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Adaptive Sliding Kalman Filter using Nonparametric Change Point Detection

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ABSTRACT

This paper aims to develop an Adaptive Sliding Kalman Filter (ASKF) by fusing the concept of change detection in a data stream, adapting noise covariance matrices and the Sliding Kalman filter (SKF). Adaptive Kalman filtering (AKF) scheme modifies the noise covariance matrix (Q and R) value based on a window of past innovation sequence whereas SKF is a window based filtering technique which uses past information to obtain the present state estimate. However, the length of the window chosen for SKF and AKF is arbitrary and a scheme has been devised here to adapt this window length according to the data stream statistics. The change detection scheme chosen here does not make any assumption on the data distribution and is sequential in nature, such that a change is triggered whenever the underlying statistics of data crosses a pre-determined threshold. The key contribution of this work is toward the formulation of a mechanism by which the window length is made adaptive such that whenever a change is detected, the window length for SKF and AKF is curtailed and restarted in an oscillatory windowing fashion. The suggested filter is robust against temporary uncertainties and appropriate for reliable estimation of signals that may arise in many engineering areas. Real world experimental results demonstrate better estimation accuracy of the proposed method than that of others.

1. Introduction

Optimal state estimation for a nonlinear system is a widely studied area applied in different engineering problems [1]. Among the several available forms, Extended Kalman Filter (EKF), Unscented Kalman Filter (UKF), and Particle Filter are few of the most extensively used techniques for state estimation [2]. These algorithms are optimal under certain assumptions and their output depends on the noise co-variance matrices of process and measurement model. A wrong selection of these parameters would lead to filter divergence and huge error in predicted states [3]. A few researchers tried to tune these parameters (Q and R) offline using optimization technique, which is then used in Kalman Filter (KF) framework [4]. However, these values tend to change over time owing to the inherent changing bias and other errors within the sensors. This, thus necessitated researchers to develop techniques which can adapt the Q and R value on its own depending on the past error statistics [5].

These adaptive techniques are basically divided into two categories: (a) Innovation Adaptive Estimation (IAE), and (b) Multiple Model Adaptive Estimation (MMAE). IAE is an adaptive filtering scheme which uses Kalman Filter with an in built framework to adapt the noise covariance matrices (Q and R) at each instance. [6]. The MMAE approach instead uses a bank of Kalman filters running in parallel (with different Q and R) to provide a weighted

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sum of their outputs and is computationally complex [7]. Thus, the IAE approach became comparatively more popular owing to its real time implement-ability and in-run Q and R adaptation. IAE approach, however, requires a window of past residual/ innovation sequence to compute the practical covariance whose length is chosen arbitrarily. These adaptive Kalman filter incorporates current measurement to update the current estimate, whereas the sliding window Kalman filter incorporates a window of past measurements to estimate the current state.

Sliding Kalman filter (SKF) is a window based filtering technique which takes advantage of the past information to obtain the best possible next state estimate [8]. The sliding window concept is not new and has been utilized in the fixed lag smoothers wherein the past information is utilized along with the future measurements to provide a better estimate of the current state [9]. The sliding mode estimator discussed in this paper is slightly different than the smoother framework as it does not incorporate the future measurements for estimating current state [10]. The concept of sliding Kalman filter has been used successfully in different frameworks varying from Visual Odometry to Simultaneous Localization and Mapping (SLAM) framework [11]. The sliding Kalman filter removes the oldest state from the sliding window as the filter moves to the next state, maintaining a constant computational resource requirement. However, a major limitation of SKF is that the length of the window (w) chosen for discarding old states is not optimal. There are both pros and cons of selecting a large or small sliding window size. A small window length is preferred for rapidly changing data, causing slow changes in the data to be ignored, whereas a large window size is preferred for slow changing data, ignoring rapid changes in data to effect current states. In order to overcome this problem of inappropriate window size selection, it is proposed here to adapt the window length on the basis of varying sequential data statistics.

Si and Mourikis discussed the concept of sliding window filter for the task of Visual Odometry and motion estimation of a mobile robot [12,13]. It marginalizes old states on the basis of a cost function minimization. The sliding Kalman filter with only one previous state being maintained in the window is an equivalent of an Extended Kalman filter. Sibley et al. applied the SKF scheme in a SLAM framework for applications related to planetary landing, employing optimization scheme to an estimation problem [14].

This paper presents the idea of utilizing Change Point Monitoring (CPM) scheme for maintaining a sliding window of varying length for the estimation problem. This work is inspired by the works of Bifet et al. which employed batch data processing for adapting the Q and R values empirically [15,16]. The main aim of this paper is to contribute toward an approach for adapting the window length of an SKF on the basis of online change point detection in the data stream and apply adaptive Kalman filter for a window with data points until the last change. This framework provides convenient delineation between change point detection for non-parametric sequential data stream and the implementation of an estimation algorithm. The modular approach allows pluggable type integration of different object oriented codes in one flow as presented in the following sections.

2. Theoretical formulation of change point monitoring

Change Point Detection (CPD) in a time series is an art of finding the point when the statistical property of an underlying process changes [17]. Change detection in data stream has a wide application in different fields such as fraud detection, market analysis, medical condition monitoring and quality control of continuous production processes [18]. For a given sequence of observations $x_1, x_2, \ldots x_n$, which is generally assumed to be independent and identically distributed (*i. i. d.*) with some probability distribution, the change point detection is hypothesized as [19]:

H0: Previously seen values are generated from the same distribution as the current ones.

H1: Current observations are generated from a different distribution as compared to the previously seen values.

CPD techniques can be categorized into parametric and non-parametric types, depending on whether the data distribution is known *apriori* or not, respectively. The non-parametric methods for CPD is more widely used and considered here, as the data processed in real time generically do not follow a specific distribution [20].

These schemes monitor a particular statistical parameter like the mean or variance of last few observations in the incoming data stream and trigger a change when this parameter crosses a pre-determined threshold. The thresholds are either computed in run-time on the basis of a past data window or are obtained from the pre-existing control chart. Among the various available CPD schemes, control chart has gained popularity owing to its ease of use and fast responsiveness at a controlled false alarm rate. Some of the classical examples of parametric CPD schemes to detect changes online are Shewarts, Exponentially Weighted Moving Average (EWMA) and Page's Cumulative Sum (CUSUM) control chart [20,21]. However, being parametric, these techniques suffer from the disadvantage of requiring in-control process parameters which are not always known exactly [22].

The CPD techniques further not only aim at a testing task, but an estimation task as well, i.e., to estimate τ, the time at which the change occurred. These specific techniques are termed as Change Point Monitoring (CPM) schemes and are formulated in two ways: Phase I and Phase II. The Phase I CPM techniques processes data in a batch, waiting for a relatively large data length to be accumulated before applying CPM. The Phase II techniques process readings subsequently, waiting for a marginal data sequence to be available before applying CPM on it. The Phase I and II techniques are also called as Batch processing and Sequential Processing with a general waiting period of 200 and 15 data points respectively. Though there have been several improvements in Phase I CPM techniques as seen in various papers, such as Sen and