A Data Fusion Algorithm for Wireless Sensor Networks

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Abstract

The scenario deployed with mobile sensors for tracking both of non-maneuvering and maneuvering targets traveling in the phenomena exploits with mobile WSN (wireless sensor networks) is simulated in this paper. In order to solve the complicated situation and reduce computation burden because of the multiple sensing event exists mobile WSN environments is proposed. Moreover, a variable structure model is established as an adaptive maneuvering compensator to solve both data association and sensor maneuvering problems simultaneously, that is, the detection algorithm for multi-mobile sensor tracking in WSN investigated too. The simulations of multi-mobile sensor tracking based on the proposed method are conducted for tracking the targets. Computer simulation results indicate that the approach successfully tracks multiple sensors and has good precision also.

***Keywords*:** CML (conditional maximum likelihood), MSDFT (mobile sensor data fusion tracking), WSN (wireless sensor networks)

Ⅰ. Introduction

In general, the mobile-sensor data association tracking is the one essential technique for WSN (wireless sensor networks) surveillance systems employ one or more sensors, which may be deployed stationary or maneuverable, and together with computer subsystems. The main objective of the data association tracking algorithm is to partition the sensor data into sets of observations produced by the same target, and the other one is to avoid the couple effect exists between the mobile sensors for the same target. Once tracks are formed and confirmed, it not the number of mobile sensors can only be estimated and quantified, but the information gathered by the tracking algorithm can also be associated and fused. It is known that, the role of multi-sensor data association in WSN environments plays to acquiring, processing and combining data coming from different sources, including sensors and database, into a more precise set of data. On the other hand, data association consists of three parts: acquiring, processing and combining [1, 2]. DAA (data association algorithm) is the most important technique in order to accomplish the maintenance of tracking procedures. Mobile sensor tracking with DAA is a prerequisite step for mobile sensor surveillance systems over the WSN deployment. Once tracks are formed and confirmed, the number of targets can be estimated and quantified information, such as the target position and velocity, computed for each track [3].

There are several algorithms of DAA in the literature have been proposed and discussed for the issue of MTT (multiple target tracking) in the past. It is well known that the DAA denoted as the JPDA (joint probabilistic data association) technique is one appropriate for a high false target density environment, was proposed in [4-8], in which focused mainly on the MTT deployment. However, these techniques of solving MTT problems may cause some unreliability (latency) as the reason that is the nearest neighbor or all neighbors-based, usually consider the relations between sensor measurements and existing target tracks independently [9]. Thus, currently the traditional HNN (Hopfield neural network), which takes weighted objective cost and constraints into an overall energy function, is employed to combine with the neural network approaches for considering to works out the well tracking results [10]. Then through the minimization of the overall energy function, the superior performance results are able to be arrived at [11]. In [12], the conventional HNN was adopted to solve the problems of multiuser reception for asynchronous MC-CDMA (multi-carrier coded-division multiple-access) system in a multipath fading channel. In additions, the CHNN (competitive Hopfield neural network) algorithm has ever been applied in image processing [13]. Since this approach has defected that the weighting values are very difficult to be properly determined, it is often that the solution will go to an irrational result, as reported in Zhou [14]. Thereafter, by virtual of conventional HNN schemes for tracking the maneuvering or non-maneuvering targets with mobile sensors over WSN deployments is very spare. However, Wang *et al.* [15], recently, combined HNN with Genetic Algorithm, called as HNN-GA, for proposed a mobile agent based strategy utilized the low network load and cooperation of mobile agents, to dynamically optimize the combination of nodes and deploy tasks among nodes. Based on HNN the selecting method investigated by Liang et al. [16], in which the sensor node with the condition of lowest cost and satisfying the distance requirement of the MIMO (multi-input multi-output) system is selected to act as the best transmitting and receiving antenna in WSN environments. By extending the ideal of [17], Wang *et al.* in [18] proposed a new dynamic sensor nodes selection strategy to implement global searching for the purpose of reducing the search space of GA and ensuring the validity of each chromosome in WSN applications.

However, in order to apply the advantages of HNN technique, in this paper the improved CHNN method, which can by means of artfully arranging the updating function and the cost measurement properly remove this dilemma mentioned above, is adopted as the scenario for solving the target tracking with mobile sensors in WSN deployments. The CHNN is an improved HNN wherein a cooperative decision is made based on the simultaneous input of a community of neurons. Each neuron receives information from other neurons and also gives information to other neurons [11, 14]. With this collective information, each neuron moves to a stable stage with the lowest value of a predefined energy function. As such a result, the operation of association between mobile sensor measurements and existing tracks can be obtained under global optimal consideration which in turn, can increase the accuracy of mobile sensor tracking systems. Furthermore, due to the embedded competitive updating scheme, the CHNN except has the capability be able to remove the burden of weight setting, it is also proved that the network is guaranteed to converge into a stable and rational stage during network evolution [13]. As such the dilemma of falling into irrational solutions such as in traditional HNN can be eliminated.

To the best of author's knowledge, the proposed mean is a brained fresh ideal discussed in the issue of addressing in the exploring field of WSN. The contribution aimed in this paper is to the enhancement of system performance by means of the DAA for the WSN environments with the basis on the CHNN to obtain a global matching between mobile sensor measurements and existing tracks. On the presentation of the scenario shown in Fig. 1 in which a two-target moving objects are considered and one improved tracking deployment for mobile-sensor data association with targets assumptions is developed. Moreover, in an environment where the dense targets would be spread out randomly, some targets can be very close to each other. The measurements produced by these close targets can confuse the data association computation algorithm and result in inaccurate relations. Consequently, the approach in solving data association problem should be considered globally. The rest of the paper is organized as follows. In Section Ⅱ the problem formulation includes the gating technique and the basic concept of HNN are illustrated, developing the DAA based on CHNN scheme is presented in Section III, and the maneuvering compensator algorithm is described in Section IV. Finally, in Section V and Section VI the simulation results for the proposed algorithm and the conclusions and the further working directions are shown and drawn, respectively.

II. Problem Formulation

A discrete model set for a multi-sensor tracking algorithm of the *i*-th sensor is able to be defined as

$$X_i(k+1) = F_i X_i(k) + G_i U_i(k) + W_i(k) \tag{1}$$

where $W_i(k)$ presents the system noise associated with the *i*-th sensor, assumed to be normally distributed with zero mean and variance $Q_i(k)$, i.e., $V_i(k) \sim N(0, Q_i(k))$, $U_i(k)$ is the forcing input gain matrix, F_i denotes the transition matrix, G_i is the input gain matrix, and the column vector $X_i(k) = [x_i\ \dot{x}_i\ y_i\ \dot{y}_i]^T$ represents the target kinematics state vector of the *i*-th sensor at time step k, where the transposition of a matrix is indicated by the superscript T.

III. Data Fusion Tracking Algorithm

For developing the tracking algorithm N distributed sensors are supposed deployed in a WSN system adopted in this research, and L_i

likely sink sensors are seen by the *i*-th sensor. The discrete-time target dynamic model and measurement model of the data fusion tracking system are defined such as the set of equation

$$X(k+1) = F(k)X(k) + G(k)W(k) \quad (2)$$

$$Y_i(k) = C_i(k)X(k) + V_i(k) \ , \ i = 1, \cdots, N \quad (3)$$

is for global model, and the other set of equation

$$X_i(k+1) = F_i(k)X_i(k) + G_i(k)W_i(k) \ , \ i = 1, \cdots, N \quad (4)$$

$$Y_i(k) = H_i(k)X(k) + V_i(k) \ , \ i = 1, \cdots, N \quad (5)$$

is for local model, respectively. Furthermore, under the basis of the assumption with index matrix, $M_i(k)$, mentioned in previous, the relationship of the data fusion between global model and local model can be estimated by the mapping equation expressed as

$$C_i(k) = H_i(k)M_i(k) \ , \ i = 1, \cdots, N \quad (6)$$

VI. Simulation Results

Developing the simulation programs (using Matlab) by virtual of the proposed DAA is implemented in this subsection. The developed DAA jointing with CHNN technique is validated by the scenario with the tracking of three targets in WSN deployments, first. It is also applied to track five targets include two non-maneuvering and three maneuvering targets. The initial condition for simulating tracking three targets is shown in Table I, which illustrated in this subsection mainly to cope with the prove proposed algorithms. The transition matrix $F(k)$ and the noise gain matrix $G(k)$ corresponding to the targets for the sampling interval *T*, which is assumed 2 seconds in the simulation, are given by

$$F(k) = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix},$$ and

$$G(k) = \begin{bmatrix} T^2/2 & 0 \\ T & 0 \\ 0 & T^2/2 \\ 0 & T \end{bmatrix},$$ respectively. The initial state value of the state error covariance is assumed default as

$$P(0|0) = \begin{bmatrix} 10000 & 100 & 0 & 0 \\ 0 & 100 & 100 & 0 \\ 0 & 0 & 10000 & 100 \\ 0 & 0 & 100 & 100 \end{bmatrix}.$$

The results from tracking three targets without the DAA calculation and with the DAA calculation are shown in Fig. 3, and Fig. 4, respectively. In these simulations eighty steps of Monte Carlo are implemented and per 10 estimated tracking (10 measurements) with data association calculating are sampled for the accuracy comparison with each other. It is easily to see that the much more match situations occur in Fig. 4. In other words, all of the tracked path can tightly match with the true path marked with circles. One thing needed to be emphasized that there is a little difference exists the path way of the true targets between the results presented in Fig. 3 and Fig. 4, since it is generated with the random function of the software package. By using of the random number generators for the measurement noise and clutter points are illustrated in the simulation.

VII. Conclusion

An improved algorithm for MSDFT tracking mobile sensors in WSN is constructed in this paper. The algorithm is implemented with an adaptive filter consisting of a data association technique.

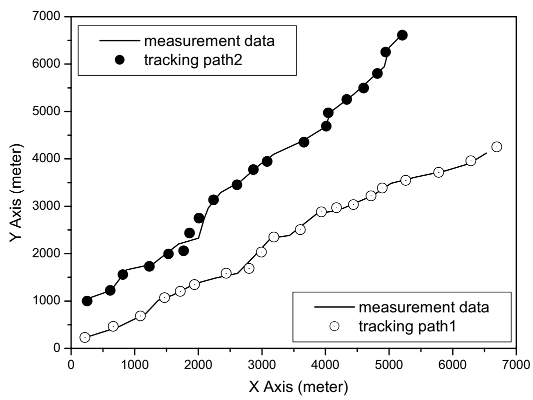

Fig. 1. The results of simulation for tracking two maneuvering targets with mobile sensors

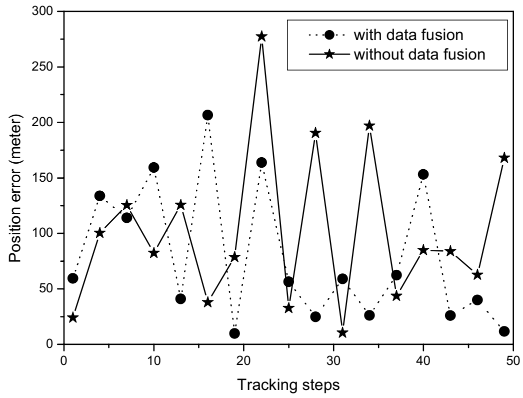

Fig. 2. The results of simulation error with and without data fusion for tracking two maneuvering targets with mobile sensors

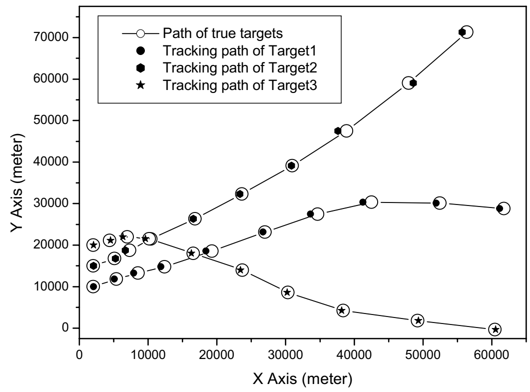

Fig. 3 Data association result for tracking three targets Before the DAA calculation

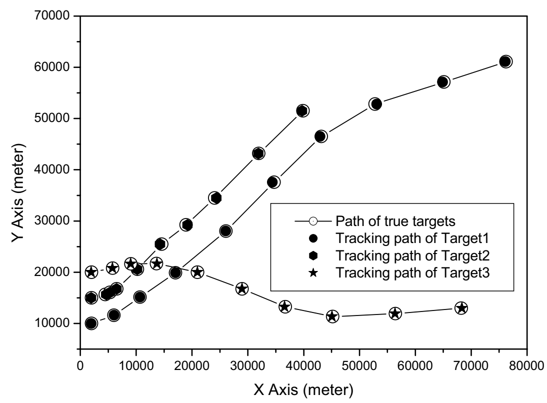

Fig. 4 Data association result for tracking three targets after the DAA calculation

References

[1] M. Cetin, *et al.*, "Distributed Fusion in Sensor Network," *IEEE Signal Processing Mag.*, no. 7, pp. 42-55, July 2006.

[2] A. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "A Survey on Sensor Networks," *IEEE Communication Mag.* pp. 102-114, Aug. 2002.

[3] Y. N. Chung, and Joy I. -Z. Chen, "Applying Both Kinematic and Attribute Information for a Target Tracking Algorithm," *Journal of Control Systems and Technology*, Vol. 5, no. 3, pp. 203-209, 1997.

[4] K. C. Chang, C. Y. Chong, and Y. Bar-Shalom, "Joint Probabilistic Data and Association Distributed Sensor Networks," *IEEE Trans. Automa. Contr.*, Vol. AC-31, pp. 889-897, Oct .1986.

[5] N. Okello and B. Ristic, "Maximum Likelihood Registration for Multiple Dissimilar Sensors," *IEEE Trans. Aerosp. Electron. Syst.*, Vol. 39, No. 3, pp. 1074-1083, 2003.

[6] Y. Bar-Shalom and T. E. Fortmann, "Tracking and Data Association," *Academic Press*, Inc., 1989.

[7] S. S Blackman, "Multiple Hypothesis Tracking for Multiple Target Tracking," *IEEE Aerosp. Electron. Syst.*, Vol. 19, pp. 5-18, Jan 2004.

[8] Y. N. Chung, and Joy I. -Z. Chen, "Applying Both Kinematic and Attribute Information for a Target Tracking Algorithm," *Journal of Control Systems and Technology*, Vol. 5, no. 3, pp. 203-209, 1997.

[9] C. Hue, C. Le, J. -P., and P. Perez, "Sequential Monte Carlo Methods for Multiple Target Tracking and Data Fusion," *IEEE Trans. on Signal Processing*, Vol. 50, Issue 2, pp.309-325, Feb. 2002.

[10] D. Sengupta and R. A. Iltis, "Neural Solution to the Multitarget Tracking Data Association Problem," *IEEE Trans. Aerosp. Electron. Syst.*, 25, 86-108, 1989.