Turk J Elec Engin, VOL.13, NO.1 2005, © TÜBİTAK

Computation of Association Probabilities for Single Target Tracking with the Use of Adaptive Neuro-Fuzzy Inference System

İlke TÜRKMEN[1] Kerim GÜNEY[2]
[1]*Department of Aircraft Electrical and Electronics, Civil Aviation School, Erciyes University, Kayseri, 38039, TURKEY*
e-mail: titi@erciyes.edu.tr
[2]*Electronic Engineering Department, Faculty of Engineering, Erciyes University, Kayseri, 38039, TURKEY*
e-mail: kguney@erciyes.edu.tr

Abstract

In this study, a simple method based on the adaptive neuro-fuzzy inference system (ANFIS) is presented for computing the association probabilities. The computed association probabilities are used to track the single manoeuvring target in the cluttered environment. A hybrid learning algorithm, which combines the least square method and the backpropagation algorithm, is used to identify the parameters of ANFIS. The tracks estimated by using the method proposed in this study are in very good agreement with the true tracks. Better accuracy with respect to the well known nearest neighbour Kalman filter and probabilistic data association algorithms is obtained.

Key Words: *Target tracking, data association, ANFIS, neuro-fuzzy inference system.*

1. Introduction

The target tracking [1-3] is an important issue in military surveillance, ballistic missile defence, satellite defence, 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, 2] 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.

The joint probabilistic data association filter (JPDAF) [3] is the extension of the PDAF to multitarget case. It works without any prior information about the targets and clutters. In the JPDAF algorithm, the association probabilities are computed from the joint likelihood functions corresponding to the joint hypotheses associating all the returns to different permutations of the targets and clutter points. The computational complexity for the joint probabilities increases exponentially as the number of targets increases. To reduce this computational complexity significantly, Fitzgerald [4] proposed the simplified version of the JPDAF, called the cheap JPDAF algorithm (CJPDAF). The association probabilities were calculated in [4] by using an ad hoc formula. The CJPDAF method is very fast and easy to implement; however, in either dense target or cluttered environment the tracking performance of the CJPDAF also decreases.

To calculate the association probabilities, different structures and architectures of artificial neural networks (ANNs) such as the standard Hopfield, the modified Hopfield, the Boltzmann machine, and the mean-field Hopfield were proposed in [5], [6], [7], and [8], respectively. In these works [5-8], the task of finding association probabilities is viewed as a constrained optimisation problem. The constraints were obtained by a careful evaluation of the properties of the JPDA rule. Some of these constraints are analogous to those of the classical travelling salesman problem. Usually, in the works [5-7] there are five constants to be decided arbitrarily. In practice, it is very difficult to choose the five constants to make sure that optimisation will be achieved. On the other hand, the Boltzmann machine's [7] convergence speed is very slow, even though it can achieve an optimal solution. To cope these problems, the mean-field Hopfield network, which is an alternative to the Hopfield network and the Boltzman machine, was proposed by Wang et al. [8]. This mean-field Hopfield network has the advantages of both the Hopfield network and the Boltzman machine; however, the higher performance of the mean-field Hopfield network was achieved at the expense of the complexity of equipment structure.

The fuzzy inference systems (FISs) [9-13] were also used in calculating the association probabilities. 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 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 the adaptive neuro-fuzzy inference system (ANFIS) [14, 15] is presented for efficiently solving this problem. First, the parameters related to the association probabilities are determined, then the association probabilities depending on these parameters are calculated by using the ANFIS.

The ANFIS can simulate and analysis the mapping relation between the input and output data through a learning algorithm to determine optimal parameters of a given FIS. It combines the explicit knowledge representation of FIS with learning power of ANN. 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 [14-19]. 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 manoeuvring target in the cluttered environment.

In previous works [20, 21], we successfully used ANFIS to compute the resonant frequency of triangular microstrip antennas and the input resistance of rectangular microstrip antennas. We also proposed FISs [22, 23] and ANNs [24-35] for computing accurately the various parameters of the rectangular, circular, and triangular microstrip antennas, and pyramidal horn antennas, and asymmetric coplanar waveguides. In the following sections, the PDAF and the ANFIS are described briefly, and the application of ANFIS to the calculation of the association probabilities for single target tracking is then explained.

2. Probabilistic Data Association Filter (PDAF)

The PDAF is a suboptimal Bayesian algorithm that associates probabilistically all the validated measurements to the target of interest [1, 2]. For n measurements falling inside validation region at time t, the probability that the j^{th} validated measurement $z_j(t)$ is target originated, denoted by β_j, is

$$\beta_j = \frac{e_j}{b + \sum_{l=1}^{n} e_l} \quad (j = 1, \ldots, n) \tag{1}$$

while the probability that none of the measurements is target originated, denoted by β_0, is

$$\beta_0 = \frac{b}{b + \sum_{l=1}^{n} e_l} \tag{2}$$

The term e_j in Eqn. (1) is given by

$$e_j = \exp\left\{ -\frac{1}{2} \upsilon_j^T(t) S^{-1}(t) \upsilon_j(t) \right\}, \tag{3}$$

where $\upsilon_j(t)$ is the residual for the j^{th} validated measurement, $S(t)$ is the residual covariance for the measurements, and the superscripts T and -1 represent the transpose and inverse of the matrix, respectively. In the standard PDAF, all measurement residuals are assumed to have same covariance. For the parametric PDAF, the term b is given by

$$b = \lambda \sqrt{\det |2\pi S(t)|} \frac{1 - P_D P_G}{P_D}, \tag{4}$$

where λ is the spatial density of the clutter (assumed known), P_D is the detection probability (assumed known), and P_G is the probability of the target-originated measurement falling inside the validation region. For the nonparametric PDAF, b is the same as in Eqn. (4), except that λ is replaced by n/V, where V is the hypervolume of the validated region at time t.

The state in the PDAF is updated using all of the validated measurements. The update is given by

$$\hat{x}(t|t) = \hat{x}(t|t-1) + K(t)\upsilon(t), \tag{5}$$

where $\hat{x}(t|t)$ is the updated state, $\hat{x}(t|t-1)$ is the predicted state, $K(t)$ is the Kalman gain, $\upsilon(t)$ is combined residual, which is given by

$$\upsilon(t) = \sum_{j=1}^{n} \beta_j \upsilon_j(t), \tag{6}$$

and $\upsilon_j(t)$ is the residual for the j^{th} validated measurement,

$$\upsilon_j(t) = z_j(t) - H(t)\hat{x}(t|t-1). \tag{7}$$

where $H(t)$ is the observation matrix.

The updated covariance can be written as

$$P(t|t) = \beta_0 P(t|t-1) + [1-\beta_0]P^c(t) + \tilde{P}(t) \tag{8}$$

with

$$P^c(t) = P(t|t-1) - K(t)S(t)K^T(t) \tag{9}$$

and

$$\tilde{P}(t) = K(t)\left[\sum_{j=1}^{n} \beta_j \upsilon_j(t)\upsilon_j^T(t) - \upsilon(t)\upsilon^T(t)\right]K^T(t). \tag{10}$$

The elements of the υ_j vector are defined by $\tilde{x}_j$ and $\tilde{y}_j$ for a cartesian sensor. Therefore, only two parameters, $\tilde{x}_j$ and $\tilde{y}_j$, are needed to describe the association probabilities. In this work, the association probabilities are calculated by using a new method based on ANFIS. Only two parameters, $\tilde{x}_j$ and $\tilde{y}_j$, are used in computing the association probabilities.

3. 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 [15]. 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. It combines the benefits of ANNs and FISs in a single model. 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.

A typical architecture of ANFIS is shown 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 used in this paper implements a first-order Sugeno fuzzy model. For this model, a typical rule set with two fuzzy if-then rules can be expressed as

$$\text{Rule 1: If } x \text{ is } A_1 \text{ and } y \text{ is } B_1\text{, then } z_1 = p_1x + q_1y + r_1 \tag{11a}$$

$$\text{Rule 2: If } x \text{ is } A_2 \text{ and } y \text{ is } B_2\text{, then } z_2 = p_2x + q_2y + r_2 \tag{11b}$$

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

$$O_i^1 = \mu_{A_i}(x), \quad i = 1, 2 \tag{12a}$$

$$O_i^1 = \mu_{B_{i-2}}(y), \quad i = 3, 4 \tag{12b}$$

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.

$$\text{gaussian}\,(x; c, \sigma) = e^{-\frac{1}{2}\left(\frac{x-c}{\sigma}\right)^2} \tag{13}$$

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.*

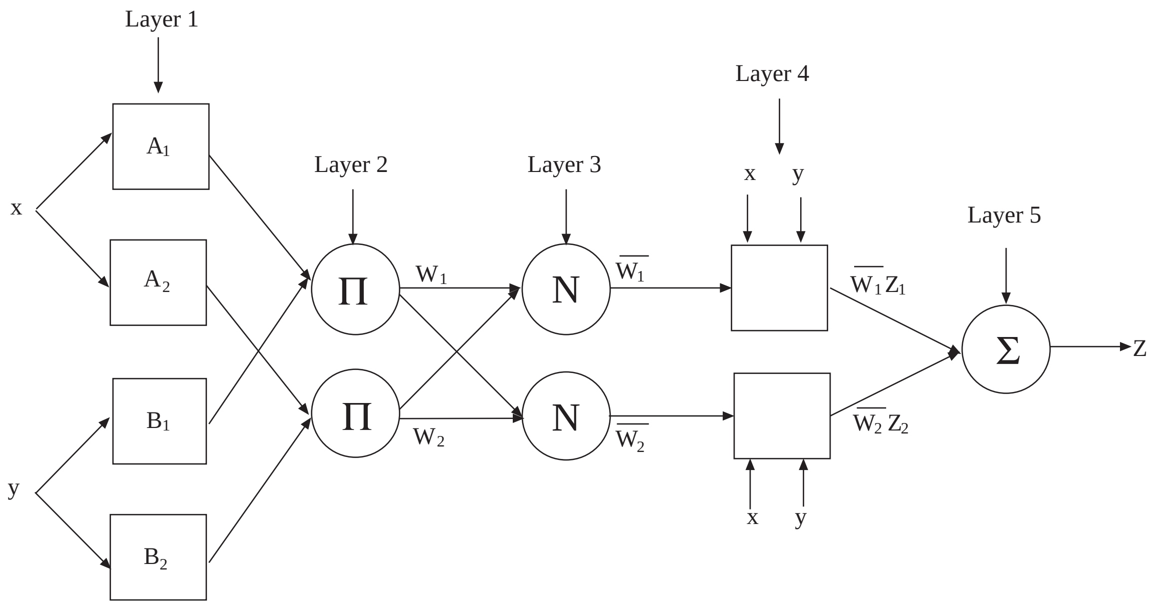

Figure 1. Architecture of ANFIS.

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

$$O_i^2 = \omega_i = \mu_{A_i}(x)\mu_{B_i}(y), \quad i = 1, 2 \tag{14}$$

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

$$O_i^3 = \overline{\omega_i} = \frac{\omega_i}{\omega_1 + \omega_2}, \quad i = 1, 2 \tag{15}$$

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

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

$$O_i^4 = \overline{\omega_i} z_i = \overline{\omega_i}(p_i x + q_i y + r_i), i = 1, 2 \tag{16}$$

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:

$$O_1^5 = \sum_{i=1}^{2} \overline{\omega_i} z_i = \frac{\omega_1 z_1 + \omega_2 z_2}{\omega_1 + \omega_2} \tag{17}$$

It is clear that the ANFIS has two set 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 [14, 15], which combines the least square method (LSM) and the backpropagation (BP) algorithm, is used to rapidly train and adapt the FIS. This algorithm converges much faster since it reduces the dimension of the search space of the BP algorithm.

It is seen from the ANFIS architecture that when the values of the premise parameters are fixed, the overall output can be expressed as a linear combination of the consequent parameters:

$$z = (\overline{\omega_1} x)p_1 + (\overline{\omega_1} y)q_1 + (\overline{\omega_1})r_1 + (\overline{\omega_2} x)p_2 + (\overline{\omega_2} y)q_2 + (\overline{\omega_2})r_2 \tag{18}$$

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.

4. Application of ANFIS to the Calculation of the Association Probabilities

In order to find the updated states of the targets, in this study the association probabilities β_j are computed by using ANFIS. For the ANFIS, the inputs are the absolute values of the elements of the measurement innovation vector υ_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.

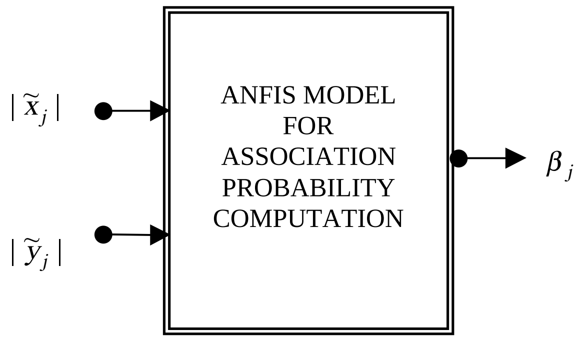

Figure 2. ANFIS model for association probability computation.

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 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. In this paper, 630 data sets, which are most suitable for the accurate computation of the association probabilities, 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. (13) 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. These computed association probabilities are used in Eqn. (6) to determine the combined residual, and then the estimated states of the targets are found by using the Kalman filter equations. The approach proposed in this paper can be called as ANFIS data association filter (ANFISDAF).

5. Simulations

In this section, the performance evaluation of the ANFISDAF proposed in this paper is presented using different simulation studies. Six different manoeuvring target trajectories shown in Figures 3-8 are considered for this evaluation. The initial positions and velocities of these targets are listed in Table 1. For all targets, a uniform clutter density was selected as about 0.1 km^{-2}. The clutter points were uniformly located in the measurement space with an average of about 3 clutter points per validation gate. In the simulation the sampling interval was assumed to be 1 s. The covariance matrix $Q(t)$ of the process noise $w(t)$ is given by

$$Q(t) = \begin{bmatrix} (\sigma_x(t))^2 & 0 \\ 0 & (\sigma_y(t))^2 \end{bmatrix}.$$

The associated variances were chosen as

$$(\sigma_x(t))^2 = 0.005 km^2 s^{-4}$$

$$(\sigma_y(t))^2 = 0.005 km^2 s^{-4}$$

.

It was assumed that only position measurements are available so that

$$H(t) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \text{ for all } t.$$

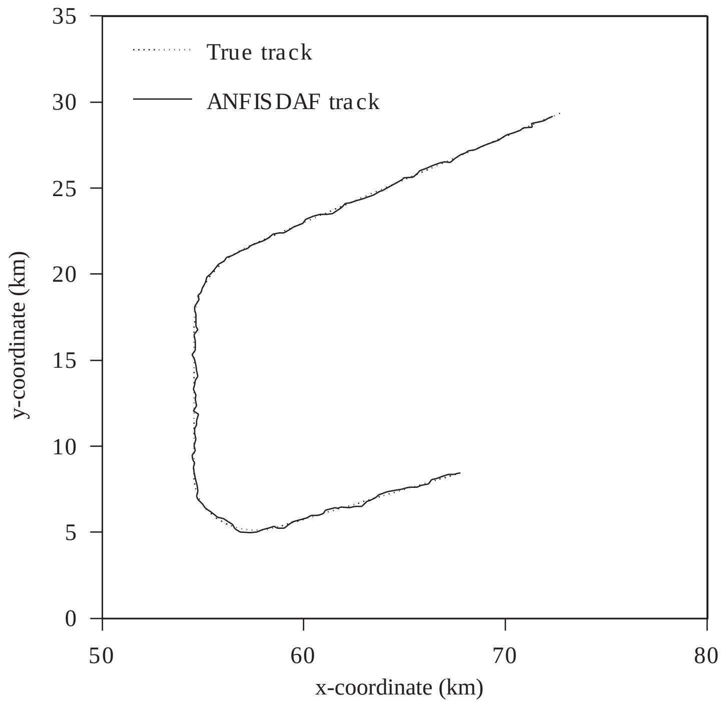

Figure 3. Tracking target 1 using ANFISDAF.

The measurement noise covariance matrix was $R(t)$=diag(0.1,0.1) assuming all the measurement noise to be uncorrelated. The probability of detection was selected as 0.9. The threshold of the validation gate was set to 10.

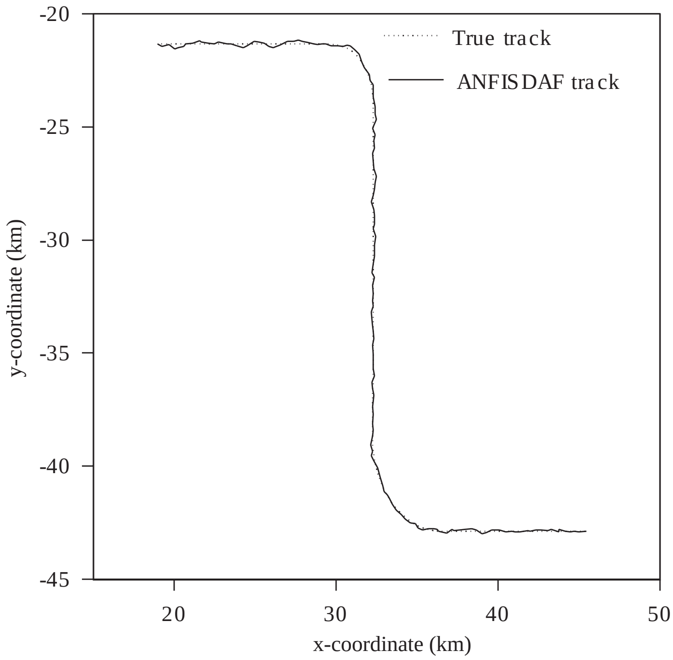

Figure 4. Tracking target 2 using ANFISDAF.

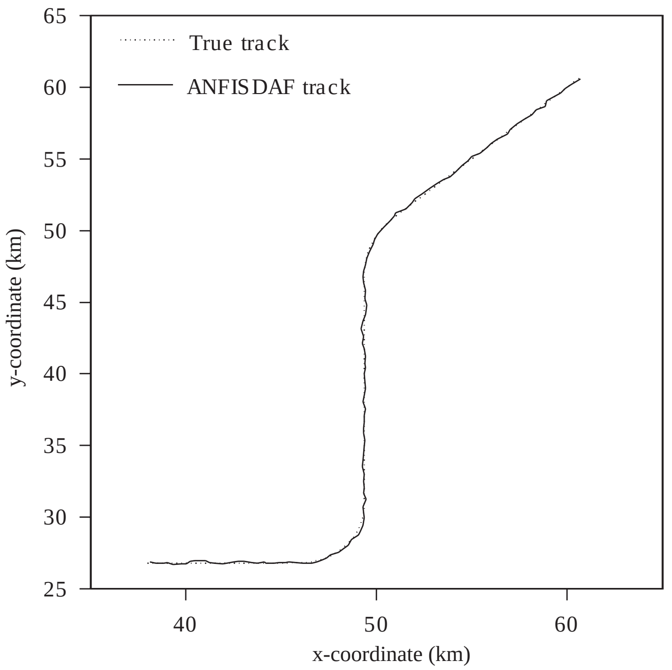

Figure 5. Tracking target 3 using ANFISDAF.

The tracking results of the ANFISDAF are presented in Figures 3-8 for six different test trajectories in the cluttered environment. It is seen from Figures 3-8 that the estimated tracks obtained from ANFISDAF are close to the true tracks for all targets. The good agreement between the ANFISDAF tracks and the true tracks supports the validity of the ANFISDAF method proposed here. For comparison, we also obtained the target tracking results of the nearest neighbour Kalman filter (NNKF) [3] and the PDAF. Table 2 gives the comparative performances of the NNKF, the PDAF, and the ANFISDAF methods in terms of RMS tracking error. The percentage improvement obtained by using the ANFISDAF is calculated as the ratio of the difference between the RMS errors of the ANFISDAF method and the competing method (NNKF or PDAF) to the RMS error of the competing method. It is clear from Table 2 that in all cases the results of the ANFISDAF are better than those of the NNKF and the PDAF methods. The RMS tracking error values clearly show that a significant improvement is obtained on the results of the NNKF and the PDAF methods. When the ANFISDAF is used, the average percentage improvements with respect to the NNKF and the PDAF are 58 % and 48 % , respectively. It is known that the track quality depends strongly on the associator's performance. The accurate association probability computation by using ANFIS leads to good accuracy in tracking single target. In addition to the association accuracy, the computational speed of the data association is also essential to target tracking system. The ANFISDAF method presented in this work does not require the excessive computational load for computing the association probabilities.

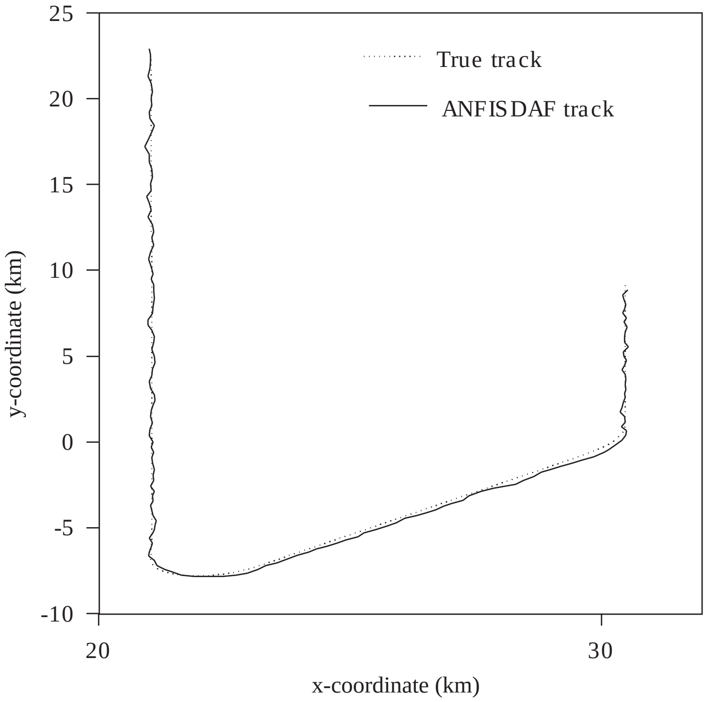

Figure 6. Tracking target 4 using ANFISDAF.

Table 1. Initial positions and velocities for six different test trajectories.

Targets	x (km)	y (km)	$\dot{x}$ (km/s)	$\dot{y}$ (km/s)
1	72.68	29.34	-0.26	-0.13
2	45.47	-42.87	-0.31	-0.01
3	60.62	60.61	-0.33	-0.32
4	30.48	9.13	0.01	-0.28
5	80.75	1.16	-0.21	0.21
6	65.93	29.38	-0.42	0.01

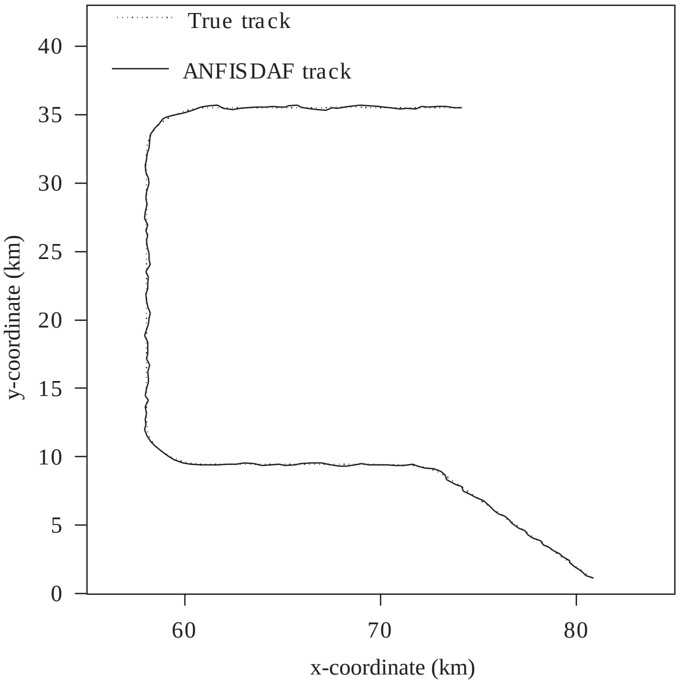

Figure 7. Tracking target 5 using ANFISDAF.

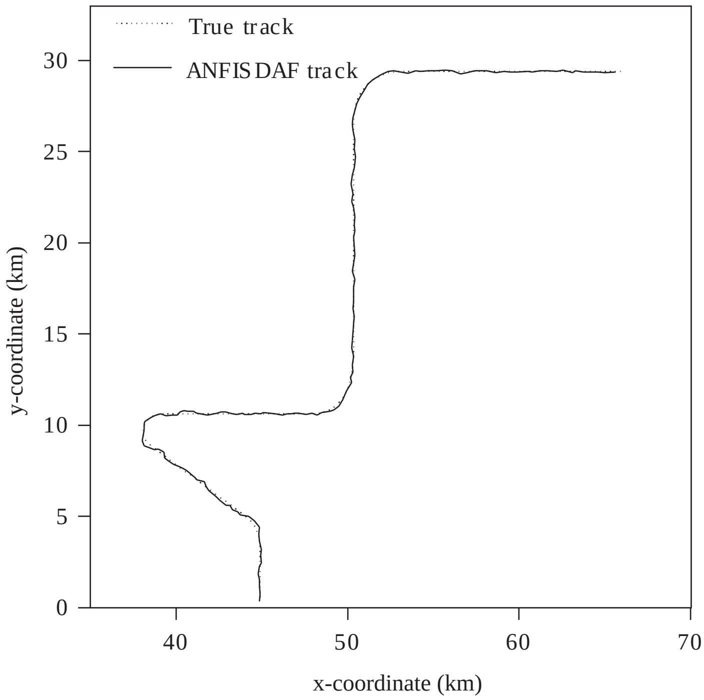

Figure 8. Tracking target 6 using ANFISDAF.

Table 2. Performance comparison of the NNKF, the PDAF, and the ANFISDAF methods.

Targets	RMS Tracking Errors (m)			Percentage Improvement with Respect to NNKF (%)	Percentage Improvement with Respect to PDAF (%)
	NNKF [3]	PDAF [1,2]	Present Method (ANFISDAF)		
1	118.2	97.3	49.1	58	50
2	119.1	97.1	49.0	59	50
3	115.2	90.2	49.3	57	45
4	118.4	97.6	49.6	58	49
5	121.8	99.1	51.2	58	48
6	122.4	98.9	53.9	56	46

6. Conclusion

The ANFIS approach is presented for single target tracking in the cluttered environment. 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 very good agreement with the true tracks. This good agreement supports the validity of the approach proposed in this paper. Better accuracy with respect to the well known NNKF and PDAF algorithms is obtained. Accurate, fast, and reliable ANFIS models can be developed from measured/simulated data. Once developed, these ANFIS models can be used in place of computationally intensive models to speed up target tracking. 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.

References

[1] Y. Bar-Shalom, E. Tse, "Tracking in a Cluttered Environment with Probabilistic Data Association," Automatica, Vol. 11, pp. 451-460, 1975.

[2] Y. Bar-Shalom, T.E. Fortmann, Tracking and Data Association, San Diego: CA: Academic Press, 1988.

[3] Y. Bar-Shalom, Multitarget-Multisensor Tracking: Principles and Techniques, YBS Publishing, 1995.

[4] R.J. Fitzgerald, "Development of Practical PDA Logic for Multitarget Tracking by Microprocessor," in Proc. of the American Control Conference, Seattle, Washington, pp. 889-897, 1986.

[5] D. Sengupta, R.A. Iltis, "Neural Solution to the Multitarget Tracking Data Association Problem," IEEE Transactions on Aerospace and Electronic Systems, Vol. 25, No. 1, pp. 96-108, 1989.

[6] H. Leung, "Neural-Network Data Association with Application to Multiple-Target Tracking," Optical Engineering, Vol. 35, No. 3, pp. 693-700, 1996.

[7] R.A. Iltis, P.Y. Ting, "Computing Association Probabilities Using Parallel Boltzmann Machines," IEEE Transactions on Neural Networks, Vol. 4, No. 2, pp. 221-233, 1993.

[8] F. Wang, J. Litva, T. Lo, E. Bosse, "Performance of Neural Data Associator," IEE Proc.- Radar, Sonar Navigation, Vol. 143, No. 2, pp. 71-78, 1996.

[9] C. Moore, C. Harris, E. Rogers, "Utilizing Fuzzy Models in the Design of Estimators and Predictors: An Agile Target Tracking Example," in Proc. of the 2^{nd} IEEE Conference on Fuzzy Systems, pp. 679-684, 1993.

[10] A. Tummert, "Fuzzy Technology Implemented in Sonar Systems," IEEE J. Oceanic Eng., Vol. 18, No. 4, pp. 483-490, 1993.

[11] O. Hossam, M. Farooq, T. Quach, "Fuzzy Logic Approach to Data Association," in Proc. SPIE 2755, pp. 313-321, 1996.

[12] R.P. Singh, W.H. Balley, "Fuzzy Logic Applications to Multi-Sensor Multitarget Correlation," IEEE Transactions on Aerospace and Electronic Systems, Vol. 33, No. 3, pp. 752-769, 1997.

[13] Y.M. Chen, H.C. Huang, "Fuzzy Logic Approach to Multisensor Data Association," Mathematics and Computers in Simulation, Vol. 52, pp. 399-412, 2000.

[14] J.S.R. Jang, "ANFIS: Adaptive-Network-Based Fuzzy Inference System," IEEE Trans. Systems, Man, and Cybernetics, Vol. 23, pp. 665-685, 1993.

[15] J.S.R. Jang, C.T. Sun, E. Mizutani, Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence, Prentice-Hall, Upper Saddle River, NJ, 1997.

[16] M. Brown, C. Haris, Neurofuzzy Adaptive Modeling and Control, Prentice-Hall, Englewood Cliffs, NJ, 1994.

[17] V.A. Constantin, Fuzzy Logic and Neuro-Fuzzy Applications Explained, Prentice-Hall, Englewood Cliffs, NJ, 1995.

[18] C.T. Lin, C.S.G. Lee, Neural Fuzzy Systems: A Neuro-Fuzzy Synergism to Intelligent Systems, Prentice-Hall, Upper Saddle River, NJ, 1996.

[19] J. Kim, N. Kasabov, "HyFIS: Adaptive Neuro-Fuzzy Inference Systems and Their Application to Nonlinear Dynamical Systems," Neural Networks, Vol. 12, pp. 1301–1319, 1999.

[20] K. Guney, N. Sarikaya, "Adaptive Neuro-Fuzzy Inference System for the Input Resistance Computation of Rectangular Microstrip Antennas with Thin and Thick Substrates," Journal of Electromagnetic Waves and Applications (JEWA), Vol. 18, pp. 23-39, 2004.

[21] K. Guney, N. Sarikaya, "Computation of Resonant Frequency for Equilateral Triangular Microstrip Antennas with the Use of Adaptive Neuro-Fuzzy Inference System," International Journal of RF and Microwave Computer-Aided Engineering, Vol. 14, pp. 134-143, 2004.

[22] S. Ozer, K. Guney, A. Kaplan, "Computation of the Resonant Frequency of Electrically Thin and Thick Rectangular Microstrip Antennas with the Use of Fuzzy Inference Systems," International Journal of RF and Microwave Computer-Aided Engineering, Vol. 10, pp. 108-119, 2000.

[23] A. Kaplan, K. Guney, S. Ozer, "Fuzzy Associative Memories for the Computation of the Bandwidth of Rectangular Microstrip Antennas with Thin and Thick Substrates," International Journal of Electronics (IJE), Vol. 88, pp. 189-195, 2001.

[24] S. Sagiroglu, K. Guney, "Calculation of Resonant Frequency for an Equilateral Triangular Microstrip Antenna with the Use of Artificial Neural Networks," Microwave and Optical Technology Letters, Vol. 14, pp. 89-93, 1997.

[25] S. Sagiroglu, K. Guney, M. Erler, "Resonant Frequency Calculation for Circular Microstrip Antennas using Artificial Neural Networks," International Journal of RF and Microwave Computer-Aided Engineering, Vol. 8, pp. 270-277, 1998.

[26] S. Sagiroglu, K. Guney, M. Erler, "Calculation of Bandwidth for Electrically Thin and Thick Rectangular Microstrip Antennas with the Use of Multilayered Perceptrons," International Journal of RF and Microwave Computer-Aided Engineering (Special Issue: Applications of Artificial Neural Networks to RF and Microwave Design), Vol. 9, pp. 277-286, 1999.

[27] D. Karaboga, K. Guney, S. Sagiroglu, M. Erler, "Neural Computation of Resonant Frequency of Electrically Thin and Thick Rectangular Microstrip Antennas," IEE Proc. Microwaves, Antennas and Propagation, Pt H, Vol. 146, pp. 155-159, 1999.

[28] K. Guney, M. Erler, S. Sagiroglu, "Artificial Neural Networks for the Resonant Resistance Calculation of Electrically Thin and Thick Rectangular Microstrip Antennas," Electromagnetics, Vol. 20, pp. 387-400, 2000.

[29] K. Guney, S. Sagiroglu, M. Erler, "Comparison of Neural Networks for Resonant Frequency Computation of Electrically Thin and Thick Rectangular Microstrip Antennas," Journal of Electromagnetic Waves and Applications (JEWA), Vol. 15, pp. 1121-1145, 2001.

[30] K. Guney, S. Sagiroglu, M. Erler, "Generalized Neural Method to Determine Resonant Frequencies of Various Microstrip Antennas," International Journal of RF and Microwave Computer-Aided Engineering (Special Issue: Applications of Artificial Neural Networks to RF and Microwave Design), Vol. 12, pp. 131-139, 2002.

[31] K. Guney, S. Sagiroglu, M. Erler, "Design of Rectangular Microstrip Antennas with the Use of Artificial Neural Networks," Neural Network World, Vol. 4, pp. 361-370, 2002.

[32] C. Yildiz, S. Gultekin, K. Guney, S. Sagiroglu, "Neural Models for the Resonant Frequency of Electrically Thin and Thick Circular Microstrip Antennas and the Characteristic Parameters of Asymmetric Coplanar Waveguides Backed with a Conductor," AEU Int J Electron Commun, Vol. 56, pp. 396-406, 2002.

[33] S. Gultekin, K. Guney, S. Sagiroglu, "Neural Networks for the Calculation of Bandwidth of Rectangular Microstrip Antennas," Applied Computational Electromagnetics Society (ACES) Journal, Vol. 18, pp. 46-56, 2003.

[34] K. Guney, N. Sarikaya, "Artificial Neural Networks for Calculating the Input Resistance of Circular Microstrip Antennas," Microwave and Optical Technology Letters, Vol. 37, pp. 107-111, 2003.

[35] K. Guney, N. Sarikaya, "Artificial Neural Networks for the Narrow Aperture Dimension Calculation of Optimum Gain Pyramidal Horns," Electrical Engineering (Archiv fur Elektrotechnik),Vol. 86, pp. 157-163, 2004.