An Estimator Based On Fuzzy If-Then Rules For The Multisensor Multidimensional Multitarget Tracking Problem

C.W. Tao[1], J.S. Taur[2], H.C. Kuo[1], J.C. Wu[1], and W.E. Thompson[3]

[1]Department of Electrical Engineering
National I-Lan Institute Of Agriculture And Technology
I-Lan, Taiwan, R.O.C.

[2]National Chung-Hsin University
Taiwan, R.O.C.

[3]Department of Electrical and Computer Engineering
New Mexico State University, Box 3-0
Las Cruces, New Mexico 88003

Abstract

In this paper, an estimator based on fuzzy if-then rules are developed for multidimensional multitarget tracking with multisensor data taken in a cluttered environment. The clustering algorithm based upon a pseudo k-means algorithm and the Match-Agreement data technique designed in our previous paper are used here for clustering multisensor data from a clustered environment and data association problem in multitarget tracking. The estimator based on fuzzy if-then rules consists of Gaussian membership functions, min-"and" inference, and centroid defuzzification. Examples are presented to illustrate the comparisons between a Kalman estimator and the fuzzy estimator.

I. Introduction

The problem of multisensor multidimensional multitarget tracking in clutter has been extensively studied [1,2]. Three important parts in this work are data clustering, data association and the design of estimators [3]. The clustering algorithm based upon a pseudo k-means algorithm and the Match-Agreement data association algorithm used here have been shown with the advantages of no required a priori information and computational efficiency, respectively, in our previous paper [4]. Therefore, this paper concentrates on the design of an estimator based on fuzzy if-then rules. As is well known, when the uncertainty may be represented statistically and the system dynamics are available, the Kalman filter has been very successful, according to its optimal property. However, when the system dynamics are unknown or the statistical model can not be properly applied to the uncertainty involved, the performance of the Kalman filter degrades. Moreover, the erroneous uncertainty model might cause divergence in a Kalman filter system [5]. In situations where the knowledge of the moving target dynamics and the statistical uncertainty model are not available, the estimator based on fuzzy if-then rules is a proper alternative.

The problem is formulated in section II. Section III presents the design of a Multidimensional multitarget fuzzy estimator. The results are shown in section IV, and the conclusion is in section V.

II. Problem Formulation

The problem considered here is that of tracking multiple targets based upon multisensor measurements taken in a cluttered environment. It is assumed that the number of targets and the statistical uncertainty model are unknown, and that n two-dimensional position measurements are available at time index k and are represented as

0-7803-1896-X/94 $4.00 ©1994 IEEE

$$p_{iqf}(k)=\tan(\theta_{iq}(k)+\Theta_{iqa}(k)+\theta_{iq1}(k-1))T+p_{iqf}(k-1);\quad k>2$$

The following parts of this section give the details of the design of the iqth fuzzy estimator from a fuzzy partition of the universe of discourse of variables $(\theta_{iq}(k),\theta_{iqa}(k))$ to defuzzification.

A. FUZZY PARTITION AND MEMBERSHIP FUNCTIONS

First, the universe of discourse of the variables $\theta_{iq}(k)$ and $\theta_{iqa}(k)$ needs to be defined. The closed range $[-\pi,\pi]$ is considered to be an universe of discourse U_{iq1} for the input variable $\theta_{iq}(k)$. In order to create effective and stable (with respect to parameter σ) membership functions, a mapping function f_{iq}: $U_{iq1} \rightarrow U_{iq}$, specifically,

$$y_{iq}(k)=f_{iq}\ (\theta_{iq}(k))=(\theta_{iq}(k)/\gamma)a$$

$$\text{where}\quad a=2\sigma(\sqrt{2\log 2}),\quad \gamma=30$$

is applied on the universe of discourse U_{iq1} which maps U_{iq1} to an universe of discourse U_{iq}=[-6a, 6a]. Secondly, the U_{iq} is fuzzily partitioned into a collection of fuzzy sets corresponding to those fuzzy sets in the fuzzy If-then rules. The membership function of each fuzzy set is defined by the bell-shaped function:

$$\mu_{iqyj}(y_{iq}(k))=\exp\{-(y_{iq}(k)-u_{iqyj})^2/2\sigma^2\}\ ;\ j=1,\ 2,....,\ 13$$

where u_{iqyj} is the middle point of the support of each fuzzy set.

The universe of discourse U_{iq2} for the variable $\theta_{iqa}(k)$ is defined to be the range $(-\infty,\infty)$. U_2 is fuzzily partitioned into a collection of 13 fuzzy sets (pvvb, pvb, pb, pm, ps, pv, ze, nvs, ns, nm, nb, nvb, nvvb). Each of the fuzzy sets has the support $(-\infty,\infty)$ and the membership function with the form

$$\mu_{iq\theta j}(\theta_{iqa}(k))=\exp\{-(\theta_{iqa}(k)-u_{iq\theta j})^2\ /2\sigma^2\ \}\ ;\ j=1,\ 2,....,\ 13$$

where $u_{iq\theta j}$ is the number with membership value 1.

These letters p, n, ze, s, m, b, v in the names of the fuzzy sets correspond, respectively, to the meaning of positive, negative, zero, small, big, and very. For example, pvvb means "positive very very big". Actually, the name of each fuzzy set really means that the element with membership value 1 in this fuzzy set has the property which is described by the name of this fuzzy set.

B. FUZZY RULE BASE

A fuzzy rule base consists of fuzzy if-then rules. There are several ways of deriving fuzzy if-then rules [6]. The fuzzy if-then rules in this paper are derived from the smoothness assumption. Each fuzzy if-then rule includes two variables $(y_{iq}(k),\ \theta_{iqa}(k))$, for example:

R1: if ($y_{iq}(k)$ is pvvb) then ($\theta_{iqa}(k)$ is nvvb)

C. DEFUZZIFICATION

Let $\mu_{iqyj}(y_{iq}(k))$'s, j=1, 2,...., 13, be membership values of input fuzzy sets, nvvb, nvb, nb, nm, ns, nvs, ze, pv, ps, pm, pb, pvb, pvvb, respectively, with input $y_{iq}(k)$. Also, let $u_{iq\theta j}$, be the maximum of the membership functions $\mu_{iq\theta j}$, j=1, 2,...., 13, of output fuzzy sets, pvvb, pvb, pb, pm, ps, pv, ze, nvs, ns, nm, nb, nvb, nvvb, respectively. The centroid method, which is the standard technique in design of a fuzzy controller [7], is used for the defuzzification, that is,

$$\Theta_{iqa}(k) = \frac{\sum_{j=1}^{13}\mu_{iqyj}(y_{iq}(k))u_{iq\,\theta j}}{\sum_{j=1}^{13}\mu_{iqj}}$$

IV. SIMULATION RESULTS

The Multisensor 2-dimensional Multitarget tracking situation involves three simulated crossing/intersecting trajectories. The multisensor measurements are corrupted by zero mean Gaussian noise with high variance of 0.2 and are shown in Figure 1. Application of the Pseudo K-means Clustering Algorithm yields the measurement cluster centers shown in Figure 2, and the Match Agreement Algorithm in combination with the fuzzy estimator and basic Kalman-filter algorithm yields the estimated trajectories shown by dashed lines in Figure 3 and Figure 4. The true trajectories are shown by solid lines in Figure 3 and Figure 4. The results indicate that when the variance of noise is high, only the fuzzy estimator obtains correct trajectories.

V. CONCLUSIONS

This paper presents one estimator based on fuzzy if-then rules for multi-dimensional multisensor multitarget tracking. The simulation results indicate that this fuzzy estimator works even better for the multidimensional multitarget tracking when the variances of noises are high. Even though only simulation results for two dimensional target tracking is shown, similar simulations can be developed for m dimensional (m>2) target tracking problems.

REFERENCE

[1] Y. Bar-Shalom, "Tracking Methods in a Multitarget Environment," IEEE Transactions on Automatic Control, AC-23, 4 (Aug. 1978).

[2] D. Sengupta, and R. Iltis, "Neural Solution to the Multitarget Tracking Data Association Problem," IEEE Transactions on Aerospace and Electronic Systems, AES-25, 1, (Jan. 1989).

[3] E. Emre, and J. Seo, "A Unifying Approach to Multitarget Tracking," IEEE Transactions on Aerospace and Electronic Systems, AES-25, 4(July 1989).

[4] W.E. Thompson, R. Parra-Loera, and C.W. Tao, "A Pseudo K-Means Approach to The Multisensor Multitarget Tracking Problem," Proceedings of the SPIE's International Symposium on Data Structures and Target Classification, Orlando, FL, April 1991, Vol. 1470, pp. 48-58.

[5] F. H. Schlee and N. F. Toda, "Divergence in the Kalman Filter," AIAA J.,vol. 5,pp.1114-1120, June 1967.

[6] C. C. Lee, "Fuzzy Logic in Control Systems: Fuzzy Logic Controller-Part I," IEEE Trans. Syst. Man Cybern., vol. SMC-20, no. 2, pp. 404-418, Mar./April 1990.

[7] B. Kosko, Neural Networks and Fuzzy Systems. New Jersey: Prentice Hall, 1992.

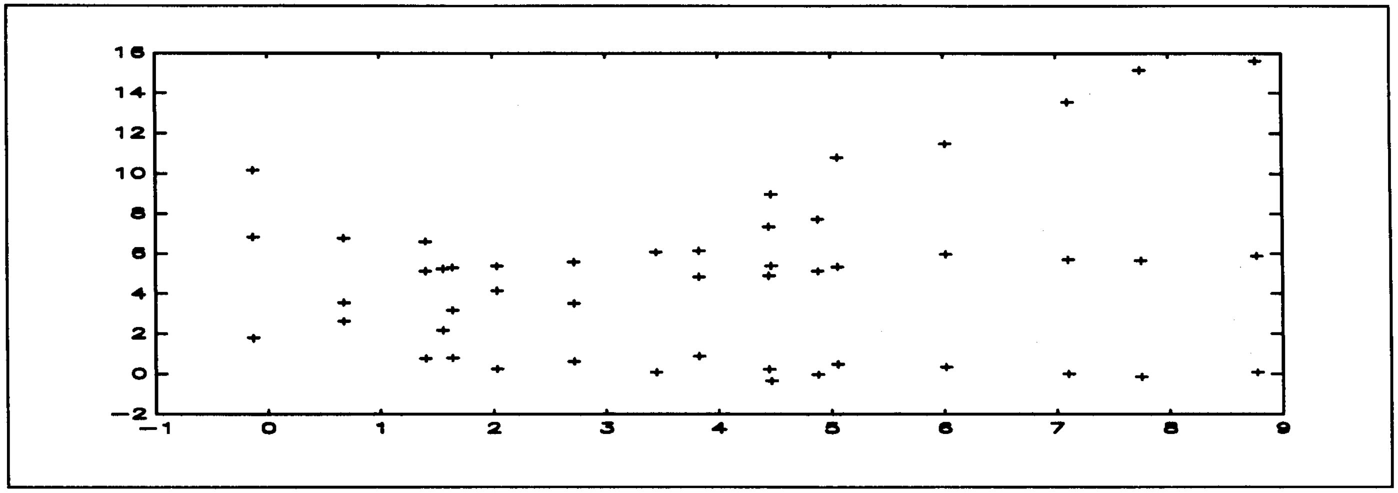

Figure 1. Multisensor Position Measurements for Three Trajectories

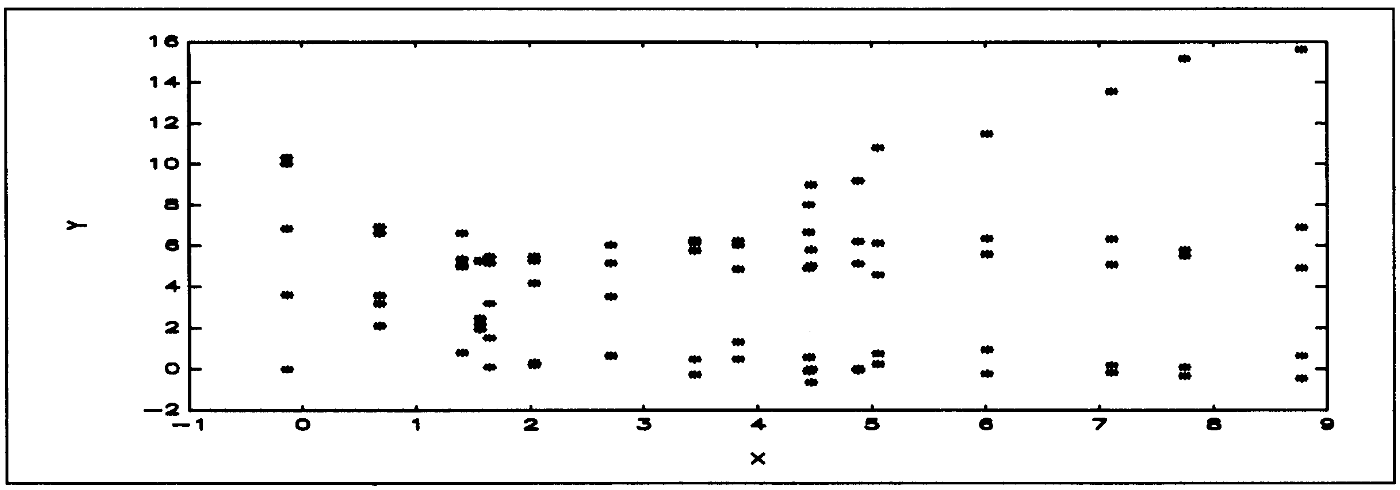

Figure 2. Cluster Centers for Multisensor Position Measurements

$$\{ (x_1(k) , y_1(k)) , (x_2(k) , y_2(k)) , . . . , (x_n(k) , y_n(k)) \}$$

The basic problems involved here include measurement clustering, data association, and tracking. Measurement clustering involves grouping the measurements into a number of groups called clusters and determining a representative point for each cluster called cluster centers. Each cluster center is then viewed as a measurement for a target. The data association problem involves identifying each target measurement as belonging to a particular trajectory. The tracking problem involves utilizing target measurements to arrive at the "best" estimates for the trajectories. Because the pseudo k-means clustering algorithm and match-agreement data association algorithm in our previous paper [4] are used directly, only tracking problem is considered in this paper.

III. Design Of A Multidimensional Multitarget Fuzzy Estimator

By utilizing the match-agreement algorithm for data association, each target measurement is associated to particular trajectories. These target measurements are used for the estimation of associated trajectories. The multidimensional multitarget fuzzy estimator developed here is constructed based on a simple fuzzy estimator. The simple fuzzy estimator (SFE) is an estimator for one target moving on one dimension. For the tracking problem of one target moving on an m dimensional space, the multi-dimensional fuzzy estimator (MFE) consists of m SFEs, and each SFE parallelly estimates one position coordinate of an m dimensional trajectory at each time index. Therefore, for the tracking problem of n targets moving on an m dimensional space, the multi-dimensional multitarget fuzzy estimator (MMFE) consists of n MFEs, and each MFE estimates the trajectory for one of n targets. The remainder of this section is the details of the design of an MMFE.

Based on common sense knowledge about moving targets with reasonable changes in velocity, it is assumed that moving targets (n targets) can not change their velocity dramatically in any one of the m dimensions, i.e., the difference $\theta_{iq}(k)$ of the angles $\theta_{iq1}(k)$ and $\theta_{iq1}(k-1)$, i=1,2, ..., m, q=1,2,....,n, shown in the following equations can not be very large:

$$\theta_{iq1}(k)=\tan^{-1}((p_{iq}(k)-p_{iqf}(k-1))/T)$$

$$\theta_{iq1}(k-1)=\tan^{-1}((p_{iqf}(k-1)-p_{iqf}(k-2))/T)$$

$$\theta_{iq}(k)=\theta_{iq1}(k)-\theta_{iq1}(k-1) \text{ ; T=sampling period}$$

where k needs to be greater than 2. The input position variable $p_{iq}(k)$, k>2, is then transformed into an angle variable $\theta_{iq}(k)$ in order to utilize the smoothness assumption. The output position variable $p_{iqf}(k)$ of the fuzzy filter is assumed to be equal to the input position variable $p_{iq}(k)$ when k is less than or equal to 2.

The smoothness assumption described above formulates the fuzzy If-then rules for the fuzzy controller in the fuzzy filter, for example:

R1: If the angle difference, $\theta_{iq}(k)$, is positive small, then the angle adjustment, $\theta_{iqa}(k)$, is negative small.

The "positive small" and "negative small" are not exact regions but are fuzzy sets which are defined by fuzzy membership functions (part A). For an input variable $\theta_{iq}(k)$, it is necessary to find the corresponding degree of "positive small" for the variables $\theta_{iq}(k)$ to be able to apply the fuzzy If-then rule R1. For each particular input variable $\theta_{iq}(k)$, every possible value of $\theta_{adj}(k)$ in its universe of discourse gives a degree of appropriateness for the control. In order to obtain the best $\Theta_{iqa}(k)$, which is a crisp value, to be the output of the fuzzy controller, a defuzzification technique is needed. Then the algorithm below is used to obtain the filtered target position.

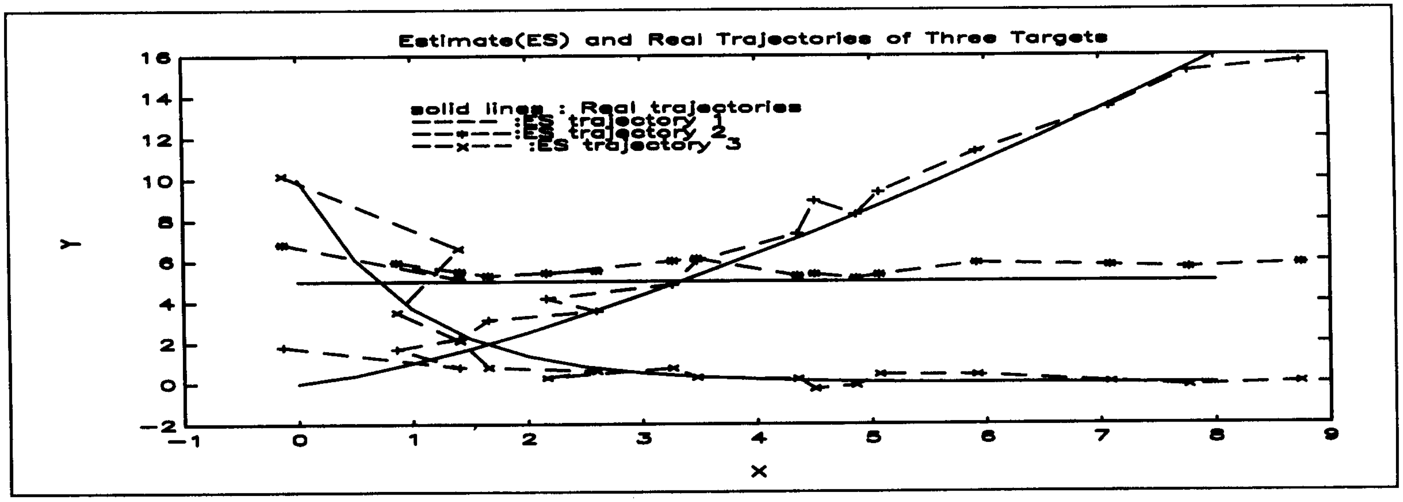

Figure 3. Estimated with fuzzy estimator and True Trajectories for Three Targets

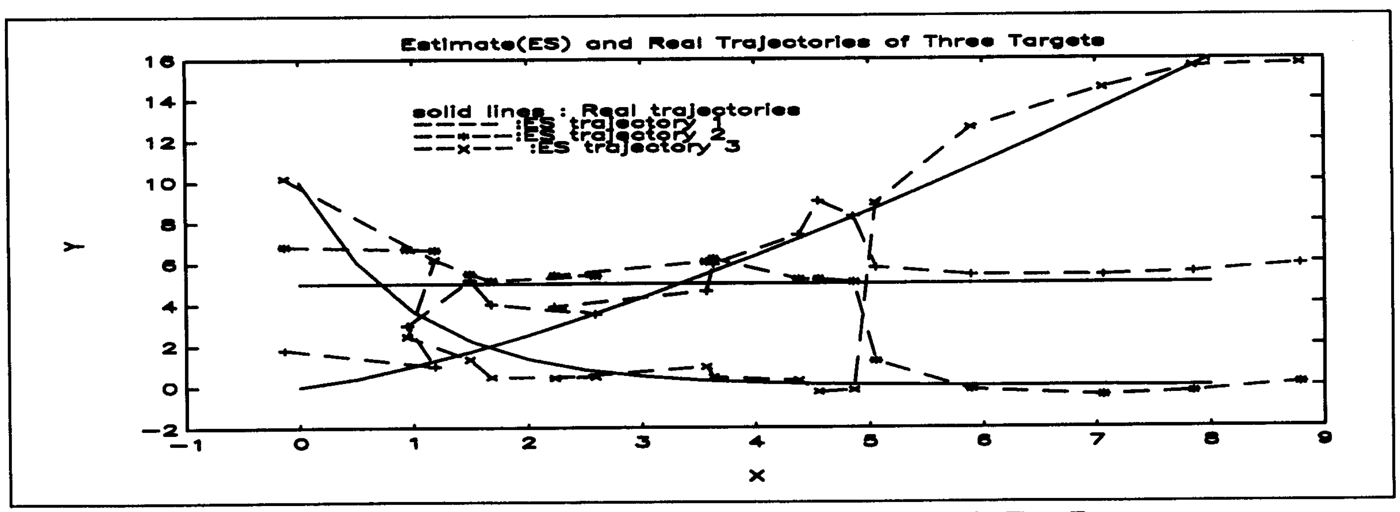

Figure 4. Estimated with Kalman filter and True Trajectories for Three Targets