Cooperation and Interaction between Human and Humanoid Robots through Integration of Symbolic Expressions and Sensorimotor Patterns

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Contents

List of Figures

List of Tables

Abstract

This paper describes a stochastic framework for intelligent humanoid robots, which can cooperate and interact with humans through integration of symbolic expressions and sensorimotor patterns. The research is divided into 4 steps. Contributions of the each research step are: 1) an estimation method of sensorimotor patterns of others without having predefined user specific model in advance through interaction between self and other, 2) a method to dynamically modify displaying motion patterns and to bind the motions with symbol expressions according to performance of human-learners, in order for conveying slight differences in motions, where robotic system coaches humans motions, 3) analysis and modeling of human-coaches' use of motions and symbolic expressions how they change them dynamically according to learners performances, and 4) demonstration of the feasibility of the robotic motion coaching system, which integrates the methods proposed in step 1) and 2), and the models gained in step 3), through experiments of actual sport coaching tasks for beginners resulted in improvements in motion learning.

In the Chapter 1, the main stream of robotics researches are introduced as improvement in individual physical ability. Then, importance of intelligence of binding symbol expressions and unobservable sensorimotor patterns, and intelligence to estimate the sensorimotor patterns from observable motions are discussed from interaction point of view.

In the Chapter 2, related works are introduced in various fields such

as Robotics, Conversation Analysis, Human-Agent Interaction, Skill and Sports Science, and Anticipation of Intention of Others from neuroscience and cognitive psychology point of view. Then, the chapter addresses challenges from the perspective of required functions for the research. After the discussion of the approach for the resolution method, the Proto-symbol Space method is introduced as a basic tool for the proposed methods.

The Chapter 3 describes an estimation method of sensorimotor patterns of others from motion observation. An approach is to bridge sensorimotor experience, or the Proto-symbol Spaces, between the self and the other. The sensorimotor experiences for each are represented by the Proto-symbol Spaces for each in the research. This approach would result in estimation error due to physical condition difference between the self and the other. To clear this problem, a method is proposed in order for adaptive acquisition of Proto-symbol Space of other by sharing motion patterns and using open questions asking the others' sensing status described by symbols. Simulation demonstrates that it is possible to estimate sensorimotor patterns of others with 10-20% errors, even when estimation target motions are not in database. In the second half of the chapter, I discusses about a method to estimate others' symbol conversion strategy from sensor patterns. The method uses closed questions asking comparative evaluation of sets of shared motions. The simulation demonstrates that the method can estimate the symbol conversion strategy properly by sharing prepared sets of motions and using closed questions.

The Chapter 4 describes a proposing method for dynamic modification of motion demonstration and for binding the motions with symbol expressions according to performance of human-learners. This method can convey slight differences between learning target motions demonstrated by a coach and motions performed by learners. Feasibility of the method is demonstrated through experiments of actual sport coaching tasks for beginners by using a robotic coaching system. The robotic system coaches human-learners tennis forehand swing, by using emphatic motions and adverbial expressions generated from the proposing method. The experiments resulted in improvements in motion learning. However, it is not possible to confirm whether either emphatic motions and/or adverbial expressions are contribution factors or not.

In the Chapter 5, I discuss about experiments for modeling how human-coaches use emphatic motions and adverbial expressions. In the experiments, human-coaches are asked to coach a robot-learner tennis forehand swing, by using the emphatic motions and adverbial expressions. Analysis of the results leads to models; two Adverbial Expression Use Models and two Emphatic Motion Use Models.

In the Chapter 6, I attempt to integrate the methods proposed in Chapter 3 and 4, and the models obtained in Chapter 5. At first, I discuss about integration of the robotic motion coaching system from Chapter 4 and the models gained from Chapter 5. I then discuss a possible integration of the method to estimate sensorimotor patterns from the Chapter 3, the robotic motion coaching system from Chapter 4, and the models gained from Chapter 5. I demonstrate the feasibility of the robotic motion coaching system integrated with one of the EMU-Model and one of the AEU-Model, by experiments of a tennis forehand swing coaching task for beginners. I confirm that the EMU-Model and the AEU-Model contribute to improvement in motion learning. It is demonstrated that value output by the EMU-Model is a contribution factor by a statistic analysis. I also find there is an improvement in motion learning when using the AEU-Models. However, even though I find positive contribution of the adverbial expressions for the improvement in motion learning, it is not able to decide whether the adverbial expressions chosen by using the AEU-Model is a contribution factor or not.

The thesis is then concluded in the Chapter 7.

Chapter 1

INTRODUCTION

In main stream robotics research, to deal with challenging issues in robotics, there has been an evolving approach called probabilistic robotics [153]. As it had been organized in the book [153], three concepts play an important role. These three as a foundation, Bayes' theorem [11][145], Markov Process [85][126] and Optimal Control Theory [70], the probabilistic robotics has been evolved.

Specifically, since humanoid robots have a large degree of freedom or lots of joints to consider, it is very useful and practical to have systems learn by themselves or by demonstration [19]. There have been learning frameworks proposed for systems to learn motions by themselves, such as, Reinforcement Learning [143], Imitation Learning [16], and combination of these [5].

It has been discussed that mechanisms of imitation and social matching play a fundamental role in development, communication, interaction, learning and culture [99]. For social learning, it cannot avoid to have interaction between robots and humans. This interaction should consist of both verbal language and non-verbal language such as motion display. Having body, as it called the embodiment, is important factor not only for the interaction, but also for understanding intelligence [115][114]. Using the embodiment with the constructive approach, robotics research can contribute not only for understanding artificial intelligence, but also for understanding real intelligence and human beings [55] [151].

Allegorically, these trends in robotics can be compared to humans' training for improvement in physical ability and skills in sports. In other words, the main stream robotics research has been focused on improvement of an individual athletic ability as a super-athlete. Then, recent focus on study in social learning can be compared to humans' training of improvement in teamwork and skills related to that. To improve the social intelligence,it is important to improve ability to communicate, ability to learn from each others, and ability to anticipate intention of other and so on.

For the future robotic system, it is needed to have a communication ability to explain subtle difference by using motion display and symbolic expressions, For this communication ability, robotics system requires to have following functions. Function to estimate others' sensorimotor patterns from motion observation. Function to explain slight difference in motions by symbolic expressions. Function to explain slight difference in sensorimotor patterns by symbolic expressions.

Once, the system acquires these functions and become capable of interaction using more complex verbal and non-verbal expressions, the robots would be able not only to coach but to learn while the robots are coaching via discussion and interaction with other humans. Being capable of having complex interaction would be an ultimate goal of the Human-Robot interaction. Then, it would open up a new learning framework for robotics that can learn while it coach, which is inspired by the Protege Effect, "While we teach, we learn" [48][22][42], In this learning framework, the robots would learn and share how to ground symbols to parameters, so that humans can understand explanation of the robots, as well as would learn novel parameters to consider. This way, robots and humans can develop their abilities together.

In this thesis, as the first phase toward establishing computational and constructive communication sciences that would lead to studying teamwork among humans and robots, I research how to realize three function in this thesis. A function to estimate sensorimotor patterns from motion observation without predefined user specific model in advance. A function to convey slight difference in motions by symbolic expressions. A function to convey slight difference in sensorimotor patterns by symbolic expressions. As an instance of the research, I develop and research about a robotic motion coaching system that uses sensorimotor patterns and verbal expressions, in order to convey slight differences in sensorimotor patterns. I believe that it will benefit not only for motion coaching but for advanced in intelligent robotics, rehabilitation robotics and human sciences.

To realize the system, the research is divided into four steps. In the Chapter 2, introducing related work, challenges are addressed and approach of resolution method and basic tools are explained. In the Chapter 3, as the 1st step, I propose and study an estimation method of others' sensorimotor patterns by motion observations. In the Chapter 4, as the 2nd step, I propose and study an method to bind emphatic motions and adverbial expressions to convey slight difference in motions, without user specific model in advance. In the Chapter 5, as the 3rd step, I analyze and model coaching skill of humans, how human coaches use emphatic motions and adverbial expressions. In the Chapter 6, as the 4th step, I integrate the methods and the models, and study a robotic motion system that coaches humans motions by referring to sensorimotor patterns. At last, the thesis is concluded in Chapter 7.

Chapter 2

Challenges, an Approach and Tools

2.1 Advance in Robotics: Physical Abilities

Since the first study of humanoid robots with WABOT-1 [66], thanks to improvement in hardware and software [182][63], the progress of humanoid robots has reached at a level to perform running [47], dancing [138][139], cooperative works with a human [64], evolving by itself [102], and establishing cognitive robotics [146].

In the development of humanoid robotics, there have been lots of challenging research topics addressed, such as, voice recognition [159][160], computer and robot vision [83][112][23][40], grasping [82][13], tool manipulation [4][106][80], locomotion [50][119], balancing [178][3][179], motion generation and planning [68][97][177], control theory [96], utilization of tactile sensors [113][105][104] and so on.

As addressed in the Chapter 1, allegorically, the main focus of these researches is to improve individual functions of robots as if human athletes train to improve their individual physical abilities. There are researches for teamwork of multi-agents [1], however, it does not consider embodiment agents and it has not been well addressed what kind of communication among humans and robots will improve team work.

2.2 Further Advance in Robotics: Communication Abilities

Further advance in robotics depends partially on acquisition of abilities for communication with humans. The communication requires not only using symbolic expressions of observable properties, but also using symbolic expressions bound to unobservable properties to have anticipation of others' intention.

For example, as discussed in the Chapter 1, proposing robotic motion coaching system uses sensorimotor patterns and verbal expressions, in order to convey slight differences in sensorimotor patterns. It requires to have an ability to estimate sensorimotor patterns and then bind the estimated sensorimotor patterns to symbolic expressions. It enables robots to recognize and convey subtle differences in sensorimotor patterns.

To have this communication ability, the proposing robotics motion coaching system requires to have following functions.

1. Motion Learning function, in order to demonstration motions when it is coaching humans motions.
2. Motion Recognition function, in order to recognize and evaluate difference in motions quantitatively.
3. Motion Generation function, in order to dynamically generate modified motions according to reaction of users.
4. Motion Coaching function, which uses motion demonstration and symbolic expressions in order to convey slight differences in sensorimotor patterns.
5. Binding function between sensorimotor patterns and symbolic expressions, in order to conveying slight differences in state of sensorimotor patterns.

6. Estimation function of sensorimotor patterns from motion observation, in order for anticipation of intention without having predefined user specific model in advance.

2.3 Challenges in Related Works

1. Motion Learning

   CPG (Central Pattern Generator) [89] has been applied for a generator of cyclic motions, such as arm movements [173] and walking of robots [69]. Reinforcement learning framework has been proposed [62][143][117], in order that a system itself can learn parameters for motions. Researchers have also developed robots that can learn to perform tasks by observing a person performing actions [77][132] [87]. This technique, often called 'learning from demonstration' or 'imitation learning', has been reviewed in detail by Schaal [132]. Atkeson demonstrated that far fewer real-world practice trials were needed if the robot could simulate its experience using a predictive forward model for a pendulum-swing-up task [5][6]. Although systems that learn from demonstration have been programmed to perform impressive feats, the systems are limited by the fact that information flows only in one direction: from human to machine. The one directionality resulted in lack of capability for interaction with humans using learned motions and symbolic expressions bound to them. While we are interested in a design of motion learning framework where the system can have bi-directional learning capability with humans. Taking advantage of binding between symbolic expressions and sensorimotor information, robots would learn and transfer back the learned skills to humans.

2. Motion Recognition

   The PCA (Principal Component Analysis) [61] has been used for categorization or recognition of data sets, and it has been applied for face recognition [181] and motion recognition [21]. In motion coaching, what needs to be considered is noise, lack of data, variety of motion speed with the same motions. For these reasons, using the Hidden Markov Model (HMM) is appreciated, since a number of researches have shown the robustness of the HMM to encode the temporal and spatial variations of complex signals [131]. The HMM has been also applied for researches, for example, recognition of para-linguistic information such as head nods and shakes [35][65], highlight extraction from a baseball game clip [24], and video segmentation [15]. These researches support use of HMM over PCA for addressing motion recognition in this thesis.

3. Motion Generation

   Sugihara proposed a method to generate motions through ZMP (Zero Moment Point) manipulation based on inverted pendulum control [142]. [107] discusses how a high level motion and action planner based motion generation functions contribute to various real world humanoid tasks and a role of perception based motion generation using a vision sensor and force sensors. The Octree [45] and the RRT (Rapidly-exploring Random Tree) [78] are known for obstacle avoidance motion generation. A compliant control of multicontact and center-of-mass behaviors in humanoid robots has been proposed [136]. Creating a virtual-linkage model for humanoid robots enables the characterization of complex whole-body multicontact interactions and the creation of new compliant skills needed to operate effectively in human environments. These method have addressed dynamic motion generation/planning according to change in environment. However, what is addressed in this thesis is how to generate motions dynamically according to reaction of users, in order to assist users to recognize slight difference in motions and to correct them.

4. Motion Coaching

   There has been great advance in activities in the area of therapeutic robotics

[167][166], medical and health care robotics [108][8], and rehabilitation robotics [73][72][88][86]. In the researches on rehabilitation robotics [88][86], where a robot interacts to motivate physical exercise, emotional effect was evaluated. However, to address the objective of this thesis, quantitative evaluation of motion learning is needed.

At clinical site of rehabilitation, for patients to learn good rehabilitation motions, it is important to explain by binding not only motions and symbols but also sensor and symbols. For example, the co-contraction [44] (contraction in muscle that is opposite to muscle used to bend joint) cannot be noticed or coached by kinematics-based information only. Studies in physical therapy shows that there is positive influence of sensory interaction on balance control [141], and shows that incorporation of external sensory cues in the rehabilitation protocol can extend the short-term benefit of physical therapy in moderately disabled patients with idiopathic Parkinson's disease, possibly as a result of the learning of new motor strategies [84].

Researches from clinical sides suggests that a method to work on somatosensor plays an important role in rehabilitation, while current researches in rehabilitation robotics has not yet addressed how to estimate sensorimotor information and bind it to symbolic expressions.

5. Binding Sensorimotor Patterns to Symbolic Expressions

   Taking advantage of the big data on the web, there are researches that generate sentences from images [28][156][158][157]. While in [28], images are described with natural sentences based on names of objects contained, Ushiku proposed a method to generate sentences that describe mutual relations of objects contained in images [156][158][157]. Even though these researches could be extended to bind motion pictures to symbolic expressions, there is no discussion on how to bind sensory information to symbolic expressions. Roy addressed method to bind visual perception, actions and symbolic expressions for a communication robot [128][127]. However, there are not enough discussion how these binding could be use for anticipation of intention of others.

6. Conversation Analysis, Interaction and Communication

   Schegloff and Sacks studied the Conversation Analysis, and introduced ideas that helped to understand communication, such as, Adjacency Pair [129], Turn-Taking for Conversation [130], and other-Correction (other-Repair) in Conversation [134]. Adjacency Pair is an idea of expected sets of pairs in conversation, such as question and answer. Idea of the other-Correction in Conversation is to repair the conversation when expected Adjacency Pair is not observed. For multi-party interaction, Kendon suggested the idea of F-formation [67], which describes a space for multi-party conversation, defined by location and direction of participants' bodies. Bono explained that study for multi-party interaction is different from two-person conversation and explained the importance of multimodality, such as gesture and eye lines [14]. In the paper [14], she discussed how these research can be applied and contribute to research of human robot interaction.

   In this paper, interaction are limited to two agents, between a robot and a human. So, mainly the Conversation Analysis can be applied instead of Discourse analysis. The communication I use in this paper is not a kind of communication using power of symbol communication that enable interaction even when communication protocol is unknown and when meaning/intention of motion is unknown. For estimation of sensorimotor patterns, interactive communication protocol is fixed and shared between agents. The protocol is share motions and exchange symbols that contains information of sensor patterns. In other words, symbolic communication is used to obtain unobservable sensor information and to correct estimation error of it. Therefore, this paper is focused on study of symbolic system rather than linguistic system.

In robotic motion coaching research, interactive communication is partially following the idea of Adjacency Pair and other-Correction in conversation. In the research, the communication is based on emphatic motion display and use of adverbial expressions. The emphatic motion is used to lead the interaction to achieve a goal, to improve performance of learners. So, when performance of learners is not improved, the system apply other-Correction by using emphatic motions and adverbial expressions. In the research, multimodality is considered by using motions and symbolic expressions, however, symbolic expressions are primitive. Timing and intonation of adverbial expression is not considered as variables even thought it is controlled and fixed. This is because of the main purpose of motion coaching research. The main purpose of the research is to show feasibility of proposing method that dynamically change and combine emphatic motions and adverbial expressions according to users reaction.

7. Human-Agent Interaction (HAI)

Yamada discussed an idea in a paper [175] that we need to design machines and interaction so that humans can be friendly to machines, instead of thinking how to design human-friendly machines. For example, there is a work suggesting that suitable appearance of agents are different according to type and content of information to convey in HAI [176]. Researches indicate that real robots with physical bodies are more capable of making humans to involved in tasks, compared to using virtual agents [71] [116] [137] [169]. In the paper [175], Yamada also suggested importance of design of interaction where agents learn how to interact with humans or rewarding interaction patterns, instead of learning how to behavior. It is because that, in HAI, there will be multimodal rewards and it is not practical to design all possible patterns of multimodal rewards in advance. Thus, it is important to learn protocol of interaction between humans and agents. For example, Austermann et al. proposed a method to learn evaluation of behavior that was given by humans with multimodal properties [7].

I agree to the idea that we should design machines and interaction so that humans can be friendly to machines and take advantage of ability of humans, instead of having automated machines with perfect ability. Based on these idea, I decide to have a humanoid agent as a suitable appearance for motion coaching task. Slight differences in motions is not easy to convey by using only motions or symbols. I believe proper combination of motion patterns and symbolic expressions according to reaction of users is important and having a human-like appearance is important. I design an interaction for motion coaching to take advantage of ability to humans. That is, to convey slight difference in motions, robotic motion coaching system does not instruct in detail, but let humans to adopt and improve performance themselves by displaying emphatic motions and adverbial expressions. However, I do not design an interaction so that agents can learn how to interact with humans. I use fixed communication protocol and ask humans to follow it.

8. Skill and Sports Science

   In sports science, there are many studies on how to improve individual physical abilities [103] [33]. However, they do not discuss well how results of analysis and discovery can be convey to players to improve their performance. I believe that quality of communication skill will affect quality of improvement of performance. Similarly, in skill science, researchers are trying to represent skills by symbolic expressions, in order to improve skill to play instruments, for example [37]. What I think is that proper combination of motion patterns and symbolic expressions according to reaction of users is required to assist skill-improvement of others. It is because that slight difference between skilled motion and decently skilled motion is not easy to convey by using either only motions nor symbols. I believe that slight differences in skillful motions is easier to convey by explaining information on relative differences in the motions.

Studies in operations research and teamwork in sports science usually falls into theoretical research by considering players as mass points [90] [144]. Imamura et al. propose a method to analyze quantitative relationship of players who are matching man to man, by representation of relative velocity of center of gravities [54]. Takanashi et al. studied soccer games from social interaction aspect considering embodiment. They discussed qualitatively about importance of anticipating intention of players by observing motions [147]. However, there is no research which integrate these researches and study them quantitatively. Applying proposing methods in this thesis can realize these. I will further discuss about this in the Chapter 7 as a future work.

9. Anticipation of Intention of Others

   In this thesis, estimation of sensorimotor patterns from motion observation will be considered as anticipation of intention of others. Since, for example, robots could initiate conversation with users to confirm whether users need help or not, if robots could properly estimate sensorimotor patterns of users. There are researches that estimate muscle tensions required to perform a given or observed motion sequence on real-time [94][26][25]. Since these methods require predefined user specific model in advance, it would not work well under situation where lots of users come in turn. While these research addressed estimation of sensory information from motion, there is no discussion how sensorimotor information can be bound to symbolic expressions.

   In cognitive science and psychology, theory of mind has been discussed as the ability to attribute mental states to oneself and others and to understand that others beliefs, desires and intentions that are different from one's own. There are two major approaches to theory of mind: theory-theory and simulation theory. The theory-theorist imagines a veritable theory -"folk psychology"- used to reason about others' minds. The theory would developed automatically and innately, though instantiated through social interactions [10] [9] [171]. Whereas, the simulation theory takes an approach: "people generally understand one another by simulating being in the other's shoes" [39] [38].

On the other hand, in computational neuroscience, researches have developed a system enabling visual image reconstruction from reading activities of brain [91][36], a system to capture visual activity in human brains and reconstruct it as digital video clips [101], and are finding an explanation of humans' perception of surface qualities [93][92]. These results could be applied for as a approach to anticipate intention of others. However, these methods requires to have information of averaged brain activities in advance, and therefore it is not practical for real-world environment considering the specialized devices requirement as well.

There are researches with data speak against both Simulation Theory and Theory-Theory in pure form and rather suggest a mixture of both concepts [165]. However, the simulation theory approach, "people generally understand one another by simulating being in the other's shoes", has been supported by a finding in the brain science or neurophysiology [39] [38].

In area F5 of the monkey premotor cortex there are neurons that discharge both when the monkey performs an action and when he observes a similar action made by another monkey or by the experimenter [124]. It is called The Mirror Neuron system, and these neurons appear to represent a system that matches observed events to similar, internally generated actions, and in this way forms a link between the observer and the actor. This observation/execution matching system provides a necessary bridge from 'doing' to 'communicating'

[122]. Furthermore, there has been discussion about relationship between the mirror-neuron system and language [123], and about the mirror neuron system also involved in understanding the intentions of others [52]. Understanding the intentions of others while watching their actions is a fundamental building block of social behavior. There are opposite opinions to the mirror neuron system, such as [46]. However, the discussion point of this thesis is not about validity of the mirror neuron system, but how it can inspire communication in robotics research.

In the next section, an approach to these issues will be addressed and followed by a section that describes basic tools to realize the approach.

2.4 Approach

In this thesis, inspired by the finding of the mirror neuron in the brain science and the idea of the simulation theory, I take the approach, "people generally understand one another by simulating being in the other's shoes", for a method to estimate sensorimotor patterns of others without preparing user specific model in advance, for a method to recognize and generate motions according to users reaction, and for a method to bind sensorimotor patterns and symbolic expressions in order to convey slight difference in sensorimotor patterns for humans to learn. To be specific I apply the Proto-symbol Space Method [56] as a basic tool for proposing methods, since it has a capability to learn, recognize and generate motion patterns in one framework as well as capability to interpolate/extrapolate motions and label them.

2.5 Basic Tools for the Approach: the Proto-symbol Space (PSS) Method

This section explains the Proto-symbol Space Method [56] as a basic tool that is applied for proposing methods in this thesis. The Proto-symbol Space method consists of three properties; acquisition of symbols by abstracting motion patterns, recognition of observed motion patterns by using these symbols, and generation of motion patterns by the symbols. This system integrates these three properties in one framework, or one Hidden Markov Model (HMM) for a motion recognition and generation.

- Motion Learning and Construction of the Proto-symbol Space

  The left-to-right continuous Hidden Markov Model (CHMM) [183] is employed to abstract motions $\boldsymbol{M}_i$. Motion patterns $\boldsymbol{M} = [\boldsymbol{\theta}[0]\boldsymbol{\theta}[1]\cdots\boldsymbol{\theta}[t]]$, which is a matrix, where $\boldsymbol{\theta}[t] = [\theta_1[t]\cdots\theta_i[t]\cdots\theta_n[t]]^T$ is a vector of time series joint angle, of humans and humanoid robots, where i is a index of a joint. It is one of the most famous tools for recognition of time series data, especially in speech recognition research. The CHMM consists of a set of parameter $\{\boldsymbol{Q}, \pi, \boldsymbol{A}, \boldsymbol{B}\}$, where $\boldsymbol{Q} = \{q_1, ..., q_N\}$ is a finite set of states, $\boldsymbol{A} = \{a_{ij}\}$ is a state transition probability matrix from q_i to q_j, and $\boldsymbol{B} = \{b_i\}$ is a vector of output probabilities of $o[t]$, at q_i, corresponding to the joint angle vector $\boldsymbol{\theta}[t]$ at a discrete time t. The $\pi = 1$ is the same for every CHMM because I assume that the Left-to-Right model is used for every CHMM; hence the set of $\lambda = \{a_{ij}, b_i\}$ determines the behavior of the stochastic process; λ is called a proto-symbol. The output probability density $o[t]$ at q_i is defined as a mixture of the Gaussian functions as

  $$b_i(\boldsymbol{o}) = \sum_{j=1}^{m} c_{ij}\mathcal{N}_{ij}(\boldsymbol{o}; \boldsymbol{\Sigma}, \boldsymbol{\mu}), \tag{2.1}$$

  where $b_i(\boldsymbol{o})$ is the probability density function for the output of continuous vector $\boldsymbol{o}$ at the ith state node, m is the number of mixture Gaussian functions, and c_{ij} is the mixture coefficient. $\mathcal{N}(\boldsymbol{o}; \boldsymbol{\Sigma}, \boldsymbol{\mu})$ is the Gaussian function,

  $$\mathcal{N}(\boldsymbol{o}; \boldsymbol{\Sigma}, \boldsymbol{\mu}) = \frac{1}{\sqrt{(2\pi)^X \det \Sigma}} \exp^{\{-\{\frac{1}{2}(\boldsymbol{O}-\vec{\mu})^T\Sigma^{-1}(\boldsymbol{O}-\boldsymbol{\mu})\}} \tag{2.2}$$

where $\mathbf{\Sigma}$ is the covariance matrix , $\boldsymbol{\mu}$ is the mean vector, and X is the number of dimensions of the continuous vector $\boldsymbol{o}$. The parameters of the HMM are optimized by the Baum-Welch algorithm [118] , which is a an Expectation-Maximization algorithm.

The Proto-symbol Space [56] is a phase space that represents the relationship between continuous motion patterns as locations of proto-symbols in the space. The location of the proto-symbols is assigned by a multi-dimensional scaling (MDS) [135] with the distance between CHMMs measured with the Bhattacharyya Distance [12].

Bhattacharyya Distance between gaussian distributions $p(x;\mu_p,\Sigma_p)$, $q(x;\mu_q,\Sigma_q)$ is denoted as $BD(p,q)$ and defined as

$$\begin{aligned} DB(p,q) &= -log\int_{-\infty}^{\infty}\sqrt{p(x)q(x)}dx \\ &= \frac{1}{8}(\mu_p-\mu_q)(\frac{\Sigma_p+\Sigma_q}{2})^{-1}(\mu_p-\mu_q)^T+\frac{1}{2}log\frac{|\frac{\Sigma_p+\Sigma_q}{2}|}{|\Sigma_p|^{\frac{1}{2}}|\Sigma_q|^{\frac{1}{2}}} \end{aligned} \quad (2.3)$$

The Bhattacharyya Distance between two CHMMs λ_1 and λ_2 is calculated by adding distance between each gaussian distributions assigned to each nodes, and it is denoted as

$$d(\lambda_1,\lambda_2)=\sum_i\sqrt{BD\left(b_{1i}\left(\mathbf{0};\mathbf{\Sigma}_{1i},\boldsymbol{\mu}_{1i}\right),b_{2i}\left(\mathbf{0};\mathbf{\Sigma}_{2i},\boldsymbol{\mu}_{2i}\right)\right)} \quad (2.4)$$

where $b_{1i}\left(\mathbf{0};\mathbf{\Sigma}_{1i},\boldsymbol{\mu}_{1i}\right)$ is a probability density function for i-th node of HMM λ_1. The reason why the Bhattacharyya Distance [12] is employed instead of Kullback-Leibler Divergence [76] is that the Bhattacharyya Distance has property of symmetry and linearity in distance with respect to ratio of weight coefficients of internal/external dividing points when motions are interpolated and extrapolated.

The MDS accepts the distance among items and outputs the location of each item $\boldsymbol{x}$ in a Euclidean space. Let the distance between the i-th item and j-th item be f_{ij} by Eq.(2.4), and let the Euclidean distance between the i-th item $\boldsymbol{x}_i$ and j-th item $\boldsymbol{x}_j$ be d_{ij}. Then, the objective of the MDS is to calculate the appropriate $\boldsymbol{x}_i$ by minimizing the criterion $S^2 = \sum_{i,j}(f_{ij} - d_{ij})^2$. $\boldsymbol{x}$ corresponds to the location of the proto-symbol in the proto-symbol space.

Therefore, when a database of motor patterns is defined as $D = \{\boldsymbol{M}_1, ..., \boldsymbol{M}_i\}$, where i is index of motion patterns, Proto-symbol space represented as P is built from D using a building process, denoted as,

$$P = F_{build}(D). \tag{2.5}$$

In the P, there are static points $\boldsymbol{x}_i$, which corresponds to $\boldsymbol{M}_i = [\boldsymbol{\theta}[0]\boldsymbol{\theta}[1] \cdots \boldsymbol{\theta}[t]]$, where $\boldsymbol{\theta}[t] = [\theta_1[t] \cdots \theta_j[t] \cdots \theta_n[t]]^T$ is a vector of time series joint angle, of humans and humanoid robots, where j is a index of a joint.

- Motion Recognition

  Motion patterns, which are not even in the D, can be recognized by first abstracting motion patterns to the CHMM, then calculating the Bhattacharyya Distance [12] among λs in the Proto-symbol Space. As a result, a motion pattern can be recognized as a static point $\boldsymbol{x}$ in the P, This recognition process is represented as F_{recog}.

$$\boldsymbol{x} = F_{recog}(\boldsymbol{M}). \tag{2.6}$$

- Motion Generation

  Using the Proto-symbol Space method, an interpolated/extrapolated novel motion pattern $\boldsymbol{M}_s$, which is not in D, can be synthesized through an internal/external dividing point $\boldsymbol{x}_s$ manipulation in the Proto-symbol space [58]. The $\boldsymbol{M}_s$ can be generated from the novel internal/external dividing point $\boldsymbol{x}_s$ [58] by using motion generation process F_{gen}, defined as

$$\boldsymbol{M}_s = F_{gen}(\boldsymbol{x}_s). \tag{2.7}$$

In detail, the averaging method over repetition of motion generation is adopted. The detailed order of the generation is as follows.

1. Initialization. Let the starting node be q_1 , let the node token be $i = 1$, and let the motion elements sequence be $\boldsymbol{O} = \phi$.
2. Deciding the transition destination node q_j using transition matrix $\boldsymbol{A}$ stochastically, by using Monte Carlo Method.
3. Deciding the output label $\boldsymbol{o}_{k_t}$ during the transition from node q_i to q_j stochastically (by Monte Carlo Method) using output matrix $\boldsymbol{B}$.
4. Adding the output label $\boldsymbol{o}_{k_t}$ to the motion elements sequence $\boldsymbol{O}$. $\boldsymbol{O} := [\boldsymbol{O}\ \boldsymbol{o}_{k_t}]$.
5. Let the generation process be stopped when the token reaches the end node q_N, or returns to step 2 letting $i := j$, $t := t + 1$.
6. Finally, the sequential motion elements are transformed into continuous joint angle representations.

The output motions using the above operations are not the same, but have different time lengths and orders of motion elements, because the output operations are stochastic. However, it is possible to generate an approximate motion pattern because the parameters $\boldsymbol{A}$ and $\boldsymbol{B}$ represent the abstraction of dynamics in the motion pattern. Therefore, the above operations are repeated, and plural generated motions are averaged.

- Association of Whole Patterns with Partially Observed Patterns

  Using the Proto-symbol Space method, it is possible to associate whole patterns with partially observed patterns [59].

$$\boldsymbol{M}_{whole} = F_{gen}(F_{recog}(\boldsymbol{M}_{partial})) \tag{2.8}$$

In other words, the Proto-symbol space method can associate whole motion patterns with partially observed motions.

From the next chapters, I will discuss about newly proposing methods which take advantage of these basic tools to realize the approach addressed in this chapter.

2.6 Conclusion of the Chapter

I briefly over-viewed robotics research as improvement in physical ability. Then, I described that communication ability is important for further advance in robotics. After listed up functions required for the communication, related works were introduced with challenges to achieve required functions. The approach taken in this thesis, "people generally understand one another by simulating being in the other's shoes", was introduced. At last, the Proto-symbol Space method was introduced as a basic tool for realizing proposing methods in this thesis.

Chapter 3

An Estimation Method of Others' Sensorimotor Patterns and Others' Symbol Conversion Strategy of the Patterns

3.1 Abstract of the Chapter

I am interested in a method to estimate sensorimotor patterns of others without having predefined user specific model in advance. This is because that a situation where lots of users comes in turns are expected in future service robots, and it is not realistic to have all the model for all the users. In the first half of this chapter, an approach bridging sensorimotor experience of self and other is taken. To realize the approach a method to estimate Proto-symbol Space of other from that of the self is proposed in this chapter. Estimation errors due to physical condition difference is cleared by sharing motions and using open questions to ask for absolute heaviness the other find the motions. Simulation demonstrated that the proposing method can be estimate sensorimotor patterns of other with 10-20% errors even for unknown motions, which are not in the database. In the second half, we addressed an issue that symbol conversion strategy from sensor was given in the first half. Proposing a method sharing sets of motions and using closed question that is a comparative evaluation question, demonstrated that it is possible to estimate others' symbol conversion strategy.

3.2 Introduction

In sports, as it was discussed in the previous chapters, proper estimation of others' sensorimotor patterns by motion observation is important for learning proper motions and for estimation of others' inner state that leads to a good teamwork.

On the other hand, similarly, it is important for service robots, which are expected to be used in near future at home environment, to have a function to estimate sensorimotor patterns of users. It is because that the robots could initiate conversation with users to confirm whether the users need help if the robots could properly estimate sensorimotor patterns by observation of users' motion. Therefore, in this chapter, we address the function for robots that are expected to serve for humans.

One of the hard problems of intelligent robots which work in daily life environment is to understand user's intention. To understand user's intention, many methods have been proposed. For instance, observation of user's activity using video camera and rooms with sensor embedded floor and use of RFID tags have been proposed [121][34][180][51][170]. However, making estimation of inner states, such as whether a user would like to be assisted is not easy to achieve by these methods. It requires estimation of sensorimotor patterns of the user and it is an important basic technology for the purpose.

Methods have been proposed to estimate tensional force on muscles with observation of a human's motion patterns by utilizing electromyography information with detailed musculo-skeletal model of human's whole body [162][163][164][94]. Other methods using measurement devices of brain activities, such as fMRI, PET and EEG, have been also developed to estimate what motor command a subject is trying to attempt [172][100][174][161][20]. These methods require preparation of user specific musculo-skeletal model or information of averaged brain activities in advance. In addition, these approaches cannot deal well with environment where many users are expected to use in turn.

We are interested in a method that can estimate sensorimotor patterns even in such environment. Therefore, we take an approach that bridging between others' and self's sensorimotor experiences in order to estimate sensorimotor patterns of the others without pre-defined user specific models in advanced. If the self can bridge their sensorimotor experiences to the others', the self could observe the others' sensorimotor patterns as if the self experienced that of the others' when motion patterns are shared. Human beings, in daily life, are thought to estimate the other's sensorimotor patterns using the other's simulated experience.This is called simulation theory [39], and it has been applied for grasping intentions of others [53].

This approach will work well if the self and the other have identical body conditions. But, it is natural that the conditions are different. Therefore, there will be estimation errors derived from the difference when the self makes the estimation based on estimated sensorimotor experiences of the other. This problem needs to be addressed especially in a situation where robots interacts with humans, since the two have very different physical conditions. In robotics, this is called *correspondence problem*[2][43][98]. Therefore, for Human-Robot interaction, it is required to have a method that can be applied even when the body conditions are not identical.

Recurrent Neural Net Parametric Bias(RNNPB) has been introduced as a framework to estimate inner information by Tani et al[152]. This system, for example, can abstract motion patterns, and be able to deal with unknown motions which are not in the database. However, it is known that calculations using RNNPB is not guaranteed to be converged and tends to have local optimality.

Mirror Neuron system has been discussed in brain science [122][27]. The mirror neuron system fires both when a subject observes a specific behavior and when the subject acts in the same manner. One of the important concepts that mirror neuron system suggests is that bridging sensorimotor experience between the self and the other.

Inspired by the these findings in brain science[122][27], Proto-symbol Space Method has been proposed by Inamura et al[59]. It is an engineering model of mirror neuron system[122]. As it was discussed in the Chapter 2, the Proto-symbol Space Method can recognize, generate motions in one framework. The method, however, assumes that both physical conditions are identical when it is used for estimating sensorimotor patterns of others[58].

The problem in the approach –to estimate others' sensorimotor patterns by bridging between others' and self's sensorimotor experiences– is how to overcome differences in physical condition between the self and the other. Thus, to address this problem, an objective of the chapter is to propose a method to estimate others' sensorimotor patterns without user specific model in advance, by sharing motions and using open questions and applying the Proto-symbol Space method.

3.3 Estimation of Others' Sensorimotor Patterns by sharing Motion Patterns and using Open Questions

3.3.1 Approach to Estimate Others' Sensorimotor Patterns

To estimate others' sensorimotor patterns without preparing user-specific model in advance, we take an approach bridging sensorimotor experience between self and other. It is natural for humans to estimate sensorimotor patterns of other, by starting assuming that the self and the other feel the same when performing identical motions.

For example, when there is a person whose size and shape are similar to the self, it is natural for the self to estimate that the person will find lifting an object heavy as same as self would find. However, the person could find it light if the person is with more muscule and less fat. In other words, there will be errors in estimation of sensorimotor patterns of others due to difference in physical conditions.

3.3.2 Method 1 -Acquisition of Others' PSS adaptively from the Self's-

Inspired by the approach and the issue discussed, we propose a method to acquire others' Proto-symbol Space (PSS) by bridging sensorimotor experience of the self and the other.

As described in the Chapter 2, the PSS method abstracts sensorimotor temporal patterns of human beings and humanoid robots. It defines a space called the *Proto-symbol Space*(PSS), according to the similarity among abstracted patterns[59]. The PSS method can recognize and generate even unknown motion patterns, or those not in database by interpolation and extrapolation of motions in the database. In addition, by abstracting motions using sensor patterns as well as motor patterns, it can associate motion patterns to corresponding sensor patterns.

In the original PSS method [59], one PSS was used to bridge between the self and the other. When it was used for estimating sensorimotor patterns of others, there was an assumption that the physical condition of both the self and the other are identical (Figure 3.1).

With the PSS method, it is possible to estimate sensorimotor patterns even when a novel motion pattern that is not in the database is observed. However, PSS of the self and PSS of the other are different due to difference in the database of sensorimotor experiences between the two. So, if we can estimate the PSS of the other adaptively from the PSS of the self, we can estimate sensorimotor patterns of the others even when we observe a novel motion pattern.

Thus, we want to acquire the others' PSS denoted as $\hat{P}_{other}$ from that of self denoted as P_{self}. For this purpose, we propose a method to estimate $\hat{P}_{other}$, by introducing the real P_{other} and by using a set of shared motions and an open question, which asks for absolute evaluation of sensor. An image of the states before the estimation $\hat{P}_{other} = P_{self}$ (Figure 3.2-③) and the state after the successful acquisition

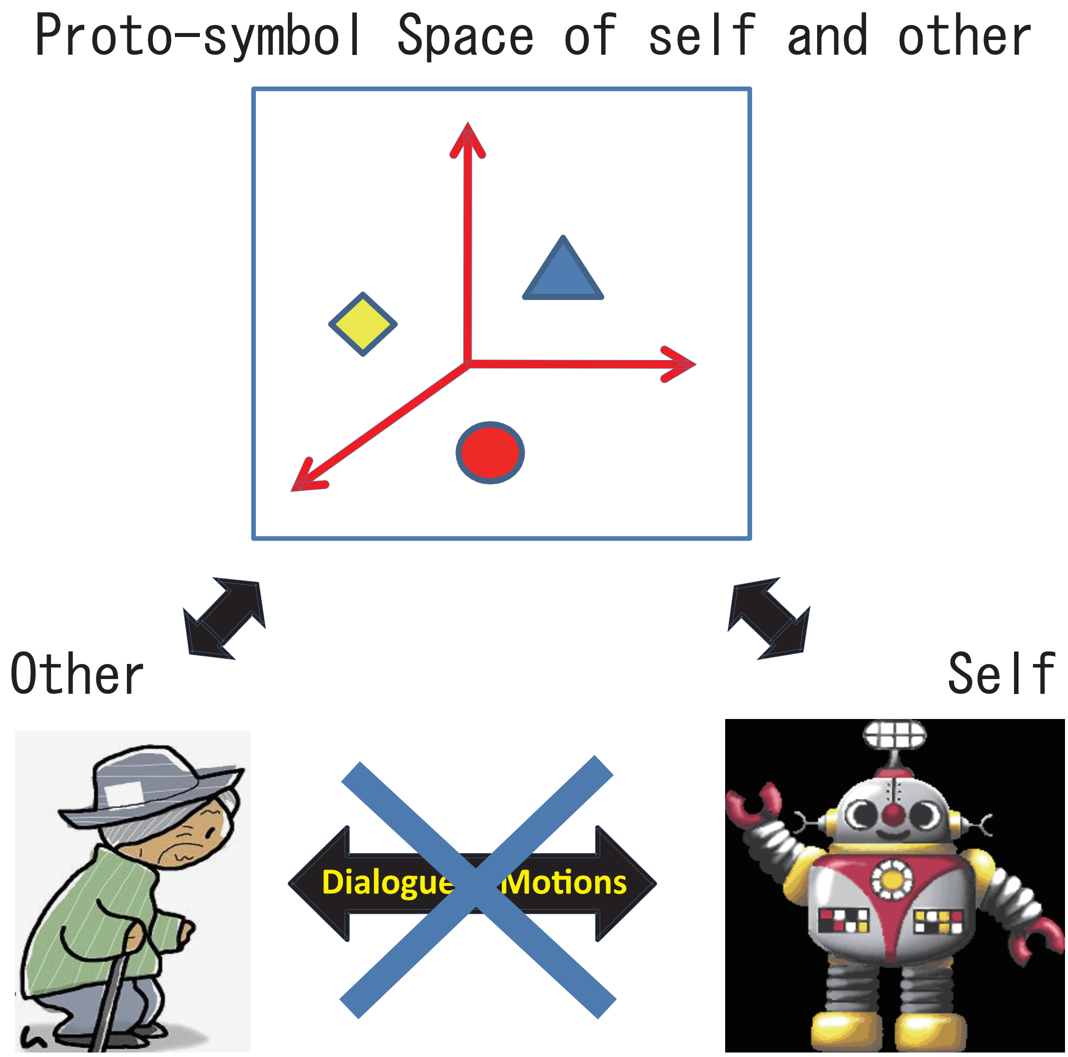

Figure 3.1: Image of acquisition of others sensorimotor experience with one PSS in the original PSS method [59].Self and Other are assumed to have identical physical conditions.

of $\hat{P}_{other}$ (Figure 3.2-③) is depicted in Figure 3.2.

A unique acquisition method of $\hat{P}_{other}$ is proposed in order to estimate the others' torque patterns. The method uses *open question* type communication to estimate the other's sensorimotor patterns, even when physical conditions are different in self and other [57]. The outline of this method is explained as follows and is depicted in Figure 3.3.

1. As an initial state, the self sets the other's inference model $\hat{P}_{other}$ based on own

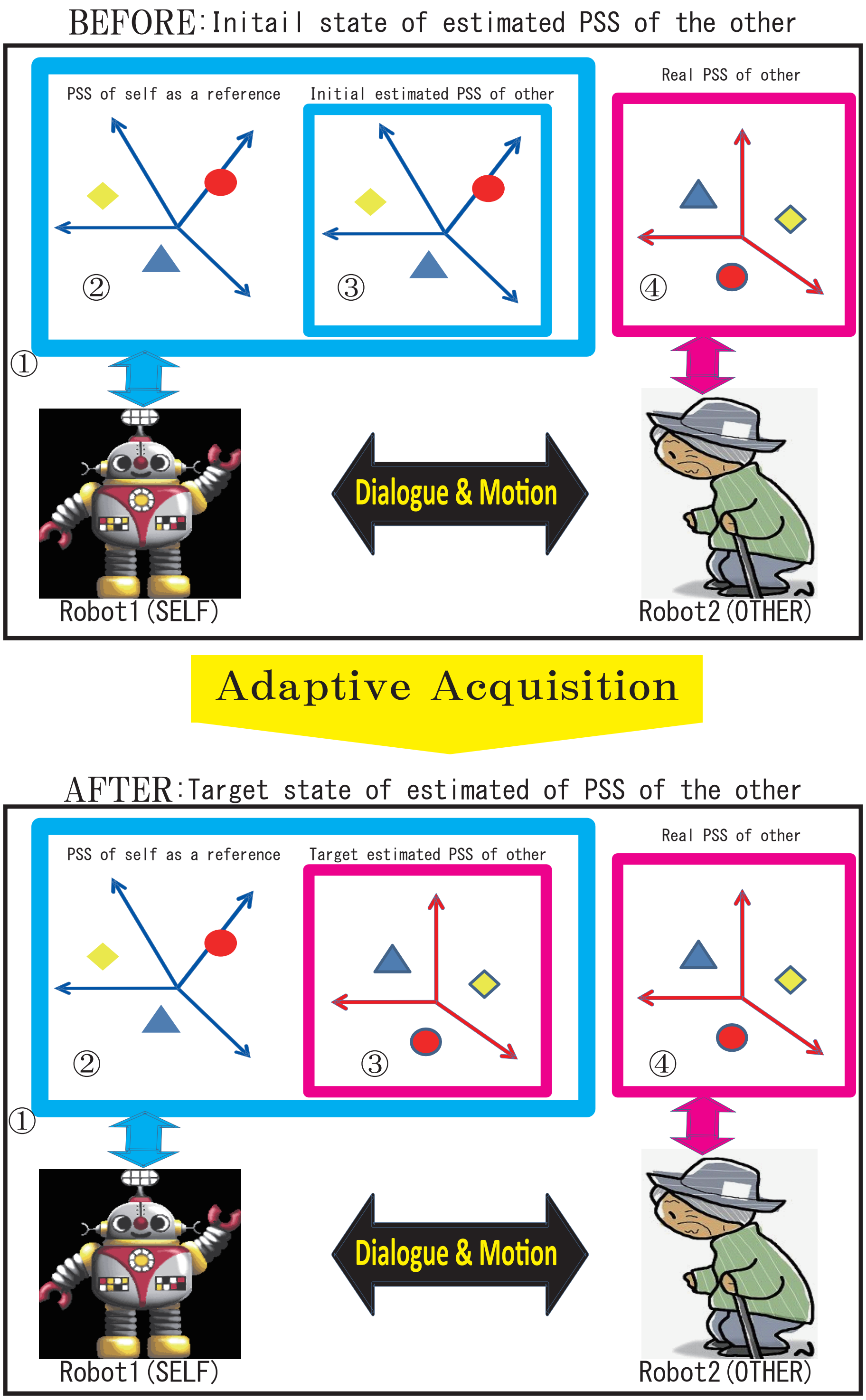

Figure 3.2: Image of acquisition of other's sensorimotor experience by estimation of other's Proto-symbol Space: Self① has *PSS* of both self② and other③. a Real *PSS* of other is presented as ④. After the success estimation the Self will have estimated *PSS* of other③ as same as the ④, while ③ is as same as ② before the acquisition.

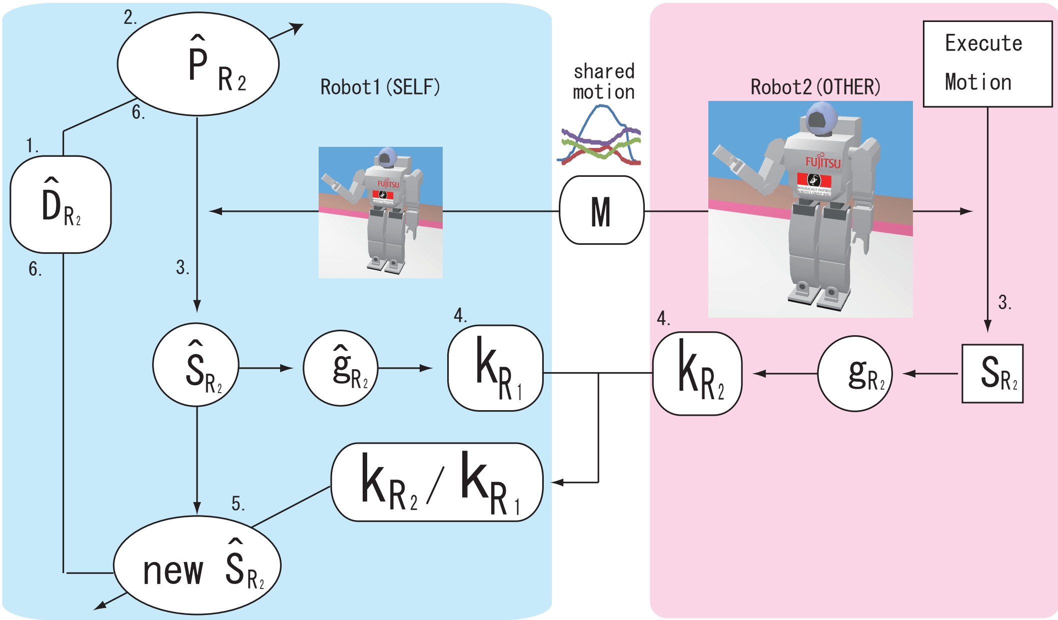

Figure 3.3: Adaptive acquisition flow diagram of the other's proto-symbol space: 1. The self sets the others' estimated $\hat{P}_{other}$ based on own experience D_{self}. 2. The self builds $\hat{P}_{other}$ using $\hat{D}_{other}$ (Eq.(3.1)). 3. The other executes the shared motion $\boldsymbol{M}$ and observes corresponding $\boldsymbol{S}_{other}$, The self obtains $\hat{\boldsymbol{S}}_{other}$ from $\boldsymbol{M}_{other}$ utilizing $\hat{P}_{other}$ (Eq.(3.2)). 4. Both the self and the other converts $\hat{\boldsymbol{S}}_{other}, \boldsymbol{S}_{other}$ into symbol-indexes k_{self}, k_{other} (Eq.(3.4)). 5. The self modifies the $\hat{\boldsymbol{S}}_{other}$ in the $\hat{D}_{other}$ (Eq.(3.5)). 6. The self reconstructs $\hat{P}_{other}$ with the newly modified $\hat{D}'_{other}$ (Eq.(3.6))

experience $\hat{D}_{other} = \{\boldsymbol{S}_{self}, \boldsymbol{M}_{self}\}$.

2. The self builds $\hat{P}_{other}$ with $\hat{D}_{other}$ by using F_{build} (Eq.(2.5)) function,

$$\hat{P}_{other} = F_{const}(\hat{D}_{other}) \tag{3.1}$$

3. The other executes the shared motion $\boldsymbol{M}$ and observes corresponding $\boldsymbol{S}_{other}$. The self obtains $\hat{\boldsymbol{S}}_{other}$ from $\boldsymbol{M}_{other}$ utilizing $\hat{P}_{other}$ as an association function(Eq(2.8)).

$$\hat{\boldsymbol{S}}_{other} = F_{gen}(F_{recog}(\boldsymbol{M})) \tag{3.2}$$

4. Both the self and the other converts $\hat{\boldsymbol{S}}_{other}, \boldsymbol{S}_{other}$ into symbol-indexes k_{self}, k_{other}

respectively using a discretization function $F_{symbolize}$,

$$k_{self} = F_{symbolize}(\hat{\boldsymbol{S}}_{other}) \quad (3.3)$$

$$k_{other} = F_{symbolize}(\boldsymbol{S}_{other}). \quad (3.4)$$

The symbol-indexs are integers corresponding to strength of the sensor $\boldsymbol{S}$s.

5. The self modifies the $\hat{\boldsymbol{S}}_{other}$ in the $\hat{D}_{other}$ according to the result of exchange of the symbols k_{self} and k_{other}.

$$\hat{\boldsymbol{S}}'_{other} = \frac{k_{other}}{k_{self}} \hat{\boldsymbol{S}}_{other} \quad (3.5)$$

6. The self rebuilds $\hat{P}_{other}$ with the newly modified $\hat{D}'_{other} = \{\boldsymbol{M_{selfr}}, \hat{\boldsymbol{S}}'_{other}\}$ by using Eq.(2.5),

$$\hat{P}_{other} = F_{build}(\hat{D}'_{other}). \quad (3.6)$$

Steps through 2 to 6 are considered as single conversation set. The self adaptively acquires $\hat{P}_{other}$ with repetition of the conversation sets.

On the other hand, the $F_{symbolize}$ consists of two functions $F_{symbolize} = F_{div}(F_{conv}(\boldsymbol{S}))$. F_{conv} is to convert vector value $\boldsymbol{S}$ into intermediate scalar vaule g.

$$g = F_{conv}(\boldsymbol{S}) \quad (3.7)$$

In this paper a condition represented by following equation is used.

$$F_{conv}(\boldsymbol{S}) = \frac{1}{T} \int_0^T \frac{|\tau_1(t)| + |\tau_2(t)| + |\tau_3(t)|}{\tau_{MAX}} dt \quad (3.8)$$

With F_{div} symbol-index k is obtained from g, by dividing the interval of g into d equal segments and assigned in accordance with Table 3.1.

3.3.3 Experimental Setup 1

The torque on joints of the other is estimated by using the proposing method. An experiment is conducted using two humanoid robots, for the sake of investigation of the concept with simple condition as an initial step.

Table 3.1: Relation between expression and density of the expression

k	d=2	d=4	d=6
1	light	light	very light
2	heavy	bit light	light
3	-	bit heavy	bit light
4	-	heavy	bit heavy
5	-	-	heavy
6	-	-	very heavy

Conditions:

- The experiment involved two virtual humanoid robots R_1 and R_2 in a simulator environment, using the Webots.
- Both robots had the same structures as HOAP-2 produced by Fujitsu Corp, with different weights; R_1 weighted 2.4[kg], R_2 weighted 4.8[kg]. The masses were unknown to each other.
- $D_{R_i} = \{\boldsymbol{M}, \boldsymbol{S}\}(i = 1, 2)$, for building P_{R_i}, were prepared with four basic motions shown in Figure 3.4.
- $\boldsymbol{M}$ consisted of joint angles for the right elbow and pitch and roll rotation torque on the right shoulder $[\theta_1\theta_2\theta_3]$.
- $\boldsymbol{S}$ consisted of torque values of the same joint angles $[\tau_1\tau_2\tau_3]$.

The Figure 3.4 shows a set of basic motions that were used for building the $\hat{P}_{R_2}$. 10 unknown motions that are not in the database were prepared for evaluation purpose of the proposed method. These unknown motions consist of moves of the considered joints randomly. The Figure 3.5 shows two sample unknown motions used for evaluation of the estimated $\hat{P}_{R_2}$.

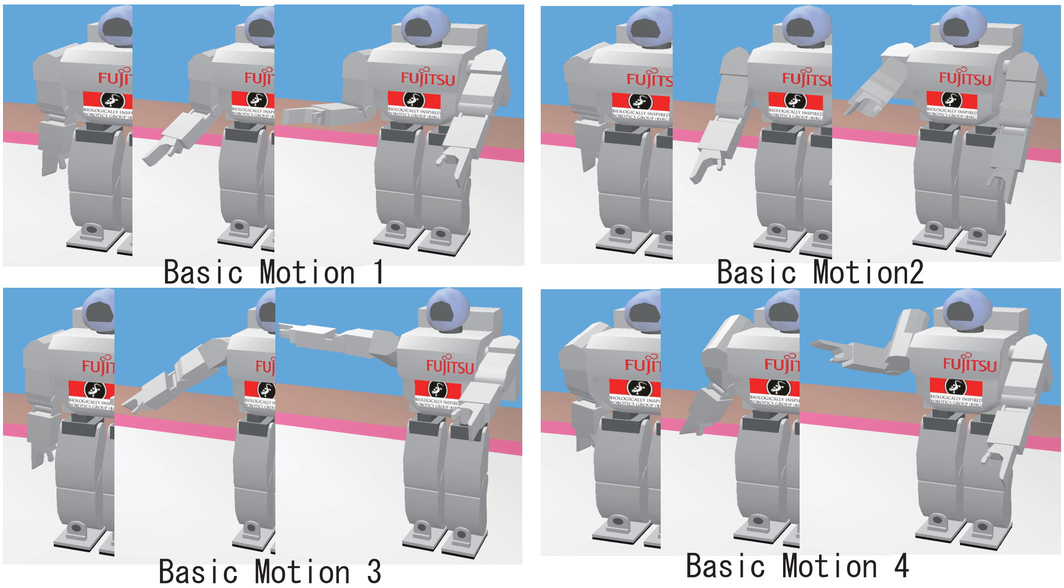

Figure 3.4: Basic shared motion patterns for constructing PSS

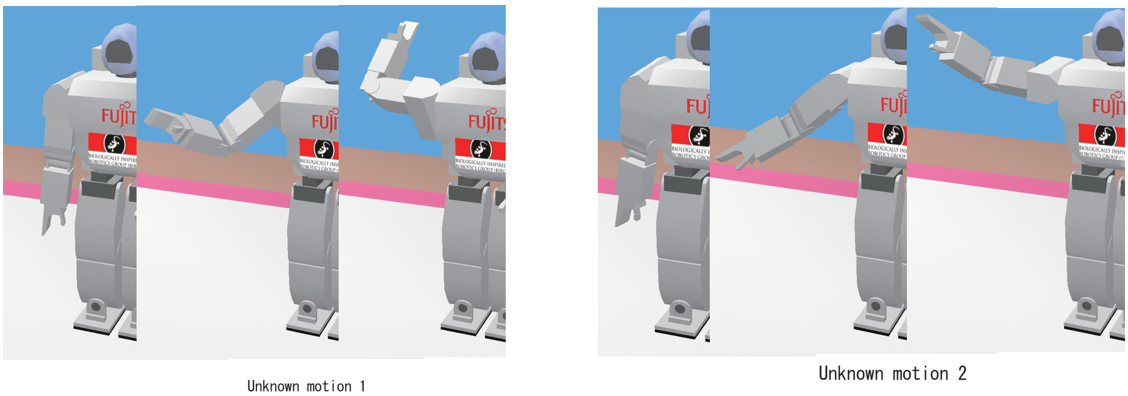

Figure 3.5: Two sample unknown motions used for evaluation of the estimated $\hat{P}_{R_2}$

3.3.4 Experimental Result 1

Sets of experiments has been conducted using the procedure explained in the previous section. For evaluation purpose, following criteria were introduced. Estimation errors ratio of real scalar value of torque (Eq.(3.7)) of other compared to estimated torque.

$$\bar{e} = \frac{\sum_i^n \frac{|g_i - \hat{g}_i|}{g_i}}{n} \tag{3.9}$$

where $n = 4$ for basic/known motions, and $n = 10$ for unknown motions.

Other evaluation criteria are matching ratio between real and estimated symbols of others, and average distance between real and estimated symbols of other as

$$\bar{l} = \frac{\sum_i^n \frac{|k_i - \hat{k}_i|}{d-1}}{n} \tag{3.10}$$

where d is the density of expressions defined in the Table 3.1, and n is number of sample data used in experiment. $n = 4$ for basic/known motions, and $n = 10$ for unknown motions.

Figure 3.6 shows that after a few conversation sets resulted in successful estimation for torque g of R_2 with approximately 10% error (Eq.(3.9)) with motion patterns in the database, and 20% errors (Eq.(3.9)) even when with unknown motion patterns. The larger d is, the less $\bar{e}$ is.

Figure 3.7 shows a matching ration between real and estimated symbols. When $d = 4$, the matching ratio between known and unknown motions are alike and around 80%. When $d = 6$, the matching ratio for known motion is 100% and the ratio for unknown motions is about 70%. When $d = 8$, the matching ratio for known motion is 100% and the ratio for unknown motions is about 30%.

Figure 3.8 shows the distance between real and estimated symbols (Eq.(3.10)). The lower the value is, the closer the symbols are even when the symbols are not the same. The result shows that estimated symbols $\hat{k}$ are close to the real symbols k used by the R_2, even for unknown motions.

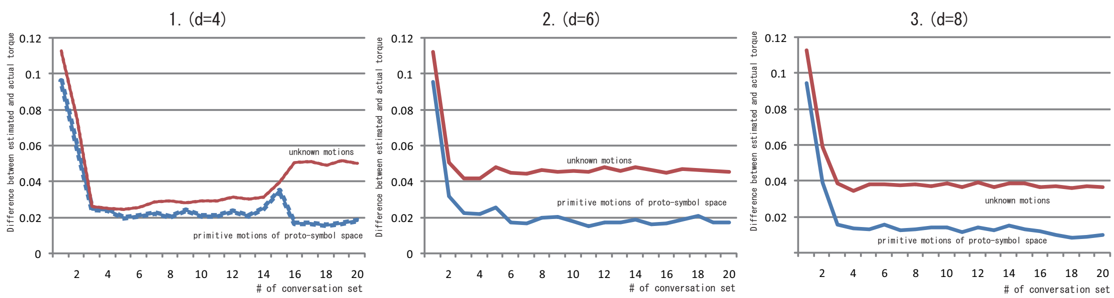

Figure 3.6: Estimation errors of others' torque (Eq.(3.9)) with different density of expression. 1.d=4, 2.d=6, 3.d=8

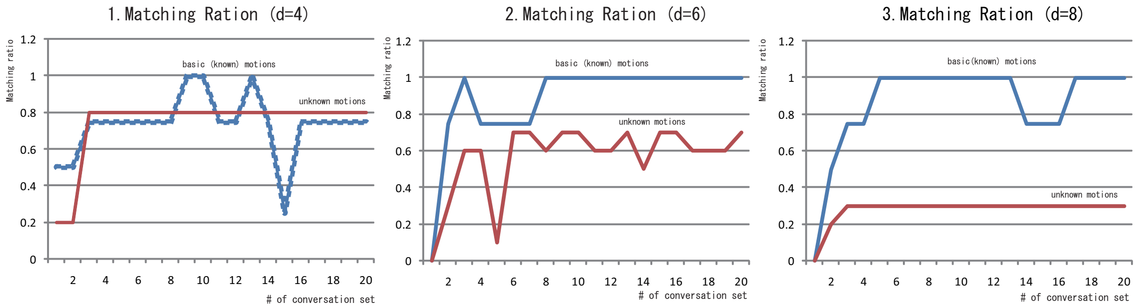

Figure 3.7: Matching ratio between real and estimated others' symbols, with different density of expression. 1.d=4, 2.d=6, 3.d=8

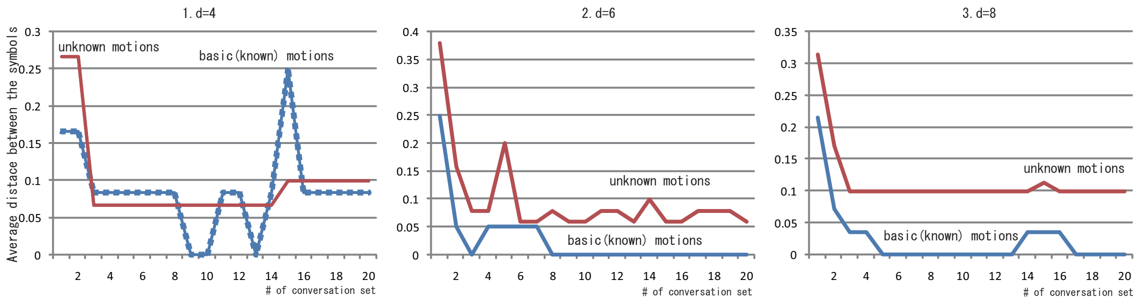

Figure 3.8: Distance between real and estimated others' symbols (Eq.(3.10)), with different density of expression. 1.d=4, 2.d=6, 3.d=8

3.3.5 sub-Conclusion

We proposed a method based on the concept to estimate unobservable information of the other when physical conditions are different. The concept is to bridge sensorimotor experience of self and others. To realize this concept, a method was proposed that is to estimate others' PSS from the self's adaptively by shared motions and open questions. Experimental result shows that a few conversation sets resulting in successful estimation of R_2's torque g with 20% error was confirmed, even when R_2 performed unknown motion patterns, and with 10% error with known motions.

The proposed method assumes that both the self and the other have identical body configuration other than having different mass in this paper. If the DoF are different, the proposed method can be used only when joint configuration are similar and movements are kinematically similar. This method will work when the self have more large DoF than the other and when the self can imitate movements of the other by simply not using one or more joints. However, there needs to be more quantitative analysis about allowed similarities.

3.4 Estimation of Others' Symbol Conversion Strategy by Sharing Sets of Motions and using Closed Questions

3.4.1 Remaining Problem from the previous Section

With the method proposed in the previous section[57], it becomes possible to estimate others' sensorimotor patterns without having pre-defined model of users in advance. The method results in a successful estimation of other's sensory patterns with 10%-20% errors[57], after a few interaction sharing motions and using open questions.

However, there was a remaining problem, a symbolization strategy how to convert sensory patterns into the symbol-index was given for sake of simplicity (Eq.(3.4), Eq.(3.8) and Table 3.1) Intrinsically, the strategy is supposed to be unknown and it should be changed dynamically according to circumstances.

It is possible to estimate the strategy by the method in the previous section [57] if sets of motions and queries are prepared properly. However, it would require as same or more number of queries as of the strategy candidates. It is because the *open question* method was used and there are almost infinite number of choices for the answers. When interactions between robots and humans are considered, it is better to limit the number of queries from the robot to the human.

Thus, in this section we propose a method that uses closed questions and sets of shared motions, in order to have less amount of queries. In this method, the other was asked to perform two kinds of motions and answer which motion was heavier, or observed larger torque on joints. The closed question is a *comparative evaluation question* of a set of shared motions, asking which motion is heavier. This comparative evaluation questions and sets of shard motions are used in the framework of the previous section [57], in order to estimate the intrinsically unknown symbolization strategy how to convert sensory patterns into the symbol-index.

The problem to solve in this section, specifically, is the function that converts

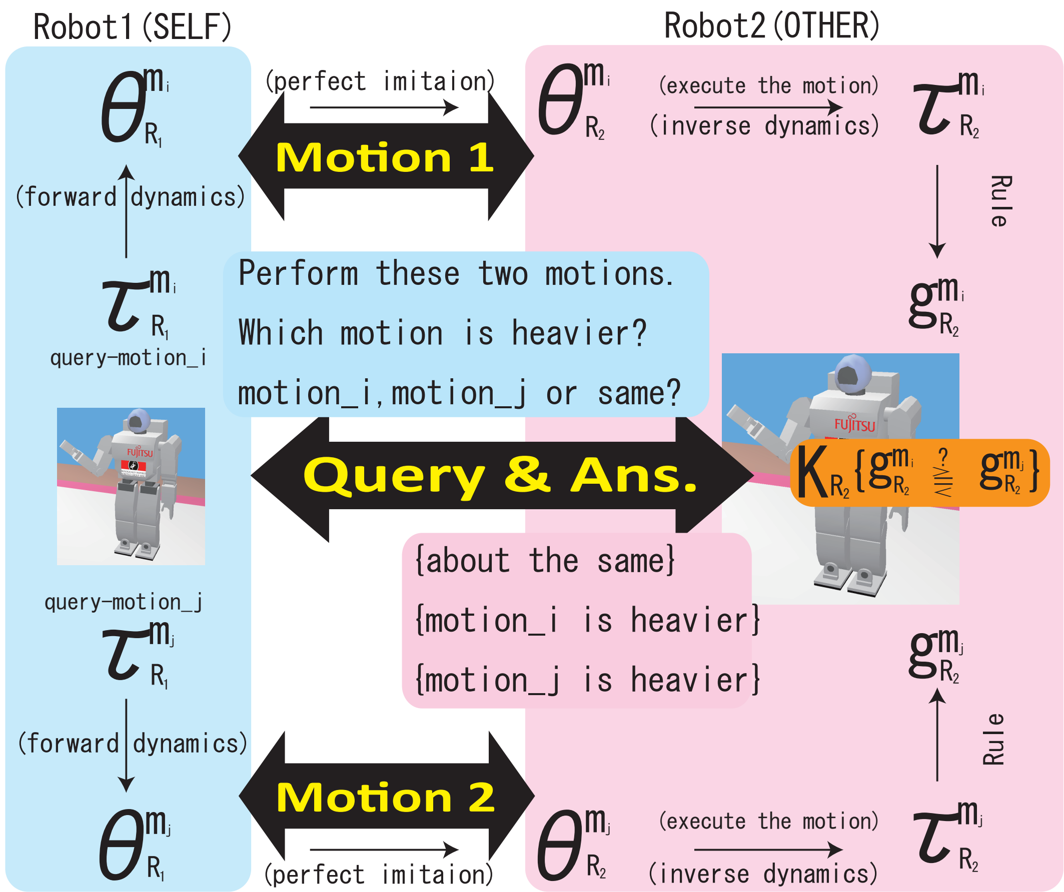

Figure 3.9: Diagram of the method to estimate others symbol conversion strategy by using comparative evaluation questions and sets of shared motions

temporal sensory patterns into a scalar value, defined in Eq.(3.7). With the proposing method, it would be possible to estimate what kind of function the others' are taking –in the previous section, it was given as Eq.(3.8)–.

3.4.2 Method 2 –How to Estimate Others' Symbol Conversion Strategy–

The proposing method uses closed questions and sets of shared motions in order for the self to estimate other's symbolization strategy $F_{symbolize}$. When the self attempts to estimate the other's $F_{symbolize}$, the self prepares more than two sets of shared motion patterns. These motion patterns are designed specifically for the estimation of other's

$F_{symbolize}$. As it was explained in the previous section, the closed question is to ask for relative relationship of the observed sensory patterns for the motions, and the closed question is called *comparative evaluation question* in this chapter. For example, an answer would be "Motion 1 is heavier".

The following procedure is used for the estimation of $\hat{F}_{symbolize}$. The concept is depicted in Figure 3.9.

1. According to the identification target $F_{symbolize}$, the self prepares motion patterns $\boldsymbol{M}_i(i = 1, 2)$.

2. The other imitates each $\boldsymbol{M}_i$ and observes corresponding sensory patterns $\boldsymbol{S}_i$.

3. The other converts $\boldsymbol{S}_i$ into scalar value g_i using conversion function $F_{symbolize}$.

$$g_i = F_{symbolize}(\boldsymbol{S}_i), \tag{3.11}$$

4. The other replies with a symbol-index K that tells the magnitude relation of the g_1, g_2.

$$K = F_{comp}(g_1, g_2), \tag{3.12}$$

   That is, K is either "M_1 is heavier" ('>'), "M_2 is heavier" ('<') or "same" ('equal').

5. The self identifies the other's $F_{symbolize}$ based on the replied symbol-index K.

If necessary, the self prepares a new set of motion patterns and repeats the steps above till identifies the $F_{symbolize}$.

3.4.3 Experimental Setups 2

The experimental condition is almost identical as the Experiment 1, but focused joints. The right elbow, pitch and roll rotation on the right shoulder and the right knee were used for $D = \{\boldsymbol{\theta}, \boldsymbol{\tau}\}$.

Conditions:

- The experiment involved two virtual humanoid robots HOAP-2 in a simulator environment called Webots.
- R_1 weighted 2.4[kg] as the self and R_2 weighted 4.8[kg] as the other were used.
- The masses were unknown to each others.
- Only symmetrical motions were used in the experiment, and considered joint angles are that of the right elbow, right shoulder's roll and pitch rotation and the right knee $\boldsymbol{\theta} = [\theta_1\theta_2\theta_3\theta_4]$.
- Considered joint torques were consisted of observed torques of the same joints $\boldsymbol{\tau} = [\tau_1\tau_2\tau_3\tau_4]$ respectively.
- The self prepared database $D_{R_1} = \{\boldsymbol{\tau}, \boldsymbol{\theta}\}$ with four basic motions(Figure 3.10) for building proto-symbol space P_{R_1}.

To verify the proposed method, four conversion rules $f_i(i = 1, .., 4)$ were prepared as the candidates of $F_{symbolize}$, for the F_{conv} that converts joint torques($\boldsymbol{\tau}$) to an intermediate scalar value g (Eq.(3.7)). 1. average torque over time period, 2. sum of maximum torque of each joints, 3. maximum torque of composition of all joints and 4. maximum among maximum torque of each joints.

1. Average of all the torque patterns

$$f_1(\boldsymbol{\tau}) = \frac{\sum_j^J \frac{\int \tau_j(t)dt}{T}}{J} \tag{3.13}$$

This strategy is thought to be taken when carrying a light weighted objects for a long time.

2. Sum of maximum values of each joint torques

$$f_2(\boldsymbol{\tau}) = \sum_j^J (\max_t\{\tau_j(t)\}) \tag{3.14}$$

This strategy is thought to be taken when carrying a heavy object.

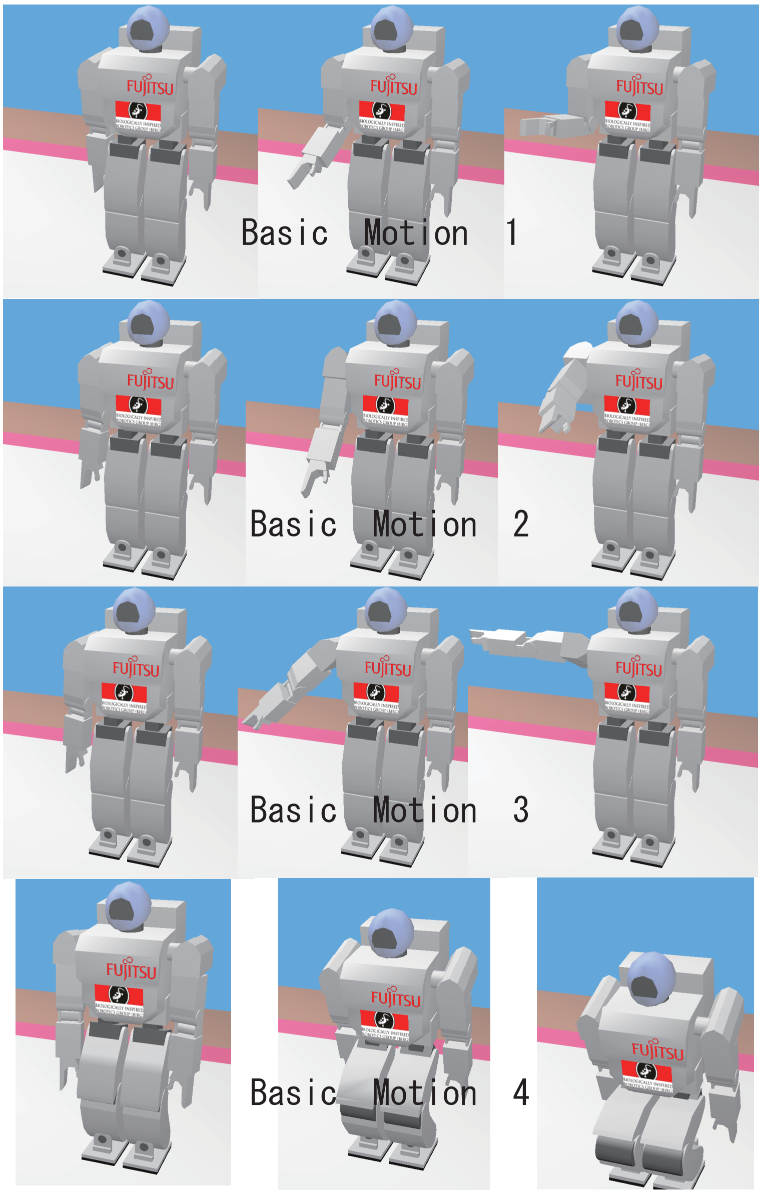

Figure 3.10: Basic shared motion patterns for building PSS

3. Maximum value of composed joint torque patterns.

$$f_3(\boldsymbol{\tau}) = \max_t\{\sum_j^J \tau_j(t)\} \tag{3.15}$$

This strategy is thought to be taken when carrying a heavy object.

4. Maximum value of maximum of each joint torques

$$f_4(\boldsymbol{\tau}) = \max_j\{\max_t\{\tau_j(t)\}\}, \tag{3.16}$$

This strategy is thought to be taken when carrying a heavy object.

where T was the time period of $\boldsymbol{\tau}$ and $J = 4$ in this paper.

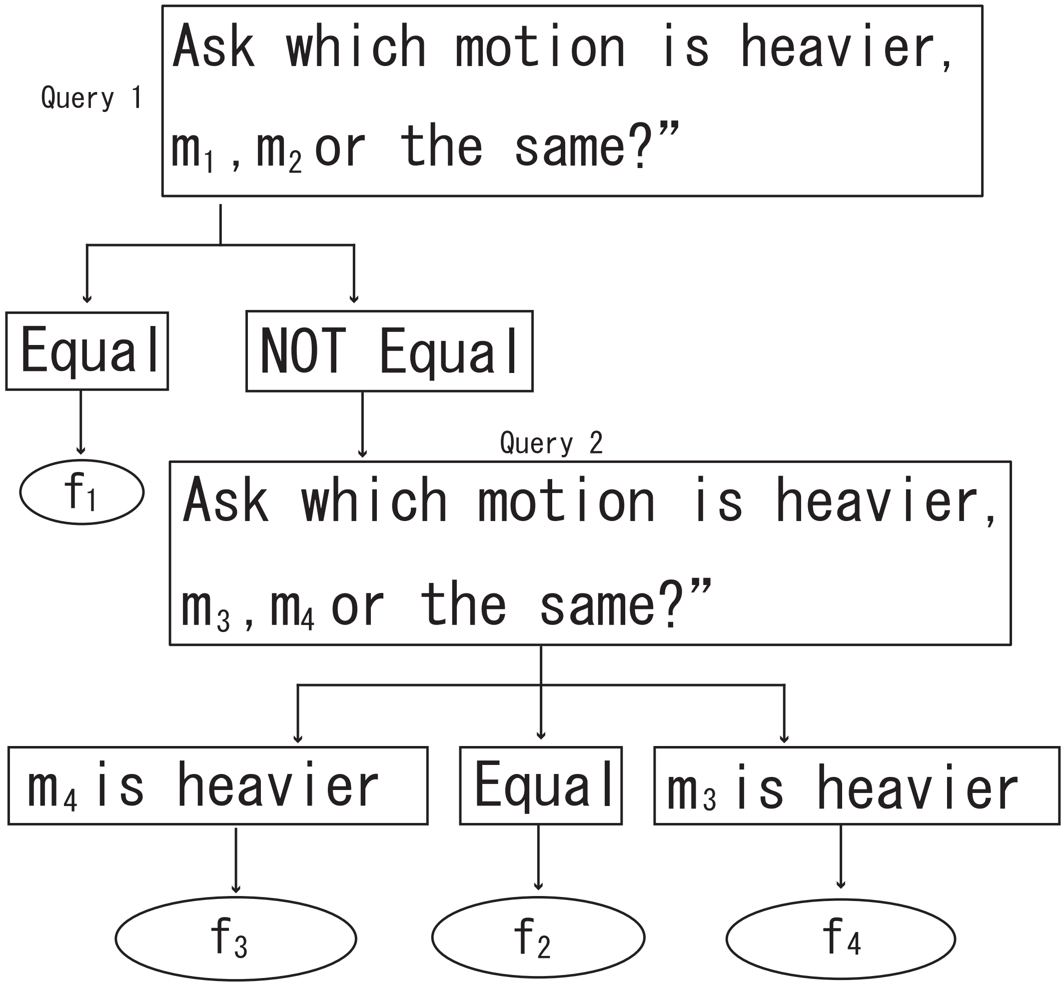

Figure 3.11: Flow diagram of the rule estimation

For the procedure, sets of motions, m_1 and m_2, and m_3 and m_4 are required to prepared in advance. The m_1 and m_2 are designed so that maximum torques are different but average torques over time period between 0 and T_1 are the same (Figure 3.12). The m_4(Figure 3.13) is a motion that the four joints bend and then stretch simultaneously, and the maximum torque are taken at the same time at the same value a. The m_3(Figure 3.13) is a motion that starts with a bending and stretching movement on the knee (a squat), followed by an up-and-down movement

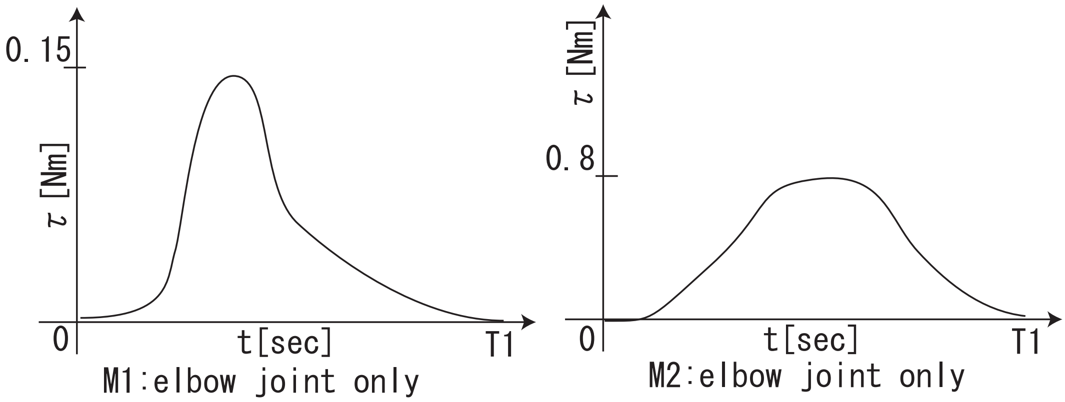

Figure 3.12: A set of motion 1 (m_1) and 2 (m_2) for use with the query 1, which is a comparative evaluation question. The m_1 and m_2 are designed so that maximum torques are different but average torques over time period between 0 and T_1 are the same.

of the pitch rotation on the shoulder, followed by an up-and-down movement of the roll rotation on the shoulder, and ended with a bending and stretching of the elbow joint. The m_3's maximum values of the joint torques are $(\tau_1^{max}, \tau_2^{max}, \tau_3^{max}, \tau_4^{max}) = (\alpha a, \beta a, \gamma a, \omega a)$. Constants $a, \alpha, \beta, \gamma, \omega$ are required to meet the following conditions for the identification of F_{conv}.

$$a < \alpha < 4a \tag{3.17}$$

$$4a = \alpha + \beta + \gamma + \omega \tag{3.18}$$

$$0 < \omega \leq \gamma \leq \beta \leq \alpha \tag{3.19}$$

In this paper,

$$\begin{aligned} (\alpha, \beta, \gamma, \omega) &= (3.0a, 0.4a, 0.4a, 0.2a) \\ a &= 0.5 \end{aligned} \tag{3.20}$$

was used.

With the condition Eq(3.20):

- if $F_{conv} = f_2$ then $f_2(\tau^{m_4}) = 4.0, f_2(\tau^{m_3}) = 4.0,$

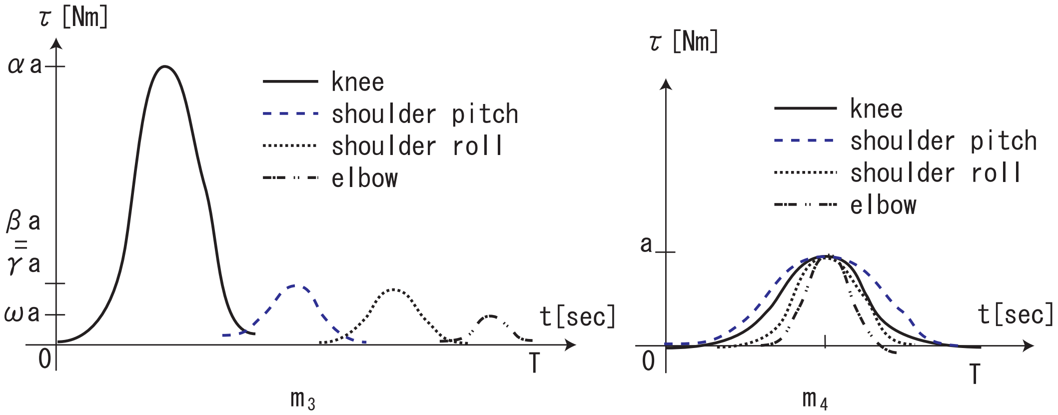

Figure 3.13: A set of motion 3 (m_3) and 4 (m_4) for use with the query 2, which is a comparative evaluation question. The m_4 is a motion that the four joints bend and then stretch simultaneously, and the maximum torque are taken at the same time at the same value a. The m_3 is a motion that starts with a bending and stretching movement on the knee (a squat), followed by an up-and-down movement of the pitch rotation on the shoulder, followed by an up-and-down movement of the roll rotation on the shoulder, and ended with a bending and stretching of the elbow joint.

- if $F_{conv} = f_3$ then $f_3(\tau^{m_4}) = 4.0, f_3(\tau^{m_3}) = 3.0,$
- if $F_{conv} = f_4$ then $f_4(\tau^{m_4}) = 1.0, f_4(\tau^{m_3}) = 3.0.$

Therefore, by the answer of the query 2, it is possible to make identification of the $\hat{F}^{R_2}_{conv}$.

The flow of the method using comparative evaluation questions and sets of shared motions is depicted in Figure 3.11 and described as below.

1. R_1 asks R_2 to imitate the motions m_1 and m_2, those meet requirements described in Figure 3.12
2. R_2 performs the m_1 and m_2, and observes corresponding $\boldsymbol{\tau}^{m_1}_{R_2}$, $\boldsymbol{\tau}^{m_2}_{R_2}$.
3. R_2 converts both $\boldsymbol{\tau}^{m_1}_{R_2}$ and $\boldsymbol{\tau}^{m_2}_{R_2}$ into $g^{m_1}_{R_2}$ and $g^{m_2}_{R_2}$ using the chosen conversion rule f^{R_2}.
4. R_2 replies with symbol K_{R_2} that explains which motion is heavier or the same.
5. if K_{R_2} ='equal' then R_1 identify as $\hat{f}^{R_2} = f_1$, otherwise ask next question.

6. Execute the same procedure as 1-4, but replacing m_1, m_2 with m_3, m_4 (Figure 3.13) respectively.

7. R_1 identify as $\hat{f}^{R_2} = f_2$ if K_{R_2} ='equal', $\hat{f}^{R_2} = f_3$ if K_{R_2} ='<', $\hat{f}^{R_2} = f_4$ if K_{R_2} ='>'.

It is assumed that the R_2 made perfect imitation of m_i performed by R_1, also assumed that the same conversion rule F_{conv} was applied to all the joints regardless of motion patterns.

3.4.4 Experimental Result 2

In the simulation, both R_1 and R_2 have identical body structures with proportional relation on the masses. This results in 100% successful identification of the conversion rule F_{conv} when the R_2 imitated the motions of R_1 perfectly. It is because that when motions are relatively simple, it can be assumed that R_2's torque patterns $\boldsymbol{\tau}_{R_2}$ and R_1's $\boldsymbol{\tau}_{R_1}$ are in proportional relationship.

To show the importance of identification of the F_{conv}, R_2's joint torques were estimated both with a successful identification of the F_{conv} and with an incorrect identification. 10 kinds of unknown motions $\boldsymbol{M'}_i (i = 1, ..., 10)$, which were different from the four basic motions shown in Figure 3.10, were introduced for the evaluation. These unknown motions consisted of arbitrary movement of the 4 joints. An error e between estimated torque $\hat{g}$ and the real g were defined as follows, using both known and unknown motions.

$$e = \frac{1}{N} \sum_{i}^{N} \frac{|\hat{g}_i - g_i|}{g_i} \tag{3.21}$$

N was the number of motion patterns used for the evaluation and in this paper it is $N = 10$. The results are shown on Figure 3.14 and Figure 3.15. The x-axis is number of conversation sets, and the y-axis is the error e (Eq.(3.21)).

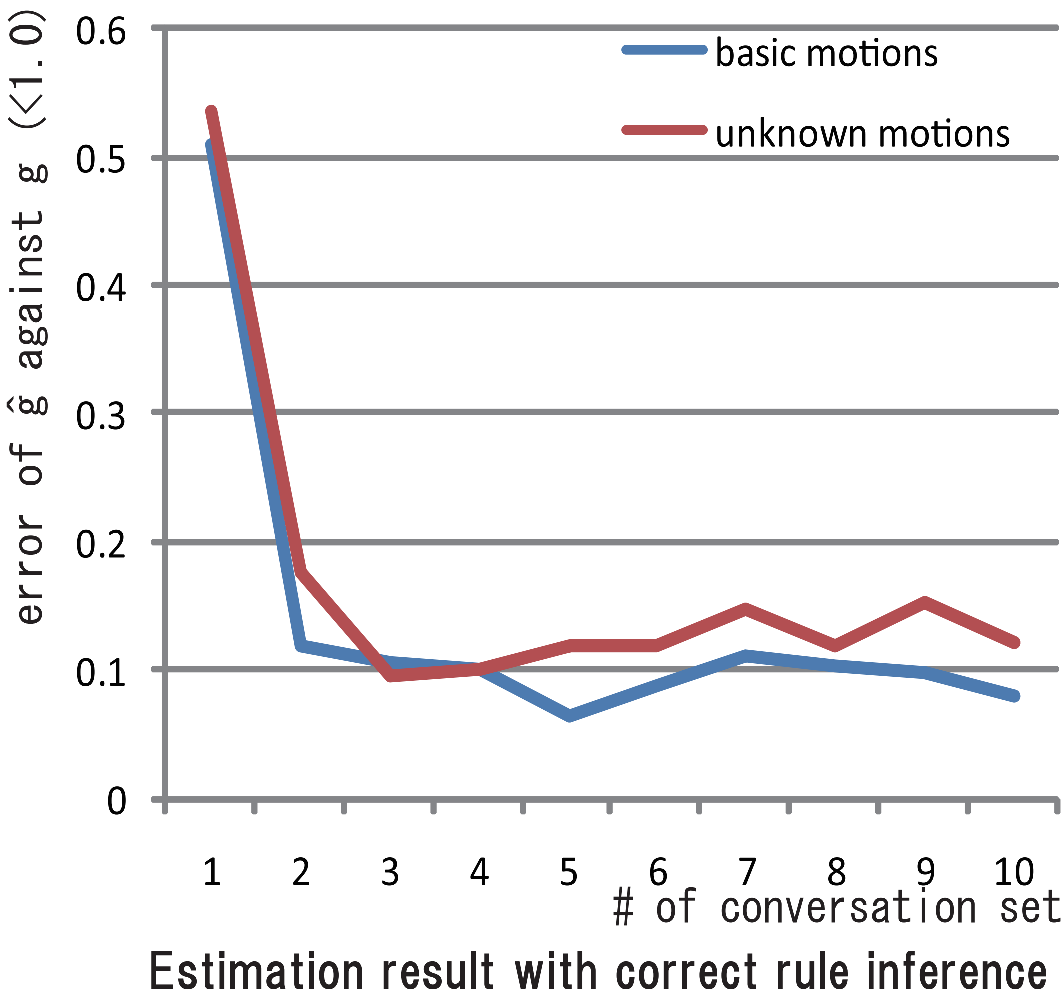

Figure 3.14: result of torque estimation with successful rule inference when $d = 5$ and $F_{conv} = f_4$

Figure 3.15 shows that errors are $45 - 60\%$ for torque estimation when the identification of the $\hat{F}_{conv}$ failed. On the other hand, after a few set of conversation, Figure 3.14 shows that estimation of the other's torque can be achieved with approximately 10% error even if the motions are unknown.

The *comparative evaluation questions* with set of shared motions can estimate 3^N kinds of symbolization strategies by making qeuries with motions N times. This efficiency is important when the human robot interaction is considered, that is, the human can use the system without complex and large amount of preparation.

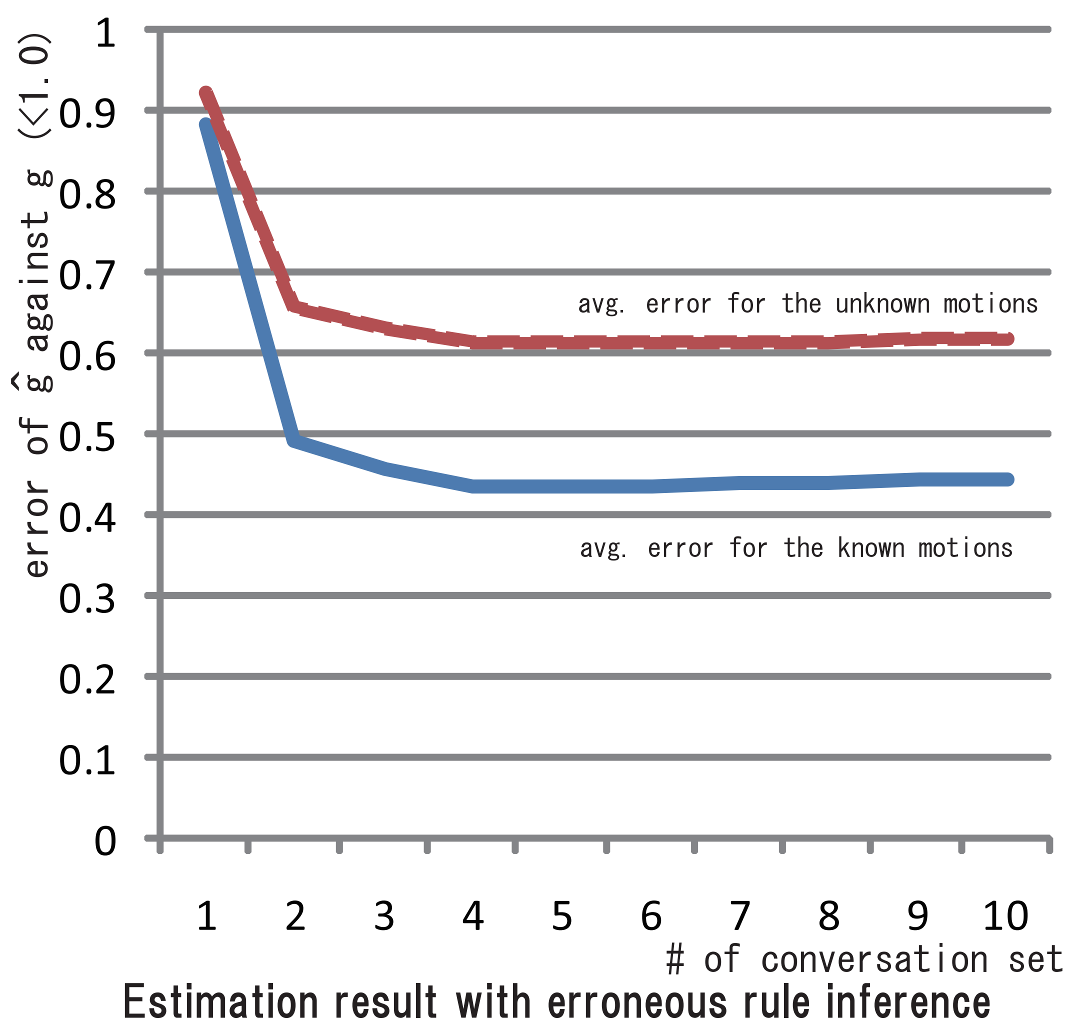

Figure 3.15: result of torque estimation with erroneous rule inference when $d = 7$, $\hat{F}_{conv} = f_0$ and $F_{conv} = f_2$

3.5 Conclusion of the Chapter

In summary, I have realized interaction and communication to estimate sensorimotor patterns of others by observing motion patterns without having user-specific model in advance. However, the proposed method is tested with simple motions, and investigation with complex motions is needed. Quantitative study for cases, when number of DoF and configuration of joints location is different, is required.

We proposed two methods based on the concept to estimate unobservable information of the other when physical conditions are different. Two kinds of communication methods were proposed to realize the concept, which is to bridge sensorimotor experience of self and other. In the first half, we proposed a method based on the concept to estimate unobservable information of the other when physical conditions are different. The concept is to bridge sensorimotor experience of self and others. To realize this concept, a method was proposed that is to estimate others' PSS from the self's adaptively by shared motions and open questions. Experimental result shows that a few conversation sets resulting in successful estimation of R_2's torque g with 20% error was confirmed, even when R_2 performed unknown motion patterns, and with 10% error with known motions.

In the second half of this chapter, we proposed a communication method, *comparative evaluation questions with sets of shared motions*. This made it possible to estimate 3^N kinds of symbolization strategies, how to convert torque patterns to symbol-indexes, by making queries with motions N times. The method consists of making queries with motions about unobservable sensory information, based on estimated others' experience $\hat{P}_{other}$ that is acquired from the self's sensorimotor experience P_{self} adaptively. We think that the method is a fundamental interaction method for estimating other's unobservable inner information, such as sensory information.

This method is also thought to be useful to deal with the *correspondence problem* [2][43][98]. The *correspondence problem* is generally considered as a problem that deal with correspondence relationship between directly observable body parts of the self and the other. However, using the proposed method, it is possible not only to deal with a new problem how to map between the self's sensory information and the other's unobservable sensory information.

In addition, with *comparative evaluation questions with set of shared motions*, it is possible to estimate continuous sensory pattern even when that cannot be expressed by symbol representations. The comparative evaluation of sensory information is an objective measure and the result is precise, even when an estimation target sensor is other's unobservable one. Taking advantage of these properties, the proposed method in this chapter can be applied, for instance, to estimate F_{div} defined at Table3.1 and weight coefficient for each joints in Eq(3.13)-Eq(3.16).

The results of the section 3.3 was presented in [57] and [109]. The results of the section 3.4 was presented in [110].

Chapter 4

A Binding Method of Motion Patterns and Verbal Expression for Conveying Subtle Difference in Motions

4.1 Abstract of the Chapter

Whole-body gestures and verbal expressions should be bound according to given tasks and the current situation in intelligent human-robot interaction systems. Modification of expressions, such as emphasis of motions and change in verbal expressions, plays an important roll for successfully completing tasks according to user reaction. For example, it is difficult to convey slight differences between learning target motion demonstrated by a coach and a motion performed by a learner. The slight differences in motions can be conveyed by binding an emphasized motions and an verbal expression. In robotics, however, even though the synthesis of gestures and speech has been discussed, how to bind synthesized emphatic motions and verbal expressions from an engineering point of view has not been adequately discussed. Synthesis of motion and speech requires recognition of user reaction, we therefore should integrate 1) recognizing reaction, 2) planning to complete tasks, 3) modification of motions and speech, and 4) maintaining a bi-directional interaction loop consisting of processes 1)–3). We think a common problem not being considered in existing works is that the four required elements were separated. Thus, in order to convey slight difference in motions, we propose a method for binding emphatic motions and adverbial expressions, and for evaluating and controlling these four required processes by using a sole scalar parameter in a phase space. In the phase space, variety of motion patterns and verbal expressions can be expressed as static points. To evaluate the feasibility of the proposed method, we demonstrated motion coaching system using the method. We show the feasibility and effectiveness of robotic motion coaching systems through experiments of actual sport coaching tasks for beginners. From the results of participants' improvements in motion learning, we discuss about factors affecting such motion coaching systems that realizes binding and controlling emphatic motions and adverbial expressions using a sole scalar parameter in a phase space.

4.2 Introduction

To develop effective and intelligent human-robot interaction systems that use whole body gestures and verbal expressions, verbal expression and gesture expression should be strongly connected according to given tasks and current situation. Additionally not only fixed expressions but also modification of the expressions such as emphasis of motions and changing speech words is also an important function to achieve tasks smoothly according to reaction from users. Analysis of the connection between gestures and speech are often discussed in the field of psychology; however synthesis and emphasis of gestures and speech from engineering point of view has not been discussed well. Since synthesis of motion and speech also requires recognition of current situation such as reaction of users, we therefore should integrate 1) recognition of reaction, 2) planning to achieve tasks, 3) synthesis and emphasis of motions and speech, and 4) keeping interaction loop consists of 1)–3).

In this chapter, we propose a robotic system that coaches human beings motions to discuss the above issues in order to convey slight difference in motions. The robotic coaching system should include all of the four elements.

1. recognition of reaction: The robot should evaluate humans' performance and analyze similarities and differences between the humans' performance and coaching target motion.

2. planning to achieve tasks: The robot should let the human subject to make better performance based on feedback consists of motion and speech expressions.

3. synthesis and emphasis of both motion and speech: The robot should modify and emphasize motion demonstrations and speech expressions based on the result of 1.'s analysis.

4. The robot repeats above three processes in order to have continuous loop of interaction for improvement of the performance.

On the other hand, in general, there are three steps to learn motions.

1. Learn motion by imitation and repetition.

2. Learn how much and when to apply forces. For example, maximum force should be applied at the time of impact when one hit a ball in tennis.

3. Learn how to adjust trajectory and timing of a swing according to trajectory and speed of the ball about to hit.

In this thesis, we focus on the step 1, and discuss how to bind motion and verbal expression for effective coaching.

With regard to researches on binding of motion patterns and verbal expressions in imitation learning frameworks, there are researches of systematic binding taking advantage of interaction, such as [60][148][149][95][150]. These work bind different but similar motions and modalities to a symbol. However, for motion coaching it is needed to bind similar but different motions and modalities to different verbal expressions to convey slight difference.

When we look at researches of robotic system that coaches human beings motions, there is a robot instructor for stroke patients [30][31][168][29]. It has realized establishing a loop of interaction controlled by the robot, with combining motion patterns and verbal expressions. However it does not consider synthesizing emphatic motions based on feedback of player's imitation performances, and the evaluation is from emotional aspect of users. We believe it is important to provide feedback not only with verbal expressions, but also with emphatic motions, and having a quantitative evaluation of learning motions.

On the other hand, there are many researches related to synthesis of motions, in the computer graphics area [17][125][41][49]. However, how to synthesize motions are subjectively decided by designers and how to bind motions and verbal expressions is not considered.

Lee proposed a method to have slight changes in motions after a robotic system learns from imitation learning [81] [79]. In this method, an appropriate impedance controller is integrated for kinesthetic teaching. However, it does not discussed how to integrate the slight modification in motions and verbal expressions.

We think a common problem not being considered in above related works is that the four required elements were separated. Since each element is complex, we propose a simple framework to integrate those elements that uses sole parameter to connect all of the processes. In motion coaching tasks, considerable factors can be evaluated by a scalar parameter such as similarity of performed motion between target motion, degree of emphasis of motion, variety of verbal expression using adverb for feedback. Furthermore we show feasibility and effectiveness of robotics motion coaching systems based on the proposed method through experiments of real sports training tasks for beginners.

In the section 4.3, method to evaluation and control of motion patterns using sole scalar parameter is explained. In the section 4.4, framework of robotic motion coaching system is explained. In the section 4.5, we show experiment results. Finally we discuss the results and conclude effective factors on motion coaching system.

4.3 Methods

In this section, proposing method, with one parameter α, how to control both synthesis of emphatic motions and choice of adverbially expressions and how to bind them will be explained.

The proposing coaching system, which uses the proposing method, is a coaching system that attempts to have proto-symbol of learners' performance be close to a proto-symbol of a learning target motion as repeat the coaching interaction. The purpose of the coaching system is not that it attempts to move proto-symbol of learners' performance to several other proto-symbols in the phase space (PSS) during a coaching task.

4.3.1 A Method to Synthesize Emphatic Motions

For synthesis of output probability $b_i(\boldsymbol{O})$, we employ a single Gaussian model for the output such that an intuitive synthesis of joint angle vectors can be achieved just by using the mean and variance vectors of a Gaussian distribution. With the the mean and variance vectors and using Monte Carlo method, the motion pattern is generated [58]. F_{gen}; a function to generate sensorimotor patterns from a $\boldsymbol{x}$, same as Eq.(2.7),

$$\boldsymbol{O} = F_{gen}(x), \tag{4.1}$$

For synthesis motion patterns, instead of directly interpolate/extrapolate of both a_{ij} and $b_i(\boldsymbol{O})$: (1) The state transition probabilities and the output probabilities are separately operated upon. (2) The state transition matrices are calculated in a different domain, i.e., the time domain. (For the detail please refer to [58]) For the simplicity, in this thesis, a function to synthesis an internal/external dividing point $\boldsymbol{x}_s$, which corresponds to interpolated/extrapolated novel motion pattern, from static points x_i, x_j is represented as F_{syn};

$$\boldsymbol{x}_s = F_{syn}(\beta x_i + \gamma x_j), \tag{4.2}$$

where β, γ are weight coefficients. To generate motion, use the $\boldsymbol{O}_s = F_{gen}(\boldsymbol{x}_s)$ (Eq.4.2).

4.3.2 A Method to Chose Adverbial Expressions

In this chapter, an adverbially expression, "more like this" was introduced. As a first step, only one kind of adverbial expression was used with the synthesized emphatic motions in experiments in this chapter. With this simple approach of the adverbial expression usage, in this chapter, we are interested in discussing whether the emphatic motion and the adverbial expression contributes to the improvement in motion learning.

4.3.3 A Method to Control Emphatic Motions and Adverbial Expressions with one Scalar Parameter in a Phase Space

We defined α as below, applying 4.2,

$$\boldsymbol{x}_s = \boldsymbol{x}_t + \alpha(\boldsymbol{x}_t - \boldsymbol{x}_p) \tag{4.3}$$

where α is a weight coefficient for extrapolation, $\boldsymbol{x}_t$ and $\boldsymbol{x}_p$ are static points in PSS corresponding to motion $\boldsymbol{O}_t$ and $\boldsymbol{P}_p$ respectively.

As it is depicted in Figure 4.1, this weight coefficient α corresponds to the degree of emphasis of the synthesis motion. In addition, for example, we assign adverbially expression such as "a little more", "more", and "much more" according to the value of the α as in Table 4.1. In this way, with one parameter α, it is possible to control both degree of emphasis of synthesized motion and choice of adverbially expression.

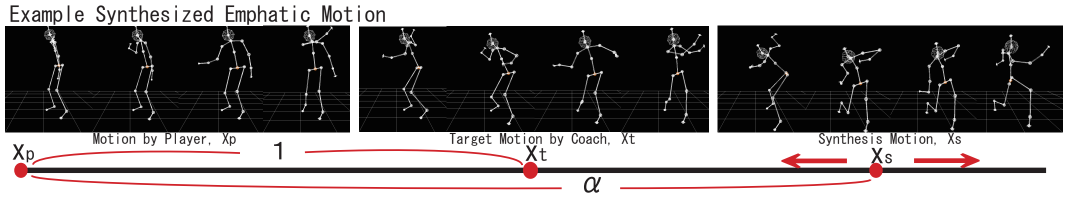

Figure 4.1: Example relationship between the weight α, adverbially expression and synthesis motion

Table 4.1: Example assignment of adverbially expressions according to α

α	1.5	2.0	2.5
adverbially expression	a little more	more	much more

4.4 Framework of a Motion Coaching System

4.4.1 Flow of a Motion Coaching System

A scene of the motion coaching is depicted in Figure 4.2.

At first, the database $D = \{\boldsymbol{\theta}_t, \boldsymbol{\theta}_p\}$ that is consisted of one imitation target motion pattern $\boldsymbol{\theta}_t$ as well as one motion pattern performed by the player $\boldsymbol{\theta}_p$. Then, Proto-symbol Space P is built with the D using F_{build} process (Eq.(2.5)). Now, let us define the static point $\boldsymbol{x}_t$ in the P, as the static point corresponds to the imitation target motion $\boldsymbol{\theta}_t$.

As depicted in Figure 4.3, the motion coaching task will be executed as follow.

1. The coach (an agent in a virtual environment in this thesis) demonstrates motion pattern $\boldsymbol{\theta}_c$ as the imitation target motion $\boldsymbol{\theta}_t$.

2. The human player imitates $\boldsymbol{\theta}_c$.

3. The coach observes the player's imitated motion pattern $\boldsymbol{\theta}_p$ and converts it to a static point $\boldsymbol{x}_p$ in the P, using recognize function F_{recog}(Eq.(2.6)).

4. If the $\boldsymbol{x}_p$ is not close to $\boldsymbol{x}_t$, then it is interpreted that the player's imitated motion is imperfect. The coach calculate the missing elements in the imperfect imitation of the player by $\boldsymbol{x}_t - \boldsymbol{x}_p$.

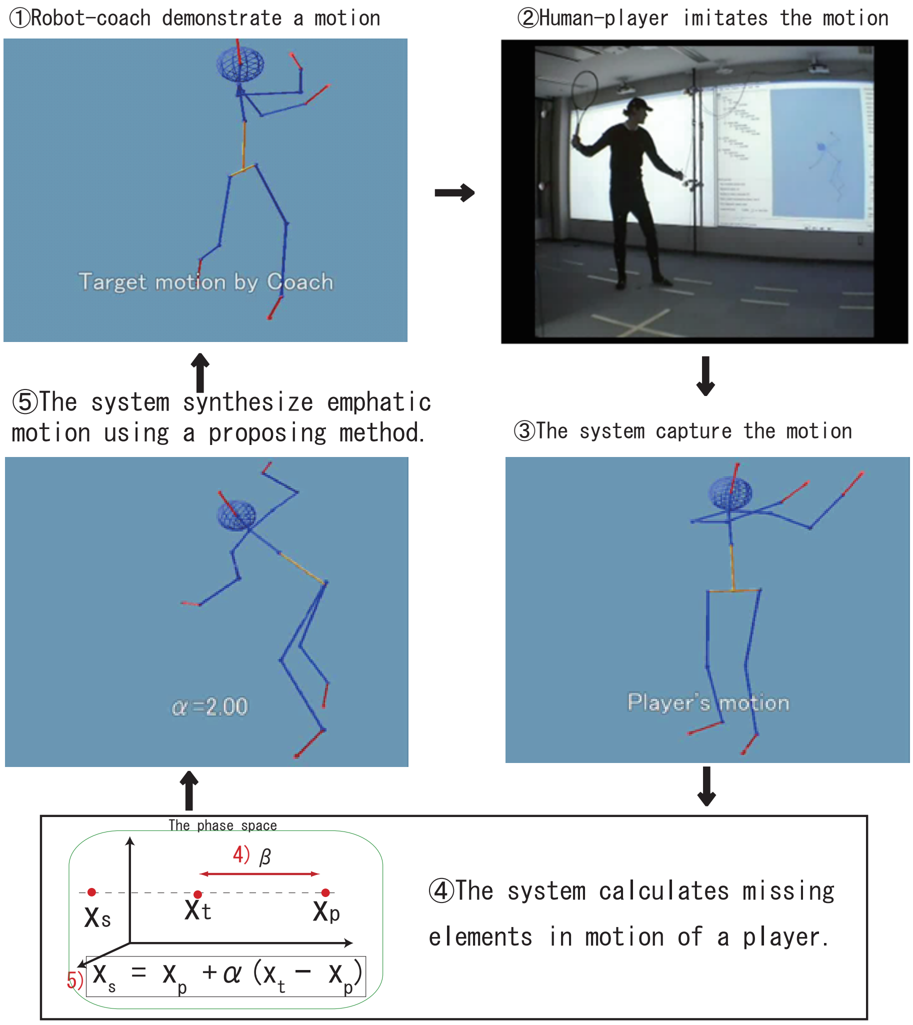

Figure 4.2: A scene of the experiment: The system repeats a loop 1-5 as needed. 1) the robot-coach demonstrates learning target motion. 2) a human player imitates. 3) the coach observes the player's motion. 4) the coach calculates the missing elements in the player's motion by comparison to the learning target motion. 5) the coach synthesize a emphatic motion.

5. The coach calculate the external dividing point $\boldsymbol{x}_s$ by adding the missing elements$(\boldsymbol{x}_t - \boldsymbol{x}_p)$ to the target motion$(\boldsymbol{x}_t)$, using Eq.(4.3).

6. $\boldsymbol{\theta}_c$ is generated from the $\boldsymbol{x}_c$, using the generation function F_{gen}(Eq.(4.1)). Use the point $\boldsymbol{x}_s$ as the $\boldsymbol{x}_c$, which corresponds to the re-demonstration motion pattern $\boldsymbol{\theta}_c$ for the next trial.

Repeat a loop 1-6 as needed. 1 loop is considered as 1 trial in the experiment.

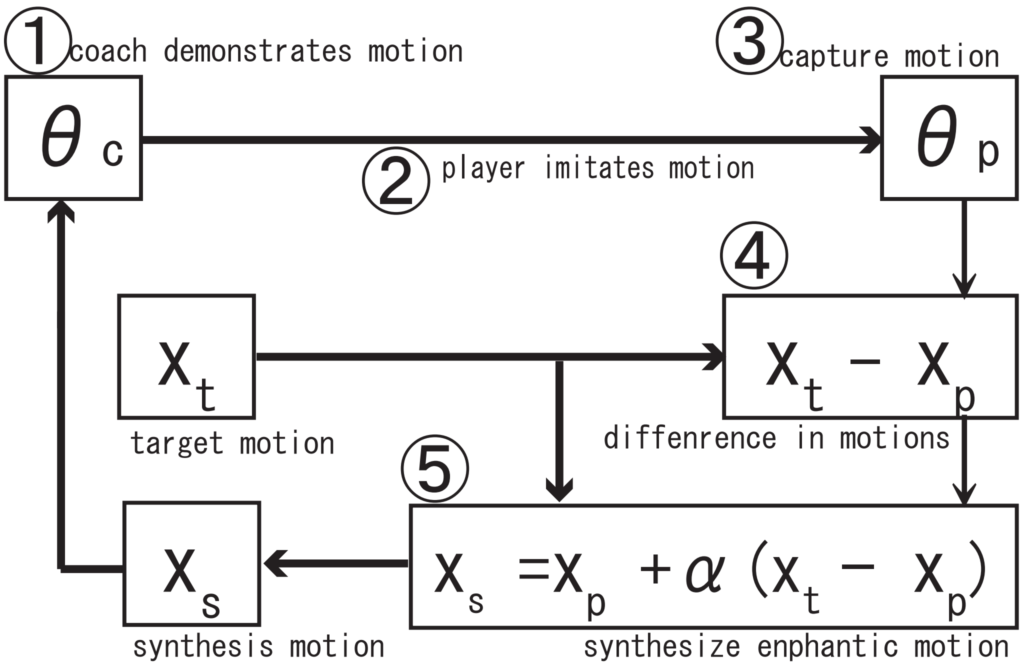

Figure 4.3: Flow of the motion coaching

4.4.2 An Example Result

An example outcome of this method are depicted in Figure 4.4, Figure 4.5 and Figure 4.6. Figure 4.4 shows the imitation target motion $\boldsymbol{\theta}_t$ demonstrated by the coach $\boldsymbol{\theta}_c$. The objective of the player is to imitate this motion as close to the target motion as possible. Figure 4.5 shows the observed motion pattern imitated by the player $\boldsymbol{\theta}_p$. As it can be seen the imitation is not perfect. For example, the left hand is not as same as in the $\boldsymbol{\theta}_c$. Figure 4.6 shows a emphatic motion synthesized by the proposing method. Not only the left hand has been considered as a missing elements, and emphasized. The degree of bending right knee and the degree of bending upper body forward are also taken into consideration for emphatic motion, synthesized by the system according to the proposing method. As a result this seems to be perfectly reasonable.

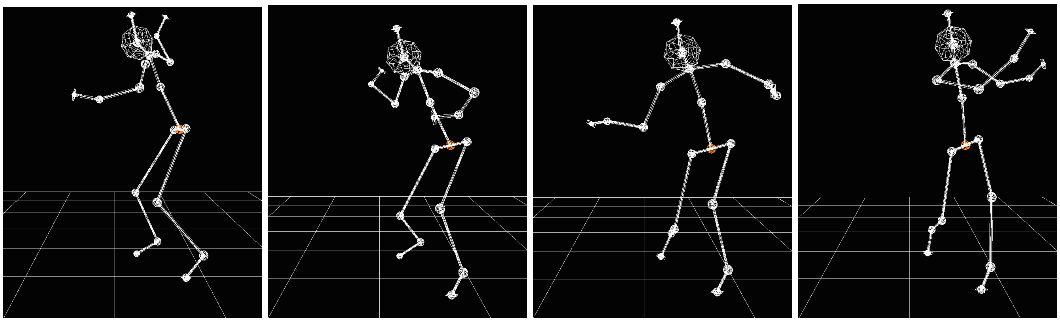

Figure 4.4: An ideal motion pattern as the coaching target (pattern: θ_t, proto-symbol: $\boldsymbol{x}_t$)

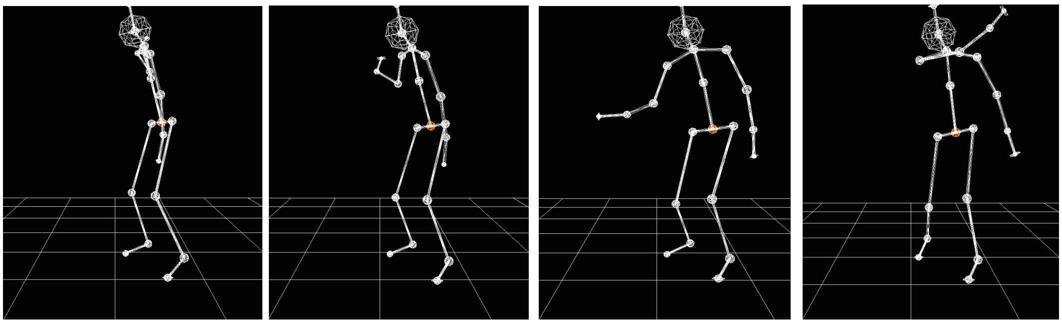

Figure 4.5: A motion pattern imitated by a beginner player (pattern: θ_p, proto-symbol: $\boldsymbol{x}_p$)

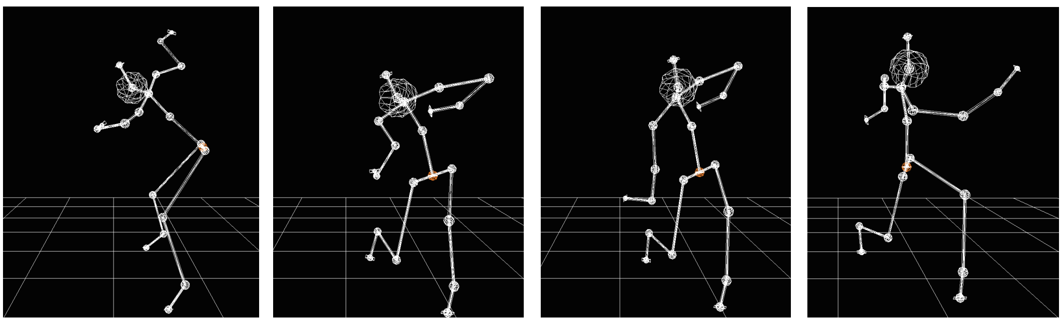

Figure 4.6: An emphatic motion pattern generated with weight $\alpha = 2$ in Eq.(4.3) (pattern: θ_s, proto-symbol: $\boldsymbol{x}_s$)

4.5 Experiments

We conducted series of experiments, in which a forehand tennis swing was coached to males by the robotic system. All of the subjects were beginners of the tennis, or never played before. A scene of the motion coaching is depicted in Figure 4.2, which follows the procedure explained in the section 4.4.1 and depicted in Figure 4.3. The proposed method and the flow of the coaching system explained in the previous section was used with conditions below.

4.5.1 Common Conditions

- The coaching agent demonstrates motion pattern $\boldsymbol{\theta}_t$, shown as Figure 4.4, as the imitation target motion and it was displayed on a large screen.
- The given instruction was "please imitate this", right before each motion demonstration.
- The view point of the imitation target motion was fixed and it was always from the front.
- $\boldsymbol{\theta}$ were consists of 17 joints, each has DoF of 3.
- The number of elements in the database D, which were used for building proto-symbol space P is 2. In other words, only the imitation target motion $\boldsymbol{\theta}_t$ and subject's imitated motion $\boldsymbol{\theta}_p$ were used. $D = \{\boldsymbol{\theta}_t, \boldsymbol{\theta}_p\}$.
- 5 swings were used to abstract each player's swing to HMM at each trials. Motion data were segmented into meaningful portions by the author subjectively, while there are method proposed for autonomous segmentation [74] [75].
- Each trials were executed with 5 minutes intervals.

4.5.2 Experimental Setup 1

In the experiment 1, we tested with a subject to learn how different α would affect to the motion learning performances. The emphatic motions with different $\alpha = \{1.25, 1.50, 1.75, 2.00, 2.25, 2.50\}$ were synthesized and shown to the subject.

4.5.3 Experimental Result 1

To evaluate the result, the distance d_{il} was introduced.

$$d_{il} = |x_t - x_p| \tag{4.4}$$

where i is an ID number of a subject, and we had only one subject ($i = 1$) in this experiment 1. where l is the trial number, and $l = 1$ was used for this experiment. The Eq.(4.4) means that the smaller the d_{il} is, the better the imitation is. When $d_{il} = 0$, the imitation is perfectly identical. Thus, d_{il} corresponds to an imitation error of subject ID i at trial l.

As it is shown in Figure 4.7, it is reasonable to decide that $\alpha = 2.0$ would provide the best result for motion learning.Thus, in the following experiment 2, $\alpha = 2.0$ was used.

4.5.4 Experimental Setup 2

In the experiment 2, four different cases were tested to evaluate the proposing method. Conditions are:

- The number of subjects were 13.
- The order of conducting each experimental cases were randomly shuffled for each subjects.
- The adverbially expression, "more like this" was introduced.

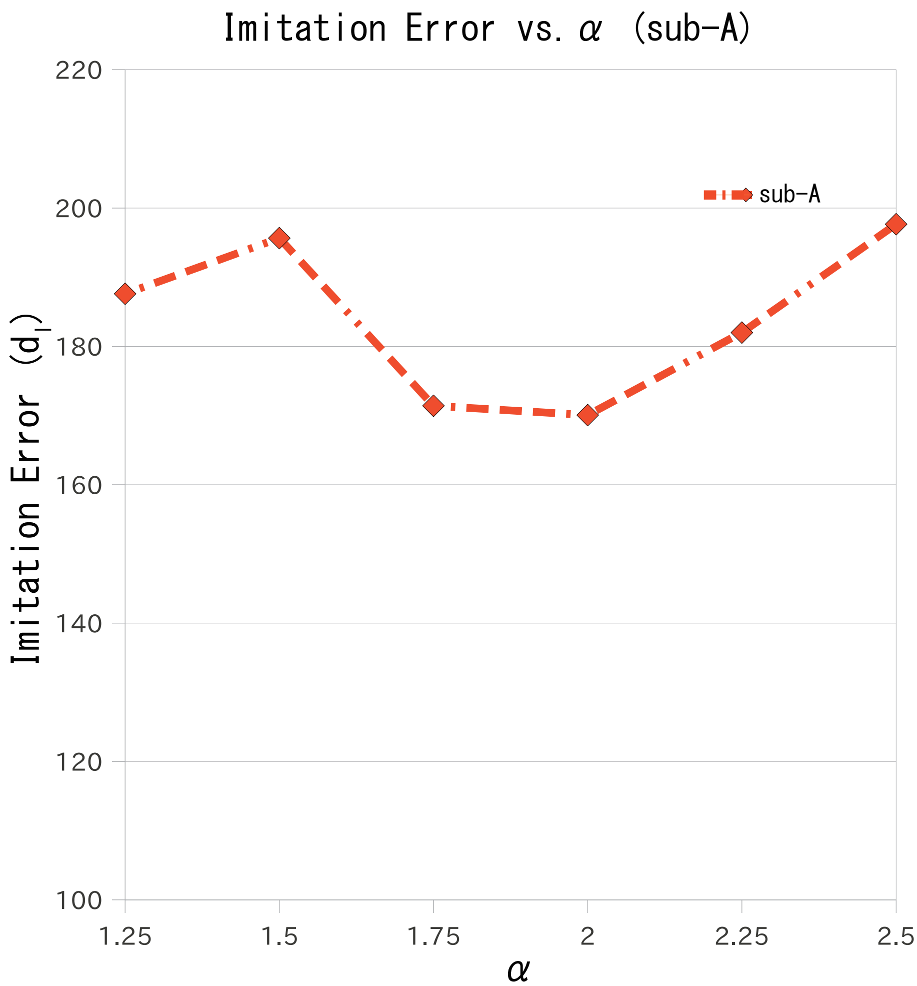

Figure 4.7: Result of experiment 1: Imitation error against different values of αs. $\bar{d}_l$ in Eq.(4.4)

- Four kinds of experimental cases were introduced to evaluate how the emphatic motion and the adverbially expression contributed.

  1. Case 1:

     The coaching agent repeated demonstrating imitation target motion $\boldsymbol{\theta}_t$ only, In other words, coached using motions with $\alpha = 0.0$ and no adverbially expression was used.

  2. Case 2:

     Coached using motions with $\alpha = 0.0$ and adverbially expression "more like this".

3. Case 3:

   The coaching agent re-demonstrated with emphatic motion patterns $\boldsymbol{\theta}_s$ synthesized by the proposed method. In other words, coached using motions with $\alpha = 2.0$ and no adverbially expression.

4. Case 4:

   Coached using motions with $\alpha = 2.0$ and adverbially expression "more like this".

The cases are also summarized in Table 4.2.

Table 4.2: Cases in Experiment 2

-	$\alpha = 0.0$	$\alpha = 2.0$
without "more like this"	Case 1	Case 3
with "more like this"	Case 2	Case 4

4.5.5 Experimental Result 2

To evaluate the results, the following measure was introduced. Average ratio of error in imitation at trial l is:

$$\bar{R}_l = \frac{\sum_{i=1}^{m} \frac{d_{il}}{d_{i1}}}{m} \tag{4.5}$$

If the imitation error is smaller compared to the initial trial in the same case, the $\bar{R}_l$ will be less than 1.0. If the imitation error is larger compared to the initial trial in the same case, the $\bar{R}_l$ will be more than 1.0. When imitation is perfect, the imitation error is zero, $\bar{R}_l = 0.0$.

From Figure 4.8 and Table 4.3 executing Tukey-Kramer Method and ANOVA for $p < .05$ with $\bar{R}_l$ at 4th trail in Eq.(4.5) for Exp.2, it would be able to say that emphatic motions contributed somehow to improve the motion learning of the players. However, we would not able to say if the adverbially expression contributed or not. It is because that between there is significant difference found between the Case 1 and 3, and Case 1 and 4 only.

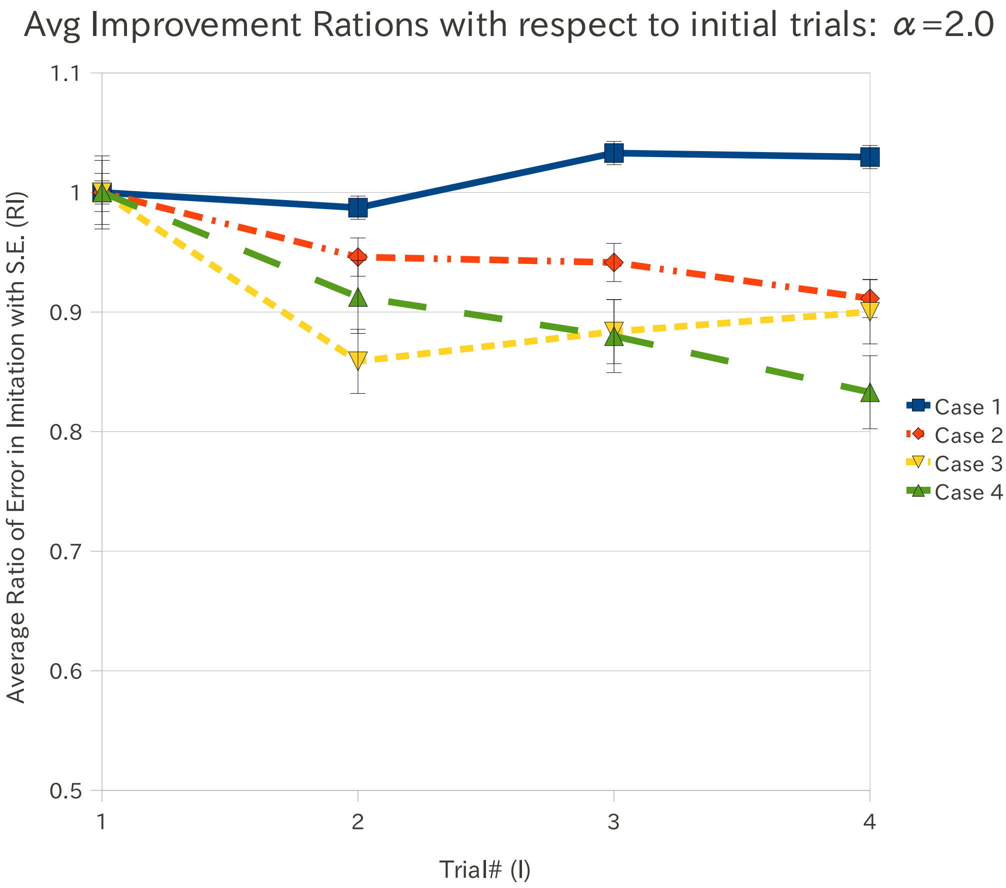

Figure 4.8: Result of experiment 2: Average ratio of imitation error: $\bar{R}_l$ in Eq.(4.5)

4.6 Conclution of the Chapter

In summary, I have realized interaction and communication to convey slight differences in motions by dynamically combining emphatic motions and symbolic expressions. I also designed an interaction in which approach to utilize humans' ability was taken, instead of an approach to have automated machine being friendly to humans. However, from HAI and communication point of view, what I have not realized was interaction and communication using power of symbol communication that enable interaction even when communication protocol is unknown and when meaning/intention of motion is unknown. In this research, the communication method adopted was fixed

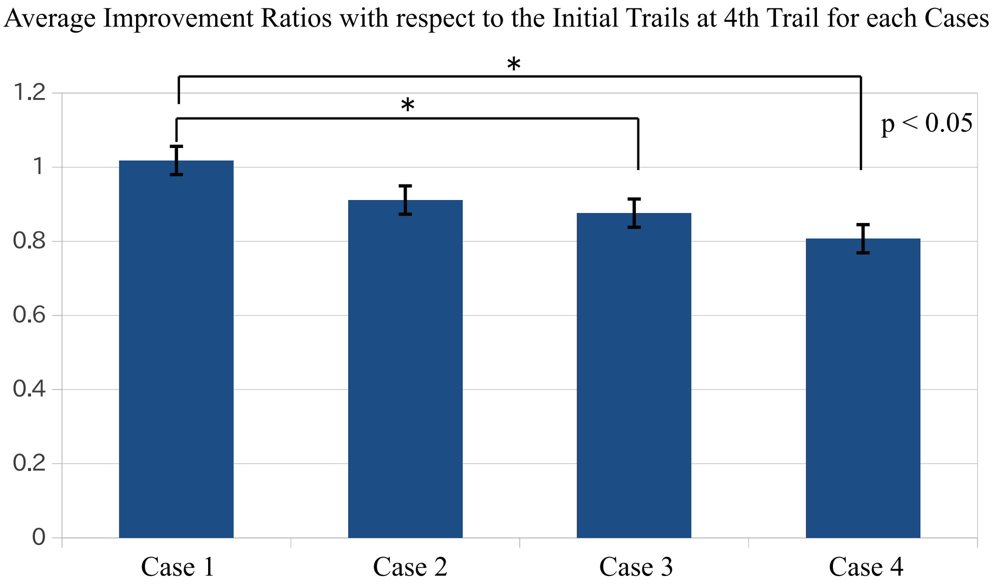

Figure 4.9: Result of experiment 2: Average improvement ratios with respect to the initial trails at 4th trail for each Cases. The average ratio of imitation error: $\bar{R}_l$ in Eq.(4.5)

and users were asked to chose symbolic expressions from limited set of choice prepared in advanced. The communication used by users were limited to motion only, while the robotic system communicated using motion display and symbolic expressions. The expressions used in the motion coaching was primitive and limited, and it was not able to generate sentences for coaching.

For effective and intelligent human-robot interaction systems that use whole body

Table 4.3: Tukey-Kramer Method for $p < .05$ with $\bar{R}_l$ at 4th trail in Eq.(4.5) for Exp.2. The numbers in the upper right are the Tukey-Kramer minimum significant differences (MSDs). The numbers in the lower left are the observed absolute value of the difference in means between each pair of groups, with an asterisk if it is greater than the Tukey-Kramer MSD.

-	Case 1	Case 2	Case 3	Case 4
Case 1	-	0.1194	0.1139	0.1139
Case 2	0.1068	-	0.1194	0.1194
Case 3	0.1421*	0.0353	-	0.1139
Case 4	0.2112*	0.1045	0.0692	-

gestures and verbal expressions, verbal expression and gesture expression should be strongly connected according to given tasks and current situation. To convey slight difference between learning target motion demonstrated by a coach and motion performed by a learner, we took an approach using the emphatic motions and adverbial expressions. The adverbial expression used is a representation of a discrete value that is meaningful and can be shared by both humans and robots. We believe that having meaningful and sharable parameter expressions is a key for the Human-Robot interaction.

In order to convey the slight differences in motions, we proposed a method to bind and and control degree of emphasis of motion and adverbial expressions, with using a solo scalar parameter in a Proto-symbol space, and to evaluate errors of performed motions compared to the learning target motion. We demonstrated the feasibility of robotics motion coaching systems through experiments of real sports training tasks for beginners. With results of players' improvement in motion learning, we validated that the proposed method benefited for robotic system to have effective interaction with human beings using whole body gestures and verbal expressions, for conveying slight differences in motions.

The purpose of the coaching system is not that it attempts to move proto-symbol of learners' performance to several other proto-symbols in the phase space (PSS) during a coaching task. This kind of approach can be applied when several learning target motions are prepared as sub-goals. For example, the future coaching system could first analyze learners' swing motions and detect degree of errors in which body part has the most, the second most and so on, compared to a learning target motion. Then, the future coaching system could set several sub-goals, that is several proto-symbols in the PSS, and attempt to coach so that proto-symbol of learners' performance moves to proto-symbols in certain order and finally get close to a learning target motion.

We neither corrected errors nor praising explicitly in the experiment using the proposed method, even though we implicitly corrected errors by demonstrating the emphatic motions and adverbial expressions. Thus, the improvement in learning motions was not effected by "Differential Reinforcement", being reported the differential reinforcement increased performance two to four times over baseline.[18]. (Differential reinforcement of other behaviors means that reinforcement/praise is provided for desired behaviors, while inappropriate behaviors are ignored.)

Since the learners were voluntarily changing the swings to learn of imitate the demonstrated emphatic motions, there might be an "operant conditioning", which is reported to enhance skill development [32]. The operant conditioning is a form of learning in which an individual's behavior is modified by its consequences, and distinguished from classical conditioning (Pavlovian conditioning [120]), or operant conditioning deals with the modification of "voluntary behavior".

Other methods could synthesis emphatic motions, but there is a strong benefit of proposing method applying the mimesis model. With the Proto-symbol Space method, for example, it would be possible to make an instruction considering tendencies of players, such as "Please, swing not like jumping, but more like squatting! ", instead of current simple verbal expression "more like this". This chapter is to present, as the first step, the feasibility of the proposed method, and therefore a simple verbal expression was used. The technical basis to realize such motion synthesis by natural expression is that the Proto-symbol Space method can convert high dimensional complex real world property to static points in low dimensional space, Proto-symbol space(PSS), and can convert back from the static points to the high dimensional property, such as motion patterns. If motions could be labeled such as "jump" and "squat" then the natural expression could be converted into external/internal division of proto-symbols in PSS; then it corresponds to proper extrapolation/interpolation of motion patterns in the high dimensional world. It means the PSS could be used as the bridge between symbolic expression and motion synthesis. This is the most important reason why the Proto-symbol Space Method was used.

In this chapter, we only used joint angles as the (O), however it can be extended to deal with sensory patterns $\boldsymbol{S} = [\boldsymbol{s}_1, ..., \boldsymbol{s}_n]^T$, where $\boldsymbol{s}$ are time series data, becoming $\boldsymbol{O} = \{\boldsymbol{M}^T, \boldsymbol{S}^T\}^T$. In the Chapter 6, we will discuss a method and experiments how the integration of motion patterns and sensory patterns works and benefits.

The results of this chapter was presented as a part of [111].

Chapter 5

A Modeling of Emphatic Motion Use and Adverbial Expressions Use –A Design of a Interactive Learning Framework–

5.1 Abstract of the Chapter

As a step of a robotics research toward integration of motion patterns and verbal expression, in this chapter, we attempt to model how human uses motions and verbal expressions for motion coaching. Through experiments of a tennis forehand swing coaching task for beginners, we observed and analyzed three kinds of motions; learning target swing performed by human coaches, swings performed by learners and emphatic motions by human coaches. With results, we modeled relationship between difference among the three motions and used verbal expressions in a phase space, and discussed how the model can be applied for realizing an efficient motion coaching system.

5.2 Introduction

When humans coach, for example, a tennis swings to human learners, the human coaches use proper whole-body motion demonstrations and verbal expressions in order to help the learners improve in motion learning according to performances of the human learners. For example, slight differences in motions is not easy to convey using only either motion demonstrations or verbal expressions. To convey slight differences, it is needed to have a method to chose both effective motions and verbal expressions and a method to bind them.

Human coaches can learn coaching skills from other coaches, when they do not know how to coach. For example, from other coaches, human-coaches can learn what to emphasize in motions and what kind of adverbial expressions should be bound to the motions as a coaching skill. Then, they can apply acquired skills to coach human-learners in order to have learners recognize their performances and improve them. This is an interactive learning, in which humans learn new skills and apply the learned skills to coach.

To realize this interactive learning between a robot and a human, a robot need to be able to covert learned parameters for motion coaching, to appropriate motions and verbal expressions. The problem is that parameters learned by robotic system are usually not friendly for humans, therefore, parameters are not meaningful for humans.

There have been a lot of research on imitation learning in robotics [133] [16]. How to learn parameters was discussed, but there is no discussion about how to communicate with humans using the learned parameters. For example, Fasola and Mataric developed a robot instructor for the elderly [30]. It motivates subjects to engaged in rehabilitation exercises, by displaying motions and words. It evaluates emotional aspect of subjects, but there is no discussion about how to communicate with humans using learned parameters. Iwahashi [60] realizes binding a verbal expression to several similar but different motion patterns. Similarly, stochastic binding method by Takano and Nakamura [148] realizes generation of a motion pattern from a sentence and of a sentence from several similar motion patterns. These methods could be extended for a bi-directional interactive learning between humans and robots even though they did not discuss about it. On the other hand, the methods cannot be used to bind several different verbal expressions to similar but different motions.

On the other hand, the robotic motion coaching system introduce in the chapter 4, needs to learn from human coaches how to bind parameters to corresponding motions and verbal expression for an effective motion coaching. This way, the robotic system can learn parameters from human coaches and then coaches humans how to swing better using the learned skill, by interaction using motions and verbal expressions.

In the chapter 4, we explained a method how to bind emphatic motions and adverbial expression, and showed feasibility of the proposed method by studying a robotic system coaching humans a tennis swing motion[111]. Emphatic motions are such that missing elements in learners' motions are emphasized in the direction of being complemented. For example, when a learner is not bending knees enough and a coach wants the learner to bend the knee more, the coach can demonstrate a motion where bent of knees are emphasized. Adverbial expression are expression using adverb such as "more" for emphasis.

However, there are two remaining problem from the chapter 4. The first remaining problem is that degree of emphasis α for emphatic motions was decided based on a preliminary experiment with one subject. The second remaining problem is that the adverbial expression was not controlled by any parameters.

Thus, the objective of this chapter is that we study human coaches to have models that output the α and chose adverbial expression based on inputs. The inputs could be parametrized representation of performance of motion learners, since it is natural to change motions and verbal expression according to the performance of the learners.

Section 5.3 describes study of human coaches for modeling how human uses emphatic motions and adverbial expressions. Section 5.4 describes study and model of relationship between improvements in motion learning and value of the α used. The chapter is then concluded in section 5.5.

5.3 Modeling Method 1: Analysis of How Human Coaches use Emphatic Motions and Adverbial Expressions

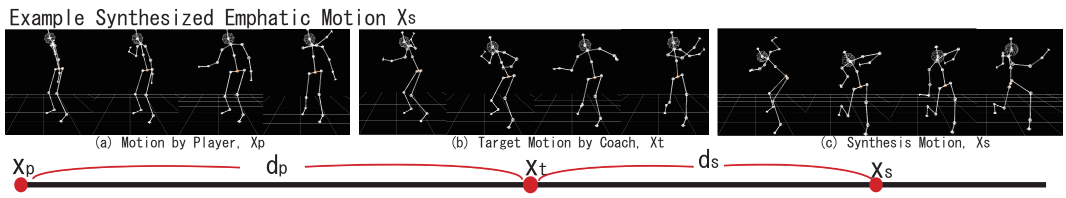

Figure 5.1: Example of relationship between degree of emphasis α and synthesized emphatic motion, distance d_s between $\boldsymbol{x}_s$ and $\boldsymbol{x}_t$, and distance d_p between $\boldsymbol{x}_p$ and $\boldsymbol{x}_t$. (a): a motion imitated by a beginner player $\boldsymbol{x}_p$, (b): the imitation target motion demonstrated by the coach $\boldsymbol{x}_t$, (c): a synthesized emphatic motion $\boldsymbol{x}_s$ with $\alpha = 2.0$. ($\alpha = (d_p + d_s)/d_p$, $d_p = |\boldsymbol{x}_t - \boldsymbol{x}_p|$, $d_s = |\boldsymbol{x}_t - \boldsymbol{x}_s|$)

As it was discussed in the section 5.2, we study human coaches to have models that output degree of emphasis α and that chose adverbial expression V_i(i is an index of adverbial expression) based on performance of motion learners. Since it is natural to change motions and verbal expression in motion coaching according to performances of the learners.

We define performance of the learners as distance d_p between a static point $\boldsymbol{x}_p$ and $\boldsymbol{x}_t$ in the Proto-symbol Space.

$$d_p = |\boldsymbol{x}_p - \boldsymbol{x}_t| \tag{5.1}$$

$\boldsymbol{x}_p$ corresponds to a motion performed by a learner (Figure 5.1-(a)) and $\boldsymbol{x}_t$ corresponds to a fixed learning target motion (Figure 5.1-(b)).

To study how humans coach a robot-learner motions by using adverbial expressions and emphatic motions, we investigated relationship between d_p (Eq.(5.1)) and d_s (Eq.(5.2), use of emphatic motions) and V_i (choice of adverbial expressions) used by human coaches. The d_s is defined as,

$$d_s = |\boldsymbol{x}_s - \boldsymbol{x}_t| \tag{5.2}$$

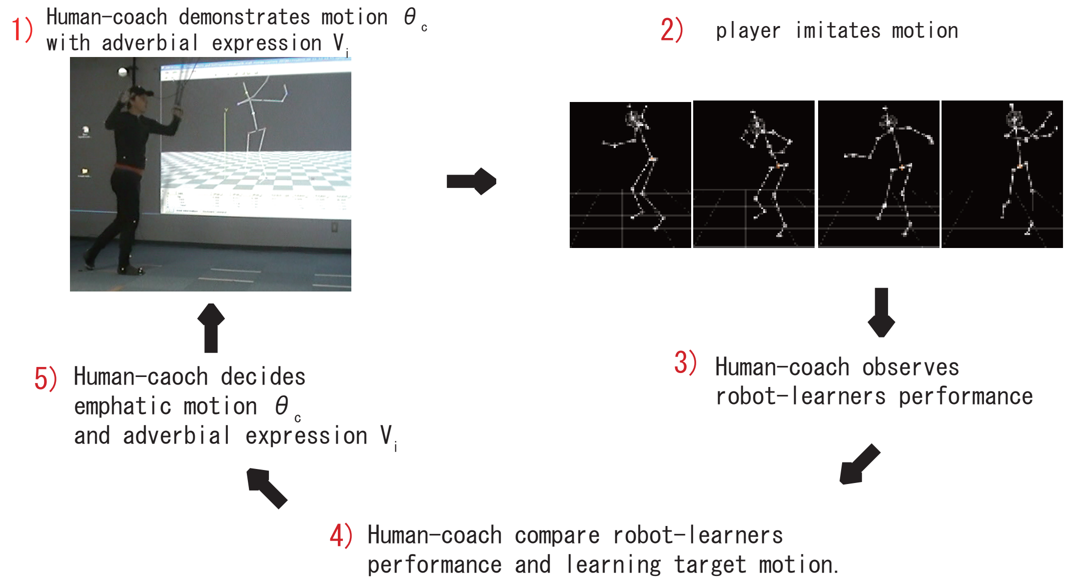

Figure 5.2: Motion coaching Scene by a Human coach

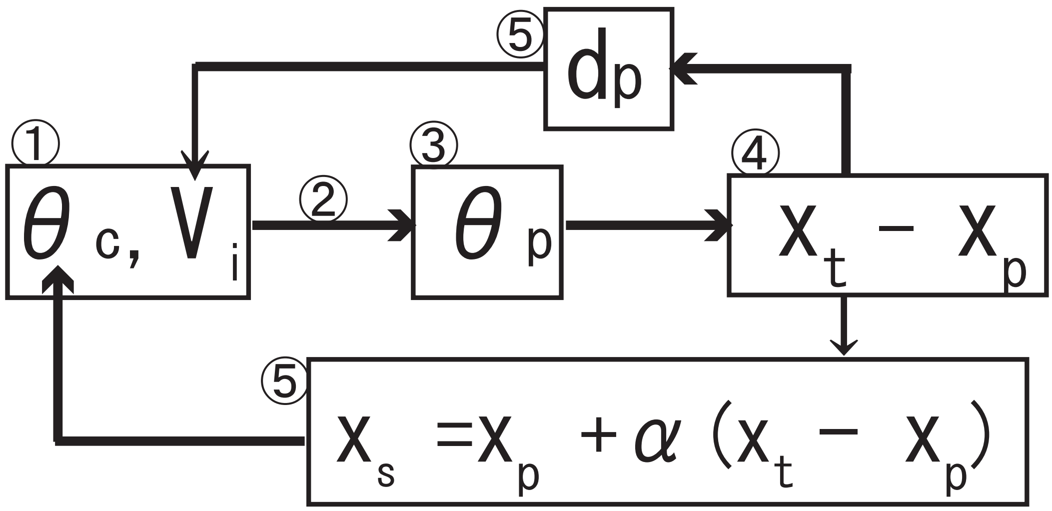

Figure 5.3: Flow of motion coaching with Emphatic Motions and Adverbial Expressions. $\boldsymbol{\theta}_c$ is a motion demonstrated by human/robot coach. V_i is an adverbial expression used in a trail. $\boldsymbol{\theta}_p$ is a captured motion performed by human/robot player. d_p is a distance between learning target motion $\boldsymbol{x}_t$ and player's performed motion $\boldsymbol{x}_p$ in the proto-symbol space. $\boldsymbol{x}_s$ is an emphatic motion. α is calculated by Eq. 5.3

The procedure is as follows and depicted in Figure 5.3 and coaching scene by a human-coach is depicted in Figure 5.2.

1. The human-coach demonstrates motion patterns $\boldsymbol{\theta}_c$, and use an adverbial expression V_i. $\boldsymbol{\theta}_c$ is from the $\boldsymbol{x}_t$ in the initial trial, and is from the emphatic

motion $\boldsymbol{x}_s$ decided in step 5. in later trials. In the initial trial, no V_i is used, and V_i is used according to the decision in step 5. in the later trials.

2. The robot player randomly performs one of pre-designed motions $\boldsymbol{\theta}_p$, which are designed by the authors. The human coaches are told that the $\boldsymbol{\theta}_p$ reflects feedback of the human coaching.

3. The human coach observes the $\boldsymbol{\theta}_p$

4. The human coach analyzes missing components in $\boldsymbol{\theta}_p$ compared to the imitation target motion $\boldsymbol{\theta}_t$.

5. The coach decides emphatic motion $\boldsymbol{x}_s$ and V_i to demonstrate in the next trail.

Repeat loop of processes 1.-5. as needed. 1 loop is considered as 1 trial in the experiment.

The choice of adverbial expression V_i, and values of d_p and d_s will be recorded in order to evaluate how humans bind the adverbial expressions and the emphatic motions. The distance d_p between motion performed by the robot player $\boldsymbol{x}_p$ and imitation target motion $\boldsymbol{x}_t$ is calculated by using Bhattacharyya Distances [12] between the corresponding CHMM of motions.

5.3.1 Experimental Setup 1

To study and model how humans bind performance of learners d_p to both emphatic motions and adverbial expressions, we conducted experiments where humans coach a robot motions by using adverbial expressions and emphatic motions.

In the experiment, a forehand tennis swing was coached to a robotic system by male beginning tennis players, using both adverbial expressions and emphatic motions. The experiment followed the procedure explained in the previous section as depicted in Figure 5.3, with conditions described below.

- There were 16 participants who were all beginners in tennis.
- They were given an instruction that the goal was to coach the robot to have it swing as same as learning target motion $\boldsymbol{x}_t$ shown in the Figure 5.1-(b).
- The $\boldsymbol{x}_t$ was played on a wall screen during the experiment, apart from the $\boldsymbol{x}_p$
- The view point of the motions were fixed and always from the front.
- Motions $\boldsymbol{\theta}$ consisted of 17 joints, each with DoF of 3.
- The values of d_p corresponding to motions performed by the robot player were ranged between 90 and 200.
- 23 different motions of the robot player were prepared in advanced, and out of them, 10 motions were randomly used for experiments of each subjects.
- 5 swings were used to abstract each human-coach's swing to an CHMM for each trial.
- 10 trials were executed with 2 minutes intervals.
- The choice of adverbial expressions were V_1 = 'little bit more', V_2 = 'more', and V_3 = 'much more'.

5.3.2 Experimental Result 1

The Figure 5.4 shows distribution of motions, d_p (Eq.(5.1)), performed by robot-learner, and overview of relationship to choices of adverbial expressions V_i by human-coaches.

From the results shown in Figure 5.5 and Table 5.1 executing Tukey-Kramer Method and ANOVA, here we found that the distance d_p (Eq.(5.1)) between $\boldsymbol{x}_p$ and $\boldsymbol{x}_t$, and the choice of adverbial expression V_i has a positive correlation. The larger

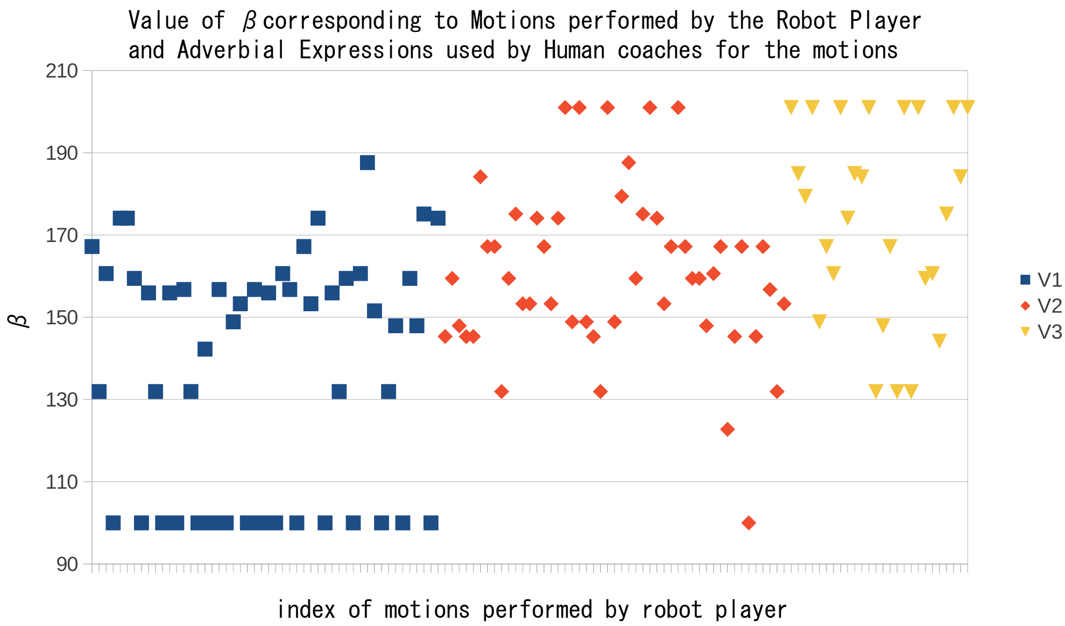

Figure 5.4: Range of d_p (Eq.(5.1)) corresponding to motions performed by the robot player and Results of adverbial expression usage by human coaches in the experiment 1

the value of d_p, the stronger adverbial expression was chosen. As the average, V_1 was bound to $\bar{d_p} = 131.8$, V_2 to $\bar{d_p} = 160.6$ and V_3 to $\bar{d_p} = 174.1$

Experimental data of 3 participants were excluded from the results shown in Figure 5.5 and Table 5.1. It is because that these participants bound V_3 to low values of d_p and V_1 to high value of d_p. For example, one of them bound V_3 to $d_p = 131.9$ as the average, and V_1 to $d_p = 165.3$ as the average. Following a common sense, as the rest did, we assumed V_3 should be bound to the larger values and V_1 to the smaller values.

Table 5.1: Tukey-Kramer Method for $p < .05$ among mean values bound to the adverbial expressions by human-coaches for experiment 1. The numbers in the upper right are the Tukey-Kramer minimum significant differences (MSDs). The numbers in the lower left are the observed absolute value of the difference in means between each pair of groups, with an asterisk if it is greater than the Tukey-Kramer MSD.

-	V_1	V_2	V_3
V_1	-	11.35	11.55
V_2	20.35*	-	11.59
V_3	32.95*	12.60*	-

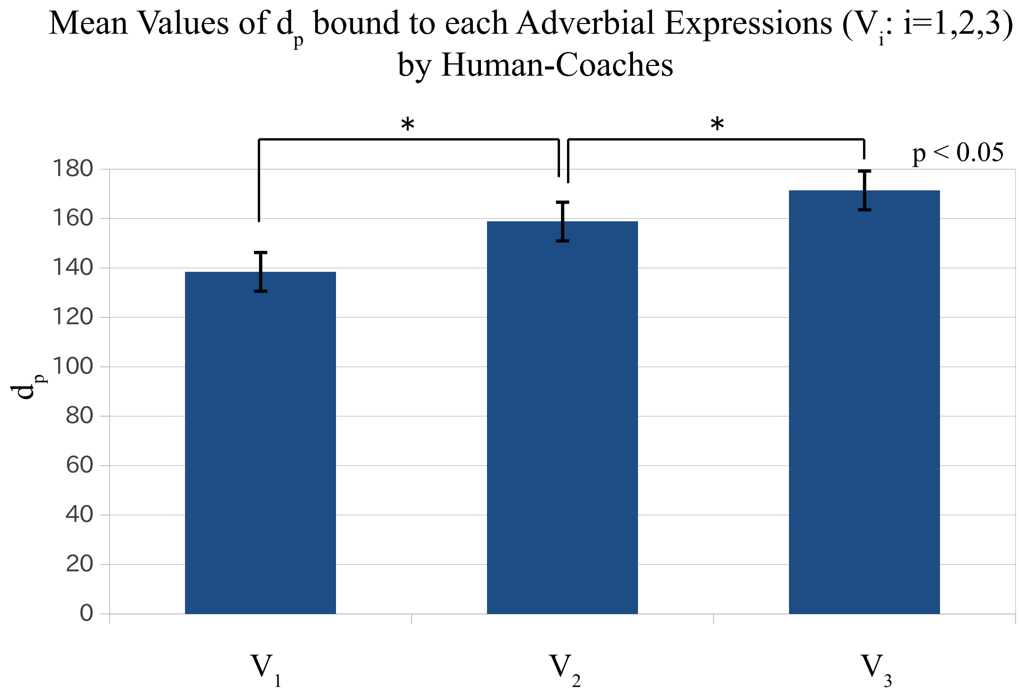

Figure 5.5: Result of the experiment 1: Learned binding strategy how adverbial expressions are bound to the d_p (Eq.(5.1)), distance between $\boldsymbol{x}_p$ and $\boldsymbol{x}_t$

The Figure 5.6 shows selected results of experiment 1, in terms of how human coaches use emphatic motion (d_s) according to performance of robot-learners (d_p). The results could be categorized into 3 different patterns.

1. Most of the data match well to the regression line as shown in Figure 5.6-(1)(2).
2. The data does not match well to the regression line as shown in Figure 5.6-(3).
3. The data does not match well to the regression line and the gradient is negative, as shown in Figure 5.6-(4).

5.3.3 AEU-Model 1: a Model of Adverbial Expressions Use

Analysis of number of adverbial expressions used by a participant showed that 7 out of 16 (43.75%) participants used only 2 adverbial expressions in the experiments. 11 of 16 (68.75%) participants used only 2 adverbial expressions in more than 90% of the

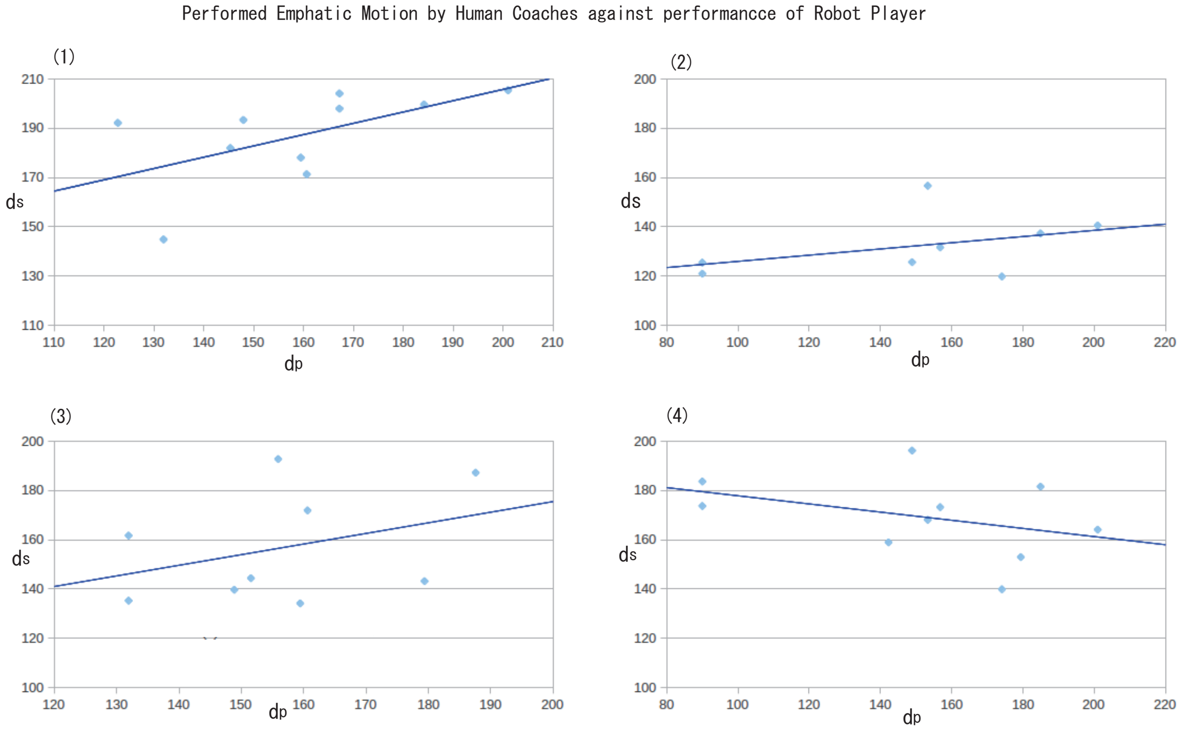

Figure 5.6: Selected Results: distance between $\boldsymbol{x}_t$ and $\boldsymbol{x}_p$, or d_p (Eq.(5.1)) as x-axis, and distance between $\boldsymbol{x}_s$ and $\boldsymbol{x}_t$, or d_s (Eq.(5.2)) as y-axis. Gradients correspond to the degree of emphasis α as difined in Eq. 5.5.

trials, or they used the least used adverbial expression by themselves for only once in the entire trials. 15 of 16 (93.75%) participants used only 2 adverbial expressions in more than 80% trials. This might suggest that the beginners can only distinguish 2 level of adverbial expressions when binding the expressions to performances. While we confirmed that in a preliminary test, an trained tennis coach used 3 adverbial expressions.

From the 13 participants, we chose 3 participants who had lots of experience in sports and considered themselves athletic, even though they were all beginners in tennis. For this 3 participants, the frequency of adverbial expressions used were fairly even in the experiments. 2 participants used V_1 for 4 times, V_2 for 3 times and V_3 for 3 times, 1 participants used V_1 for 4 times, V_2 for 4 times and V_3 for 2 times.

This fact led to a hypothesis that trained coaches or those who have lots of experience in sports, can recognize and use at least 3 adverbial expressions evenly. These 3 participants provided a different results for the binding strategy, compared to the beginners.

For the beginners, as the average, V_1 was bound to $\bar{d_p} = 121.8$, V_2 to $\bar{d_p} = 160.6$ and V_3 to $\bar{d_p} = 174.1$. For the experienced, as the average, V_1 was bound to $\bar{d_p} = 139.2$, V_2 to $\bar{d_p} = 169.1$ and V_3 to $\bar{d_p} = 183.2$.

Therefore, we decide to have 2 different model of adverbial expression use as shown below and in Table 6.3. The models was denoted as AEU-Model 1 (from the beginners) and AEU-Model 2 (from the experienced).

- AEU-Model 1:

  Use V_1 when $d_p \leq 130$, V_2 when $130 < d_p \leq 165$, and V_3 when $165 < d_p$.

- AEU-Model 2:

  V_1 when $d_p \leq 160$, V_2 when $160 < d_p \leq 180$, and V_3 when $180 < d_p$.

Table 5.2: Model of Adverbial Expressions Use 1

Choice of Adverbial Expression	V_1	V_2	V_3
AEU-Model 1	$d_p \leq 130$	$130 < d_p \leq 165$	$165 < d_p$
AEU-Model 2	$d_p \leq 160$	$160 < d_p \leq 180$	$180 < d_p$

5.3.4 EMU-Model 1: a Model of Emphatic Motion Use 1

The original definition of the degree of emphasis α is,

$$\alpha = (d_p + d_s)/d_p \tag{5.3}$$

where $d_p = |\boldsymbol{x}_t - \boldsymbol{x}_p|$ and $d_s = |\boldsymbol{x}_t - \boldsymbol{x}_s|$, where $\boldsymbol{x}_t$, $\boldsymbol{x}_p$ and $\boldsymbol{x}_s$ are static points in the Proto-symbol Space corresponding to 'learning target motion', 'motion performed by a learner' and 'emphatic motion' respectively.

This can be changed as,

$$\alpha = 1 + \frac{d_s}{d_p} \tag{5.4}$$

Thus, we define a model of Emphatic Motion Use, by substituting $\frac{d_s}{d_p}$ in Eq.(5.4) by values of gradients of regression lines shown in Figure 5.6 and denoted as

- EMU-Model 1:

$$\alpha = 1 + \frac{d}{dd_p} d_s \tag{5.5}$$

Using this formula, Eq.(5.5), we calculated α for each participants. Results is that value of α ranged between 0.75 and 1.46. The negative value contradicts to the result from the Chapter 4, and the average of positive values is 1.17. As a degree of emphasis, 1.17 is not convincing. It is because that emphatic motions with $\alpha = 1.17$ seems almost as same as no emphasis and the result from the Chapter 4 indicates that repetition of motion without emphasis resulted in no improvement. Thus we attempt an extra analysis in the next section.

5.4 Modeling Method 2: Subject-Optimized α based on Improvement in Motion Learning Experiments

In this section, alternative modeling method is executed in order to study a model of emphatic motion use. From the experimental result 1 of Chapter 4, it is known that degree of improvement in motion learning has a relationship to value of α used.

Thus, we study by executing a modeling method where we investigate relationship between value of α (Eq.(4.3)) and performance of human-learners (Eq. 4.4) This way, we expect to gain subject-optimized α for each subjects. For motion coaching, the motion coaching system introduced in the Chapter 4 was used. The motion coaching task was executed as explained in the Chapter 4 and as depicted in Figure 4.3.

5.4.1 Experimental Setup 2

In the experiment, we tested with 11 subjects to learn how different α would affect to the motion learning performances. The emphatic motions with different $\alpha = \{1.25, 1.50, 1.75, 2.00, 2.25, 2.50\}$ were synthesized and shown to the subjects. There were two cases considered, case (a): without adverbially expression, and case (b): with adverbially expression "more like this". The condition was as same as the common condition in the Chapter 4.

5.4.2 Experimental Result 2

To evaluate the result, the distance (d_{il}) was introduced, which is identical to Eq.(4.4),

$$d_{il} = |x_t - x_p| \tag{5.6}$$

where i is an ID number of a subject. where l is the trial number, and $l = 1, 2, 3, 4$ was used for this paper. This means that the smaller the d_{il} is, the better the imitation is. When $d_{il} = 0$, the imitation is perfectly identical. Thus, d_{il} corresponds to an imitation error of subject ID i at trial l.

Then, average of the distance d at trial l was also introduced,

$$\bar{d_l} = \frac{\sum_{i=1}^{m} d_{il}}{m} \tag{5.7}$$

where m is number of subjects and $m = 11$ was used for this experiment.

As it is shown in Figure 5.7, it is reasonable to decide that average value of $\alpha = 2.0$ would provide the best result for motion learning in both cases. However, use of $\alpha = 2.0$ will result in as same result as in Chapter 4 where $\alpha = 2.0$ was used.

We then do farther analysis and come up with a hypothesis that optimized α, which results in better improvement in motion learning, is different from subjects to subjects. This fact can be explained by that sensitivity to degree of emphasis is depending on individual abilities, such as cognitive ability of motions and so on.

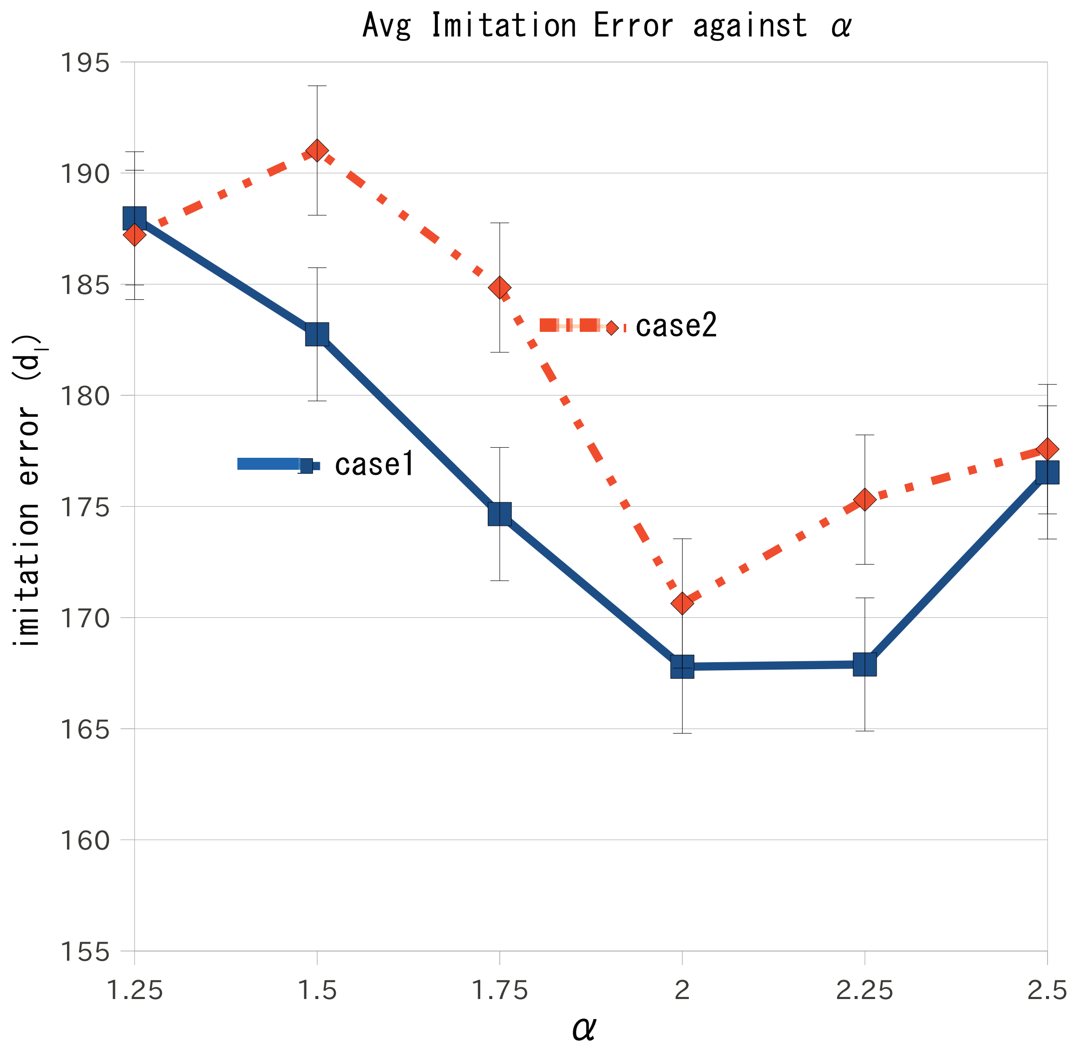

Figure 5.7: Results of experiment 1: Imitation error $\bar{d_l}$ in Eq.(5.7) against different values of α ($\bar{d_l}$ adjusted so that maximum value of each participant would be 200)

From results shown in Figure (5.8), the optimized α to improve motion learning is different from subjects to subjects. For example, subject-A had optimized-$\alpha = 1.5$ for case (a) and optimized-$\alpha = 2.0$ for case (b). Similarly, subject-B had optimized-$\alpha = 2.5$ for case (a) and optimized-$\alpha = 2.25$ for case (b). Same method was applied to determine optimized α for the rest of the subjects.

5.4.3 EMU-Model 2: a Model of Emphatic Motion Use 2

As shown in Figure 5.8, the Model of (E)mphatic (M)otion (U)se 2 is decided empirically for each subjects, denoted as 'EMU-Model 2'.

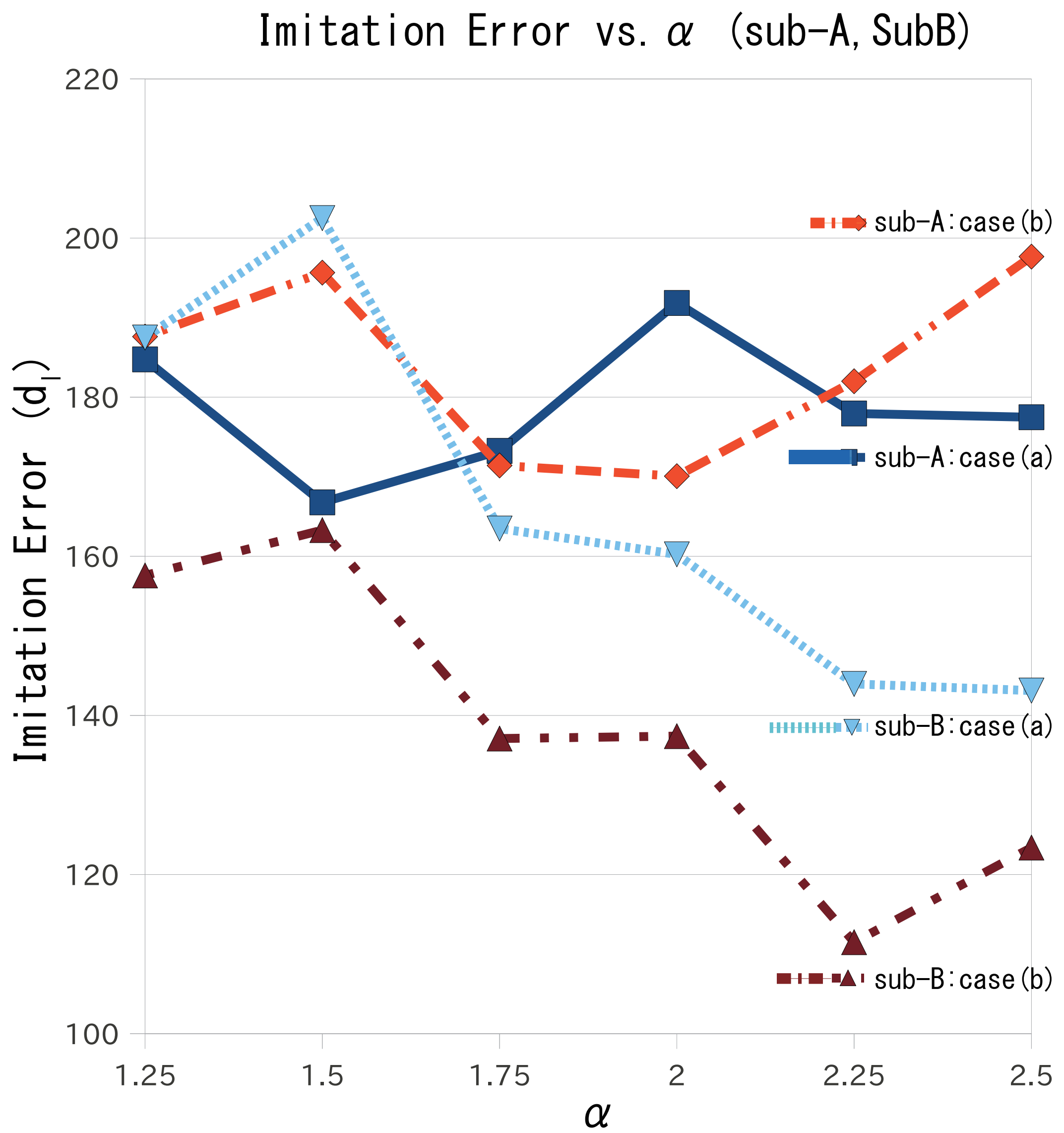

Figure 5.8: example individual imitation error against different values of αs (subject-A and subject-B): $\bar{d}_l$ in Eq.(5.7)

- EMU-Model 2:

  α is decided empirically for each subjects.

  (Example)

  Subject-A had optimized-$\alpha = 1.5$ for case (a) and optimized-$\alpha = 2.0$ for case (b). (From Figure 5.8)

5.5 Future Work: EMU-Model 1 with Corrected Data Set

After analyzing the results for 'EMU-Model 1', we come up with a hypothesis that the beginners as the coach is not good. It is because that it is not easy for a beginner to perform as a coach especially when performance of the robot-player is good, in other words, when value of d_p is small. The beginners performance, in general, ranges in 150 to 190. This fact suggests that the smaller the value of d_p is, the more inaccurate the d_s is from a coaching point of view.

Therefore, we correct the data by introducing a new parameter d_h,

$$d_h = |x_t - x_h| \tag{5.8}$$

where, x_h is a static point on a line defined by x_p and x_t. projection of the emphatic motion performed by a human-coach x_s onto the line defined by x_p and x_t is the x_h. It is depicted in Figure 5.9.

For the EMU-Model 1 with corrected data set, d_h will be used instead of d_s as,

- EMU-Model 1 with corrected data set

$$\alpha = 1 + \frac{d}{dd_p} d_h \tag{5.9}$$

5.6 Conclusion of the Chapter

In summary, I have realized interaction and communication to obtain models of emphatic motion use and adverbial expression use. However, collecting data from experts is missing and need to be done as soon as possible. Then, comparison among models gained from beginners(EMU-Model 1), experts, and empirically approach(EMU-Model 2), is needed to be done. The the model (EMU-Model 1) is obtained assuming linearity, but investigation of non-linear model is required.

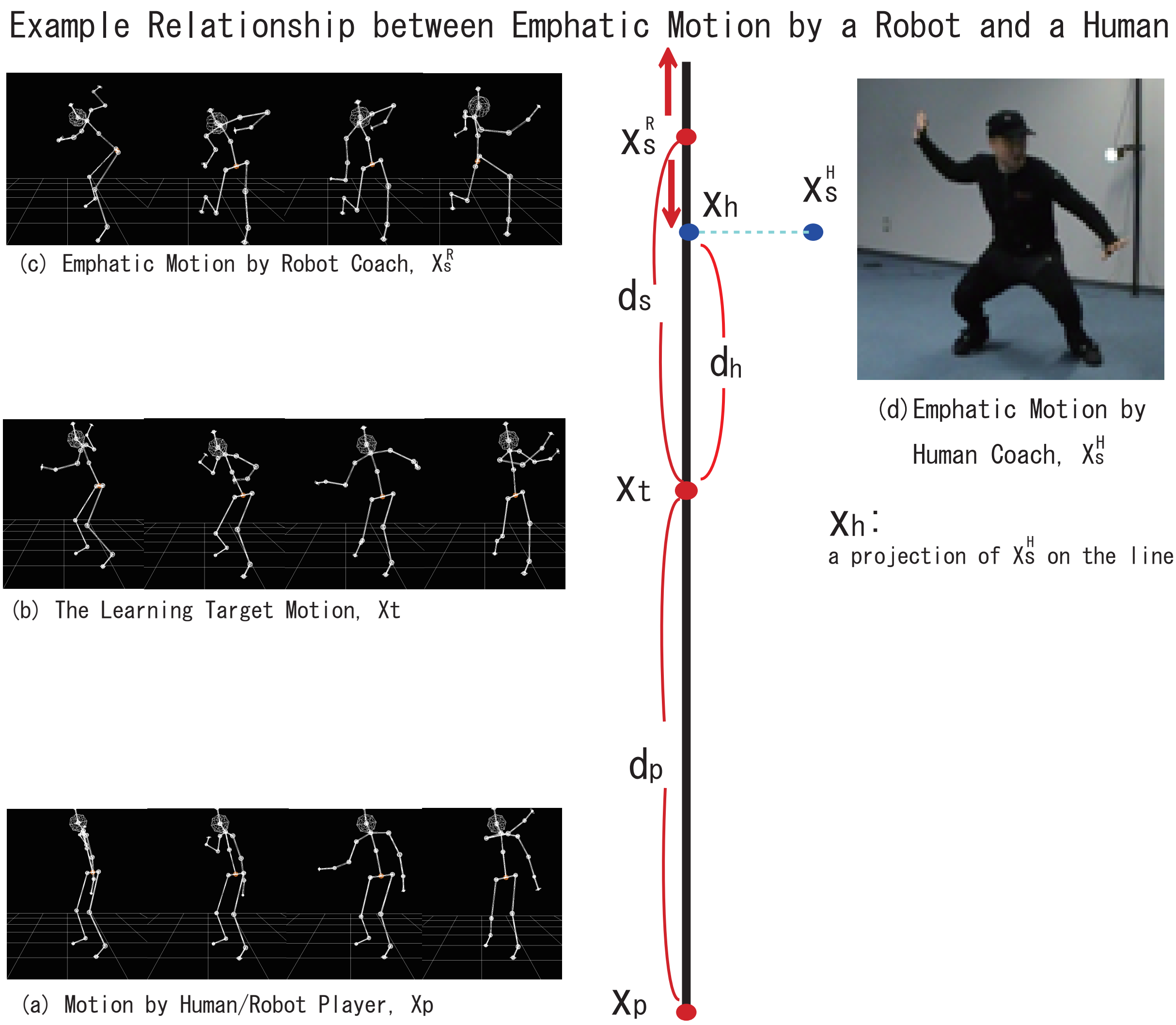

Figure 5.9: x_h is a static point on a line defined by x_p and x_t and projection of the emphatic motion performed by a human-coach x_s^H onto the line defined by x_p and x_t is the x_h

In this chapter, we discussed about an interactive learning system, which can learn skill from humans and teach skill to humans, by introducing a parameter space shared by humans and robots. As an example of the system, we study how a motion coaching robot can learn a binding strategy of emphatic motions and adverbial expressions from humans, In this study, we dealt with remaining problem from the Chapter 4, which is to study and have models of emphatic motion use and adverbial expression use for motion coaching.

In the experiment 1, as shown in Figure 5.5 and Table 5.1, we found that the distance d_p between learning target motion and learner's performed motion and the choice of adverbial expression V_i has a positive correlation. In the experiment 2, as shown in Figure 5.8, we found that optimized α for improvement in motion learning vary from subjects.

From the experimental result 1, we defined model of both emphatic motion use as EMU-Model 1 and adverbial expression use as AEU-Model 1 and 2. From the experimental result 2, we defined alternative model of emphatic motion use as EMU-Model 2.

We have demonstrated that the robotic coaching system can learn the binding strategy between emphatic motions and adverbial expressions, by studying how humans coaches a robot. The learned binding strategy is represented in a parametric representation that is interpretable and therefore sharable between humans and robots.

The results in the section 5.4 was partially presented in [111].

Chapter 6

An Integration of the Methods and the Models –A Robotic System that Coaches Humans Motions–

6.1 Abstract of the Chapter

In this chapter, we discuss how the methods from the Chapter 3 and 4, and the Models from the Chapter 5 can be integrated. We demonstrate integration of method to estimate sensorimotor patterns from the Chapter 3, the robotic motion coaching system from the Chapter 4, and Models of emphatic motions and adverbial expressions use from Chapter 5.

We demonstrates the feasibility of the robotic motion coaching system integrated with the emphatic motion use model and adverbial expression use model, by experiments of a tennis forehand swing coaching task for beginners. We confirmed that EMU-Model 2 and AEU-Model 2 contribute to improvement in motion learning.

At the end we propose a method and share a learning task that requires functions to bind sensorimotor patterns and emphatic motions to convey slight difference in sensorimotor patterns to learn.

6.2 Introduction

In the previous Chapters,we have discussed about:

- Chapter 3: a method how to estimate others' sensorimotor patterns, without preparing user specific model in advance.
- Chapter 4: a method how to bind emphatic motions and adverbial expressions for the motion coaching robot, in order to convey slight differences in motions.
- Chapter 5: models of how human use emphatic motions and adverbial expressions for an effective motion coaching.

In this chapter, these methods and models are integrated and demonstrated as motion coaching tasks.

In Section 6.3, integration of the method in chapter 4 and the models of emphatic motion use in chapter 5 is demonstrated. In Section 6.4, integration of the method in chapter 4 and the models of adverbial expression use in chapter 5 is demonstrated. In Section 6.5, integration of the method in chapter 3 and 4, and the models of emphatic motion use in chapter 5 is demonstrated. The chapter is concluded in Section 6.6.

6.3 Integration of the Motion Coaching System and the Model of Emphatic Motion Use 2

6.3.1 A Motion Coaching Experiment using the Model of Emphatic Motion Use 2

In this section, integration of the method in chapter 4 and the Models of Emphatic Motion Use in chapter 5 is demonstrated. The experiment demonstrates integration of EMU-Model 2 and the robotic motion coaching system, which uses emphatic motions and adverbial expressions. In the experiment, to investigate how the learned EMU-Model 2 effects improvement in motion learning, we conduct experiments where a robotic system coaches humans motions. This way we demonstrate the feasibility of the interactive learning robotic system, where the robot applies a skill acquired through imitation learning to coach humans.

6.3.2 Experimental Setups 1

In the experiment 1, a forehand tennis swing was coached to male beginning tennis player by a robotic system explained in the Chapter 4. The procedure of the motion coaching is as same as in the Chapter 4.

To investigate contribution of emphatic motions and adverbially expression, we conducted experiments as Case 5 and 6 with 12 participants, using the EMU-Model 2 from the Chapter 5.

- Case 5:

  Coached using motions with optimized α obtained by using EMU-Model 2 and and no adverbially expression.

- Case 6:

  Coached using motions with optimized α obtained by using EMU-Model 2 and adverbially expression "more".

Table 6.1: Cases in Experiment 1

-	$\alpha = 0.0$	optimized α
without "more"	Case 1	Case 5
with "more"	Case 2	Case 6

The EMU-Model 2 gives subject optimized α. For example, as shown in Figure 5.8, subject-A had optimized-$\alpha = 1.5$ for the Case 5 and optimized-$\alpha = 2.0$ for the Case 6. Similarly, subject-B had optimized-$\alpha = 2.5$ for the Case 5 and optimized-$\alpha = 2.25$ for the Case 6. Same method was applied to determine optimized α for the rest of the subjects.

6.3.3 Experimental Results 1

As results shown in Figure 6.1 and Table 6.2, we are more confident that the emphatic motions contributed to the learning performances. This is because that there was a significant difference found between the Case 2 and the Case 6, by executing the Tukey-Kramer Method. On the other hand, we could not yet conclude that the adverbial expressions contributed to the learning performances, since

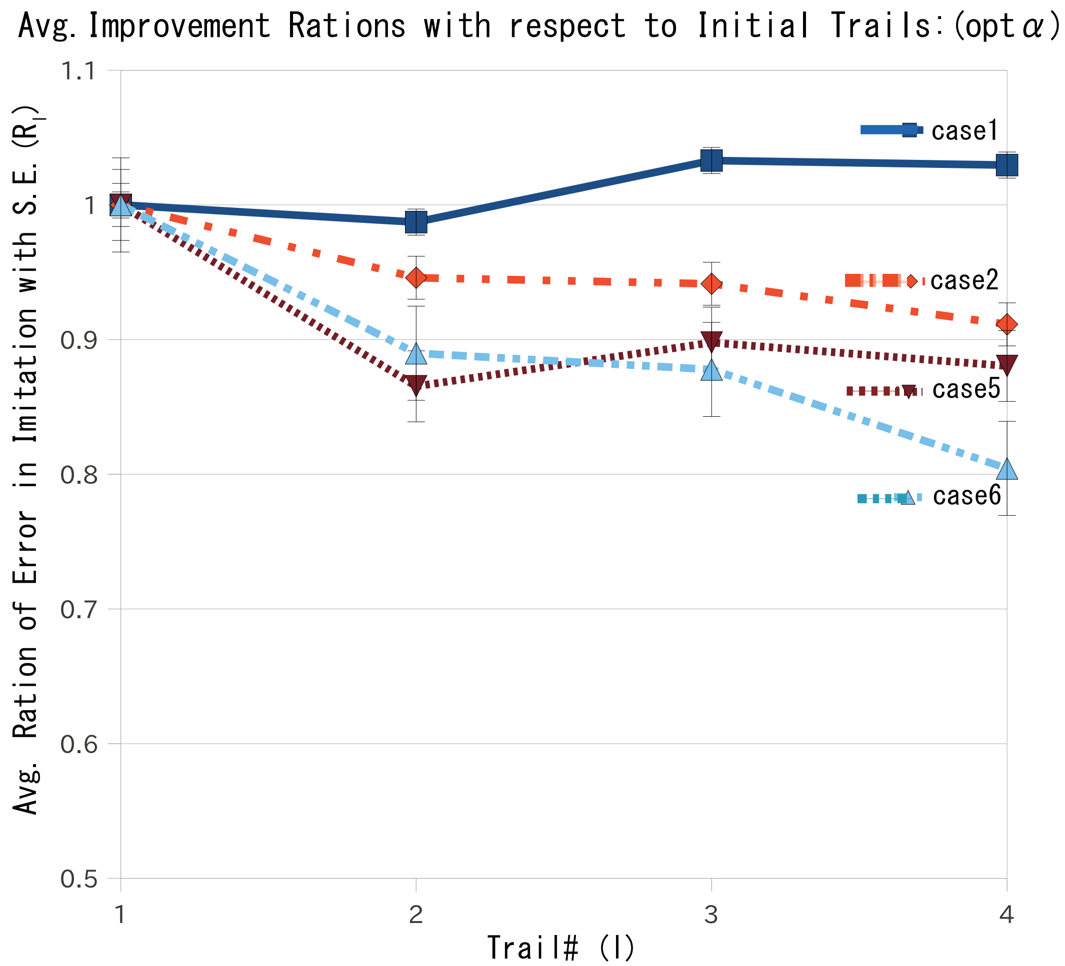

Figure 6.1: Result of experiment 1: Average ratio of imitation error, $\bar{R}_l$ in Eq.(6.3), with optimized α for each subjects

6.3.4 sub-Conclusion 1

Results shown as Figure 6.1 and Table 6.2 demonstrates that the emphatic motions contributed for improvement in motion learning and that the subject optimized α

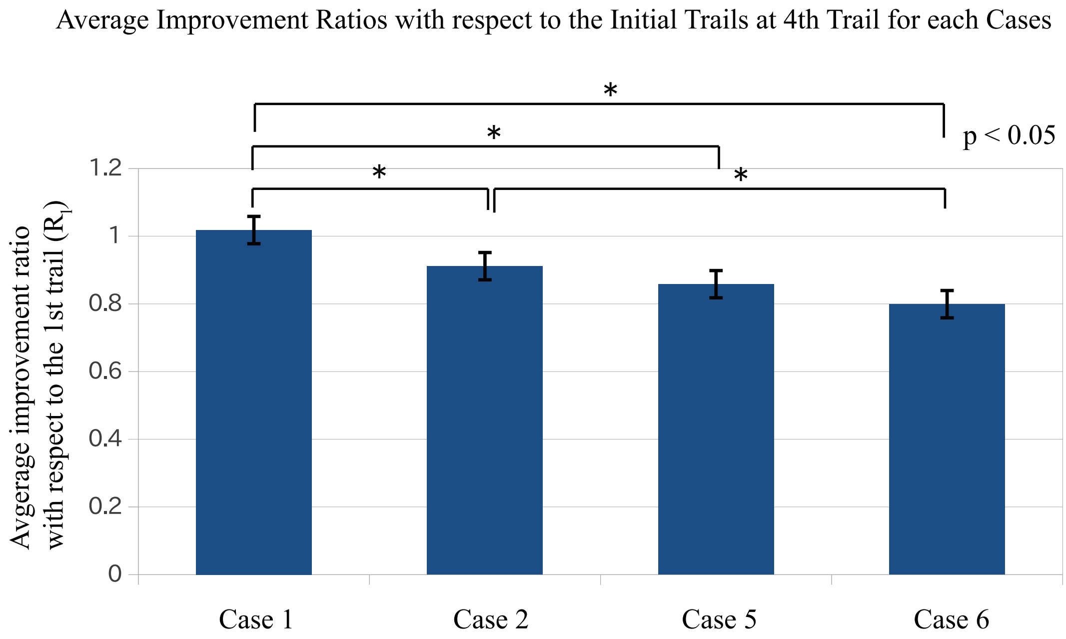

Figure 6.2: Result of experiment 1: Average improvement ratios with respect to the initial trails at 4th trail for each Cases. The average ratio of imitation error, $\bar{R}_l$ in Eq.(6.3), with optimized α for each subjects

is the contribution factor. On the other hand, we could not conclude whether the adverbially expression contributed to improvement in motion learning or not.

Table 6.2: Tukey-Kramer Method for $p < .05$ with $\bar{R}_l$(Eq.6.3) at 4th trail (l=4) for Experiment 1. The numbers in the upper right are the Tukey-Kramer minimum significant differences (MSDs). The numbers in the lower left are the observed absolute value of the difference in means between each pair of groups, with an asterisk if it is greater than the Tukey-Kramer MSD.

-	Case 1	Case 2	Case 5	Case 6
Case 1	-	0.1106	0.1106	0.1054
Case 2	0.1068*	-	0.1155	0.1106
Case 5	0.1599*	0.05312	-	0.1106
Case 6	0.2191*	0.1123*	0.05916	-

6.4 Integration of the Motion Coaching System and the Model of Adverbial Expressions Use

6.4.1 A Motion Coaching Experiment using the Model of Adverbial Expressions Use

In this section, integration of the method in chapter 4 and the models of adverbial expression use in chapter 5 is demonstrated. The experiment demonstrates integration of the AEU-Model 1 and 2, and the robotic motion coaching system, which uses emphatic motions and adverbial expressions. In the experiment, to investigate how the learned binding strategy effects improvement in motion learning, we conduct experiments where a robotic system coaches humans motions. This way we demonstrate the feasibility of the interactive learning robotic system where the robot applies a skill of adverbial expression usage, acquired through imitation learning from human-coaches, to coach human-learners.

6.4.2 Experimental Setups 2

We conducted experiments where a robot coached humans motions using the learned binding strategy of adverbial expressions, or AEU-Model 1 and 2 in the Chapter 5. In the experiment 2, a forehand tennis swing was coached to male beginning tennis player by a robotic system explained in the Chapter 4. The procedure of the motion coaching is similar to what is explained in the Chapter 4, but different.

At first, database $D = \{\boldsymbol{\theta}_t, \boldsymbol{\theta}_p\}$, which consists of one imitation target motion pattern $\boldsymbol{\theta}_t$ and one motion pattern performed by a player $\boldsymbol{\theta}_p$, is prepared for the coaching system. Then, Proto-symbol Space, denoted as P, is built using D with the F_{build} process (Eq.(2.5)). Let us define the static point $\boldsymbol{x}_t$ in the P as that corresponding to the imitation target motion $\boldsymbol{\theta}_t$. As depicted in Figure 6.3, the motion coaching task is executed as follows.

1. The coach (an agent in a virtual environment in the paper) demonstrates motion

pattern $\boldsymbol{\theta}_c$ as the imitation target motion and an adverbial expression V_i. Using the generation function F_{gen} (Eq.(2.7)), $\boldsymbol{\theta}_c$ is generated from $\boldsymbol{x}_t$ in the initial trial, and from $\boldsymbol{x}_s$ synthesized in step 5. in later trials. No V_i is used in the initial trial, but V_i is used according to the decision in step 5. in the later trials.

2. The human player imitates $\boldsymbol{\theta}_c$.

3. The coach observes the player's imitated motion pattern $\boldsymbol{\theta}_p$ and converts it to a static point $\boldsymbol{x}_p$ in the P, using recognize function F_{recog} (Eq.(2.6)).

4. The coach calculates the missing elements in the imperfect imitation of the player by $\boldsymbol{x}_t - \boldsymbol{x}_p$ and the distance d_p (Eq.(5.1)).

5. The coach calculates the external dividing point $\boldsymbol{x}_s$ by adding missing elements $(\boldsymbol{x}_t - \boldsymbol{x}_p)$ to $\boldsymbol{x}_p$, using Eq.(4.2). The $\boldsymbol{x}_s$ is then used as a re-demonstration motion pattern $\boldsymbol{\theta}_c$ (Eq.(2.7)) for the next trial. The coach also decides V_i to be used in the next trail based on the AEU-Models and the d_p.

Repeat loop of processes 1)-5) as needed. 1 loop is considered as 1 trial in the experiment.

- There were 14 participants.

- The coaching agent demonstrated motion pattern $\boldsymbol{x}_t$, shown in Figure 6.4, as the imitation target motion.

- The given instruction was 'please imitate V_i like this', where V_1 ='little bit more', V_2 ='more' and V_3 ='much more'.

- The view point of the imitation target motion was fixed and always from the front.

- Motions $\boldsymbol{\theta}$ consists of 17 joints, each with DoF of 3.

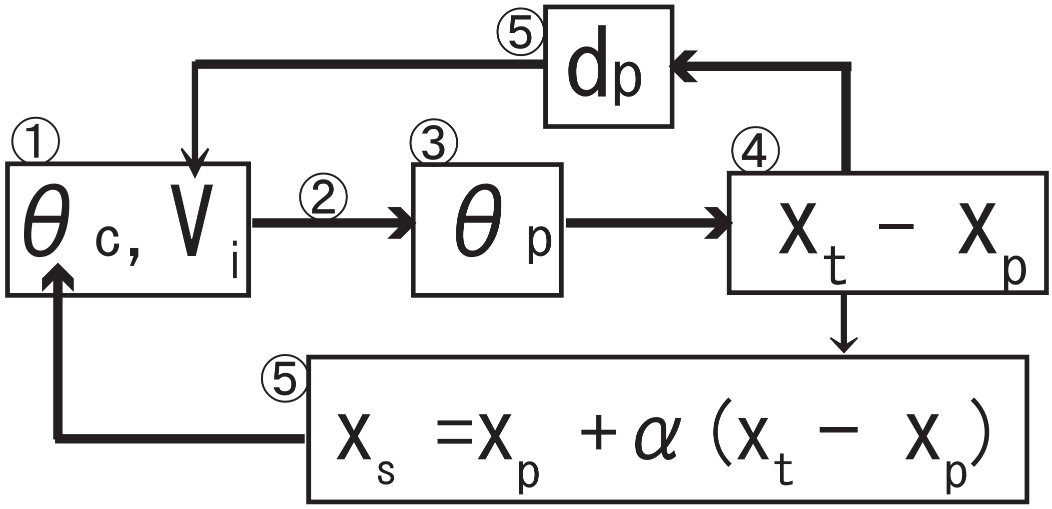

Figure 6.3: Flow of motion coaching with Emphatic Motions and Adverbial Expressions. $\boldsymbol{\theta}_c$ is a motion demonstrated by human/robot coach. V_i is an adverbial expression used in a trail. $\boldsymbol{\theta}_p$ is a captured motion performed by human/robot player. d_p is a distance between learning target motion $\boldsymbol{x}_t$ and player's performed motion $\boldsymbol{x}_p$ in the proto-symbol space. $\boldsymbol{x}_s$ is an emphatic motion. α is calculated by Eq. 5.3

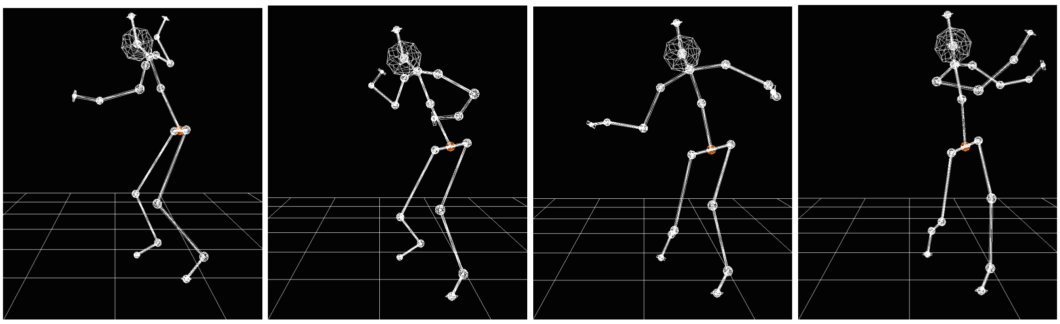

Figure 6.4: An ideal motion pattern as the coaching target (pattern: θ_t, proto-symbol: $\boldsymbol{x}_t$)

- Five swings were used to abstract each player's swing to an CHMM for each trial.
- Each trial is executed at 5 minutes intervals.

For emphatic motion synthesis, we used $\alpha = 2.0$ since we knew that it was reasonable choice from the results in the Chapter 4 and can be used as a baseline for comparision. From the result in the Chapter 4, we have already confirmed that emphatic motion, not repetition of observing similar motions, was an effective factor.

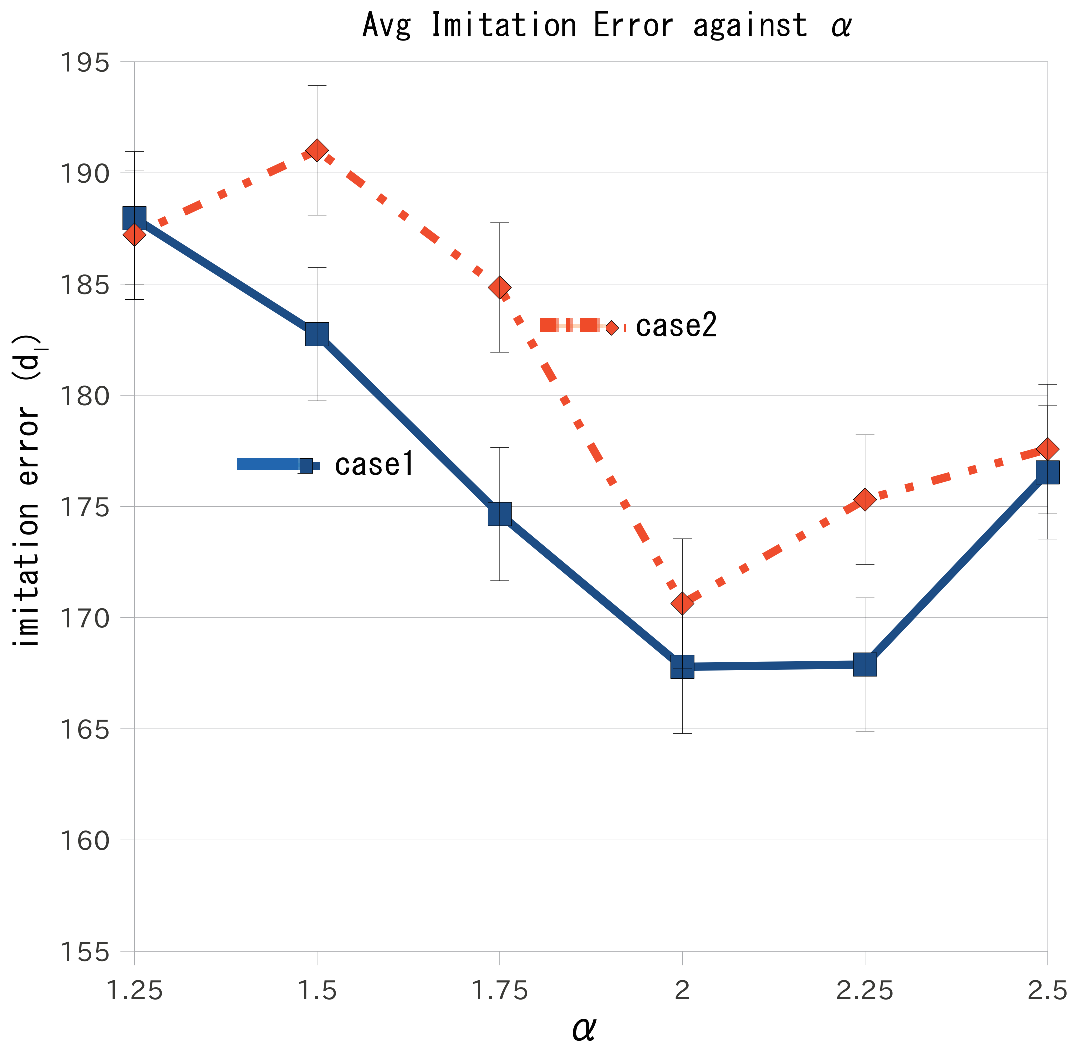

Figure 6.5: Results of experiment 2: average value of imitation error $\bar{d}_l$ in Eq.(6.2) against different values of α. ($\bar{d}_l$ adjusted so that maximum error of each participant would be 200)

To investigate how the AEU-Models 1 and 2 effects improvement in motion learning, Cases 7 and 8 were conducted and compared to the Case 3 that was conducted in the Chapter 4.

The AEU-Model 1 reflects results of the beginners, and AEU-Model 2 reflects results of the experienced as it was discussed in the Chapter 5.

- AEU-Model 1:

  Use V_1 when $d_p \leq 130$, V_2 when $130 < d_p \leq 165$, and V_3 when $165 < d_p$.

- AEU-Model 2:

  V_1 when $d_p \leq 160$, V_2 when $160 < d_p \leq 180$, and V_3 when $180 < d_p$.

Table 6.3: Model of Adverbial Expressions Use 1

Choice of Adverbial Expression	V_1	V_2	V_3
AEU-Model 1	$d_p \leq 130$	$130 < d_p \leq 165$	$165 < d_p$
AEU-Model 2	$d_p \leq 160$	$160 < d_p \leq 180$	$180 < d_p$

The order of conducting each experimental cases was randomly shuffled for each participants. The cases are summarized in Table 6.4.

Table 6.4: Cases in Experiment 2

-	$\alpha = 2.0$
with no adverbial expression V_i	Case 3
with adverbial expression V_i	Case 7 and 8

- Case 3:

  The robotic coach re-demonstrated with emphatic motion patterns $\boldsymbol{x}_s$, i.e., the robotic coach coached using motions with $\alpha = 2.0$ and with no adverbial expression.

- Case 7:

  The robotic coach demonstrated emphatic motions with $\alpha = 2.0$. The coach chose adverbial expressions using the AEU-Model 1.

- Case 8:

  The robotic coach demonstrated emphatic motions with $\alpha = 2.0$. The coach chose adverbial expressions using the AEU-Model 2.

6.4.3 Experimental Results 2

To evaluate the results, distance d_{il} was introduced as

$$d_{il} = |x_t - x_p^{il}|, \tag{6.1}$$

where i was an ID number of a participant, $l = \{1, 2, 3, 4\}$ was the trial number. The $\boldsymbol{x}_p^{il}$ corresponded to the performance of participant i in trial l. This meant that the smaller the d_{il}, the better the imitation. When $d_{il} = 0$, the imitation was perfectly identical. Thus, d_{il} corresponded to an imitation error of participant ID i in trial l. To minimize possible errors in the evaluation results that could be caused by the difference in frame number of the evaluated motions, we used motion clips that had a similar frame number, at most 20% differences. The average distance of d_{il} in trial l was introduced as

$$\bar{d}_l = \frac{\sum_{i=1}^{m} d_{il}}{m}, \tag{6.2}$$

where m was the number of participants ($m = 11$ for the experiment 2). Finally, the average error ratio in imitation at trial l was defined as

$$\bar{R}_l = \frac{\sum_{i=1}^{m} \frac{d_{il}}{d_{i1}}}{m}. \tag{6.3}$$

If the imitation error is smaller than the initial trial in the same case, $\bar{R}_l$ will be less than 1.0. If the imitation error is larger than the initial trial in the same case, $\bar{R}_l$ will be larger than 1.0. When imitation is perfect, $\bar{R}_l = 0.0$. The d_{i1} would not be zero in practice because $d_{i1} = 0$ means perfect imitation of the target motion and it would not happen.

From the results shown in Figure 6.6 and Table 6.5 executing the Tukey-Kramer Method and ANOVA for $p < .05$ with $\bar{R}_l$ (Eq. 6.3) in 4th trial, $l = 4$, for experiment 2, here we found there was a better improvement in motion learning in both Case 7 and 8 compared to that of Case 3. Specifically, even though the improvements between Case 3 and 7, and Case 3 and 8 were not statistically superior, we found positive contribution of the adverbial expressions, which was changed dynamically according to the distance d_p between the target motion θ_t and performed motions θ_p.

Figure 6.6: Results of experiment 2: average ratio of imitation error, $\bar{R}_l$ in Eq.(6.3)

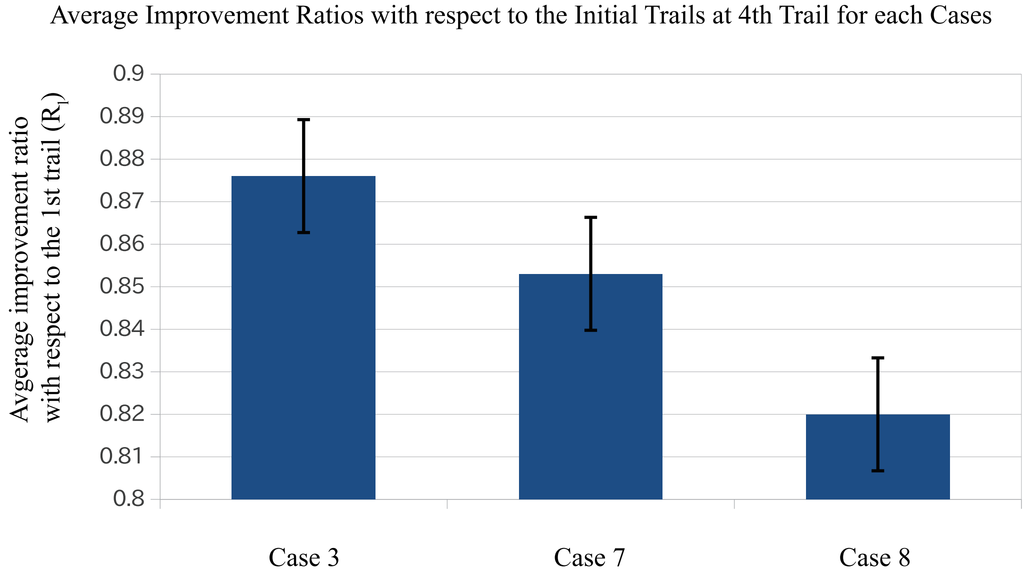

Figure 6.7: Results of experiment 2: Average improvement ratios with respect to the initial trails at 4th trail for each Cases. The average ratio of imitation error: $\bar{R}_l$ in Eq.(6.3)

Table 6.5: Tukey-Kramer Method for $p < .05$ with $\bar{R}_l$ (Eq. 6.3) in 4th trial, $l = 4$, for experiment 2. The numbers in the upper right are the Tukey-Kramer minimum significant differences (MSDs). The numbers in the lower left are the observed absolute value of the difference in means between each pair of groups, with an asterisk if it is greater than the Tukey-Kramer MSD.

-	Case 3	Case 7	Case 8
Case 3	-	0.08094	0.08094
Case 7	0.02300	-	0.07777
Case 8	0.05605	0.03305	-

6.4.4 sub-Conclusion 2

We found there was an improvement in motion learning in both Case 7 and 8 compared to that of Case 3, and found AEU-Model 2 was better than AEU-Model 1. Even though the improvements between Case 3 and 7, and Case 3 and 8 were not statistically superior, we found positive contribution of the adverbial expressions, which was changed dynamically according to AEU-Model 1 and 2.

6.5 A Future Work and Discussions

6.5.1 Integration of the Sensorimotor Patterns Estimation and the Motion Coaching System

In this section, we discuss about a robotic coaching system that coaches humans motions using emphatic motions and adverbial expressions bound to sensorimotor patterns. This way, the robotic system can refer to how motion learners should realize shift of center of gravity that cannot be observed directly and not easy to mention.

In this thesis, only the method is explained and there will be no demonstration of experiments using the robotic system with proposing method. This is partially due to lack of time for submission of this thesis. The experimental result will be demonstrated in a separate paper.

The method can be divided into 2 steps.

[Step 1]

In the first step, the robot-coach attempts to coach humans and sharing throwing motions of a medicine ball, which is a heavy and large ball used widely in sports training and rehabilitation to correct how humans move their bodies. In this step, in order for robot-coach to learn how a human-learner bind sensorimotor patterns to symbolic expressions, the robot-coach shares emphatic motions with human-learners when coaching human-learners to throw the ball as far as possible.

The system prepares and records following properties for coaching and evaluation purpose. Learning target motion in the step 1, $\boldsymbol{\theta}_t^s$, demonstrates by robot-coach. Motion performed by human-learners in the step 1, $\boldsymbol{\theta}_p^s$. Emphatic motion demonstrates by robot-coach in the step 1, $\boldsymbol{\theta}_t^s$. Learning target trajectory of shift of center of gravity demonstrated by robot-coach, $\boldsymbol{x}_{cop}^t$. Trajectory of shift of center of gravity of human-learner, $\boldsymbol{x}_{cop}^p$.

With these recorded data, performance of human learner is calculated as,

$$d_p^s = |\boldsymbol{x}_t^s - \boldsymbol{x}_p^s| \tag{6.4}$$

where $\boldsymbol{x}_t^s$ and $\boldsymbol{x}_p^s$ are static points in Proto-symbol Space, corresponding to $\boldsymbol{\theta}_t^s$ and $\boldsymbol{\theta}_p^s$ respectively.

$\boldsymbol{x}_{cop}$ are abstracted into CHMM, λ_{cop} , to define distance between $\boldsymbol{x}_{cop}^t$ and $\boldsymbol{x}_{cop}^p$ as,

$$d_{cop} = |\lambda_{cop}^t - \lambda_{cop}^p| \tag{6.5}$$

The flow of motion coaching in step 1 is as follow.

1. The coach (an agent in a virtual environment in this thesis) demonstrates motion pattern $\boldsymbol{\theta}_c^s$ as the imitation target motion $\boldsymbol{\theta}_t^s$, and an adverbial expression V_i. $\boldsymbol{\theta}_c^s$ is generated from $\boldsymbol{x}_t^s$ in the initial trial, and from $\boldsymbol{x}_s^s$ synthesized in step

5. in later trials. No V_i is used in the initial trial, but V_i is used according to the decision in step 5. in the later trials.

2. The human player imitates $\boldsymbol{\theta}_c^s$.
3. The coach observes the player's imitated motion pattern $\boldsymbol{\theta}_p^s$ and converts it to a static point $\boldsymbol{x}_p^s$ in the P,
4. The coach calculates the missing elements in the imperfect imitation of the player by $\boldsymbol{x}_t^s - \boldsymbol{x}_p^s$ and the distance d_p^s (Eq.(6.4))
5. The coach calculate the external dividing point $\boldsymbol{x}_s^s$ by adding the missing elements($\boldsymbol{x}_t^s - \boldsymbol{x}_p^s$) to the target motion($\boldsymbol{x}_t^s$).
6. $\boldsymbol{\theta}_c^s$ is generated from the $\boldsymbol{x}_c^s$, using degree of emphasis α calculated by using one of the EMU-Model in the Chapter 5. Use the point $\boldsymbol{x}_s^s$ as the $\boldsymbol{x}_c^s$, which corresponds to the re-demonstration motion pattern $\boldsymbol{\theta}_c^s$ for the next trial. The coach also decides V_i to be used in the next trail based on the AEU-Models and the d_p^s.

Repeat a loop 1-6 as needed. 1 loop is considered as 1 trial in the experiment.

[Step 2]

From the step 1, we have learned how a human-learn bind sensorimotor patterns to adverbial symbolic expressions. Here, we chose appropriate adverbial symbolic expressions V_{NB} by using the Naive Bayesian Classifier, where $d_p^s \equiv d_p$ and d_{cop} as attributes a_1 and a_2, and V as class.

$$V_{NB} = \operatorname*{argmax}_{V_j \in V} P(V_j) \prod_i P(a_i|V_i) \tag{6.6}$$

The flow of motion coaching in step 2 is as follow, denotation ^{K} is used to distinguish variables, for example tennis swing motions, from the step 1,

1. The coach (an agent in a virtual environment in this thesis) demonstrates motion pattern $\boldsymbol{\theta}_c^K$ as the imitation target motion $\boldsymbol{\theta}_t^K$, and an adverbial expression V_i. $\boldsymbol{\theta}_c^K$ is generated from $\boldsymbol{x}_t^K$ in the initial trial, and from $\boldsymbol{x}_s^K$ synthesized in step 5. in later trials. No V_i is used in the initial trial, but V_i is used according to the decision in step 5. in the later trials.

2. The human player imitates $\boldsymbol{\theta}_c^K$.

3. The coach observes the player's imitated motion pattern $\boldsymbol{\theta}_p^K$ and converts it to a static point $\boldsymbol{x}_p^K$ in the P,

4. The coach calculates the missing elements in the imperfect imitation of the player by $\boldsymbol{x}_t^K - \boldsymbol{x}_p^K$ and the distance d_p (Eq.(5.1))

5. The coach calculate the external dividing point $\boldsymbol{x}_s^K$ by adding the missing elements($\boldsymbol{x}_t^K - \boldsymbol{x}_p^K$) to the target motion($\boldsymbol{x}_t^K$).

6. $\boldsymbol{\theta}_c^K$ is generated from the $\boldsymbol{x}_c^K$, using degree of emphasis α calculated by using one of the EMU-Model in the Chapter 5. Use the point $\boldsymbol{x}_s^K$ as the $\boldsymbol{x}_c^K$, which corresponds to the re-demonstration motion pattern $\boldsymbol{\theta}_c^K$ for the next trial. The coach also decides V_i to be used in the next trail based on the calculation result of V_{NB} (Eq.(6.6))

Repeat a loop 1-6 as needed. 1 loop is considered as 1 trial in the experiment.

6.5.2 Discussion

A skilled human coach can coach motion of a body part by coaching motion of a different body part from the target portion. For example, when human chiropractors coach a human hip-extension as a rehabilitation, they touch abdominal muscle that they want patient to use for realizing a proper motion, but not to overuse the latissimus dorsi muscle. To realize this, they also use a verbal instruction mentioning a feeling of another muscle that the patient should feel while exercising. This skill is based on knowledge of human anatomy and learned from experience. Thus, introducing and using with knowledge, the proposed method and system can be extended further and applied for rehabilitation.

The motion coaching method adopted in this research is using the emphatic motion of the whole body motion. This motion coaching can be progressed into next phases where specific portion of body part, such as right/left arm and lower body, can be coached separately. This can be done by generating emphatic motions by having partial inputs, such as right/left arm and lower body, instead of having entire joint angles as input. For this purpose, we need to be sure which joints can be considered, for example, as right/left arm and lower body. Survey with shoulder, elbow joints (each has 3 DoF) will be needed to confirm what kind of emphatic motion would be generated. How to assign score for each portion needs to be considered as well, in order to have a system that can decide which part of body should be emphasized in orders.

6.6 Conclusion of the Chapter

In summary, I have realized interaction and communication so that robotic system learns models and uses the learned models to convey slight differences in motions. However, I have only realized motion coaching that emphasize entire body motion, and emphasize of portion should be studied. This can be realize by having partial set of joint angles as input, however how to classify will require some investigation. It requires model to decide which partially emphatic motion should be displayed, and model to decide when to switch to next partially emphatic motions and so on.

In this chapter, we demonstrated integration of method to estimate sensorimotor patterns from the Chapter 3, the robotic motion coaching system from the Chapter 4, and Models of emphatic motions and adverbial expressions use from Chapter 5.

Experimental results 1 demonstrated that the emphatic motions contributed for improvement in motion learning. It also demonstrated that the subject optimized α, obtained by using the EMU-Model 2, is the contribution factor.

The range of the value α, degree of emphasis, is $1.0 \geq 2.25$ for practical use in simulation. To emphasize missing elements in motion performed by learners, compared to learning a target motion performed by a coach, the lower value of the α has to be more than 1.0. If the value of the α becomes too large the emphasis would become too much and hard to recognize generated motions. It is because that too much emphasis would result in maximum angles for many joints and then the generated motions cannot be recognized as swings anymore. This consideration can be supported by experimental result 2 in which subject optimized α was decided empirically.

In the paper, there was no experiment with real humanoid robots. With use of humanoid robots, considering balancing, I assume that the maximum value for the α need to be less. Subjectively speaking, the value of *alpha* would not surpass 2.0, however, this issue is remained to be tested in experiments with real humanoid robots.

The method for motion coaching proposed in the paper would work well to learn motions with certain form. However, discussion about kind of form the method work well and kind of form the method would not work well remains to be investigated in the future.

The result from the experiment 2 demonstrated that there was an improvement in motion learning in both Case 7 and 8 compared to that of Case 3, and found AEU-Model 2 was better than AEU-Model 1. That is, the use of adverbial expressions contributed to improvement in motion learning, even though the improvements between Case 3 and 7, and Case 3 and 8 were not statistically superior, we found positive contribution of the adverbial expressions, which was changed dynamically according to AEU-Model 1 and 2.

In the section 6.5, as a next step of the future work, a method to learn binding rule between sensorimotor patterns and symbolic expression was proposed. Another method for motion coaching using the learned binding rule was proposed in this section with no demonstration of experiments using the proposed methods. Then, how the proposed method can be applied was discussed with an example of chiropractic rehabilitation, followed by a discussion of motion coaching by portion but not by whole body.

The results in the section 6.3 was partially presented in [111].

Chapter 7

Conclusion

7.1 Summary

This paper describes a stochastic framework for intelligent humanoid robots, which can cooperate and interact with humans through integration of symbolic expressions and sensorimotor patterns.

The main contributions of the research are:

1) The novel estimation method of sensorimotor patterns of others without having predefined user specific model in advance through interaction between self and other sharing motions.

2) The novel method to dynamically modify displaying motion patterns and to bind the motions with symbol expressions according to performance of human-learners, in order for conveying slight differences in motions where robotic system coaches humans motions.

3) Analysis and modeling of human-coaches' use of motions and symbolic expressions how they change them dynamically according to learners performances.

4) the demonstration of the feasibility of the robotic system that coaches humans motions, which integrated the methods proposed in step 1) and 2), and the models gained in step 3), through experiments of actual sport coaching tasks for beginners resulted in improvements in motion learning.

In the Chapter 1, using an example of ability needed for good teamwork in sports, main stream robotics researches were introduced as improvement in individual physical ability. Then, the significance of intelligent humanoid robots, especially intelligence of binding symbol expressions and unobservable sensorimotor patterns, and intelligence to estimate the sensorimotor patterns from observable motions, was discussed. These intelligence were important for establishing joint attention of unobservable with others to improve teamwork.

In the Chapter 2, related works were introduced in various fields such as neuroscience, cognitive psychology, education, sports science, rehabilitation, robotics, informatics and so on. Then, the chapter discussed and addressed challenges from the perspective of required functions for the research addressed in this thesis. After the discussion of the approach for the resolution method, the Proto-symbol Space method was introduced as a basic tool for the proposed methods in the thesis.

The Chapter 3 described a estimation method of sensorimotor patterns of others from motion observation. The approach was to bridge sensorimotor experience, or the Proto-symbol Spaces, between the self and the other. This approach would result in estimation error due to physical condition difference between the self and the other. To clear this problem, a method was proposed in order for adaptive acquisition of Proto-symbol Space of other by sharing motion patterns and using open questions asking if the other find it heavy or not. The simulation results demonstrates that it is possible to estimate sensorimotor patterns of others with 10-20% errors, even when estimation target motions are not in the database. In the second half of the chapter, a method to estimate others' symbol conversion strategy from sensor patterns was proposed. The method uses closed questions asking comparative evaluation of sets of shared motions. The simulation results demonstrated that the method can estimate the symbol conversion strategy properly by sharing prepared sets of motions and using the closed questions.

The Chapter 4 described the proposed novel method for binding emphatic motions and adverbial expressions, and for controlling degree of emphasis. This method can convey slight differences between learning target motions demonstrated by a coach and motions performed by learners. Feasibility of the method was demonstrated through experiments of actual sport coaching tasks for beginners by using a robotic coaching system. The experiments resulted in improvements in motion learning. However, it was not possible to confirm whether either emphatic motions or adverbial expressions was a contribution factor or not by having a statistically significant differences.

In the Chapter 5, experiments for modeling how human-coaches use emphatic motions and adverbial expressions were executed. In the experiments, human-coaches were asked to coach a robot-learner tennis forehand swing, by using the emphatic motions and adverbial expressions. The analysis of the results leads to the models. Adverbial Expression Use Model (AEU-Model 1 and 2) shown as Table 6.3 in chapter 5.3.3. Emphatic Motion Use Model (EMU-Model 1 and 2) shown as Eq.(5.5)(5.9) in chapter 5.3.4 and 5.3.5, and in chapter 5.4.3 respectively.

In the Chapter 6, the methods and the models were integrated. We realized integration of the method to estimate sensorimotor patterns from the Chapter 3, the robotic motion coaching system from the Chapter 4 that uses emphatic motions and adverbial expressions in order to convey slight difference in motions, and Models of emphatic motions and adverbial expressions use from Chapter 5. We demonstrated the feasibility of the robotic motion coaching system integrated with the emphatic motion use model and adverbial expression use model, by experiments of a tennis forehand swing coaching task for beginners. We confirmed that EMU-Model 2 and AEU-Model 2 contribute to improvement in motion learning. It also demonstrated that the subject optimized α, obtained by using the EMU-Model 2, is the contribution factor. We found there was an improvement in motion learning when using the AEU-Models, and found AEU-Model 2 was better than AEU-Model 1. Even though the improvements were not statistically superior, we found positive contribution of the adverbial expressions being changed dynamically according to AEU-Model 1 and 2.

Summary of what I have realized in this research: 1) Interaction and communication to estimate sensorimotor patterns of others by observing motion patterns without having user-specific model in advance, 2) interaction and communication to convey slight differences in motions by dynamically combining emphatic motions and symbolic expressions according to users' performance, 3) interaction and communication to obtain models of emphatic motion use and adverbial expression use, 4) interaction and communication so that robotic system can learn models and use the learned models to convey slight differences in motions.

7.2 Remaining Issues

Summary of remaining issues in this paper are as follow.

The proposed method to estimate sensorimotor patterns of others' is tested with simple motions only. Investigation with complex motions is needed. Quantitative study for cases, when number of DoF and configuration of joints location is different, is required.

From HAI and communication point of view, what I have not realized was interaction and communication using power of symbol communication that enable interaction even when communication protocol is unknown and when meaning/intention of motion is unknown. In this paper, the communication method adopted was fixed and users were asked to chose symbolic expressions from limited set of choice prepared in advanced. In the motion coaching, communication used by users were limited to motion only, while the robotic system communicated using motion display and symbolic expressions. The expressions used in the motion coaching was primitive and limited, and it was not able to generate sentences for coaching.

From modeling aspect, collecting data from experts is missing and need to be done as soon as possible. Then, comparison among models gained from beginners(EMU-Model 1), experts, and empirically approach(EMU-Model 2), is needed to be done. The the model (EMU-Model 1) is obtained assuming linearity, but investigation of non-linear model is required.

From motion coaching point of view, I have only realized motion coaching that emphasize entire body motion, and emphasize of portion should be studied. This can be realize by having partial set of joint angles as input, however how to classify will require some investigation. It requires model to decide which partially emphatic motion should be displayed, and model to decide when to switch to next partially emphatic motions and so on.

In the Chapter 5 Section 3, it was not able to come up with a conclusive model of emphatic motion use (EMU-Model 1). It might be partially because that the subjects were all beginner in tennis, and the beginners were asked to coach motions using emphatic motions. It is very natural to conclude that the beginners were not able to demonstrate using suitable emphatic motion especially when robot-player's motions were good in the first place. The good motions means the value d_p (Eq.(5.1)) is small. Thus, we hypothesis that there needs to be additional experiments with human-coaches who are experienced in tennis or tennis coaching.

In the paper, there was no experiment conducted with using real humanoid robots. With use of humanoid robots, considering balancing, I assume that the maximum value for the α, the degree of emphasis, should not surpass 2.0. however, this issue is remained to be investigated in experiments with real humanoid robots.

The method for motion coaching proposed in the paper would work well to learn motions with certain form. However, discussion about kind of form the method work well and kind of form the method would not work well remains to be investigated in the future.

The system proposed in this thesis is not fully automated. To verify proposing methods, we carefully excluded inevitable factors that might affect evaluation and result of the methods, and designed experimental scenarios to demonstrate effective factors by finding statistically significant differences. However, it is very natural to think that there might be new insights found with fully automated system interacting with humans real-time and dynamically learn and adjust on-line.

The research was not demonstrated using a real humanoid robots, it was partially because that there was not enough time for generation of emphatic motions with balancing considered. There were only very primitive symbolic expressions used in the research, and it was not considered as intelligent dialog.

In the research, symbolic expressions, which were used to convey slight difference in sensorimotor patterns, were just bound to emphatic motions according to the simple model (AEU-Model, Table 6.3). These binding of the symbolic expressions is far from being called language since language has two main characters of meaning and grammar. Further research is needed on language modeling aspect.

7.3 Future Works

The purpose of the coaching system introduced in this paper is not that it attempts to move proto-symbol of learners' performance to several other proto-symbols in the phase space (PSS) during a coaching task. This kind of approach can be applied when several learning target motions are prepared as sub-goals.

For example, the future coaching system could first analyze learners' swing motions and detect degree of errors in which body part has the most, the second most and so on, compared to a learning target motion. Then, the future coaching system could set several sub-goals, that is several proto-symbols in the PSS, and attempt to coach so that proto-symbol of learners' performance moves to proto-symbols in certain order and finally get close to a learning target motion. This way the work, focused on symbolic system, presented in this paper would be extended to a study of linguistic system.

The author believe that the work presented in this paper can be applied in the future to study teamwork from embodiment social interaction, engineering and constructive approach perspective. Good teamwork as a team can be defined as having both a good understanding in tactics and shared selection of strategy according to dynamic environment. How to improve the understanding and execution level of the team tactics and shared selection of strategy? Members of a team are required to share keys and share how to make decision of next actions based on the shared keys and team tactics. Sharing keys of directly observable property is called the joint attention [155][154]. However, what is needed to be discussed more is a joint attention of estimated value of unobservable property such as center of gravity. Estimation of unobservable would contribute for anticipation of intention of others, and then for establishing a better teamwork. By extending the proposed methods in the paper and with some more ideas, the author believe that this can be done.

If I consider future research addressing computational and constructive communication method for studying a good teamwork from an engineering point of view, the motion capture device might be a bottleneck that requires closed stage setting with controlled lighting. To overcome this issue, a new motion capture system, motion capture from body-mounted cameras [140] will be the motion capture of the future. This method allow us to capture motions that requires an outdoor settings. Current problem of this method is that it requires large calculation cost, so that it would take about 24 hours for processing 5 minutes motion capture clip. However, this issue will be resolved by research advancement in algorithm and computational power.

After more development, the system would be capable of interaction using more complex verbal and non-verbal expressions. Then, the robots would be able not only to coach but to learn while the robots are coaching via discussion and interaction with other humans. Being capable of having complex interaction would be an ultimate goal of the Human-Robot interaction. Then, it would open up a new learning framework for robotics that can learn while it coach, which is inspired by the Protege Effect ”While we teach, we learn” [48][22][42], In this learning framework, the robots would learn and share how to ground symbols to parameters, so that humans can understand explanation of the robots, as well as robots would learn novel parameters through interaction with humans according to tasks. This way, robots and humans can develop their abilities together.

This might then lead to a computational and constructive communication and leadership research from an engineering point of view. It would open up an opportunity for robotics research for having consumer market, whereas current robotics researches are strongly driven by industry and military demand.

Chapter 8

Publications

Journal Papers

1. 奥野敬丞, 稲邑哲也. 動作コーチングロボットにおけるデフォルメ動作と注意的言語表現のスカラーパラメータによる統合手法. 計測自動制御学会論文集 **48**(7) pp.406-412 2012 年 7 月.

Refereed Papers as the First Author

1. Keisuke Okuno and Tetsunari Inamura. Analysis and Modeling of Emphatic Motion Use and Symbolic Expression Use by Observing Humans' Motion Coaching Task -Models for Robotic Motion Coaching System-. Proc. of 21st IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN), (accepted) Sep. 2012

2. Keisuke Okuno and Tetsunari Inamura. Motion Coaching with Emphatic Motions and Adverbial Expressions for Human beings by Robotic System -Method for Controlling Motions and Expressions with Sole Parameter-. Proc. of IEEE/RSJ International Conference on Intelligent Robots and Systems pp. 3381-3386 Sep. 2011.

3. 奥野敬丞, 稲邑哲也. デフォルメ動作と言語注意を使用したロボットシステムによる動作コーチングの研究－ミメシスモデルによるコーチングの定量的・定

性的評価の実現ー．第 16 回ロボティクスシンポジア予稿集 pp. 436-411 2011 年 3 月.

4. 奥野敬丞，稲邑哲也．動作模倣と対話に基づく他者感覚パターンの推定に関する研究 相対評価型質問による感覚パターンのシンボル化戦略の特定．第 15 回ロボティクスシンポジア予稿集 pp. 52-57 2010 年 3 月.
5. Keisuke Okuno and Tetsunari Inamura. Estimation of other 's sensor patterns based on motion imitation and communication. Proc. of International Symposium on Artificial Life and Robotics pp. 893-897 Feb. 2010.
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Refereed Papers as non-First Author

1. Tetsunari Inamura and Keisuke Okuno. Robotic Motion Coach: Effect of Motion Emphasis and Verbal Expression for Imitation Learning. Proc. of the 3rd International Conference on Cognitive Neurodynamics, June 2011.
2. 稲邑哲也, 奥野敬丞. 感覚運動情報のシンボル化と強調動作提示法に基づくコーチングロボット．信学技報 HIP2010(82) pp.17-22 2011 年 3 月.
3. Tetsunari Inamura and Keisuke Okuno. Estimation of other's sensory patterns based on dialogue and shared motion experiences. Proc. of IEEE/RAS International Conference on Humanoid Robots, pp. 617-623, 12 2009.
4. Ngoc Hung Pham, Kim Khanh Nguyen, Cabanillas Aurelien, Keisuke Okuno, Ohhoon Kwon and Tetsunari Inamura Generating motions for humanoid robots using a motion capture system in real time Proc. of IEEE RIVF International

Conference on Computing and Communication Technologies, Research, Innovation, and Vision for the Future, 10 2010

5. 稲邑哲也，奥野敬丞. ヒューマノイド間の対話に基づくミメシスモデルの適応的獲得. 第 14 回ロボティクスシンポジア予稿集 393-398 2009 年 3 月.

non-Refereed Papers as the First Author

1. 奥野敬丞，稲邑哲也. 動作コーチングにおける手本動作の強調と言語的注意表現の統合に関する分析とモデル化 2012 年度人工知能学会全国大会（第 26 回） 3O2-OS-3b-10 2012 年 6 月.

2. 奥野敬丞，稲邑哲也. デフォルメ動作と注意的言語表現を用いて人間の動作をコーチングするロボットシステムの研究 -デフォルメ度合いと言語表現の個人適応に関する考察-. 2011 年度人工知能学会全国大会（第 25 回） 3D2-OS8-5 2011 年 6 月.

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4. Keisuke Okuno and Tetsunari Inamura. A Research on Motion Coaching for Human Beings by a Robotics System that uses Emphatic Motion and Verbal Attention – Qualitative and Quantitative Evaluation by Applying the Mimesis Model–. IEEE/RAS Humanoids 2010 Workshop on Humanoid Robots Learning from Human Interaction Dec. 2010.

5. 奥野敬丞，稲邑哲也. ミメシスモデルを用いたデフォルメ動作提示と言語コミュニケーションによって人間をコーチするロボットシステムの研究. 第 28 回日本ロボット学会学術講演会予稿集 2010 年 9 月.

6. 奥野敬丞，稲邑哲也．運動から感覚を推定可能なプリミティブ表現とコミュニケーションに基づく動作コーチング．包括型脳科学研究推進支援ネットワーク夏のワークショップ 2010 2010 年 8 月.

7. 奥野敬丞，稲邑哲也．シンボルコミュニケーションに基づく他者の感覚運動情報の推定〜感覚運動情報のシンボル化戦略の獲得に関する考察〜．日本機械学会ロボティクス・メカトロニクス講演会 2009 予稿集 2A1-A21 2009 年 5 月.

8. 奥野敬丞，稲邑哲也．言語コミュニケーションに基づく他者の感覚運動情報の推定モデルの適応的獲得．第 9 回計測自動制御学会システムインテグレーション部門講演会予稿集 3-4 2008 年 12 月.

non-Refereed Papers as non-First Author

1. 稲邑哲也，奥野敬丞．原始シンボル表現を用いた動作のデフォルメ提示による動作コーチング．人工知能学会全国大会 (第 24 回) 予稿集 2010 年 6 月.

2. 稲邑哲也，奥野敬丞．他者の感覚運動情報の推定のためのシンボルコミュニケーション．第 23 回人工知能学会全国大会論文集 1F2-OS7-10- 2009 年 6 月.

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