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An event based multi-sensor fusion algorithm with deadzone like measurements☆

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ABSTRACT

Event based strategy has received increasing attention recent years since it can provide a useful compromise between estimation performance and constrained energy or communication resources. In this paper, we propose an event based multi-sensor fusion algorithm with deadzone like measurements, where every sensor compares its measurements with an interval, and only elements beyond the thresholds, i.e., outside the deadzone, are sent to the fusion centre. To fuse this kind of deadzone like measurement, we firstly derive a modified Kalman filter (KF), which is based on the statistical properties of measurements. Then we obtain its information form, which is utilised in our event based information fusion algorithm to further release the computation burden caused by multi-sensor. Existing standard Tobit KF and KF are special cases of our modified KF, and simulation results demonstrate the advantages of the proposed event based algorithm as compared with several existing methods.

1. Introduction

With the advance of sensor technology, a considerable attention has been devoted to the topic of information fusion using Kalman filter (KF) based algorithms over sensor networks, aiming to estimate the unknown system sate through noisy measurements of sensors, and its applications include target tracking, power grids, integrated navigation, environment surveillance, cyber-physical system, multi-agents system, and so on [1–3]. Sensor network provides more fruitful measurements to extract valuable information for more accurate estimation results. However it does not help unconditionally unless proper strategy is utilized to design the fusion algorithm.

A direct idea is that every sensor sends all raw measurements to a fusion centre, and then runs a standard KF to obtain the optimal estimation. Unfortunately, with the number of sensors increasing, the communication burden at the fusion centre may be unaffordable restrained by the communication bandwidths. This problem will be more challenging for applications with limited bandwidth. For example, in underwater sensor networks, the bandwidth of acoustic communication is limited to only a few kHz [4]. To solve this kind of dilemma over multi-sensor systems, some methods have been designed to reduce the communication load of every sensor while keeping limited performance degradations. The stochastic sensor activation scheme is introduced in [5] to reduce the communication burden as well as the sensor energy consumption over sensor networks, and the optimal distributed estimator is then designed. In [6], dimension reduction is realised through Krylov subspaces to reduce the communication cost. To satisfy the communication bandwidth constraints, only partial elements of the local information are transmitted to the fusion centre, then the fusion KF is obtained after compensation of the untransmitted elements [7]. Besides those time driven strategy, another important strategy is the event based one [8], which has become an active research topic recently, and it is our concern in this paper.

The core idea underlying event based strategy is that, sensors transmit data to the estimator or fusion centre only when a certain event is satisfied, aiming to make a balance between estimation performance and restricted resources [8]. One popular event triggering rule is send-on-delta (SoD) [8,9], where measurement is transmitted when the change between current measurement and last one violates a predefined value. Note that SoD rule is sensitive to measurement noise, and may cause unnecessary triggering. Another popular approach is using the innovation information [10–12], which is the error between the true and estimated measurement, to define the triggering mechanism. This rule needs every sensor runs its own estimator to calculate its innovation and then decides whether or not send data according to the innovation based triggering rules. Other definition of events can be found in [13,14], where the authors perform Mahalanobis transformation on the innovation to define the event in [13], and the error

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1566-2535/

Table 1
Several existing event triggering rules.

References	Event triggering rules
[9]	$\lvert z_k - z_{k-1} \rvert$
[10]	$((z_a - \boldsymbol{C}\hat{\boldsymbol{x}}_{a\|a-1}) - (z_k - \boldsymbol{C}\hat{\boldsymbol{x}}_{k\|k-1}))^{\mathrm{T}}((z_a - \boldsymbol{C}\hat{\boldsymbol{x}}_{a\|a-1}) - (z_k - \boldsymbol{C}\hat{\boldsymbol{x}}_{k\|k-1}))$
[11]	$((z_k - \boldsymbol{C}\hat{\boldsymbol{x}}_{k\|k-1}))^{\mathrm{T}}R^{-1}((z_k - \boldsymbol{C}\hat{\boldsymbol{x}}_{k\|k-1}))$
[12]	$(z_k - \boldsymbol{C}\hat{\boldsymbol{x}}_{k\|k-1})(\sqrt{\boldsymbol{C}\boldsymbol{P}_{k\|k-1}\boldsymbol{C}^{\mathrm{T}} + R})^{-1}$
[13]	$\lVert \boldsymbol{F}_k^{\mathrm{T}}(z_k - \hat{z}_k)\rVert_\infty$, where $\boldsymbol{F}_k^{\mathrm{T}}\boldsymbol{F}_k = (\sqrt{\boldsymbol{C}\boldsymbol{P}_{k\|k-1}\boldsymbol{C}^{\mathrm{T}} + R})^{-1}$
[14]	$\lVert \hat{\boldsymbol{x}}_k - \hat{\boldsymbol{x}}_{k-1}\rVert_\infty$

* The subscript 'k' denotes time instant, the subscript 'a' is the time of last event happening, z_k is the measurement, $\boldsymbol{C}$ is the measurement matrix, R is the measurement noise covariance, $\hat{\boldsymbol{x}}_k$ is the state estimation, $\hat{\boldsymbol{x}}_{k|k-1}$ is the one step estimation, $\widehat{\boldsymbol{P}}_{k|k-1}$ is the one step estimation error covariance, and $\hat{z}_k$is the estimation of measurement.

between current estimation and last one is used in [14]. The detailed definition of events in those papers are given in Table 1, where the meaning of symbols can also refer to Section 2. Recently, in [15–17], the authors derive a new estimator called Tobit KF (TKF) for the right censored (which implies measurement is sent only when its values below a threshold) and saturated measurements. Inspired by their work, we here study the deadzone like measurements, that is the sensor only sends its measurement when its value goes beyond a certain interval. An example of deadzone like measurement is the output of ring laser gyroscope due to mechanical stiction or lock-in [18].

The main challenge in the event based algorithm is the way to extract the information contained in unideal measurements. Some papers treat the censored measurements as missed, using the KF designed for intermittent observations [19,20]. However, it is unsuitable for our event rule since the censored measurement is no longer a Gaussian distribution. Standard nonlinear filters, such as extended Kalman filter (EKF) or sigma-point based filters [21], can't be applied to this situation too. The authors in [11,22] use particle filter to fuse the censored measurement of sensors. However, it is generally computation costly to implement the particle filter. In [23], the authors design a filter by using the whole information about past censored measurements, thus it is still costly in both computation load and data storage.

In this paper, we focus on design a new event based multi-sensor fusion algorithm, where sensors send their measurements to the fusion centre only when the measurement value exceeds a certain predefined interval. We propose a modified KF for the case with deadzone like measurements using innovation analysis approach, and the TKF in [15] and standard KF are special cases of our proposed method. The information form of the proposed modified KF is given through some mathematical techniques, and the event based multi-sensor fusion algorithm is obtained based on this information filter to avoid the computation cost using the augmented measurement equation.

The rest of this paper is outlined as follows. In Section 2, we derive the modified KF with deadzone like measurements, and its information filter is obtained in Section 3. After that, the proposed event based multi-sensor fusion algorithm is described in Section 4. Simulation results are demonstrated in Section 5 to elaborate the effectiveness of the proposed algorithms. Conclusion remarks are given in the final section.

2. Modified KF for deadzone like measurements

In this section, an introduction of a scalar output linear system and the statistical properties of deadzone like measurements are given firstly. Based on which a modified KF for generally linear systems is then derived.

2.1. Scalar output system model

Consider the following scalar output system:

$$\boldsymbol{x}_k = \boldsymbol{A}\boldsymbol{x}_{k-1} + \boldsymbol{w}_{k-1} \tag{1}$$

$$z_k = \boldsymbol{C}\boldsymbol{x}_k + v_k \tag{2}$$

$$y_k = \begin{cases} z_k, & z_k \geq T_h \\ T_m, & T_h > z_k > T_l \\ z_k, & z_k \leq T_l \end{cases} \tag{3}$$

where $\boldsymbol{x}_k \in \mathbb{R}^{n\times 1}$ is the system state, $z_k \in \mathbb{R}^{1\times 1}$ is the scalar measurement, $T_l \leq T_h$, T_m is a constant value, and set it equal to $(T_h + T_l)/2$ to be general. $\boldsymbol{w}_k$ and v_k are the process and measurement noises, which are uncorrelated zero mean Gaussian white noise sequences with covariances $\boldsymbol{Q} \in \mathbb{R}^{n\times n}$ and $R = \sigma^2 \in \mathbb{R}^{1\times 1}$. The initial state $\boldsymbol{x}_0$ is uncorrelated with $\boldsymbol{w}_k$ and v_k, and its mean and covariance are known. $\boldsymbol{A}$ and $\boldsymbol{C}$ are also known matrices with proper dimensions.

In this paper, we consider the case that measurement z_k is censored by an interval, causing the output y_k. We should note that, the standard KF is no longer suitable for this case because the noise is correlated to real state, which violates the assumption of standard KF. New methods must be used to design the estimator, and the recent appeared TKF [15–17] provides us a new way to solve the state estimation problem with censored measurement by introducing the statistical information of Tobit model, which was used in economical fields originally. However, the case of state estimation with deadzone like measurement has not been considered, which inspires the following derivations.

2.2. Statistical characteristics of deadzone like measurement

As can be seen from Fig. 1, the probability distribution of this deadzone like measurement is [15]:

$$f(y_k|\boldsymbol{x}_k) = \frac{1}{\sigma}\phi\left(\frac{y_k - \boldsymbol{C}\boldsymbol{x}_k}{\sigma}\right)u(T_l - y_k) + \frac{1}{\sigma}\phi\left(\frac{y_k - \boldsymbol{C}\boldsymbol{x}_k}{\sigma}\right)u(y_k - T_h) + \delta(y_k - T_m)\left(\Phi\left(\frac{T_h - \boldsymbol{C}\boldsymbol{x}_k}{\sigma}\right) - \Phi\left(\frac{T_l - \boldsymbol{C}\boldsymbol{x}_k}{\sigma}\right)\right) \tag{4}$$

where

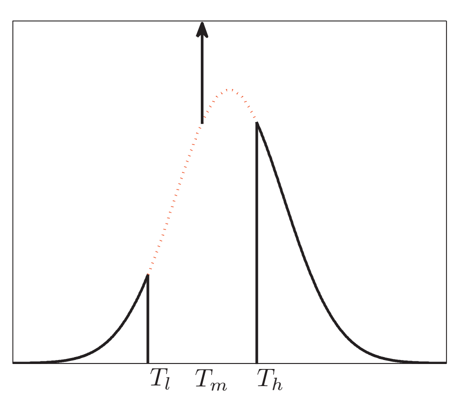

Fig. 1. Probability distribution of deadzone like measurement.