ADAPTIVE NEURO-FUZZY AIDED KALMAN FILTER FOR TARGET TRACKING

İlke Titi[1] Kerim Güney[2]
e-mail: titi@erciyes.edu.tr e-mail: kguney@erciyes.edu.tr

[1]Erciyes University, Civil Aviation School, 38039, Kayseri, Turkey
[2]Erciyes University, Faculty of Engineering, Department of Electronics Engineering, 38039, Kayseri, Turkey

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ABSTRACT
In this work, an adaptive neuro-fuzzy system aided Kalman filter (KF) for target tracking is presented to reduce the prediction errors of KF. Target trajectories are obtained from the real aircraft radars such as cargo, bomber, fighter and commercial aircrafts. Adaptive neuro-fuzzy system is trained by using the parameters of KF and is used for modeling the errors of KF. It was shown that the results of the adaptive neuro-fuzzy system aided KF are better than those predicted by the KF and also by the neural network aided KF.

I. INTRODUCTION
Target tracking is an important issue in military surveillance systems, especially when such systems employ multiple sensors to interpret the environment. A target tracking KF estimates the state of a maneuvering target from noisy radar measurements in the polar coordinates [1].

KF is effective for simple scenarios such as in a clutterless environment or a single sensor single target tracking. However, under dense target environment, extraneous sensor reports may be incorrectly used by the KF for track update, thus resulting in degraded performance, possibly loss of track may occur. Because of shortcomings of the KF approach, a hybrid neural network (NN) approach is proposed by Chin [2] for tracking a non maneuvering target in one dimension two state scenario. His approach combines the estimation capability of the KF and the learning capability of the NN thus resulting in improved tracking accuracy. This approach is developed later for multiple maneuvering targets [3,4]. For tracking the maneuvering targets, the complex modeling requirement in the KF is also eliminated by the back propagation neural networks in [3,4]. Moreover, the real implementation time is reduced to the sum of the acceleration model implementation time and the NN recall time which is lesser than the computational requirements of the existing interacting multiple model tracking schemes.

In previous works [5-13], we also successfully introduced NNs and fuzzy inference systems (FISs) to compute the various parameters of the triangular, rectangular and circular microstrip antennas. The purpose of this study is to show an improvement in target tracking by using an adaptive neuro-fuzzy system aided Kalman filter (ANFSAKF). The simulation results of ANFSAKF are compared with by the KF and also by the neural network aided Kalman Filter (NNAKF).

II. KALMAN TRACKING ALGORİTHM
For the estimation of target position and velocity from track data, it is common to use recursive Kalman filtering algorithms. The motion of a target being tracked is modelled as

$$X_{t+1} = \Phi X_t + q_t \tag{1}$$

with

$$\Phi = \begin{bmatrix} I_3 & \Delta t I_3 & 1/2\Delta t^2 I_3 \\ 0_3 & I_3 & \Delta t I_3 \\ 0_3 & 0_3 & I_3 \end{bmatrix} \tag{2}$$

where Φ describes the system dynamics, Δt is sampling interval and corresponds to time interval assumed uniform, at which measurement data are received, I_3 denotes the (3x3) identity matrix and 0_3 represents the (3x3) null matrix. In equation (1), X_t represents position and velocity in each of the Cartesian coordinates axes x, y, z as

$$X_t = [x\ y\ z\ \dot{x}\ \dot{y}\ \dot{z}\ \ddot{x}\ \ddot{y}\ \ddot{z}]^T \tag{3}$$

where $x, \dot{x}$ and $\ddot{x}$ are the target position, velocity and acceleration along x axis at time t, respectively, and T is the transpose operation. In equation (1), q_t is zero mean, white and Gaussian process noise with assumed known covariance Q.

Measurements are in the form of linear combination of the system state variables, corrupted by uncorrelated noise. The m-dimensional measurement vector is modelled as

$$Z_t = HX_t + v_t \tag{4}$$

where H is measurement matrix given by $[I_3\ 0_3\ 0_3]$; v_t is the zero-mean, white Gaussian measurement noise with covariance R_c.

The Kalman algorithm works in two stages, viz., time update and measurement update. Time update equations are given by

$$X_{t|t-1} = \Phi X_{t-1|t-1} \tag{5}$$

$$P_{t|t-1} = \Phi P_{t-1|t-1}\Phi^T + Q \tag{6}$$

and measurement update equations are given by

$$K_t = P_{t|t-1}H^T[HP_{t|t-1}H^T + R_{C_t}]^{-1} \tag{7}$$

$$P_{t|t} = [I - K_t H]P_{t|t-1} \tag{8}$$

$$X_{t|t} = X_{t|t-1} + K_t[Z_t - HX_{t|t-1}] \tag{9}$$

The working of the Kalman algorithm is as follows. At time t, before the measurement y_t is received, using the previous filtered estimate $X_{t-1|t-1}$ and filtered error covariance $P_{t-1|t-1}$ the best estimate of the state $X_{t|t-1}$ and the corresponding $P_{t|t-1}$ are obtained using the equations (5)-(6). This is referred as time update stage. Once the prediction is completed the Kalman gain K_t is evaluated. As soon as the measurements are available the innovation Z_t-$HX_{t|t-1}$ is determined. The innovation is weighed by the gain K_t to correct the predicted state estimates. In the measurement update stage of the algorithm, the filtered state estimate $X_{t|t}$ and filtered error covariances $P_{t|t}$ are obtained using equations (8) and (9). The algorithm then awaits the next measurement at time t+1 and the above process is repeated for each of the subsequent measurements.

III. ADAPTIVE NEURO-FUZZY SYSTEM AIDED KALMAN FILTER (ANFSAKF) FOR TARGET TRACKING

The basic concept of ANFSAKF method proposed in this work is shown in Figure 1. To reduce the estimation error, an adaptive neuro-fuzzy inference system is employed to aid the KF.

ANFIS, known as Adaptive Neuro-Fuzzy Inference System, is used for constructing a set of fuzzy IF-THEN rules with appropriate membership functions [14,15]. The basic idea behind these neuro-adaptive learning techniques is very simple. These techniques provide a method for the fuzzy modeling procedure to learn information about a data set, in order to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data. This learning method works similarly to that of neural networks. With a gradient descent or back propagation algorithm based on the training data of desired input-output pairs, ANFIS is to tune the membership functions of a fuzzy inference system to minimize the rms error.

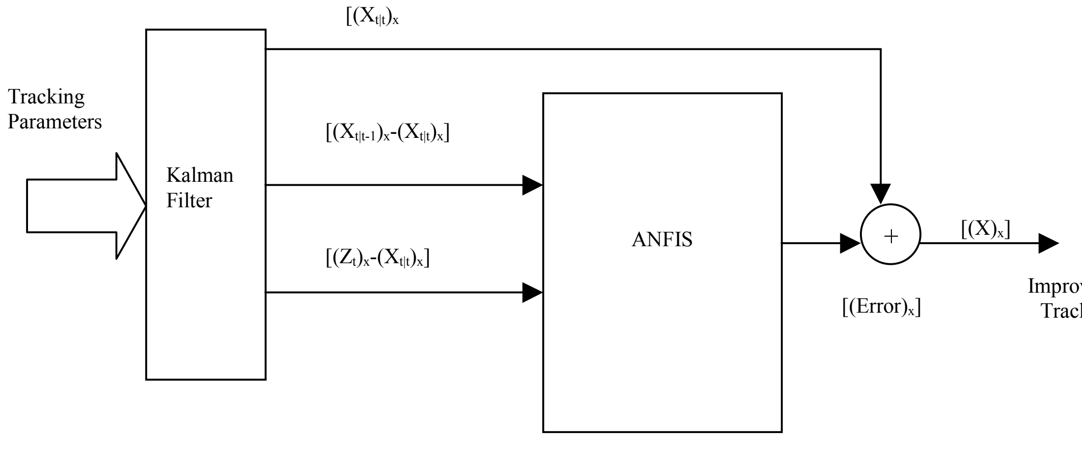

Figure 1. ANFSAKF Target Tracker.

The parameters associated with the membership functions will change through the learning process. The computation of these parameters (or their adjustment) is facilitated by a gradient vector, which provides a measure of how well the fuzzy inference system is modeling the input/output data for a given set of parameters. Once the gradient vector is obtained, any of several optimization routines could be applied in order to adjust the parameters so as to reduce some error measure (usually defined by the sum of the squared difference between actual and desired outputs). ANFIS uses either back propagation or a combination of least squares estimation and backpropagation for membership function parameter estimation. In this study, ANFIS with back-propagation algorithm is pretrained using the difference between the range measurement (z) and estimated range ($x_{t|t}$) and the difference between the predicted range ($x_{t|t}$) and estimated range ($x_{t|t-1}$).

IV. RESULTS AND CONCLUSIONS

In this paper, ANFSAKF was applied to reduce tracking error of maneuvering targets in a cluttered environment. To achieve good results of tracking performance, a given set of training data should be processed many times so that the best trained data is selected for the simulation programs. In this simulation, each set of data pairs (3300*3 matrix) is trained continuously for 10 times, and the FIS matrix with small error is selected. Target trajectories are obtained from real aircraft radars such as cargo, bomber, fighter, commercial aircraft [16]. In this study, the trajectory of a cargo aircraft which is shown in Figure 2 was used. Only, the x position results of this target was given. It was observed that the types and numbers of MFs affect on the rms training error of ANFIS. In this work, the best results were obtained from the triangular MF with the number of 4.

The output of training data set (Error of KF) is given in Figure 3a. Figure 3b shows the output of ANFIS. It is apparent from Figure 3 that the output of the KF is very similar to that of ANFIS. To decrease the tracking error of KF, the output of ANFIS is aided to the estimation of KF. Thus, the complex modelling requirement in the KF for tracking the maneuvering targets is also eliminated by the adaptive neuro-fuzzy system.

In Figure 4, the tracking performance of the ANFSAKF is compared with that of the KF for x position. It is evident from Figure 4 that the ANFSAKF tracks are closer to the original tracks than the tracks predicted by the KF. In Figure 5, the tracking errors of the ANFSAKF are also compared with those of the KF and the NNAKF. It can be seen from Figure 5 that the results of the ANFSAKF are better than those of the KF and the NNAKF. Similar good results were obtained for y and z positions and another target trajectories. The good agreement between the original tracks and the ANFSAKF tracks supports the validity of the ANFSAKF. The advantages of the ANFSAKF are the simplicity and accuracy.

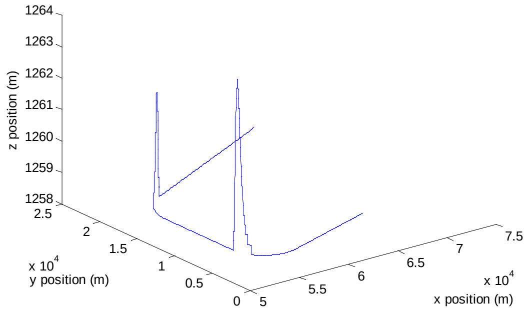

Figure 2 Trajectory of Target

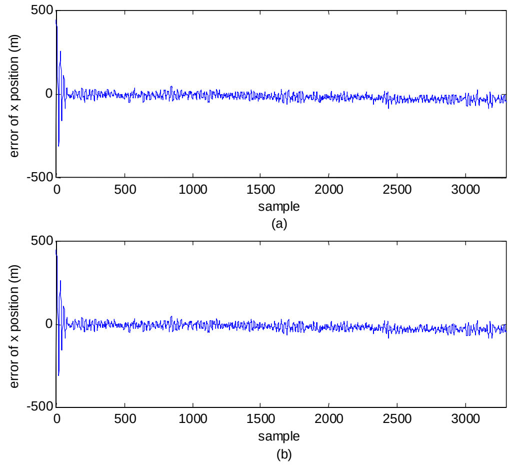

Figure 3. (a) Output of training data set (Error of Kalman Filter) (b) Output of ANFIS

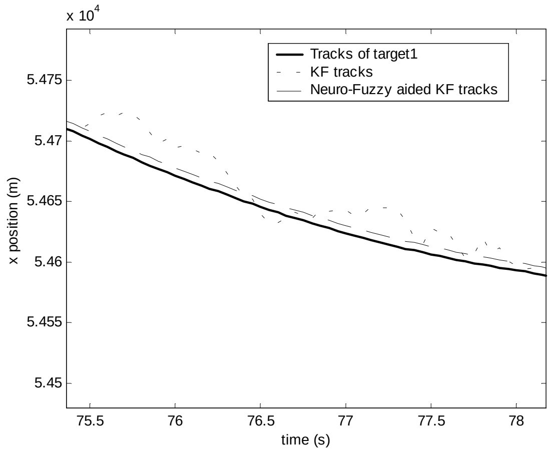

Figure 4. Performance of the KF and the NF aided KF

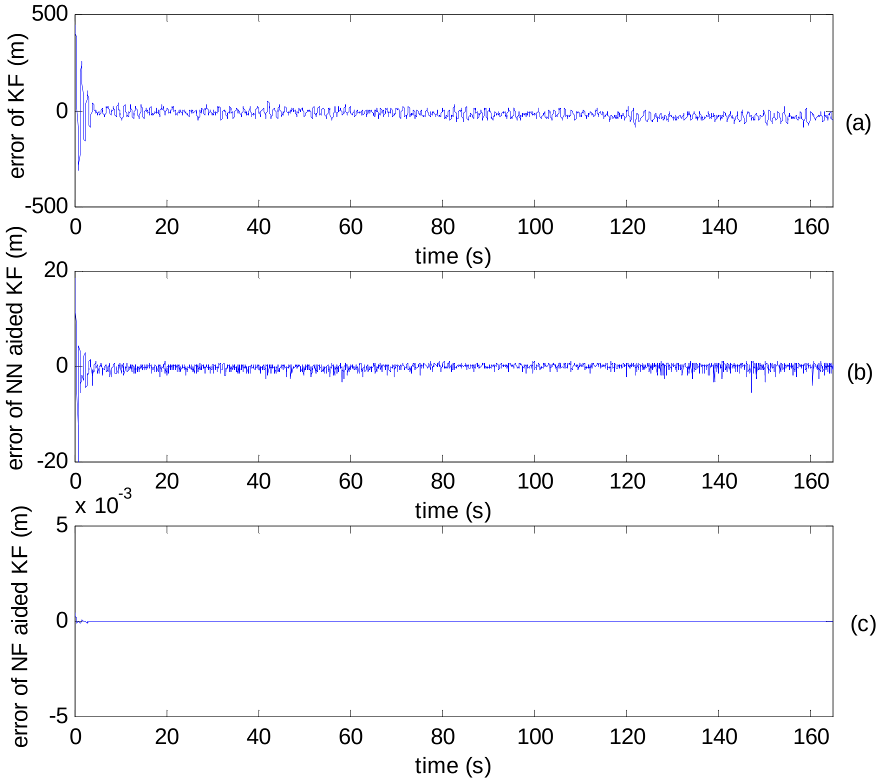

Figure 5. Error of (a) KF, (b) NNAKF and (c) ANFSAKF

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