Tracking Aircrafts by Using Impulse Exclusive Filter with RBF Neural Networks

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Abstract. Target Tracking based on Artificial Neural Networks has become a very important research field in *Dynamic Signal Processing*. In this paper, a new Target Tracking filter, entitled RBF neural network based Target Tracking Filter, RBF-TT, has been proposed. The tracking performance of the proposed filter, RBF-TT, has also been compared with the classical *Kalman Filter* based Target Tracking algorithm. Predictions during experiments have been made for the civil aircraft positions, one step ahead in real time. Extensive simulations revealed that the proposed filter supplies superior tracking performances to the Kalman Filter based comparison filter.

1 Introduction

One of the most important requirements for surveillance systems, e.g. *Civil Aviation Air Traffic Control*, is Target Tracking (TT), which employs one or more sensors, together with computer subsystems, to interpret the environment [1,2,3,4,5,6,7,8,9,10,11]. Typical sensor systems, such as *Sonar*, *Tracking-Radar* and *Infrared*, report measurements from diverse sources: targets of interest, background noise sources such as clutter, or internal error sources such as *thermal noise* and *impulsive noise*. The objective of TT is based on the collection of sensor data from a field of view containing one or more potential targets of interest and then to partition the sensor data into sets of observations, or tracks, that are produced by the same sources. After the tracks are formed and confirmed, the number of targets can be estimated and quantities, such as target velocity, future predictions, and target classification characteristics, can be computed for each of the track [1,2,3].

There are three main areas in which neural network technology is applied to tracking, data association, and related problems [1,4,5]. These applications are the solutions of assignment-type problems via the Hopfield neural network approach [6], the use of neurons to represent bins in target state space for the TT application discussed in the [1,2], and tracking filter design and data association in TT [1,2,6].

The purpose of TT is to estimate various aspects of motion such as 3D spatial location of the target based on information obtained by Tracking-Radar sensors

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in *Civil Aviation* [1,2]. Many discussions are available on TT using active sensor systems [1,2,3,4,5,7,8,9,10,11,12].

On the other hand, due to recent advances in radar technology [13], it is now possible to use passive sensors such as infrared sensors and sonar systems for TT. When the passive sensors are used, only the information on the target angle seen from the sensor is obtained with a single sensor. A successful performance of TT is obtained when the optimal extraction of useful information about the state of the target is selected from the noisy observations [1,2,3,7,8,9,10,11,12]. A good model of the target certainly facilitates this extraction of information to a great extent. Hence, one can easily say that a good model is worth a thousand pieces of data.

Most of the TT algorithms are *model-based* because a good model-based tracking algorithm greatly outperforms any model-free tracking algorithm if the underlying model turns out to be a good one. *Target detection*, *tracking*, *classification* and *identification* (recognition) are closely interrelated areas of TT, with significant overlaps [7,8,9,10,11,12].

In this paper, a new TT filter based on impulse exclusive filter with RBF neural networks has been proposed. The remaining part of the paper is organized as follows. Section 2 briefly gives *Radar Technology and Uncertainty of Target Positioning*. Section 3 describes *Kalman Filter Based Target Tracking*. The presentation of the *Proposed Method*, *Experiments* and *Results and Conclusions* are given in Sections 4, 5 and 6, respectively.

2 Radar Technology and Uncertainty of Target Positioning

One important function of each radar surveillance system is to keep and improve target tracking maintenance performance [13]. It becomes a crucial and challenging problem especially in complicated situations of closely spaced, or crossing targets [1,2,3,4,5,7,8,9,10,11].

There are approximately 11,000 aircrafts on the *Civil Aircraft Registry* [14]. Therefore, TT has a vital importance in *Civil Aviation Safety*. The scientific researches on Avionics were concentrated on *Communications*, *Radar* and *TT*, which are main research areas of Ultra-Wideband technologies [12,13]. The radar sensor is probably the most used active sensor for TT applications [1,2,3,12,13]. The technical details of the Radar Systems have not been mentioned in this paper due to paper length limitations. An excellent tutorial of Radar Systems can be found in [13].

The radar sensor emits *microwave-energy* and then measures the returned energy. Hence, it is possible to calculate the distance to the target from the time delay and the speed of light. The sensor can be used in a passive mode, searching for targets emitting radar signals. This is often referred to as a radar warning receiver. Depending on the particular application and radar sensor, different features are measured by the sensor. The most common one is measuring angles (azimuth (θ), and elevation) and range (R) or 3D spatial positions, x-y-z, of

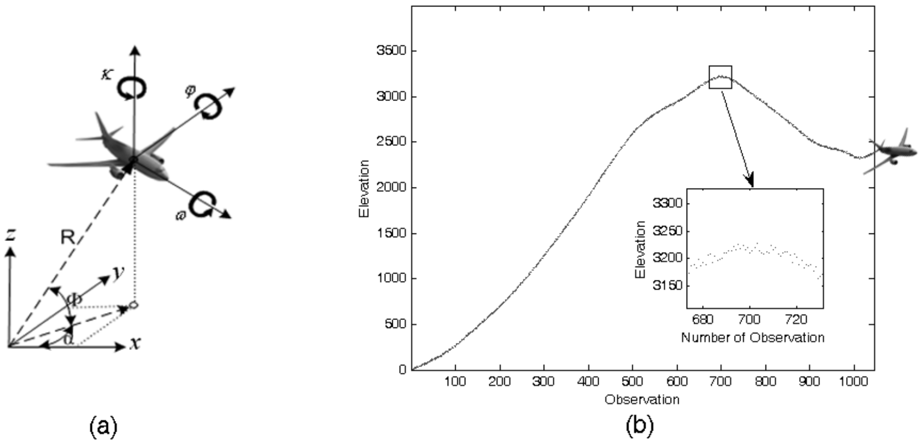

Fig. 1. (a) Target and Cartesian Coordinate System, (b) Observations

the target [12,13]. If a doppler-radar is used, the range rate is available. The range and resolution of the measurements are dependent on the used signal processing technique and also on the physical constraints, especially the antenna aperture [13]. Different signal processing techniques used in radar applications are constant false-alarm rate and *Synthetic Aperture Radar*.

Selection of coordinate systems for TT problem has been examined in various studies. In general, θ and R have been used for radar measurements and x-y-z spatial-cartesian coordinates have been used for TT purposes [12,13]. Some of the basic tracking models, such as Tracking-Radars, use cartesian coordinates in order to trace targets. In this paper a total of 1050 x-y-z data of a Tracking-Radar system have been employed. The spatial relations of the Target (e.g., Aircraft) and cartesian coordinate system have been illustrated in Fig. 1(a). The tracking data, which have the standard deviation of $\sigma = 5.00$, have been illustrated with pseudo-scaling in Fig. 1(b).

3 Kalman Filter Based Target Tracking

Kalman filtering [12] is a relatively recent development in filtering, although it has roots going far back to Gauss [1,2,3,12]. Kalman filtering has been applied in many areas as diverse as *aerospace*, *marine navigation*, *nuclear power plant instrumentation*, *demographic modeling* and so on.

The Kalman filter is an *on-line*, recursive algorithm which tries to estimate the true state of a system where noisy observations or measurements are available. In Bayesian terms, it is wished to propagate the conditional probability density of the true state, given knowledge on previous measurements. The Kalman filter contains a linear model for the process and a linear model for the measurement. The former model describes how the current state of the tracker is changing, given the previous instance:

$$\begin{pmatrix} x_k \\ y_k \end{pmatrix} = \begin{pmatrix} 1\,0 \\ 0\,1 \end{pmatrix} \begin{pmatrix} x_{k-1} \\ y_{k-1} \end{pmatrix} + \begin{pmatrix} \tilde{x}_{k+1} \\ \tilde{y}_{k+1} \end{pmatrix} \tag{1}$$

or in a shorter notation:

$$p_k = Ap_{k-1} + \tilde{p}_{k-1} \tag{2}$$

with A the state transition matrix and $\tilde{p}$ the process noise vector.

The measurement model of the filter is straightforward as well:

$$\begin{pmatrix} u_k \\ v_k \end{pmatrix} = \begin{pmatrix} H_x & 0 \\ 0 & H_y \end{pmatrix} \begin{pmatrix} x_k \\ y_k \end{pmatrix} + \begin{pmatrix} \tilde{u}_{k-1} \\ \tilde{v}_{k-1} \end{pmatrix} \tag{3}$$

or shorter:

$$m_k = Hp_k + \tilde{m}_{k-1} \tag{4}$$

with H the measurement matrix and $\tilde{m}$ the measurement noise vector. H describes how the measured data relate (linearly) to the state. We define,

$$Q = E\left[\tilde{p} * \tilde{p}^T\right] = \begin{pmatrix} Q_x & 0 \\ 0 & Q_y \end{pmatrix} \tag{5}$$

and

$$\xi = E\left[\tilde{m} * \tilde{m}^T\right] = \begin{pmatrix} \xi_x & 0 \\ 0 & \xi_y \end{pmatrix} \tag{6}$$

as the covariance matrices of the process and measurement noise respectively.

We start the initial state: $p_0 = Hm_0$ and define $P_0 = \begin{pmatrix} e\;0 \\ 0\;e \end{pmatrix}$ with e and update the Kalman variables in a two-step predict-correct loop, until we run out of data.

Predict the next state: $p_k^- = Ap_{k-1}$. Predict the next error covariance: $P_k^- = AP_{k-1}A^T + Q$.

Compute Kalman gain: $K = P_k^- H^T \left(HP_k^- H^T + R\right)^{-1}$. Update estimated state with measurement: $p_k = p_k^- + K\left(m_k - Hp_k^-\right)$. Update the error covariance: $P_k = (I - K|H)\, P_k^-$.

4 Proposed Method

The capability of neural networks [4,5,6] for approximating arbitrary *input-output* mappings give a simple way to identify unknown dynamic functions in order to predict the needed output one step ahead or more. In a tracking system [15], measured radar signals are mostly mixed with additive white noise [1,2,3,16]. In order to filter out or minimize this measured noise on-line and to predict the aircraft position one step ahead, a simple back propagation algorithm has been used.

The proposed RBF-TT has three-input neurons, and three-output neurons. The inputs use the spatial positions, *x-y-z*, of the target for the times of (t-2,t-1,t), and the outputs represent the spatial positions of the target, *x-y-z*, at times of (t-1,t,t+1).Therefore, RBF-TT is a sliding system [16,17,18] for tacking over the time domain. The flowing chart of the RBF-TT has been illustrated in Fig. 2.

When the size of the training set is not big enough, target tracking performance decreases due to the deviations from the target positions that the RBF network produces. RBF-TT uses a traning set which has only 3-elements with three parameters, *x-y-z*. Therefore, in order to improve the performance of the RBF-TT a smoothing operator, namely impulse exclusive filter [16,17,18], is required for the post-processing of the neural network outputs. The impulse exclusion algorithms have been previously studied in detail in [16,17,18]. The impulse exclusive filter, which has been employed in this paper, is based on the filter proposed in [18], but two of the properties have been used as diferent from [18]: The sliding window size is equal to 3x1 instead of 3x3 and the extreme value within the window is accepted as corruption. The mathematical details of the impulse exclusive filter can be found in [18].

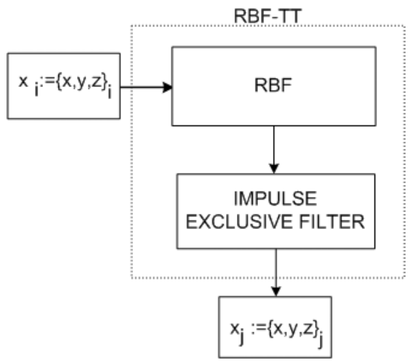

Fig. 2. Flowing Chart of Proposed Method, where the indices of i and j denote the observations at the times of (t-2,t-1,t) and (t-1,t,t+1), respectively

4.1 Radial Basis Function Artificial Neural Network

An alternative network architecture to the Multilayered Perceptrons is the Radial Basis Function Artificial Neural Network (RBFN), which can be represented with radially symmetric hidden neurons [6,19]. The topology of the RBFN is similar to the three-layered MLP but the characteristics of the hidden neurons are different. RBFNs require more neurons than standard feed-forward backpropagation networks, but they can be usually designed in a less time than it takes to train standard feed-forward networks. RBFNs can be employed to approximate functions and they work best when many training arrays are used. Basically, the structure of an RBFN involves three different layers. The input layer is made up of source neurons. The second layer is a hidden layer of high dimension serving a different purpose from that of an MLP. This layer consists of an array of neurons where each neuron contains a parameter vector called a center. The neurons calculate the *Euclidean Distance* between the center and the network

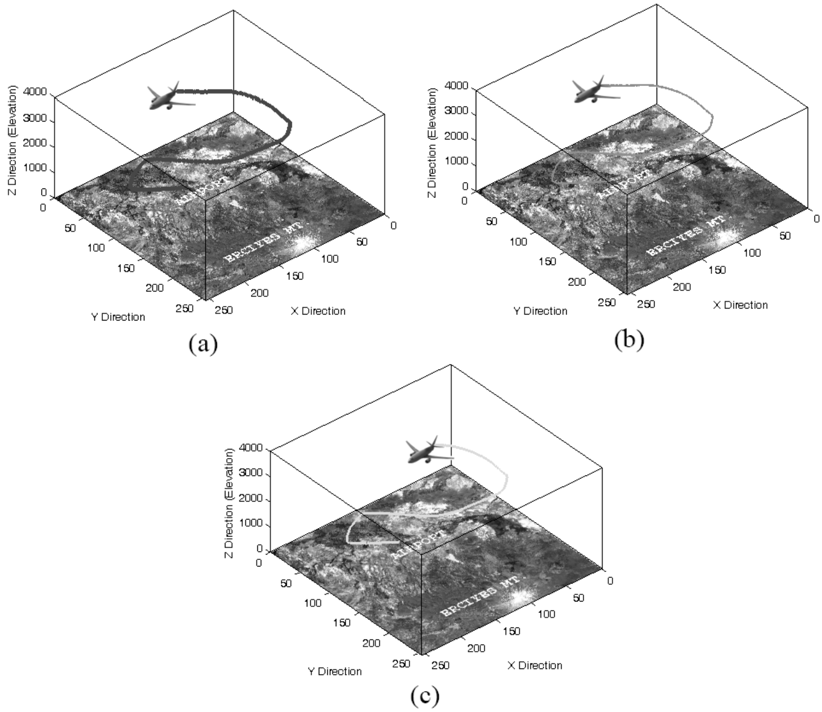

Fig. 3. (a) Radar Observations, (b) KALMAN Filter based TT, (c) RBF-TT

input vector, and then pass the result through a nonlinear function. The output layer, which supplies the response of the network, is a set of linear combiners. The transformation from input layer to the hidden layer is nonlinear but the transformation from the hidden layer to the output layer is linear. The output of a hidden layer is a function of the distance between the input vector and the stored center, which is calculated as,

$$O_s = \|B - Cs\| = \sqrt{\sum_{j=1}^{T} (B_j - C_{sj})^2} \tag{7}$$

The learning phase consists of using a clustering algorithm and a nearest neighbor heuristic in order to determine the C_s cluster centers. The weights from the hidden layer to the output layer are determined by using linear regression or a gradient descent algorithm. Exact design of RBFN constitutes a radial basis network very quickly with zero error on the design vectors [18,19].

5 Experiments

In this paper, the flight data of a Tracking-Radar of a single Civil Aircraft, which has taken-off from Kayseri Erkilet Airport, have been used. Radar data

Table 1. Quality measures of target tracking algorithms

Tracking Filters	Comparison Measures	
	MSE	MAE
KALMAN Filter based TT	53.59	5.77
RBF-TT	4e-25	5e-13

association process is performed by using a nearest point search algorithm but data-gating [1,2,3] is not required for the single targets.

In multi-target tracking, data association and data-gating are important issues for improving tracking performance. However, tracking filter performance is the basis of TT in both multi-target TT and maneuvering TT. Therefore, TT performance for the single target of RBF-TT is examined in this paper. The Tracking-Radar data (θ, R) were converted into three dimensional spatial positions, x-y-z.

The performances of the proposed RBF-TT and Kalman filter based TT have been quantitatively evaluated with the quality measures of *Mean Square Error* (MSE) and *Mean Absolute Error* (MAE) and tabulated in Table 1. The visual performances are illustrated in Fig. 3.

6 Results and Conclusion

In this paper, a novel RBF neural network based target tracking filter, RBF-TT, has been proposed for the prediction of one step ahead position of maneuvering targets. RBF-TT is effective and simple to implement. The tracking success of the proposed filter has been validated over the real data of civil aircraft positions in real time and the performance of the RBF-TT has been compared with the performance of the classical Kalman Filter based Target Tracking algorithm.

Extensive simulations reveal that the proposed filter, RBF-TT, supplies superior tracking performances to the Kalman Filter based comparison filter and tracking is achieved with high precision. The computational burden and computational complexity of the RBF-TT is also smaller than the Kalman filter based TT.

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