Adaptive Techniques for Kalman Filter Estimation based on Multibody Models

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EXTENDED ABSTRACT

1 Introduction

Estimation techniques have become a useful method for increasing the available information of a particular system. From a reduced set of sensors and a model of the system, not-sensed variables can be estimated. In most cases, the estimator belongs to Kalman filter family. The filter corrects the possible drift between model and real system based on a reduced set of sensor measurements.

The Kalman filter assumes that the system is linear and that the noises of the measurements and the system are gaussian white noise and with known statistical properties. None of these assumptions are usually fulfilled in real applications: most systems are non-linear and their statistical properties are hard to obtain. This is the case when a multibody model is employed to represent the system. To deal with non-linear systems, several filters have been proposed [1]. From them, the error extended Kalman filter (errorEKF) stands out as one of the best in terms of accuracy and efficiency [2]. The determination of the statistics of the sensors and system (also known as covariance noise matrices) is typically based on a trial-and-error procedure. However, it is important to have knowledge on the statistics, since wrong values can be turned into estimation errors and divergence issues.

As a solution to this difficulty, Adaptive Kalman filters (AKF) are proposed. The most popular approaches rely on the innovation sequence of the filter, that is, the difference between the real and estimated measurements. From the Kalman filter theory, for the true value of the covariance noise matrices, the innovation sequence must be white noise. Based on the previous principle, several methods have been developed such as the maximum likelihood estimation [3], Sage-Husa filter [4] or variational Bayesian estimation [5]. The maximum likelihood looks for the covariance matrices which result in the maximum probability of observing a certain innovation sequence. The Sage-Husa filter is based on the maximum a posterior principle, which is similar to find the maximum likelihood weighting the most recent estimations. The variational Bayesian, instead of giving a unique value for the matrices, estimates a probability density function.

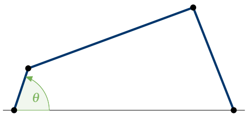
From the previous methods, only the maximum likelihood has proven to be capable of estimating the measurement noise covariance matrix (MNCM) and process (system) noise covariance matrix (PNCM). Although Sage-Husa filter can theoretically estimate both matrices, it has shown stability issues when both matrices are estimated at the same time. With respect to the variational Bayesian, it is only used for estimating the MNCM, since it assumes that the PNCM is known. This constitutes an important limitation, since an acceptable value of the MNCM can be obtained from the manufacturer of the sensors. Meanwhile, it is difficult to be certain with any initial guessing of the PNCM.

Adaptive Kalman filters are traditionally employed in navigation problems. Hence, it is necessary to address its combination for multibody-based state estimation and evaluate its performance. Due to the a priori benefits of the maximum likelihood, this work presents an extended Kalman filter combined with the maximum likelihood approach for estimating the covariance noise matrices.

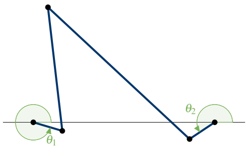
2 Methodology

The performance of the proposed filter is evaluated in terms of robustness and accuracy. For that purpose, two mechanisms are modeled: a four-bar linkage (Figure 1a) and a five-bar linkage (Figure 1b). Each mechanism is modeled in natural coordinates and using the augmented Lagrangian of index-3 (ALI3P) [6] as formulation to solve the motion of the mechanism. Since all the tests are performed in a simulation environment, three multibody models are employed. The first one is considered as the *real mechanism*. The sensor measurements are obtained from this model. The second multibody model acts as a *model* of the *real mechanism*. In order to replicate a real situation, modeling errors are introduced. Finally, the third model is the *model* combined with the proposed filter, which would correct the errors based on the information provided by the measurements taken from the *real mechanism*.

The accuracy of the filter is evaluated through a batch of tests with different initial values of the covariance noise matrices. The filter is expected to estimate an adequate value of the covariance noise matrices and lead to a solution with the same magnitude of error with independence of the initial covariance values. During these tests, the mechanism is only affected by the gravity force. To asses the robustness of the filter, a torsional spring is added to the crank. After some seconds, the spring breaks simulating a failure on a real machine. The filter should re-adapt its estimation on the covariance matrices to the new scenario in order to keep the accuracy on the estimations.



(a) Four-bar linkage.



(b) Five-bar linkage.

Figure 1: Mechanisms employed in this work.

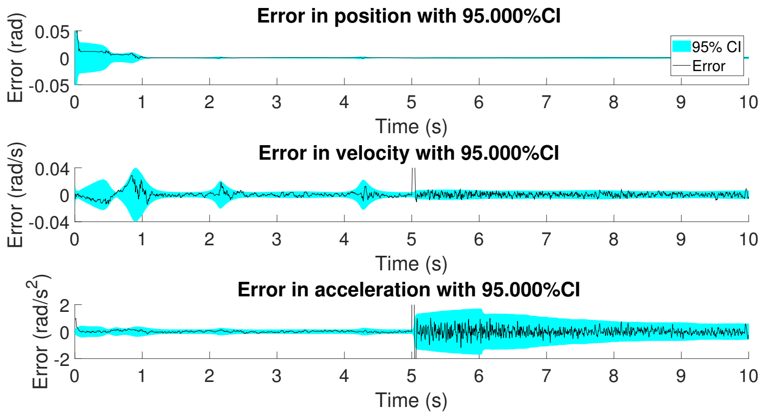


Figure 2: Error and confidence interval of the position, velocity and acceleration of the crank angle in the four-bar linkage during the robustness test.

3 Results

The results show that the proposed filter can be used to estimate the values of the process noise covariance matrix. However, the algorithm showed divergence issues when estimating also the measurement noise covariance matrix in some scenarios. Nevertheless, the estimation of the MNCM did not improve the accuracy of the state estimation.

Regarding the accuracy, the proposed filter converged to a solution which minimizes the error of the estimations with independence of the assumptions for the initial covariance matrices. With respect to the robustness, it showed to provide accurate estimations even with unexpected changes in the real system, tracking the effects of the new scenario quickly.

These conclusions can be extracted from Figure 2, where it can be seen how the confidence interval becomes wider when the spring breaks, keeping the error in the estimations under a confidence interval of 95%, showing accuracy and reliability in the estimations. It means that when the AerrorEKF-FE detects the new scenario, it increases the values of the PNCM giving more relevance to the sensor measurements in order to track the new state of the system. Once that the *observer* tracks the new scenario of the *real mechanism*, the covariances are reduced.

However, the computational cost of the proposed adaptive filter is higher than the errorEKF-FE. The additional cost of estimating the process noise covariance matrix implies that the filter requires about the double of time per time-step to perform the estimations.

Finally, this work shows the benefits of adaptive Kalman filtering based on multibody models. In most applications, the process noise covariance matrix can not be known and, hence, the accuracy and stability of the filter is compromised. With adaptive methods, the process noise covariance matrix can be estimated increasing the accuracy and robustness of the estimator.

Acknowledgments

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