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Kalman filter for mobile-robot attitude estimation: Novel optimized and adaptive solutions

Ákos Odry [a,*], Róbert Fullér [b,c], Imre J. Rudas [b,d], Péter Odry [a]

[a] Department of Control Engineering and Information Technology, University of Dunaújváros, Dunaújváros, Hungary
[b] Institute of Applied Mathematics, Óbuda University, Budapest, Hungary
[c] Department of Informatics, Széchenyi István University, Győr, Hungary
[d] University Research, Innovation and Service Center, Óbuda University, Budapest, Hungary

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ABSTRACT

This paper proposes two novel approaches to estimate accurately mobile robot attitudes based on the fusion of low-cost accelerometers and gyroscopes. The first part of the paper demonstrates the use of a special test bench that both enables simulations of various dynamic behaviors of wheeled robots and measures their real attitude angles along with the raw sensor data. These measurements are applied in a simulation environment and we outline an offline optimization of Kalman filter parameters. The second part of the paper introduces a novel adaptive Kalman filter structure that modifies the noise covariance values according to the system dynamics. The instantaneous dynamics are characterized regarding the magnitudes of both the instantaneous vibration and the external acceleration. The proposed adaptive solution measures these magnitudes and utilizes fuzzy-logic to modify the filter parameters in real time. The results show that the adaptive filter improves the overall filter convergence by a remarkable 10.9% over using the optimized Kalman filter, thereby demonstrating its efficacy as an accurate and robust attitude filter. The proposed filter performances are also benchmarked against other common methods indicating that the flexibility of the developed adaptive filter allowed it to compete and even outperform the benchmark filters.

1. Introduction

1.1. Attitude estimation

Micro-electro-mechanical systems (MEMS), such as gyroscopes and accelerometers, are characterized by low costs, low power consumptions, and small sizes, which make them popular candidates for implementation in embedded systems. These sensors are generally applied to solve the relative localization problem, where the positions and orientation information of moving objects are determined using a MEMS-based inertial measurement unit (IMU) composed of the aforementioned MEMS sensors. The MEMS-based localization approach has been widely investigated and is widely utilized in robotics [1–7], human position tracking [8,9], medical fields [10], sports equipment [11,12], and automated driving [13–17] both in industry and in scientific research. Independent of the specific application, it is always advantageous to

* Corresponding author at: University of Dunaújváros, Táncsics Mihály u. 1, 2400 Dunaújváros, Hungary.
E-mail addresses: odrya@uniduna.hu (Á. Odry), fuller.robert@nik.uni-obuda.hu (R. Fullér), rudas@uni-obuda.hu (I.J. Rudas), podry@uniduna.hu (P. Odry).

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combine the accelerometer and gyroscope sensors, utilizing their individual features to provide accurate and robust orientation results.

Gyroscopes measure angular rates. Therefore, the orientation of a moving object can be obtained via numerical integration. However, the output of an MEMS gyroscope contains both temperature dependent bias and noise, which inevitably cause cumulative errors (boundless drift). This error renders attitude calculation unviable, especially for long-term measurements. Accelerometers provide measurements that are complementary to the angular rate measurements. These sensors can be used as inclinometers, providing accurate orientation results even over long periods. However, accelerometers only produce reliable orientation-related sensor data when they are in stationary states (there is no external acceleration or vibration). This means that the decomposition of the pure gravity vector can be used to determine the orientation. Conversely, in a dynamic situation, the external acceleration cannot be distinguished from the gravity vector. Therefore, the effects of external acceleration drastically decrease the reliability of accelerometer-based orientation calculation.

Due to the aforementioned difficulties, various sensor fusion techniques that combine gyro-based high frequency attitude estimation with the rough, low-frequency attitude correction (drift cancellation) provided by the accelerometer have been developed. Among these sensor fusion techniques, the Kalman filter (KF) and its variant for nonlinear cases, the extended KF (EKF), are among the solutions most often applied to MEMS-IMU based attitude estimation. These algorithms are recursive, optimal state estimators under the minimum mean square error (MMSE) criterion for Gaussian stochastic dynamic systems. In this paper the authors investigate state estimation, based on signals corrupted by Gaussian noises. Therefore, the paragraphs below offer a detailed discussion of the techniques applied for performance enhancement of (E) KF-based state estimation, but for the sake of comprehensiveness, the penultimate paragraph briefly mentions the so-called maximum correntropy filtering, developed recently for state estimation of non-Gaussian stochastic systems.

The KF produces an optimal filter performance, if the characteristics of the modeled noise in the Gaussian stochastic system are known completely (and modeled by candidate noise covariance values). However, in most cases the noise statistics of the analyzed state space model cannot be determined. This is an even more critical problem for MEMS-IMU based orientation calculations of moving objects, since neither the external accelerations nor vibrations are deterministic, resulting in radical measurement noise that cannot be modeled appropriately. Therefore, the covariance matrices are usually selected on an ad hoc basis via time-consuming trial-and-error procedures performed based on engineering intuition. This iterative process represents a compromise between the accuracy and filter dynamics in which the ultimately determined noise covariance values both roughly describe the measurement noise and cover the model approximations.

To overcome the difficulties related to trial-and-error tuning and to achieve superior filter performances, there are two common approaches in the literature. On the one hand, the filter convergence can be enhanced by numerical optimization (usually performed offline). To optimize, an environment is created (with the assistance of other sensors or filters) in which the true state can be measured along with the IMU data. By evaluating the performance index, the KF noise covariance values are tuned with an optimization algorithm. This procedure, along with the application of the downhill simplex algorithm, is explained in detail through various theoretical examples in [18]. Similarly, a neural-network based approach to tuning the noise statistics was investigated in [19]. Kownacki [20] dealt with the filtration of accelerometer and gyroscope signals. Separate KFs were designed and tuned based on the assumption that the sensors were in stationary states (no external acceleration was present). The noise covariance values were tuned with the simplex search method through the minimization of a defined cost function. The differential evolution [21] and genetic algorithms (GAs) [22] have also been applied to the optimization of extended KF (EKF) covariance matrices.

Other filter performance enhancement techniques tune the KF matrix covariance values adaptively, usually based on the magnitude of external (dynamic) acceleration. The dynamic acceleration is defined as the difference between the magnitudes of the accelerometer reading and the gravity vector. In both [23,24], an EKF with the aforementioned adaptation technique was proposed for a miniature attitude and heading reference system (AHRS) in which different measurement noise variances are taken into account based on the identified stationary-, low-, and high-acceleration modes (i.e., threshold-based switching of covariance matrices). A similar adaptation approach to estimating lower trunk orientations was investigated by Mazza et al. [8]. Moreover, both the threshold levels and the noise statistics were optimized using the PatternSearch algorithm. Suh [7] describes an adaptive KF solution for preventing vibrations from affecting the attitude estimations of unmanned aerial vehicles (UAVs), whereas Jurman et al. [25] proposed adaptation laws for both the process and measurement noise covariance values. Lee et al. [26] investigated an acceleration-model based approach to attitude estimation in which the dynamic acceleration is also estimated and utilized to compensate for the external acceleration in the attitude determination process. Furthermore, this approach was compared with the threshold-based switching technique, but it did not demonstrate significant improvements in estimation accuracy over the threshold-based technique. Goślinski et al. [27] proposed an adaptive KF for estimating human body orientation during walking based on the data acquired from inertial sensors of a present-day smartphone. In the adaptation law, the noise covariance matrix was modified based on the variance of input signal, moreover, the upper and lower bounds of covariance values were determined with the aid of optimization. The proposed filtering technique was benchmarked against the Android OS estimation algorithm and a complementary filter consisting of first order low-pass and high-pass filters [28].

It is worth mentioning that the estimation performance of KF is likely to deteriorate considerably, if signals are corrupted by non-Gaussian impulsive noises [29]. The maximum correntropy KF (MCKF) and its constrained state estimator variant (MCKF-SC) efficiently estimate the states of a non-Gaussian stochastic system by using the maximum correntropy criterion (MCC) instead of the MMSE in the development of filter equations [30,31]. Additionally, an improved MCKF and its