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学 位 記 番 号	総研大甲第 1968 号
学位授与の日付	平成29年9月28日
学位授与の要件	複合科学研究科　統計科学専攻 学位規則第6条第1項該当
学 位 論 文 題 目	Adaptive Nonlinear Kalman Filters for Non-stationary Observation Errors
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(別紙様式 2)
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論文の要旨

Summary (Abstract) of doctoral thesis contents

This thesis concerns an adaptive treatment of an observation error model used in nonlinear Kalman filtering methods to increase accuracy of state estimation and usability.

Filtering for estimating an unobserved system state from the observations using a state-space model (SSM) is one of the most important data analytical techniques in engineering. An SSM consists of a system model that defines time-evolution of the system state and an observation model that defines how the state is observed. With the two models, the technique predicts a next observation and correct the estimate of the state based on the prediction error of an obtained observation, which is referred to as innovation, alternately. There are a number of applications of filtering: for examples, position tracking for mobile navigation, state estimation for feedback control, system identification for simulation or optimization, and so on.

The Kalman filter (KF) is one of the fundamental algorithms for a linear Gaussian SSM. The original KF have been proposed as the minimum variance estimator for the system state using the orthogonal projection. It is also known to a sequential Bayesian estimator of the posterior distribution, which is referred to as the filtered distribution in this context. The algorithm of the KF can be expressed with basic linear algebra concept and is easy to implement. This is the reason why the KF is widely applied in actual applications.

Recently, derivative-free Kalman filters that can deal with nonlinear SSMs have received considerable attentions of practitioners. The unscented Kalman filter (UKF) [1] uses the sigma points, which are temporarily and deterministically drawn samples from a distribution to be transformed. The UKF performs nonlinear calculus for each of the sigma points and approximates the nonlinearly transformed distribution with the points. The ensemble Kalman filter (EnKF) [2,3] is a filtering method originated in geophysics, which handles a very large problem with, sometimes, more than a million variables in the state. The EnKF use an ensemble-based distribution, which consists of a finite number of samples, for the state vector to deal with nonlinearity.

In such Kalman filtering methods, one has to specify a SSM typically consisting of a transition function, a model error, an observation function, and an observation error. Of course, although appropriate design of each building block of the SSM is crucial for filtering, we focus on the observation error.

Design of the observation error, that is, what kind of a probabilistic model is assumed for the observation error is directly connected to the performance of filtering. For an observation error model with small variance, that is, assuming low uncertainty for observation, state estimation will be performed to mimic observations as possible. In this case, if observations are actually uncertain, state estimation will

be biased as a result of over-fitting to observations. While, for an observation error model with large variance, that is, assuming high uncertainty for observation, the observations might be neglected in the state estimation. If observations are actually certain, under-fitting to observations will happen.

However, since there are essential unknowns in characteristics of the observation error, the design is not trivial task. To discuss in depth, we decompose the observation error on the basis of the concept of representativeness error [4]. The observation error can be regarded as consisting of two kinds of errors: one is referred to as a measurement error, and another is referred to as a representativeness error.

The measurement error comes from an uncertainty of measurement instruments. The sources are, for example, precision of calibration curve, noises in transmission, quantization error of AD converter, and so on. To know the statistics, a specification including the precision provided by manufacturers of measurement instruments is helpful. However, there are cases where self-build or experimental instruments, whose specifications are inaccurate, are installed.

While, the representativeness error originates from deviation between an assumed SSM and an ideal SSM, and thus the characteristics is inherently unknown. It is because a system model and an observation function are usually developed from partial but best-effort understanding of the target system.

So far, although we have discussed the difficulties in designing a model for the observation error from the stationary characteristics, there are mainly two other difficulties related to the non-stationary characteristics of the observation error: one is the long-term temporal change, and another is the impulsive change.

For the long-term temporal change of characteristics, in the case of the measurement error, the sources could be deterioration or maintenance of measurement instruments. For example, the deterioration of a measurement instruments increases the error scale in general. In the case of the representativeness error, the source could be increase of the discrepancy of the assumed SSM on a particular time or spatial region. For example, if an empirical model identified with experimental data is incorporated in a system model, the precision might be deteriorated in extrapolation.

For the impulsive change of characteristics, the problem of outliers is known. Outliers are unexpectedly gross observation error, which are unpredictably present. Appearance of outliers is very common in actual systems. There are variety of the sources: e.g., a large disturbance to the target system, temporal malfunction of measurement instruments, human error in data manipulation, and so on. Especially, for a Gaussian observation error model, which is often assumed in actual applications, it is well known that the outliers severely decrease the accuracy of the state estimation [5].

It is natural that the observation error model is hard to develop due to unknowns in both stationary and non-stationary characteristics. If there is discrepancy between an assumed model and the actual behavior of the observation error, the accuracy of state estimation in filtering is severely decreased. Therefore, we have studied adaptive filtering methods for the observation errors.

We have addressed the theme from two points of views: one is the case for the long-term temporal change of characteristics of the observation error, and another is the case for the impulsive change of the characteristics. In this thesis, we presents two methods for these cases. The key idea of the methods is to use an adaptive observation error model, which includes time-indexed parameters, and estimate the parameters in filtering at each time step. The enabler is the variational Bayes method which approximates the joint filtered distribution of the state vector and the time-index parameters with another tractable distribution. We have examined the methods in several numerical experiments and found that the methods can improve the accuracy of state estimation as a result of appropriately handling the observation errors. The presented methods are expected to contribute to increase the value of the applications of filtering.

References:

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(別紙様式 3)
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博士論文審査結果の要旨

Summary of the results of the doctoral thesis screening

中林暁男氏の博士論文審査を，2017 年 8 月 25 日午後 4 時から約 2 時間にわたって，本人と 5 名の委員全員の出席のもとに行い，論文発表会および審査のための会議を行った．

提出された論文は本文 5 章と付録を合わせて 83 頁からなり，英語で執筆されている．状態空間モデルにおける観測ノイズに注目し，その確率分布のパラメータとして，最適な分散共分散行列を推定する方法を提案する研究である．ノイズの性質に時間変化が見られる場合，外れ値のようなノイズが見られる場合を想定して，分散共分散行列に時変性を持たせてモデリングすることが一貫したテーマである．

第 1 章では，非線形フィルタの利用の観点から，観測ノイズのパラメータの適応的な推定が望ましいという研究動機が述べられると同時に，先行研究のレビューが述べられている．第 2 章では，基本的な時系列フィルタ手法の紹介，および本論文でのパラメータ推定において中心的な役割を果たす変分ベイズ法を紹介する一方，潜在変数の事後分布が独立としてその積で同時フィルタ分布を近似することが推定結果に及ぼす影響も分析している．第 3 章と第 4 章が主たる研究成果に充てられている．第 3 章では，観測ノイズの性質が時間変化する場合を想定して，状態変数と観測ノイズ分散共分散行列をまとめた確率変数を考え，その同時分布に関する逐次フィルタ手法を提案している．第 4 章では，観測データに外れ値が入る場合を想定して，状態変数・外れ値の指標・外れ値の大きさの尺度の 3 変数をまとめ,同時分布に関する逐次フィルタ手法を提案している.いずれの章においても，試験的な問題設定を用いて，先行研究にあるフィルタ手法と比較し，推定精度に関する優位性を示している．第 5 章は，本研究の要旨と結論にあてられている．

状態空間モデルにおけるシステムノイズ，観測ノイズなどのノイズの分散共分散行列は，フィルタリングの実施に先立ってその値を与える必要があり，その設定値に状態推定値が大きく依存するという重要なパラメータであり，いわゆる正則化のパラメータにあたる．しかし，観測ノイズの性質が時間的に変化する状況においては，そのパラメータの設定に関しては汎用的に有効な方法は知られていない．出願者は分散共分散行列を観測データに適応的に，各時刻の状態変数と同時に推定する方法を提案し，精度のよいフィルタリングを可能にした．パラメータの事前設定と試行錯誤が不要になり，非線形フィルタを用いた実務者への利便性を提供できる，という点で評価できる．なお，論文の第 3 章は，査読付英文学術誌 Monthly Weather Review 誌 145 巻 199-213 頁(2017 年)に掲載済みである．

総合研究大学院大学複合科学研究科における課程博士及び修士の学位の学位授与に係る論文審査等の手続き等に関する規程第10条に基づいて，口述による試験を実施した．その結果，出願者はその博士論文を中心としてそれに関連がある専門分野，その基礎となる分野および英語の能力について博士（統計科学）の学位の授与に十分な学識を有するものと判断し，合格と判定した．