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Distributed asynchronous multiple sensor fusion with nonlinear multiple models

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This article studies a distributed estimation fusion problem with nonlinear multiple dynamic models under asynchronous multi-rate multi-sensor conditions. Such conditions allow for more comprehensive and various dynamic modes and reflect more practical sensor environments than have previously been studied. Whereas other estimation fusion algorithms are limited in that they are based on an assumption of either a linear dynamic model or synchronous sensors, the present algorithms proposed in this study can handle both nonlinear multiple models and asynchronous sensor observations. A distributed fusion algorithm for a single nonlinear model with asynchronous multiple sensors is proposed using the fusion of the information matrix and information state contribution, which have been reconstructed with statistical linear error propagation based on unscented transformation. The distributed fusion algorithm is then applied to multiple nonlinear models using an interacting multiple model (IMM) approach. In this study, one-step prediction for each dynamic model included in the IMM is performed instead of prediction of the fused estimates. This accounts for the lack of a global model for IMM. Then the information matrix, information state contribution, and mode likelihood function for each model obtained from each local sensor are fused. Simulation studies for tracking with both a single comprehensive nonlinear model and multiple models using asynchronous multiple sensors are conducted to illustrate the proposed algorithms.

1. Introduction

Multiple sensor fusion is widely used as a method of extracting useful information from observations obtained from multiple sensors. The information can then be applied to practical situations, such as target tracking for air traffic control. There are basically two fusion architectures: centralized and distributed. Centralized fusion, which is also called measurement fusion in target tracking, uses all local raw measurements sent to a central processor. The processor categorizes all the available information and updates the estimates using these measurements. On the other hand, distributed fusion, called track fusion in target tracking, uses estimates processed by each sensor [22,4,2].

Compared with centralized fusion, distributed fusion is more challenging, and lots of fusion studies for the past several decades have focused on it. In spite of contributions by previous studies, the functionality of many distributed fusion methods such as [4,2,7,23,6,8] are limited in that sensors are assumed to be single-rate and synchronous. In real-world applications, sensors usually operate asynchronously and provide data at different rates. For instance, multiple radars have been widely used for air traffic surveillance and control in order to continue the same system track over wider areas, to use other radar sources if local radar fades or fails, and to improve track accuracy by using more sources of radar measurements. In these cases, the radars operate at multiple rates and asynchronously. Moreover, different types of sensors such as Automatic Dependent Surveillance-Broadcast (ADS-B) and Multilateration (MLAT) have recently begun participating in the sensor fusion of air traffic surveillance areas. Overall, when addressing estimation fusion, it is more practical to consider asynchronous multi-rate sensors than synchronous single-rate ones.

It is also helpful to have comprehensive system models rather than a single linear model for practical applications of estimation fusion. For example, the targets to be tracked in air traffic control environments cannot be well defined with a single linear model. This is why a more comprehensive nonlinear model [14] or multiple models [21,3,19] are used for target tracking. In addition to

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position-only measurements, further information that has recently become available in ADS-B, MLAT, and mode-S radar for air traffic control also supports the need for more sophisticated models.

The objective of this article is to implement not only asynchronous multi-rate sensors but also comprehensive system models into the problem of distributed estimation fusion for practical applications. There follow the literature reviews for two areas: asynchronous multi-rate sensor fusion and sensor fusion for nonlinear and/or multiple models.

First, asynchronous multi-rate multi-sensor fusion has been investigated and extensive results have been obtained. Hong [11] proposed an algorithm for multi-resolutional distributed filtering with the wavelet transform as a linking mechanism between different resolution sensor domains. Yan et al. [27] presented a novel fusion algorithm for multiple asynchronous multi-rate sensors by establishing state-space models for each scale and recursively fusing the data from many sensors, where the ratio between the sampling rates of different sensors is allowed to be any positive integer. Alouani et al. [1] proposed a general sensor-to-sensor-track fusion algorithm for multiple sensors that are asynchronous and have arbitrary communication rates. However, these studies are still limited in several aspects. For example, Hong and Yan et al. assumed that the sampling rates are powers of two and positive integers, respectively. The algorithm of Alouani et al. uses only the latest local estimates of each sensor for fusion and does not take the one-step prediction from the previous fused estimate into account. It also has the disadvantage of requiring measurement covariance matrices of local sensors and gain matrices of local filters at the fusion center. Hu et al. [13] proposed a novel fusion algorithm that could be applied to general asynchronous multi-rate sensors. They derived a centralized fusion algorithm using an optimal batch asynchronous fusion algorithm [12] and extended it to a distributed fusion algorithm. The algorithms they developed do not require any constraints on the number, sampling rates, or initial sampling time instants of the sensors. Compared with the work done in [1], the communication loads are reduced because neither sensor measurement covariance matrices nor local filtering gains need to be sent to the fusion center. In addition, all available local estimates and the fused one-step prediction are used, which improve the fusion performance. However, Hu et al.'s works are also limited in that the algorithms are applicable only for a linear system model.

Another research area for estimation fusion comprises how to handle sophisticated models such as nonlinear and/or multiple models within the fusion architecture. Ding and Hong [9,10] developed a distributed fusion algorithm using an interacting multiple model (IMM) [21,3,19] approach. Lee [18] proposed a method of implementing a nonlinear model for estimation fusion, using statistical linear error propagation methodology [25] based on unscented transformation [16,17]. Li and Jia [20] derived a distributed nonlinear multiple model estimation algorithm that applies a consensus-based approach in a synchronous multi-sensor environment. Jeon et al. [15] proposed the unscented information filtering methodology combined with an IMM approach. However, their studies were all based on synchronous sensors.

To the best of the authors' knowledge, a general method has not yet been proposed for a distributed estimation fusion using asynchronous multiple sensors with nonlinear models. This study proposes asynchronous multi-rate multi-sensor fusion algorithms with nonlinear single and multiple models for distributed fusion systems. A distributed fusion algorithm for a single nonlinear model is proposed using the fusion of the information matrix and information state contribution reconstructed with statistical linear error propagation based on unscented transformation. The algorithm is then applied to multiple nonlinear models using an IMM approach. In this study, one-step prediction for each dynamic model included in IMM is performed rather than the prediction of the fused estimates, because a global model in IMM does not exist. The information matrix, information state contribution, and mode likelihood function for each model obtained from each local sensor are then fused.

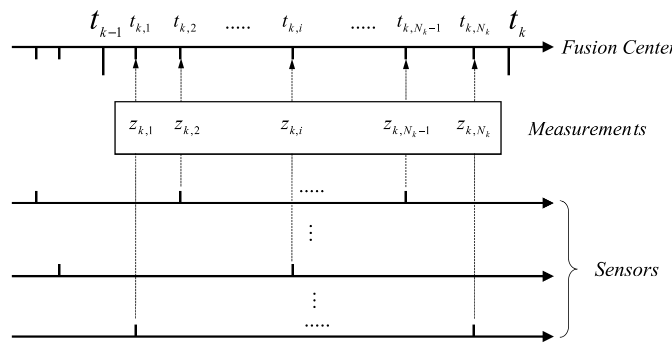

Fig. 1. Centralized fusion architecture.

This paper is organized as follows: The formulation of the problem is presented in Section 2. In Section 3, distributed asynchronous fusion algorithms for nonlinear single and multiple models are derived. The simulation results are presented in Section 4, and concluding remarks are given in Section 5.

2. Problem formulation

Consider the following discrete-time nonlinear multiple model system:

$$x_k = f(x_{k-1}, n_k) + v_{k-1}(n_k) \tag{1}$$

where $x_k \in \Re^{d_x}$ is the state vector and f is the system dynamics function. n_k denotes the system mode or model at time t_k, which is described by a discrete-time Markov chain. The mode at t_k is assumed to be among the possible r modes $n_k \in \{1, \dots, r\}$ with the mode transition probabilities $p^{ab} \equiv \Pr\{n_k = b | n_{k-1} = a\}$. The process noises $v_{k-1}(n_k)$ are assumed to be zero-mean white Gaussian processes with covariance matrices $Q_{k-1}(n_k)$. For simplicity of notation, $f(x_{k-1}, n_k) = f^n(x_{k-1})$ and $Q_{k-1}(n_k) = Q^n_{k-1}$ are denoted for $n \in \{1, \dots, r\}$.

The state is measured by a finite but arbitrary number of sensors with arbitrary sampling rates. It is assumed that N_k observations are collected by multiple sensors during the time interval $(t_{k-1}, t_k]$. As can be seen in Fig. 1, N_k observations obtained asynchronously are ordered in the time sequence as $\{z_{k,i}\}_{i=1}^{N_k}$, where $z_{k,i} \in \Re^{d_z}$ is the ith measurement at $t_{k,i}$, which should be $t_{k-1} < t_{k,1} \le t_{k,2} \le \cdots \le t_{k,N_k} \le t_k$.

$z_{k,i}$ is given by

$$z_{k,i} = h_{k,i}(x_{k,i}, n_{k,i}) + w_{k,i}(n_{k,i}) \tag{2}$$

where $h_{k,i}$ is the measurement function, $x_{k,i}$ is the state at $t_{k,i}$, and $w_{k,i}(n_{k,i})$ is the mode-dependent measurement noise sequence with zero-mean white Gaussian covariance $R_{k,i}(n_{k,i})$, denoted as $R^n_{k,i}$. It should be noted that the measurements $z_{k,i}$ $(i = 1, \dots, N_k)$ can be obtained from one sensor or several sensors, as can be seen in Fig. 1.

The objective of this study is to derive distributed fusion algorithms for nonlinear multiple models. As Fig. 1 shows, all available measurements obtained from local sensors are used for the centralized fusion. Local estimates instead of measurements are used for the distributed fusion shown in Fig. 2. The definitions of the local estimates in Fig. 2, such as local information state contribution vector $\breve{m}^n_{k,i}$, local information matrix $M^n_{k,i}$, and mode likelihood function $\Lambda^n_{k,i}$, are described in detail in Section 3.