Information Sciences 324 (2015) 186–196

Contents lists available at ScienceDirect

Information Sciences

journal homepage: www.elsevier.com/locate/ins

A joint data association, registration, and fusion approach for distributed tracking[☆]

Hao Zhu[a,*], Henry Leung[b], Ka-Veng Yuen[c]

[a] Automotive Electronics and Embedded System Engineering Research Center, Department of Automation, Chongqing University of Posts and Telecommunications, Chongqing, 400065, PR China
[b] Department of Electrical and Computer Engineering, University of Calgary, 2500 University Drive NW Calgary, Alberta, T2N 1N4, Canada
[c] Faculty of Science and Technology, University of Macau, Macao, PR China

ARTICLE INFO

Article history:
Received 24 September 2014
Revised 12 April 2015
Accepted 24 June 2015
Available online 2 July 2015

Keywords:
Sensor registration
Distributed tracking
Track fusion
Pseudo measurement
Expectation maximization

ABSTRACT

In this paper, a joint data association, registration, and fusion method is proposed for distributed tracking. As sensor biases are implicitly hidden behind the local tracks, a pseudo measurement method is used here to allow registration at the track level. A maximum likelihood function is formulated for association, registration and fusion. An expectation maximization (EM) algorithm is then developed to perform the track registration, association, and fusion simultaneously. Computer simulation results demonstrate the proposed method has an improved parameters and state estimation performance.

1. Introduction

Sensor fusion is an essential component in a sensor network for sensing and monitoring [4,23,25,30,36]. It can be performed in centralized or distributed sensor network. In centralized sensor network, sensor fusion carries out most of the processing components at the fusion center. In distributed sensor network, fusion performs local processing such as, detection and tracking at local sensors and then performs decision or feature level fusion at the fusion center. Normally, the centralized fusion is more accurate, and the tradeoff is a heavier communication and computation load [38]. With communications bandwidth and energy constraints, distributed sensor network has been attracting a lot of attention in the recent past [19].

Before information from different sensors is fused, sensors have to be registered properly. Or else, it will result in large sensing errors and lead to ghost targets [9]. As sensor biases are additive to the measurements, sensor registration is usually performed at the measurement level. Many sensor registration algorithms at measurement level have been proposed in the literature such as the least squares (LS) method [18], and the maximum likelihood estimator (MLE) method [28]. In addition, registration and fusion processes have also been proposed to be performed together so that tracking and registration can be carried out simultaneously in a nonstationary environment [15,20]. However, the registration process in these approaches is carried out at the measurement level which assumes a centralized processing for sensor networks. To have a truly distributed sensor network, registration should be performed at the track level to avoid sending all the local sensor measurement to the fusion center.

☆ This work is jointly supported by the Scientific and Technological Research Program of Chongqing Municipal Education Commission (Grant No. KJ130516), by the Research Funds of Chongqing Science and Technology Commission (Grant No. cstc2013jcyjA40042), by the Research Committee of the University of Macau (Grant No. MYRG081(Y1-L2)-FST13-YKV), and by the National Natural Science Foundation of China (Grant No. 61301033)

* Corresponding author. Tel.: +86 023 68037028.
E-mail addresses: haozhu1982@gmail.com, sandwish@163.com (H. Zhu), leungh@ucalgary.ca (H. Leung).

http://dx.doi.org/10.1016/j.ins.2015.06.042
0020-0255/

Table 1
Some representative works about joint methods.

Research study	Method	Architecture
Li and Leung [20]	Joint method of registration and fusion	Centralized
Huang and Leung [15]	Joint method of registration and fusion	Centralized
Sarkka et al. [32]	Joint method of association and fusion	Centralized
Li et al. [21]	Joint method of registration, association, and fusion	Centralized
Zeng [37]	Joint method of registration and fusion	Centralized
Okello and Challa [27]	Joint method of registration and fusion	Distributed
Papageorgiou and Holender [29]	Joint method of registration and association	Distributed
Huang et al. [16]	Joint method of registration and fusion	Distributed

In [27], an equivalent measurement method is proposed by augmenting the sensor biases with the state vector to obtain the estimates at the track level. In [22], the pseudo measurement is proposed with respect to the sensor biases by subtracting two sensors outputs. In [16], another pseudo measurement approach is developed to perform unbiased registration bias estimation. Comparing with the equivalent measurement method, the pseudo measurement method is shown to be more accurate and has a lower communication cost [16].

Data association is another main component in a multi-sensor multi-target system. Many algorithms have been developed for data association including the nearest-neighbor (NN) algorithm, the joint probabilistic data association (JPDA) method [3], the multiple hypothesis tracking approach (MHT) [4], and many others for various types of association [2,5,10,12,17,24,33–35] such as measurement to target association, and track to track association. One issue that has drawn attention is that data association and registration are two correlated processes. It has been proposed recently that registration and association can be carried simultaneously in a sensor network for multi-target tracking. A combined method is proposed for sensor registration and fusion approach for cooperative driving in intelligent transportation systems [15]. A joint approach is proposed to address the joint registration, association and fusion problem in multi-sensor and multi-target surveillance [8,21]. Furthermore, some representative works about joint methods of the registration, data association, and fusion are given in Table. 1.

From Table 1, it is observed that the joint method of registration, association and fusion has only been applied at the measurement level for centralized processing. To the best of our knowledge, no work has been done on performing simultaneously registration, association and fusion in a distributed architecture. In this paper, we propose a novel approach of joint data association, registration, and fusion to distributed sensor networks. In this architecture, each sensor reports the local estimated track to fusion center, then the fusion center associates and fuses those tracks [6]–[7]. We propose using the pseudo measurement to carry out registration at the track level and then apply the expectation maximization (EM) algorithm to perform the data association, registration, and fusion simultaneously. The EM method guarantees to find a local maximum in the likelihood function space by iteratively increasing the likelihood of the complete data [11–39]. In the E-step, an approximated expectation of the log-likelihood function with the complete data by a Kalman filter (KF) is computed based on the current parameter estimates. In the M-step, new parameter estimates including the registration parameters are computed.

The rest of paper is organized as follows. The problem of joint sensor registration, association and fusion at the track level is formulated in Section 2. The proposed EM method is described in Section 3. Computer simulations are shown in Section 4. Finally, the conclusions are given in Section 5.

2. Problem formulation

In multi-sensor multi-target tracking, the target state can be expressed as

$$\mathbf{x}_{t,k} = \mathbf{F}\mathbf{x}_{t,k-1} + \mathbf{w}_{t,k}, \quad k = 1, 2, \ldots N, t = 1, 2, \ldots, N_t(k) \tag{1}$$

where $\mathbf{x}_{t,k} = [x_{t,k} \quad \dot{x}_{t,k} \quad y_{t,k} \quad \dot{y}_{t,k}]^{\mathrm{T}} \in \Re^d$ is the state vector of target t at time k in the global Cartesian coordinate system (GCCS), the superscript T represents the transpose of a matrix. $N_t(k)$ denotes the number of targets at time k. N is the number of measurement samples. $\mathbf{F}$ is the known transition matrix and $\mathbf{w}_{t,k}$ is a zero mean, white Gaussian noise with covariance matrix $\mathbf{Q}$. The target measurement of target t for sensor s is described by

$$\mathbf{z}^s_{t,k} = \mathbf{H}_s\mathbf{x}_{t,k} + \eta_s + \mathbf{v}_{s,k}, \quad s = 1, 2, \ldots, N_s \tag{2}$$

where $\mathbf{z}^s_{t,k} \in \Re^n$ is the sensor s measurement of target t at time k, $\mathbf{H}_s = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$ is the measurement function, $\boldsymbol{\eta}_s$ denote the sensor bias of sensor s, $\mathbf{v}_{t,k}$ is a zero mean, white Gaussian noise with covariance matrix $\mathbf{R}_s$. N_s is the number of sensors.

For the distributed tracking, the local processes usually employ local tracker to obtain the local state estimates and report them to the global node for fusion. These local trackers are ignorant of the sensor biases and generate unregistered target state estimates and covariances, i.e.,

$$\{\hat{\mathbf{x}}^s_{j,k}, \hat{\mathbf{p}}^s_{j,k} \quad s = 1, 2, \ldots N_s, j = 1, 2, \ldots N_{ts}(k)\} \tag{3}$$

where $\hat{\mathbf{x}}^s_{j,k}$ and $\hat{\mathbf{p}}^s_{j,k}$ denote unregistered target state estimates and covariances at the sensor s at time k for the tracked object j, respectively. $N_{ts}(k)$ is number of tracked objects at time k by sensor s.