, pages 141–148. ACM, 2015.

[58] Alan R Wagner. Robots that stereotype: creating and using categories of people for human-robot interaction. *Journal of Human-Robot Interaction*, 4(2):97–124, 2015.

[59] Vaibhav V. Unhelkar, Ho Chit Siu, and Julie A. Shah. Comparative performance of human and mobile robotic assistants in collaborative fetch-and-deliver tasks.

In *Proceedings of the 2014 ACM/IEEE International Conference on Human-robot Interaction*, HRI '14, pages 82–89, New York, NY, USA, 2014. ACM.

[60] Manja Lohse, Reinier Rothuis, Jorge Gallego-Pérez, Daphne E. Karreman, and Vanessa Evers. Robot gestures make difficult tasks easier: The impact of gestures on perceived workload and task performance. In *Proceedings of the 2014 SIGCHI Conference on Human Factors in Computing Systems*, pages 1459–1466, New York, NY, USA, 2014. ACM.

[61] Jocelyn Scheirer and Rosalind Picard. Affective objects, 2000.

[62] Nicole Mirnig, Ewald Strasser, Astrid Weiss, Barbara Kühnlenz, Dirk Wollherr, and Manfred Tscheligi. Can You Read My Face?: A Methodological Variation for Assessing Facial Expressions of Robotic Heads. *International Journal of Social Robotics*, 7(1):63–76, 2015.

[63] Christoph Bartneck and Juliane Reichenbach. Subtle emotional expressions of synthetic characters. *International Journal of Human-Computer Studies*, 62(2):179–192, 2005. Subtle expressivity for characters and robots.

[64] Celso M. de Melo, Peter Carnevale, and Jonathan Gratch. The effect of expression of anger and happiness in computer agents on negotiations with humans. In *Proceedings of the 10th International Conference on Autonomous Agents and Multiagent Systems*, pages 937–944, Richland, SC, 2011. International Foundation for Autonomous Agents and Multiagent Systems.

[65] Toshio Fukuda, Jun Taguri, Fumihito Arai, Masakazu Nakashima, Daisuke Tachibana, and Yasuhisa Hasegawa. Facial expression of robot face for human-robot mutual communication. In *Robotics and Automation, 2002. Proceedings. ICRA'02. IEEE International Conference on*, volume 1, pages 46–51. IEEE, 2002.

[66] Shih-Chung Hsu, Hsin-Hui Huang, and Chung-Lin Huang. Facial expression recognition for human-robot interaction. In *Robotic Computing (IRC), IEEE International Conference on*, pages 1–7. IEEE, 2017.

[67] David McNeill. *Hand and mind: What gestures reveal about thought.* University of Chicago press, 1992.

[68] Allison Sauppé and Bilge Mutlu. Robot deictics: How gesture and context shape referential communication. In *Proceedings of the 2014 ACM/IEEE international conference on Human-robot interaction*, pages 342–349. ACM, 2014.

[69] Henny Admoni, Thomas Weng, Bradley Hayes, and Brian Scassellati. Robot nonverbal behavior improves task performance in difficult collaborations. In *The Eleventh ACM/IEEE International Conference on Human Robot Interaction*, pages 51–58. IEEE Press, 2016.

[70] Maha Salem, Friederike Eyssel, Katharina Rohlfing, Stefan Kopp, and Frank Joublin. To Err is Human(-like): Effects of Robot Gesture on Perceived Anthropomorphism and Likability. *International Journal of Social Robotics*, 5(3):313–323, 2013.

[71] Ritta Baddoura and Gentiane Venture. This robot is sociable: close-up on the gestures and measured motion of a human responding to a proactive robot. *International Journal of Social Robotics*, 7(4):489–496, 2015.

[72] Aelee Kim, Jooyun Han, Younbo Jung, and Kwanmin Lee. The effects of familiarity and robot gesture on user acceptance of information. In *Human-Robot Interaction (HRI), 2013 8th ACM/IEEE International Conference on*, pages 159–160. IEEE, 2013.

[73] Henny Admoni and Brian Scassellati. Social eye gaze in human-robot interaction: a review. *Journal of Human-Robot Interaction*, 6(1):25–63, 2017.

[74] Hideki Kozima, Cocoro Nakagawa, and Hiroyuki Yano. Can a robot empathize with people? *Artificial Life and Robotics*, 8(1):83–88, 2004.

[75] AJung Moon, Daniel M Troniak, Brian Gleeson, Matthew KXJ Pan, Minhua Zheng, Benjamin A Blumer, Karon MacLean, and Elizabeth A Croft. Meet me where i'm gazing: how shared attention gaze affects human-robot handover timing. In *Proceedings of the 2014 ACM/IEEE international conference on Human-robot interaction*, pages 334–341. ACM, 2014.

[76] Tatsuya Nomura and Takayuki Kanda. Influences of evaluation and gaze from a robot and humans? fear of negative evaluation on their preferences of the robot. *International Journal of Social Robotics*, 7(2):155–164, 2015.

[77] Ryo Ishii, Yukiko I Nakano, and Toyoaki Nishida. Gaze awareness in conversational agents: Estimating a user's conversational engagement from eye gaze. *ACM Transactions on Interactive Intelligent Systems (TiiS)*, 3(2):11, 2013.

[78] Gianluigi Guido, Luigi Piper, M. Irene Prete, Antonio Mileti, and Carla M. Trisolini. Effects of blue lighting in ambient and mobile settings on the intention to buy hedonic and utilitarian products. *Psychology & Marketing*, 34(2):215–226, 2017.

[79] Beaven C. Martyn and Johan Ekström. A comparison of blue light and caffeine effects on cognitive function and alertness in humans. *PLOS ONE*, 8(10), 10 2013.

[80] Bilge Mutlu, Jodi Forlizzi, Illah Nourbakhsh, and Jessica Hodgins. The use of abstraction and motion in the design of social interfaces. In *Proceedings of the 6th Conference on Designing Interactive Systems*, pages 251–260, New York, NY, USA, 2006. ACM.

[81] Andrii Matviienko, Maria Rauschenberger, Vanessa Cobus, Janko Timmermann, Heiko Müller, Jutta Fortmann, Andreas Löcken, Christoph Trappe, Wilko Heuten, and Susanne Boll. Deriving design guidelines for ambient light systems. In *Proceedings of the 14th International Conference on Mobile and Ubiquitous Multimedia*, pages 267–277, New York, NY, USA, 2015. ACM.

[82] Joseph 'Jofish' Kaye. I just clicked to say i love you: Rich evaluations of minimal communication. In *CHI '06 Extended Abstracts on Human Factors in Computing Systems*, pages 363–368, New York, NY, USA, 2006. ACM.

[83] Kazuki Kobayashi, Kotaro Funakoshi, Seiji Yamada, Mikio Nakano, Takanori Komatsu, and Yasunori Saito. Blinking light patterns as artificial subtle expressions in human-robot speech interaction. In *Proceedings of the 20th IEEE International Symposium on Robot and Human Interaction Communication*, pages 181–186, Atlanta, GA, USA, 2011. IEEE.

[84] Kim Baraka, Ana Paiva, and Manuela Veloso. *Expressive Lights for Revealing Mobile Service Robot State*, pages 107–119. Springer International Publishing, Cham, 2016.

[85] Daniel Szafir, Bilge Mutlu, and Terry Fong. Communicating directionality in flying robots. In *Proceedings of the 10th Annual ACM/IEEE International Conference on Human-Robot Interaction*, pages 19–26, New York, NY, USA, 2015. ACM.

[86] Kazunori Terada, Atsushi Yamauchi, and Akira Ito. Artificial emotion expression for a robot by dynamic color change. In *Proceedings of the 21st IEEE International Symposium on Robot and Human Interactive Communication*, pages 314–321, Sept 2012.

[87] Daniel J Rea, James E Young, and Pourang Irani. The roomba mood ring: an ambient-display robot. In *Proceedings of the seventh annual ACM/IEEE international conference on Human-Robot Interaction*, pages 217–218. ACM, 2012.

[88] Jessica Rebecca Cauchard, Kevin Y. Zhai, Marco Spadafora, and James A. Landay. Emotion encoding in human-drone interaction. In *The Eleventh ACM/IEEE International Conference on Human Robot Interaction*, pages 263–270, Piscataway, NJ, USA, 2016. IEEE Press.

[89] Anca D Dragan, Kenton CT Lee, and Siddhartha S Srinivasa. Legibility and predictability of robot motion. In *Proceedings of the 8th ACM/IEEE international conference on Human-robot interaction*, pages 301–308. IEEE Press, 2013.

[90] Anca D Dragan, Shira Bauman, Jodi Forlizzi, and Siddhartha S Srinivasa. Effects of robot motion on human-robot collaboration. In *Proceedings of the Tenth Annual ACM/IEEE International Conference on Human-Robot Interaction*, pages 51–58. ACM, 2015.

[91] Alvin X Li, Maria Florendo, Luke E Miller, Hiroshi Ishiguro, and Ayse P Saygin. Robot form and motion influences social attention. In *Proceedings of the Tenth Annual ACM/IEEE International Conference on Human-Robot Interaction*, pages 43–50. ACM, 2015.

[92] Yuto Yamaji, Taisuke Miyake, Yuta Yoshiike, P Ravindra S De Silva, and Michio Okada. Stb: Child-dependent sociable trash box. *International Journal of Social Robotics*, 3(4):359–370, 2011.

[93] Selma Yilmazyildiz, Robin Read, Tony Belpeame, and Werner Verhelst. Review of semantic-free utterances in social human-robot interaction. *International Journal of Human-Computer Interaction*, 32(1):63–85, 2016.

[94] Diana Löffler, Nina Schmidt, and Robert Tscharn. Multimodal expression of artificial emotion in social robots using color, motion and sound. In *Proceedings of the 2018 ACM/IEEE International Conference on Human-Robot Interaction*, pages 334–343. ACM, 2018.

[95] Kazuki Kobayashi, Yasuhiko Kitamura, and Seiji Yamada. Action sloping as a way for users to notice a robot's function. In *Robot and Human interactive Communication, 2007. RO-MAN 2007. The 16th IEEE International Symposium on*, pages 445–450. IEEE, 2007.

[96] Takanori Komatsu. Toward making humans empathize with artificial agents by means of subtle expressions. In *Proceedings of the 1st International Conference on Affective Computing and Intelligent Interaction*, pages 458–465. Springer, 2005.

[97] Takanori Komatsu, Kazuki Kobayashi, Seiji Yamada, Kotaro Funakoshi, and Mikio Nakano. Vibrational artificial subtle expressions: Conveying system's confidence level to users by means of smartphone vibration. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, page 478. ACM, 2018.

[98] Taiga Machida, Nem Khan Dim, and Xiangshi Ren. Suitable body parts for vibration feedback in walking navigation systems. In *Proceedings of the Third International Symposium of Chinese CHI*, pages 32–36. ACM, 2015.

[99] Shafiq Ur Réhman and Li Liu. Vibrotactile emotions on a mobile phone. In *Proceedings of the 4th IEEE International Conference on Signal Image Technology and Internet Based Systems*, pages 239–243, Nov 2008.

[100] Shafiq ur Réhman and Li Liu. *iFeeling: Vibrotactile Rendering of Human Emotions on Mobile Phones*, pages 1–20. Springer Berlin Heidelberg, Berlin, Heidelberg, 2010.

[101] Dzmitry Tsetserukou and Alena Neviarouskaya. World's first wearable humanoid robot that augments our emotions. In *Proceedings of the 1st Augmented Human International Conference*, page 8. ACM, 2010.

[102] Jan BF Van Erp. Guidelines for the use of vibro-tactile displays in human computer interaction. In *Proceedings of eurohaptics*, volume 2002, pages 18–22. Citeseer, 2002.

[103] Thijs Roumen, Simon T Perrault, and Shengdong Zhao. Notiring: A comparative study of notification channels for wearable interactive rings. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, pages 2497–2500. ACM, 2015.

[104] Paul Bremner and Ute Leonards. Speech and gesture emphasis effects for robotic and human communicators: A direct comparison. In *Proceedings of the Tenth Annual ACM/IEEE International Conference on Human-Robot Interaction*, pages 255–262, New York, NY, USA, 2015. ACM.

[105] Tatsuya Nomura and Takayuki Kanda. Influences of Evaluation and Gaze from a Robot and Humans' Fear of Negative Evaluation on Their Preferences of the Robot. *International Journal of Social Robotics*, 7(2):155–164, 2015.

[106] Sean Andrist, Bilge Mutlu, and Michael Gleicher. *Conversational Gaze Aversion for Virtual Agents*, pages 249–262. Springer Berlin Heidelberg, Berlin, Heidelberg, 2013.

[107] Thomas Fincannon, Laura Barnes, Murphy Robin R., and Dawn Riddle. Evidence of the need for social intelligence in rescue robots. In *Proceedings of the 14th IEEE/RSJ International Conference on Intelligent Robots and Systems*, volume 2, pages 1089–1095, Sept 2004.

[108] Murphy Robin R., Dawn Riddle, and Eric Rasmussen. Robot-assisted medical reachback: a survey of how medical personnel expect to interact with rescue

robots. In *Proceedings of the 13th IEEE International Workshop on Robot and Human Interactive Communication*, pages 301–306, Sept 2004.

[109] Shigeki Sugano and Tetsuya Ogata. Emergence of mind in robots for human interface - research methodology and robot model. In *Proceedings of the 13th IEEE International Conference on Robotics and Automation*, volume 2, pages 1191–1198, Apr 1996.

[110] Lilia Moshkina and Ronald C Arkin. Human perspective on affective robotic behavior: a longitudinal study. In *Proceedings of the 15th IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 1444–1451, Aug 2005.

[111] Byron Reeves and Clifford Ivar Nass. *The media equation: How people treat computers, television, and new media like real people and places.* Cambridge University Press, New York, NY, US, 1996.

[112] Susan R. Fussell, Sara Kiesler, Leslie D. Setlock, and Victoria Yew. How people anthropomorphize robots. In *Proceedings of the 3rd ACM/IEEE International Conference on Human Robot Interaction*, pages 145–152, New York, NY, USA, 2008. ACM.

[113] Patrice D Tremoulet and Jacob Feldman. Perception of animacy from the motion of a single object. *Perception*, 29(8):943–951, 2000. PMID: 11145086.

[114] Hirotaka Osawa and Michita Imai. Morphing agency: Deconstruction of an agent with transformative agential triggers. In *CHI '13 Extended Abstracts on Human Factors in Computing Systems*, pages 2237–2246, New York, NY, USA, 2013. ACM.

[115] Guy Hoffman, Oren Zuckerman, Gilad Hirschberger, Michal Luria, and Tal Shani Sherman. Design and evaluation of a peripheral robotic conversation companion. In *Proceedings of the 10th Annual ACM/IEEE International Conference on Human-Robot Interaction*, pages 3–10, New York, NY, USA, 2015. ACM.

[116] Sichao Song and Seiji Yamada. Expressing emotions through color, sound, and vibration with an appearance-constrained social robot. In *Proceedings of the 2017*

ACM/IEEE International Conference on Human-Robot Interaction, pages 2–11, New York, NY, USA, 2017. ACM.

[117] Marina V Sokolova and Antonio Fernández-Caballero. A review on the role of color and light in affective computing. *Applied Sciences*, 5(3):275–293, 2015.

[118] Jaime Snyder, Mark Matthews, Jacqueline Chien, Pamara F. Chang, Emily Sun, Saeed Abdullah, and Geri Gay. Moodlight: Exploring personal and social implications of ambient display of biosensor data. In *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing*, pages 143–153, New York, NY, USA, 2015. ACM.

[119] Rosalind W. Picard. Emotion research by the people, for the people. *Emotion Review*, 2(3):250–254, 2010.

[120] Johannes Feldmaier, Tamara Marmat, Johannes Kuhn, and Klaus Diepold. Evaluation of a rgb-led-based emotion display for affective agents. *arXiv preprint arXiv:1612.07303*, 2016.

[121] Mark Weiser and John Seely Brown. Designing calm technology. *PowerGrid Journal*, 1(1):75–85, 1996.

[122] Heiko Müller, Anastasia Kazakova, Wilko Heuten, and Susanne Boll. Lighten up! — an ambient light progress bar using individually controllable leds. In *Ambient Intelligence*, pages 109–124, Cham, 2015. Springer International Publishing.

[123] Sichao Song and Seiji Yamada. Investigating effects of light animations on perceptions of a computer: Preliminary results. In *Proceedings of the 26th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)*, pages 17–22, Aug 2017.

[124] Seiji Yamada, Naoki Mori, and Kazuki Kobayashi. Peripheral agent: Implementation of peripheral cognition technology. In *CHI '13 Extended Abstracts on Human Factors in Computing Systems*, pages 1701–1706, New York, NY, USA, 2013. ACM.

[125] Werner Güth and Reinhard Tietz. Ultimatum bargaining behavior: A survey and comparison of experimental results. *Journal of Economic Psychology*, 11(3):417–449, 1990.

[126] Sandra G Hart and Lowell E Staveland. Development of nasa-tlx (task load index): Results of empirical and theoretical research. In *Advances in psychology*, volume 52, pages 139–183. Elsevier, 1988.

[127] Christoph Bartneck, Dana Kulić, Elizabeth Croft, and Susana Zoghbi. Measurement instruments for the anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety of robots. *International Journal of Social Robotics*, 1(1):71–81, Jan 2009.

[128] Andrew J. Elliot and Markus A. Maier. Color and psychological functioning. *Current Directions in Psychological Science*, 16(5):250–254, 2007.

[129] Andrew J. Elliot and Markus A. Maier. Color psychology: Effects of perceiving color on psychological functioning in humans. *Annual Review of Psychology*, 65(1):95–120, 2014. PMID: 23808916.

[130] Elena Torta, Elisabeth van Dijk, Peter A. M. Ruijten, and Raymond H. Cuijpers. The ultimatum game as measurement tool for anthropomorphism in human–robot interaction. In *Social Robotics*, pages 209–217, Cham, 2013. Springer International Publishing.

[131] Alan G. Sanfey, James K. Rilling, Jessica A. Aronson, Leigh E. Nystrom, and Jonathan D. Cohen. The neural basis of economic decision-making in the ultimatum game. *Science*, 300(5626):1755–1758, 2003.

[132] David DeSteno, Cynthia Breazeal, Robert H. Frank, David Pizarro, Jolie Baumann, Leah Dickens, and Jin Joo Lee. Detecting the trustworthiness of novel partners in economic exchange. *Psychological Science*, 23(12):1549–1556, 2012. PMID: 23129062.

[133] *What is bioluminescence?*, 2017 (Accessed September 5, 2017).

[134] Widder Edith. A. Bioluminescence in the ocean: Origins of biological, chemical, and ecological diversity. *Science*, 328(5979):704–708, 2010.

[135] Levillain Florent, Zibetti Elisabetta, and Lefort Sébastien. Interacting with non-anthropomorphic robotic artworks and interpreting their behaviour. *International Journal of Social Robotics*, 9(1):141–161, Jan 2017.

[136] Yusuke Kato, Takayuki Kanda, and Hiroshi Ishiguro. May i help you?: Design of human-like polite approaching behavior. In *Proceedings of the Tenth Annual ACM/IEEE International Conference on Human-Robot Interaction*, pages 35–42, New York, NY, USA, 2015. ACM.

[137] Drazen Brscić., Hiroyuki Kidokoro, Yoshitaka Suehiro, and Takayuki Kanda. Escaping from children's abuse of social robots. In *Proceedings of the Tenth Annual ACM/IEEE International Conference on Human-Robot Interaction*, pages 59–66, New York, NY, USA, 2015. ACM.

[138] Pericle Salvini, Gaetano Ciaravella, Wantai Yu., Giuseppe Ferri, Alessandro Manzi, Barbara Mazzolai, Cecilia Laschi, Sang-Rok Oh, and Paolo Dario. How safe are service robots in urban environments? Bullying a robot. *19th International Symposium in Robot and Human Interactive Communication*, pages 1–7, 2010.

[139] Christoph Bartneck, Rosalia Chioke, Rutger Menges, and Inez Deckers. Robot abuse–a limitation of the media equation. In *Interact 2005 Workshop on Abuse*, Rome, 2005.

[140] Elliot Andrew J., Fairchild Mark D., and Franklin Anna. *Handbook of Color Psychology*. Cambridge University Press, 2015.

[141] Elliot Andrew J. Color and psychological functioning: A review of theoretical and empirical work. *Frontiers in Psychology*, 6(APR):1–8, 2015.

[142] Mehta Ravi and Rui Juliet Zhu. Blue or red? exploring the effect of color on cognitive task performances. *Science*, 323(5918):1226–1229, 2009.

[143] Adam Akers, Jo Barton, Rachel Cossey, Patrick Gainsford, Murray Griffin, and Dominic Micklewright. Visual Colour Perception in Green Exercise: Positive Effects on Mood and Perceived Exertion. *Environmental Science and Technology*, 46(16):1–6, 2012.

[144] Eva Lenz, Sarah Diefenbach, and Marc Hassenzahl. Exploring relationships between interaction attributes and experience. In *Proceedings of the 6th International Conference on Designing Pleasurable Products and Interfaces*, pages 126–135, New York, NY, USA, 2013. ACM.

[145] Youn-kyung Lim, Sang-Su Lee, and Da-jung Kim. Interactivity attributes for expression-oriented interaction design. *International Journal of Design*, 5(3), 2011.

[146] Sichao Song and Seiji Yamada. Bioluminescence-inspired human-robot interaction: Designing expressive lights that affect human's willingness to interact with a robot. In *Proceedings of the 2018 ACM/IEEE International Conference on Human-Robot Interaction*, HRI '18, pages 224–232, New York, NY, USA, 2018. ACM.

[147] Virginia Braun and Victoria Clarke. Using thematic analysis in psychology. *Qualitative Research in Psychology*, 3(2):77–101, 2006.

[148] Paul Bucci, Lotus Zhang, Xi Laura Cang, and Karon E. MacLean. Is it happy?: Behavioural and narrative frame complexity impact perceptions of a simple furry robot's emotions. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, CHI '18, pages 509:1–509:11, New York, NY, USA, 2018. ACM.

[149] Jekaterina Novikova and Leon Watts. A design model of emotional body expressions in non-humanoid robots. In *Proceedings of the Second International Conference on Human-agent Interaction*, HAI '14, pages 353–360, New York, NY, USA, 2014. ACM.

[150] Changizi Mark A., Qiong Zhang, and Shinsuke Shimojo. Bare skin, blood and the evolution of primate colour vision. *Biology Letters*, 2(2):217–221, 2006.

[151] Stevens Martin and Graeme D. Ruxton. Linking the evolution and form of warning coloration in nature. *Proceedings of the Royal Society of London B: Biological Sciences*, 279(1728):417–426, 2011.

[152] Labrecque Lauren I. and George R. Milne. Exciting red and competent blue: The importance of color in marketing. *Journal of the Academy of Marketing Science*, 40(5):711–727, 2012.

[153] Chris Harrison, Gary Hsieh, Karl D.D. Willis, Jodi Forlizzi, and Scott E. Hudson. Kineticons: Using iconographic motion in graphical user interface design. In

Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, CHI '11, pages 1999–2008, New York, NY, USA, 2011. ACM.

[154] Klaus Krippendorff. Computing krippendorff's alpha-reliability. 2011.

[155] Hatice Köse, Pınar Uluer, Neziha Akalın, Rabia Yorgancı, Ahmet Özkul, and Gökhan Ince. The effect of embodiment in sign language tutoring with assistive humanoid robots. *International Journal of Social Robotics*, 7(4):537–548, Aug 2015.

[156] Robert A. Paauwe, Johan F. Hoorn, Elly A. Konijn, and David V. Keyson. Designing robot embodiments for social interaction: Affordances topple realism and aesthetics. *International Journal of Social Robotics*, 7(5):697–708, Nov 2015.

[157] Hiroshi Ishiguro. Interactive humanoids and androids as ideal interfaces for humans. In *Proceedings of the 11th International Conference on Intelligent User Interfaces*, pages 2–9, New York, NY, USA, 2006. ACM.

[158] Takanori Komatsu and Seiji Yamada. How does the agents' appearance affect users' interpretation of the agents' attitudes: Experimental investigation on expressing the same artificial sounds from agents with different appearances. *International Journal of Human–Computer Interaction*, 27(3):260–279, 2011.

[159] Takanori Komatsu, Seiji Yamada, Kazuki Kobayashi, Kotaro Funakoshi, and Mikio Nakano. Artificial subtle expressions: Intuitive notification methodology of artifacts. In *Proceedings of the 28th SIGCHI Conference on Human Factors in Computing Systems*, pages 1941–1944, New York, NY, USA, 2010. ACM.

[160] Faisal Arafsha, Kazi Masudul Alam, and Abdulmotaleb El Saddik. Design and development of a user centric affective haptic jacket. *Multimedia Tools and Applications*, 74(9):3035–3052, May 2015.

[161] Andrew J Elliot, Markus A Maier, Arlen C Moller, Ron Friedman, and Jörg Meinhardt. Color and psychological functioning: the effect of red on performance attainment. *Journal of experimental psychology: General*, 136(1):154–168, 2007.

[162] KAYA Naz and H Helen. Color-emotion associations: Past experience and personal preference. In *AIC 2004 Color and Paints, Interim Meeting of the International Color Association, Proceedings*, pages 31–34. Jose Luis Caivano, 2004.

[163] Rikard Küller, Byron Mikellides, and Jan Janssens. Color, arousal, and performance - a comparison of three experiments. *Color Research & Application*, 34(2):141–152, 2009.

[164] Jonathan Posner, James A. Russell, and Bradley S. Peterson. The circumplex model of affect: An integrative approach to affective neuroscience, cognitive development, and psychopathology. *Development and Psychopathology*, 17(3):715–734, 2005.

[165] Barbara L Fredrickson. What good are positive emotions? *Review of general psychology*, 2(3):300–319, 1998.

[166] Paul Strohmeier, Juan Pablo Carrascal, Bernard Cheng, Margaret Meban, and Roel Vertegaal. An evaluation of shape changes for conveying emotions. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, pages 3781–3792. ACM, 2016.

[167] James A Russell. A circumplex model of affect. *Journal of personality and social psychology*, 39(6):1161, 1980.

[168] Peter J Lang. International affective picture system (iaps): Affective ratings of pictures and instruction manual. *Technical report*, 2005.

[169] Dag Sverre Syrdal, Kheng Lee Koay, Márta Gácsi, Michael L Walters, and Kerstin Dautenhahn. Video prototyping of dog-inspired non-verbal affective communication for an appearance constrained robot. In *RO-MAN, 2010 IEEE*, pages 632–637. IEEE, 2010.

[170] Markus Häring, Nikolaus Bee, and Elisabeth André. Creation and evaluation of emotion expression with body movement, sound and eye color for humanoid robots. In *Ro-Man, 2011 Ieee*, pages 204–209. IEEE, 2011.

[171] Paul Ekman and Wallace V Friesen. *Unmasking the face: A guide to recognizing emotions from facial clues.* Ishk, 2003.

[172] Tadas Baltrušaitis, Laurel D Riek, and Peter Robinson. Synthesizing expressions using facial feature point tracking: how emotion is conveyed. In *Proceedings of*

the 3rd international workshop on Affective interaction in natural environments, pages 27–32. ACM, 2010.

[173] Lola Cañamero and Jakob Fredslund. I show you how i like you-can you read it in my face?[robotics]. *IEEE Transactions on systems, man, and cybernetics-Part A: Systems and humans*, 31(5):454–459, 2001.

[174] Nathan J Emery. The eyes have it: the neuroethology, function and evolution of social gaze. *Neuroscience & Biobehavioral Reviews*, 24(6):581–604, 2000.

[175] Maria Staudte and Matthew Crocker. The utility of gaze in spoken human-robot interaction. In *Proceedings of Workshop on Metrics for Human-Robot Interaction 2008, March 12th*, pages 53–59, 2008.

[176] Markus Häring, Jessica Eichberg, and Elisabeth André. Studies on grounding with gaze and pointing gestures in human-robot-interaction. In *International Conference on Social Robotics*, pages 378–387. Springer, 2012.

[177] Gabriel Skantze, Anna Hjalmarsson, and Catharine Oertel. Exploring the effects of gaze and pauses in situated human-robot interaction. In *Proceedings of the SIGDIAL 2013 Conference*, pages 163–172, 2013.

[178] Takanori Komatsu, Rie Kurosawa, and Seiji Yamada. How does the difference between users? expectations and perceptions about a robotic agent affect their behavior? *International Journal of Social Robotics*, 4(2):109–116, 2012.