COMPUTATION OF ASSOCIATION PROBABILITIES FOR SINGLE TARGET TRACKING WITH THE USE OF ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

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ABSTRACT

In this study, a simple method based on the adaptive neuro-fuzzy inference system is presented for computing the association probabilities. The computed association probabilities are used to track the single target in the cluttered environments. The adaptive neuro-fuzzy inference system is trained with the hybrid learning algorithm, which combines the least square method and the backpropagation algorithm. The tracks estimated by using the method proposed in this study are in good agreement with the original tracks. Better accuracy with respect to the well known probabilistic data association algorithm is obtained.

I. INTRODUCTION

The target tracking [1, 2] is an important issue in military surveillance, ballistic missile defense, satellite defense and air traffic control systems. The objective of the target tracking is to partition sensor data into sets of observations, or tracks produced by same source. Once tracks are formed and confirmed, the number of targets can be estimated and parameters such as position, velocity and acceleration can be obtained from each track.

The probabilistic data association filter (PDAF) approach [1] is one of the methods commonly used in the target tracking. This approach is a bayesian approach that computes the probability that each measurement in a track's validation region is the correct measurements and the probability that none of the validated measurements is target originated. The association probabilities and all of the validated measurements are used in the PDAF to update the target state. Several methods [3, 4] varying in accuracy and computational effort have been presented and used to calculate the association probabilities.

The problem in the literature is that a method that is as simple as possible for calculating the association probabilities should be obtained, but the estimated tracks obtained by using these association probabilities must be in good agreement with the true tracks. In this study, a simple method based on adaptive neuro-fuzzy inference system (ANFIS) [5, 6] is presented for efficiently solving this problem. Fast and accurate learning, excellent explanation facilities in the form of semantically meaningful fuzzy rules, the ability to accommodate both data and existing expert knowledge about the problem, and good generalization capability features have made neuro-fuzzy systems popular in the last few years [5-10]. Because of these fascinating features, the ANFIS in this study is used to accurately compute the association probabilities. These computed association probabilities are used to track the single target in the cluttered environments.

The ANFIS combines the benefits of artificial neural networks and fuzzy inference systems (FISs) in a single model. The ANFIS can be considered as a class of adaptive networks which are functionally equivalent to FISs. Usually, the transformation of human knowledge into a fuzzy system (in the form of rules and membership functions) does not give exactly the target response. So, the parameters of the FIS should be determined optimally. The main aim of ANFIS is to optimize the parameters of the equivalent FIS by applying a learning algorithm using input-output data sets. The parameter optimization is done in a way such that the error measure between the target and the actual output is minimized. In this paper, the hybrid learning algorithm [5, 6], which combines the least square method and the standard backpropagation algorithm, is used to identify the parameters of ANFIS.

In previous works [11-19], we also successfully introduced artificial neural networks and FISs to compute the various parameters of the triangular, rectangular and circular microstrip antennas. In the following sections, the ANFIS is described briefly, and the application of ANFIS to the calculation of the association probabilities for single target tracking is then explained.

II. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

The FIS is a popular computing framework based on the concepts of fuzzy set theory, fuzzy if-then rules, and fuzzy reasoning [6]. Among many FIS models, the Sugeno fuzzy model is the most widely applied one for its high interpretability and computational efficiency, and built-in optimal and adaptive techniques. The Sugeno fuzzy model provides a systematic approach to generate fuzzy rules from a set of input-output data pairs.

The ANFIS is a FIS implemented in the framework of an adaptive fuzzy neural network. A typical architecture of ANFIS is depicted in Figure 1, in which a circle indicates a fixed node, whereas a square indicates an adaptive node. For simplicity, it was assumed that the FIS has two inputs x and y and one output z. The ANFIS implements a first-order Sugeno fuzzy model. For this model, a typical rule set with two fuzzy if-then rules can be expressed as

Rule 1: If x is A_1 and y is B_1, then $z_1 = p_1 x + q_1 y + r_1$ (1a)

Rule 2: If x is A_2 and y is B_2, then $z_2 = p_2 x + q_2 y + r_2$ (1b)

where A_i and B_i are the fuzzy sets in the antecedent, and p_i, q_i and r_i are the design parameters that are determined during the training process. As in Figure 1, the ANFIS consists of five layers:

Layer 1: Each node in the first layer employs a node function given by

$$O_i^1 = \mu_{A_i}(x), \qquad i = 1,2 \tag{2a}$$

$$O_i^1 = \mu_{B_{i-2}}(y), \qquad i = 3,4 \tag{2b}$$

where $\mu_{A_i}(x)$ and $\mu_{B_{i-2}}(y)$ can adopt any fuzzy membership function (MF). In this paper, the following Gaussian MF is used.

$$gaussian(x; c, \sigma) = e^{-\frac{1}{2}\left(\frac{x-c}{\sigma}\right)^2} \tag{3}$$

where $\{c_i, \sigma_i\}$ is the parameter set that changes the shapes of the MF. Parameters in this layer are referred to as *the premise parameters.*

Layer 2: Each node in this layer calculates the firing strength of a rule via multiplication:

$$O_i^2 = \omega_i = \mu_{A_i}(x)\mu_{B_i}(y), \qquad i = 1,2 \tag{4}$$

Layer 3: The *i*th node in this layer calculates the ratio of the *i*th rule's firing strength to the sum of all rules' firing strengths:

$$O_i^3 = \overline{\omega_i} = \frac{\omega_i}{\omega_1 + \omega_2}, \qquad i = 1,2 \tag{5}$$

where $\overline{\omega_i}$ is referred to as *the normalized firing strengths*.

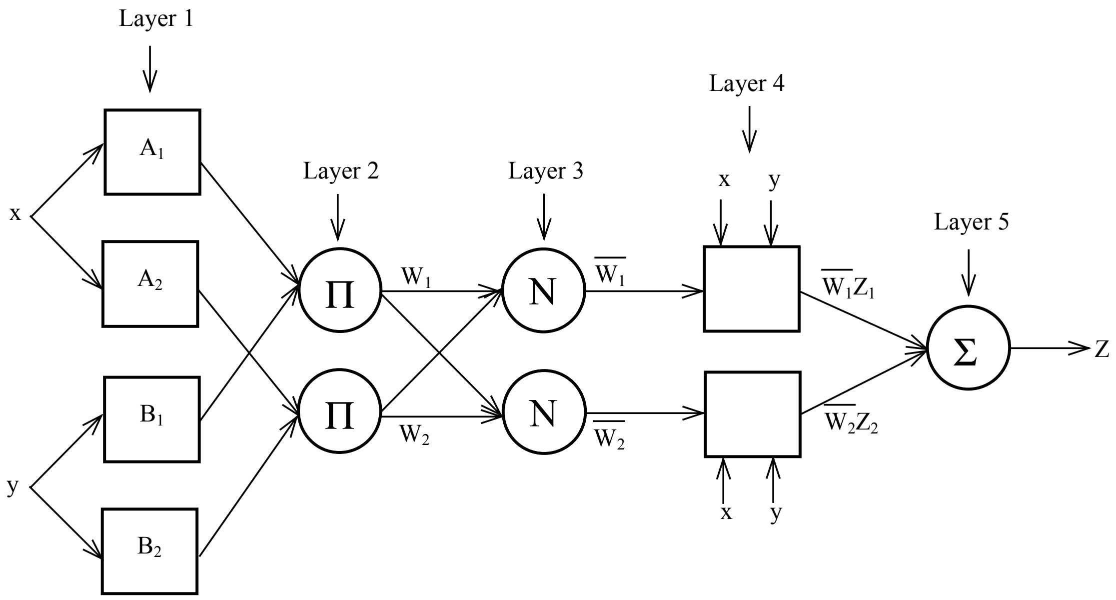


Figure 1. Architecture of ANFIS

Layer 4: In this layer, each node has the following function:

$$O_i^4 = \overline{\omega_i} z_i = \overline{\omega_i}(p_i x + q_i y + r_i), \quad i = 1, 2 \quad (6)$$

where $\overline{\omega_i}$ is the output of layer 3, and $\{p_i, q_i, r_i\}$ is the parameter set. Parameters in this layer are referred to as *the consequent parameters.*

Layer 5: The single node in this layer computes the overall output as the summation of all incoming signals, which is expressed as:

$$O_1^5 = \sum_{i=1}^{2} \overline{\omega_i} z_i = \frac{\omega_1 z_1 + \omega_2 z_2}{\omega_1 + \omega_2} \quad (7)$$

It is clear that the ANFIS has two sets of adjustable parameters, namely the premise and consequent parameters. During the learning process, the premise parameters in the layer 1 and the consequent parameters in the layer 4 are tuned until the desired response of the FIS is achieved. In this paper, the hybrid learning algorithm [5, 6], which combines the least square method (LSM) and the backpropagation (BP) algorithm, is used to rapidly train and adapt the FIS.

When the premise parameter values of the MF are fixed, the output of the ANFIS can be written as a linear combination of the consequent parameters:

$$z = (\overline{\omega_1} x)p_1 + (\overline{\omega_1} y)q_1 + (\overline{\omega_1})r_1 + (\overline{\omega_2} x)p_2 + (\overline{\omega_2} y)q_2 + (\overline{\omega_2})r_2 \quad (8)$$

The LSM can be used to determine optimally the values of the consequent parameters. When the premise parameters are not fixed, the search space becomes larger and the convergence of training becomes slower. The hybrid learning algorithm can be used to solve this problem. This algorithm is composed of a forward pass and a backward pass. In the forward pass, while holding the premise parameters fixed, the functional signals are propagated forward to layer 4, where the consequent parameters are identified by the LSM. In the backward pass, the consequent parameters are held fixed while the error signals, the derivative of the error measure with respect to each node output, are propagated from the output end to the input end, and the premise parameters are updated by the standard BP algorithm.

III. APPLICATION OF ANFIS TO THE CALCULATION OF THE ASSOCIATION PROBABILITIES FOR SINGLE TARGET TRACKING

The dynamics and measurement model of the interested target are given by

$$\begin{cases} x(t+1) = Fx(t) + w(t) \\ y(t) = Hx(t) + v(t) \end{cases} \quad (9)$$

where *x(t)* is the state vector, *F* is the state transition matrix, *w(t)* is the process noise, *y(t)* is the measurement vector, *H* is the measurement matrix, *v(t)* is the measurement noise, and *t* is the sampling time. The residual for the validated measurements is given by

$$\nu_j(t+1) = y_j(t+1) - H\hat{x}(t+1 \mid t) \quad (10)$$

where $\hat{x}(t+1|t)$ is the predicted state vector. The combined innovation is computed by using the following formula

$$\nu(t+1) = \sum_{j=1}^{m} \beta_j \nu_j(t+1). \quad (11)$$

where β_j is the association probabilities and *m* is the number of the validated measurements. The updated states of the targets are found by using

$$\hat{x}(t+1 \mid t+1) = \hat{x}(t+1 \mid t) + K(t)\upsilon(t+1) \quad (12)$$

where *K(t)* is Kalman gain. In order to find the updated states of the targets, in this study the association probabilities β_j are computed with ANFIS. For the ANFIS, the inputs are the absolute values of the elements of the measurement innovation vector ν_j ($|\tilde{x}_j|$ and $|\tilde{y}_j|$), and the output is the association probabilities β_j. The ANFIS model used in calculating β_j is shown in Figure 2.

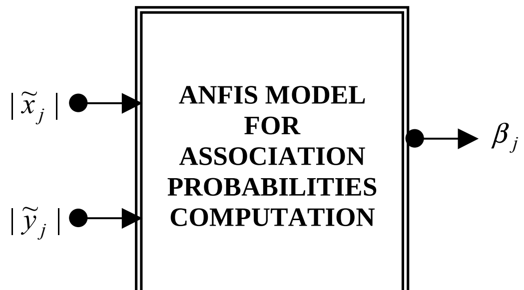


Figure 2. ANFIS model for association probabilities computation

Training an ANFIS with the use of the hybrid learning algorithm to compute the association probabilities involves presenting it sequentially with different sets ($|\tilde{x}_j|$ and $|\tilde{y}_j|$) and corresponding desired β_j values. Differences between the desired output β_j and the actual output of the ANFIS are evaluated by the hybrid learning algorithm. The adaptation is carried out after the presentation of each set ($|\tilde{x}_j|$ and $|\tilde{y}_j|$) until the calculation accuracy of the ANFIS is deemed satisfactory according to some criterion (for example, when the error between the desired β_j and the actual output for all the training set falls below a given threshold) or when the maximum allowable number of epochs is reached.

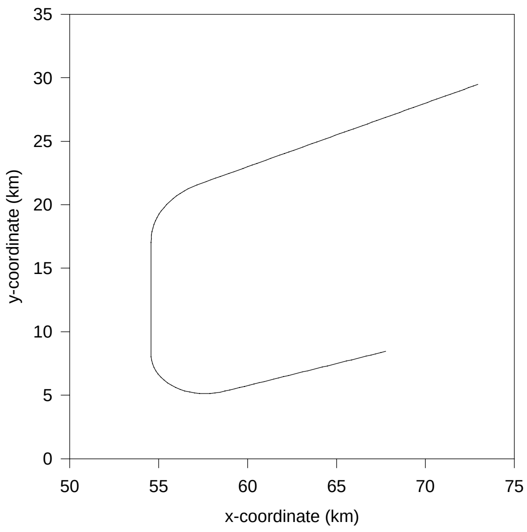
The values of the input variables $|\tilde{x}_j|$ and $|\tilde{y}_j|$ used in this paper are between 0 and 1.2 km. The β_j values, which depend on the absolute values of the input variables, must be between 0 and 1. While the values of the input variables approach to zero, the value of β_j approaches to 1. After many trials, the desired β_j values, which lead to an excellent agreement between the true tracks and estimated tracks, are determined. The 630 data sets were used to train the ANFIS.

The input and output data sets were scaled between 0 and 1 before training. The number of epoch was 10 for training. The hybrid learning algorithm can dramatically reduce the required training epochs because the training errors are de-coupled and treated separately. The number of membership functions for the input variables $|\tilde{x}_j|$ and $|\tilde{y}_j|$ are 5 and 5, respectively. The number of rules is then 25 (5x5=25). The gaussian MF is used for two input variables $|\tilde{x}_j|$ and $|\tilde{y}_j|$. It is clear from Eqn. (3) that the gaussian MF is specified by two parameters. Therefore, the ANFIS used here contains a total of 95 fitting parameters, of which 20 (5x2+5x2=20) are the premise parameters and 75 (3x25=75) are the consequent parameters.

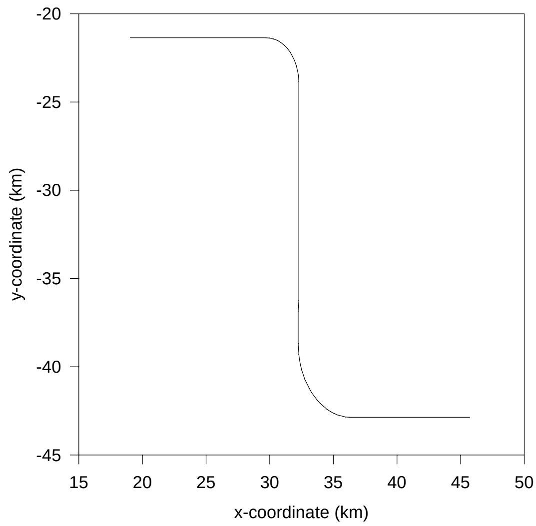
After training, the association probabilities (β_j) are computed rapidly by using the ANFIS for different test trajectories. The approach proposed in this paper can be called as ANFIS data association filter (ANFISDAF).

IV. SIMULATIONS

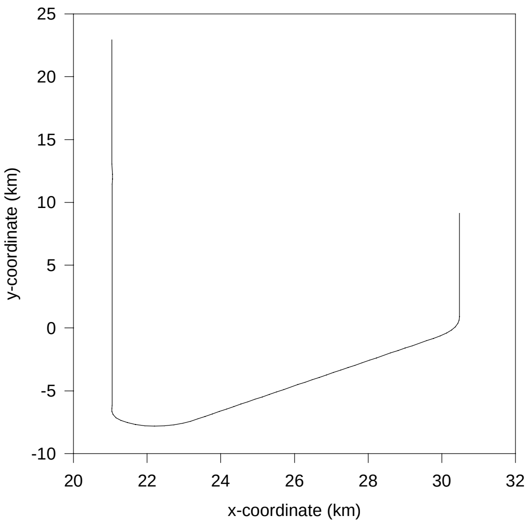
In this section, the performance evaluation of the ANFISDAF proposed in this paper is presented using different simulation studies. Three different target trajectories shown in Figure 3 are considered for this evaluation. A uniform clutter density was selected as about 0.1 km^{-2} for all targets. In the simulation the sampling interval was assumed to be 1 s. For comparison, we also obtained the target tracking results of the PDAF. Table 1 displays the performance comparison between the PDAF and the ANFISDAF in terms of RMS tracking error. The percentage improvement due to the ANFISDAF is evaluated as the ratio of the difference in the RMS error in the PDAF and the ANFISDAF to the RMS error in the PDAF in percent. It is clear from Table 1 that the test results of the ANFISDAF are better than those of the PDAF. The average percentage improvement using ANFISDAF is % 50.



(a) Target 1



(b) Target 2



(c) Target 3

Figure 3. Trajectories of the targets

Table 1. Performance comparison between the PDAF and the ANFISDAF

Targets	**RMS Tracking Error (m)**		**Percentage Improvement with ANFISDAF (%)**
	PDAF [1, 2]	**Present Method (ANFISDAF)**	
1	97.3	49.1	50
2	97.1	49.0	50
3	97.6	49.6	49

V. CONCLUSION

The ANFIS approach is presented for single target tracking in the cluttered environments. In this approach, the association probabilities are computed with the use of ANFIS. These computed association probabilities are used to determine the updated states of the targets. It was shown that the ANFISDAF tracks are in good agreement with the original tracks. This good agreement supports the validity of the approach proposed in this paper. Better accuracy with respect to the well known PDAF algorithm is obtained. A distinct advantage of ANFIS computation is that, after proper training, ANFIS completely bypasses the repeated use of complex iterative processes for new cases presented to it. Thus, the ANFIS computation is very fast after training phase.

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