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Bias estimation for asynchronous multi-rate multi-sensor fusion with unknown inputs

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ABSTRACT

In asynchronous multi-sensor fusion, it is hard to guarantee that all sensors work at the single sampling rate, especially in the distributive and heterogeneous case. Meanwhile, the time-varying sensor bias driven by unknown inputs (UIs) are likely to occur in complex environments when conducting the sensor registration. In this paper, a two-stage fusion scheme is proposed to estimate the state, the UI and the UI-driven bias for asynchronous multi-sensor fusion. By establishing the dynamic system model at each scale and deriving its corresponding equivalent UI-decoupled bias dynamic model, the proposed scheme is implemented in two stages. At the first stage, each sensor collects its own measurements and generates the local optimal estimates of the state and the bias which are later used to compute the local estimate of the UI via the least squares method. At the second stage, local estimates of the state and the UI are distributively fused via network consensus to obtain the consensus state and UI estimates which are fed back to refine the local bias estimate. Local estimators are designed via the orthogonal projection principle and the least squares method, and the fusion estimators are designed via the average consensus fusion rule weighted by matrices. Simulation experiments are given to show the effectiveness of the developed method.

1. Introduction

Multi-sensor data fusion refers to the process of effectively combining data from multiple homogeneous or heterogeneous sensors. Up to now, the multi-sensor data fusion technique has been applied in a variety of fields such as target tracking, traffic control, health monitoring and body sensor/area networks. Among them, the data fusion in body sensor/area networks appears to be quite interesting and promising due to the rapid development of low-cost micro-sensor devices and the necessity for the real-time monitoring of the patients' physical conditions, see e.g. [1,2] and the references therein. An important and practical problem for multi-sensor data fusion systems is to find an optimal state estimate based on the given measurements. Meanwhile, in multi-sensor systems, it is often unrealistic to guarantee that all sensors operate at one common rate. For example, for signals with different bandwidths, better trade-offs between performance and implementation cost can be obtained using A/D and D/A converters at different rates. On the other hand, for processed/estimated quantities, sometimes users may specify rates which are different from the sampling rates of sensors. Therefore, a great deal of attention has been paid to the issue on multi-rate multi-sensor data fusion arises in the past decades [3].

State estimation with multi-rate sensors was first proposed by Andiusani and Gau [4]. In their strategy the dynamic system was decomposed into dual subsystems corresponding to the dual-rate sensors and the filtering residual of one Kalman filter for the fast-rate subsystem was fused with the estimate of the other Kalman filter for the slow-rate subsystem. By adopting the Haar wavelet [5] or the compactly supported wavelet [6] as a linear projection operator, the multi-resolution multi-rate (MRMR) estimation can be transformed into a single-rate Kalman estimation with a special structure, and its projection operator was estimated adaptively from measurements by using a recursive least squares estimation algorithm [7]. State estimation with multi-rate measurements was solved by the use of a variable structure of moving horizon estimator, which provides a framework for constrained estimation that systematically handles constraints caused by a batch of

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multi-rate measurements [8]. Since different dynamic models always have different frequency properties in multiple model systems, the fast-rate sensor measurement was thus compressed to a slow-rate one with little or no accuracy degradation in low-frequency models, resulting in multi-rate interacting multiple model estimators [9] and applications in target-tracking with out-of-sequence GMTI data [10,11]. In the case that the updating rate of the state estimate is different from the measurement sampling rate, the wavelet-transformation-based [12] and the optimal H_2/H_∞-based [13] estimation schemes were proposed. For systems having measurement missing or packet losses, the multi-rate H_∞ filter [14], the optimal linear minimum variance estimators [15], and the multi-rate distributed estimation fusion algorithm were proposed [16], respectively. When faults and external disturbances occur in systems, the fault detection problem for multi-sensor fusion under multiple uncertainties were also investigated [17,18].

One common precondition for applying the above multi-sensor data fusion methods is that sensors should have been registered properly [19]. For example, in target tracking, multi-sensor measurements should be transformed into a common spatial reference frame before data fusion. However, the registration error caused by the range offset bias and the positioning bias of moving sensor platforms often exists [20]. The presence of the registration error caused by the bias deteriorates the fusion performance seriously, and even leads to ghost tracks. To remove the registration error and improve the fusion accuracy, bias estimation is exceedingly vital. To date, a vast research related to bias estimation has been done which can be divided into four categories.

In the case that the bias is zero-mean and white with unknown covariances, the minimum upper bound estimators in pursuit of the best upper bounds of estimation error covariances for time-varying systems [21], jump Markov stochastic systems [22] with generalized UIs were proposed. In the case that the bias is constant but unknown, the least squares method was utilized to estimate the bias which was piecewise-constant [23] or a sum of basis functions with piecewise-constant weights [24]. The generalized least squares method was adopted to map the sensor measurements to the Earth-centered Earth-fixed coordinates and then estimate the bias from the discrepancy reported by each sensor based on the moving-window hypothesis testing approach [25]. For sensor alignment in radar networks, the exact maximum likelihood (ML) method was presented for online estimation of measurement errors [26]. In the case that the bias evolves according to a dynamic model, a two-stage Kalman estimation scheme was proposed, where the joint estimation of the state and the bias was decoupled and implemented in two parallel reduced-order filters, respectively [27]. Through transforming the multi-sensor multi-frame measurements into the state-free bias pseudo-measurements via the exact method, the Kalman filter was utilized to estimate the sensor bias [28]. In the case that the bias is absolutely unknown, the ML method was given for the spatial alignment of multiple dissimilar sensors [29] and the joint estimation of bias and target state in the Bayesian framework [30]. The unscented Kalman filter (UKF) was proposed to fuse and register sensors with both spatial and temporal biases [31]. The expectation-maximization (EM) and the interacting multiple models (IMMs) were integrated to estimate the bias in a unified framework to solve the simultaneous registration and fusion of the electronic support measure sensors [32]. Later, the EM optimization was further used for joint data association, registration and fusion, where the data association and bias estimation were obtained in the M-step and the state estimation and track fusion were updated in the E-step [33]. To reduce the high computation cost of [31–33], the fast maximum a posteriori (FMAP) algorithm for joint registration and tracking was derived [34]. In general, most of the above work has been done in the case of synchronous sensors, whereas sensors may have different sampling rates, different initial sampling instants, or even different communication delays to the fusion center. For instance, in the infrared and laser detection systems, the azimuth angle and the elevation angle of the target are acquired from the infrared detection system with a higher sampling rate at the finest scale, while the range of the target is acquired from the laser detection system with a lower sampling rate at the coarsest scale. In addition, the sampling of the infrared detection system and the laser detection system are usually initialized at different time instants. This gives rise to the asynchronous sensor fusion.

Regarding asynchronous multi-rate multi-sensor fusion, the multiscale system theory [35–39] the bach process method [40–42], and the multi-rate filter banks approach [43] were presented. In the multiscale system theory, state estimation with complete measurements [35,36] and incomplete measurements [37] were developed and extended to remove delay effect by allowing delays to occur between two consecutive sampling time and assuming that the measurement loss detection is done via data validity checking mechanism [38]. For target detection and tracking using infrared/laser systems, a novel state estimation algorithm is devised by combining the multiscale system theory and the converted measurement Kalman filter [39]. In the batch process method, the general sensor-to-sensor-track fusion for asynchronous sensor systems [40], the centralized/distributed fusion algorithms for asynchronous sensors with arbitrary communication [41], and the IMM fusion estimation algorithm for stochastic multi-model systems were presented [42], respectively. In the multi-rate filter banks approach, a bank of multirate filters were designed and fused to achieve the global optimal estimates for asynchronous sensor fusion [43]. With respect to asynchronous multi-rate bias estimation, algorithms for two asynchronous sensors were provided for constant [44] and time-varying [45] biases within a proper time slot. By decoupling the bias estimation from the target estimation, the bias estimation algorithm for multiple asynchronous sensors was presented [46] and extended to a more general case by allowing the number of sensors to be arbitrary, removing the constraint on the arriving sequence of the sensor measurements, and considering the correlations between various kinds of noises [47]. However, the UI-driven bias, for example, the homologous sensor bias corrupted by countermeasure parameter uncertainties in target tracking systems and the sensor bias contaminated by unexpected drift increments, is not considered in the above asynchronous sensor fusion algorithms. Nevertheless, this appears to be a non-trivial question for the following two reasons: (1) it is unclear how to establish a system model to incorporate the UI-driven bias and the asynchronous sampling in; (2) it is pretty hard to find a decoupling condition that simultaneously decouple the state and the UI from the pseudo-measurement model. This motivates us to conduct the present research.

In this paper, we investigate the problem of the joint estimation of the state, the UI and the sensor bias for asynchronous multi-rate sensor fusion driven by UIs. The state space model is first modeled at the highest sampling rate (also the finest scale). Then, by applying the lifting technique, the asynchronous multi-rate estimation problem is transformed into a single-rate one where the state space models are established at each scale for each sensor. Based on the obtained system models, the joint estimation of the state and the bias is carried out in two stages. At the first stage, every sensor in the system collects its own measurements asynchronously to obtain the local estimates of the state, the bias and the UI. At the second stage, the local estimates from neighboring sensors are collected and fused to obtain the consensus estimates via the network consensus. The main contributions are as follows. *(i) To the best of the authors' knowledge, this is the first attempt at the bias estimation for asynchronous multi-rate multi-sensor fusion with UIs. The system model is quite comprehensive that caters for*