An Algorithm of Maneuvering Target Tracking Based on Interacting Multiple Models and Fuzzy Neural Network

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[1]*Abstract*—**An algorithm which interacts current statistical model and constant speed model together can have no limit to the magnitude of target turn rate and its variety. The network which combines neural network with fuzzy logic inference not only has the ability of self-learning, association, and optimization structure in neural network, but also has the advantage of easy understanding of fuzzy inference. In this paper, fuzzy neural network is introduced into the interacting multiple model algorithms. It can adjust the structure of network itself according to input parameters. The Monte-Carlo simulation results show the method is valid.**

Keywords—**Maneuvering Target Tracking, Fuzzy Neural Network, Interacting Multiple Model, Current Statistical Model**

I. INTRODUCTION

At present, maneuvering target tracking algorithms mainly have two types: single-model algorithm and multiple-model algorithm. In single-model algorithm, only one model is used While in multiple-model algorithm, a series of models are designed to stand for possible system action manners or structures (which are called system modes).Each model uses its own filter, and its whole estimation can be obtained by a certain combination of estimation from each single filter. Multiple-model algorithm plays an important role in maneuvering target tracking in recent years, because of its special way of processing uncertain and/or changeable structure and parameters and predigesting problems.

II. IMPROVABLE IMM ALGORITHMS

IMM algorithm uses many different movement models to match different movement states of target. The transfer probability between models is a Markov chain; the estimation of target state and update of model probability use Kalman filters. It mainly has four parts: the design of model sets, selection of filters, fusion of states, renew initialization of filters.

A. Design of model sets

The selection of model sets is the chief task of maneuvering target tracking. In IMM algorithm, using multiple models can improve tracking precision of target. When the number of models increases, it can easily bring unnecessary competitions between models and explosive computation. Therefore reasonable selection of models and their numbers can play an important role to tracking precision of maneuvering target.

In this paper, a new IMM algorithm is proposed, which only uses two models that consist of a "Current Statistical "(CS) model and an augmented Constant-Velocity (CV) model for interaction. The CS model is an adaptive acceleration mean value model, which contains a normal acceleration and a tangent acceleration.

CS model is proposed by Zhou HongRen. Its basic idea is that when target maneuvers at a firm acceleration, the fetching value of next acceleration is finite, and it can be only in the adjacent domain of current acceleration. That is to say maneuvering acceleration is accord with zero-mean value time correlation processing. Its probability density is described by correctional Rayleiqh distribution. As Rayleiqh distribution changes according to mean value and variance is determined by mean value, we can assume that acceleration mean value equals to acceleration predict value on current moment. In this way mean value and variance can achieve self-adaptive filtering. The current statistic model in this paper is based on normal acceleration and tangent acceleration.

In order to obtain the same state vector of CS model, the dimension of CV model is usually enlarged.

$$X(k) = F_{cv}^{a} X(k-1) + G_{cv}^{a} W(k-1) \tag{1}$$

In formula (1), $W(k-1)$ is zero-mean value random disturbance noise.

To turn movement mode, the CS model has a high tracking precision, while CV model precisely matches the constant speed movement mode. When these two models are interacted, it has no restriction in the magnitude and change of turn rate,

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and has more flexibility for adjusting uncertain parameters. So high tracking precision of target can be achieved [11].

B. Filter algorithm

The purpose of filtering is to estimate the current movement state of target. The Kalman filtering algorithm is one of the most precise and convenient filtering algorithms. As the data from radar and infrared is non-linear, extended Kalman filter algorithm is proposed in this paper.

1) Extended Kalman Filtering Algorithm

First, linearize non-linear processing according to current state estimation, then resolve filter problems of non-linear system by Kalman filtering algorithm, finally filtering. The filtering algorithm of disposing non-linear processing is called extended Kalman filter algorithm.

To discrete non-linear system, suppose state equation and measurement equation of tracking target as follows:

$$X(k) = \phi[X(k-1), k-1] + G[X(k-1), k-1]W(k-1) \quad (2)$$

$$Z(k) = H[X(k), k] + V(k) \quad (3)$$

Different from linear system, using the method of linearization, non-linear function $\phi[(k-1), k-1]$ and $H[X(k), k]$ can be developed to Taylor Series around the state estimation value $\hat{X}(k-1 \mid k-1)$ and prediction value $\hat{X}(k \mid k-1)$. After simplification its first term is,

$$X(k) = \phi[X(k-1), k-1] + U(k-1) + G(k, k-1)W(k-1) \quad (4)$$

$$Z(k) = H(k)X(k) + Y(k) + V(k) \quad (5)$$

Where,

$$\phi(k, k-1) = \frac{\partial F[X(k-1), k-1]}{\partial X(k-1)}\Big|_{X(k-1)=\hat{X}(k-1)} \quad (6)$$

$$G(k, k-1) = G[\hat{X}(k-1 \mid k-1), k-1] \quad (7)$$

$$H(k) = \frac{\partial H[X(k), k]}{\partial X(k)}\Big|_{X(k)=\hat{X}(k|k-1)} \quad (8)$$

$$U(k-1) = \phi[\hat{X}(k-1 \mid k-1), k-1] - F(k, k-1)\hat{X}(k-1 \mid k-1) \quad (9)$$

$$Y(k) = H[\hat{X}(k \mid k-1), k-1] - H(k)\hat{X}(k \mid k-1) \quad (10)$$

C. Fuzzy neural network

Fuzzy neural network is not only good at using experience information, but also has the advantage of logic inference. At the same time, because of introducing the mechanism of self-learning of neural network, it increases the ability of self-adaptation of network. Therefore, it can be widely used in the fields of intelligence control, mode identification, artificial intelligence and signal processing [13-16]. The network is used in maneuvering target tracking algorithms, which means human fuzzy judgment is introduced in it. The accuracy of target tracking can be improved and have good abilities of anti-disturbance and fault tolerant.

1) Structure of fuzzy neural network

In the fuzzy neural network there are two-input and two-output. The structure of the network is not full-joints. It connects each other according to fuzzy regulations. The network has a five-layer structure, as figure 1 is shown.

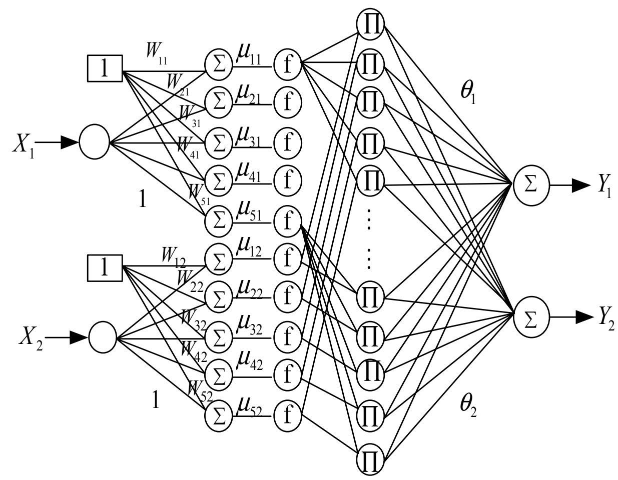

Figure1. Network Structure of fuzzy neural network

The first-layer is input layer. Each node connects an input directly. In this layer, each nerve cell stands for one input. The number of nerve cells equals to the number of inputs. The output of this layer equals to the input of next layer. Vacant circles mean un-processed inputs. The weighted value to the node of next layer is one. The"1"s in the diamonds stand for firm inputs, and their weighted values are W_{ij} , $i = 1, 2, \cdots 5$ $j = 1, 2$ (i stands for the number of fuzzy sub-sets; j stands for the number of inputs.)

The second-layer is an excursion layer. There are ten nodes and each node has two inputs x_1 (or x_2) and W_{ij} ($i = 1, 2, \cdots 5$ $j = 1, 2$) . The operation of $X_j - W_{ij}$ is performed in the nodes. The weighted value to next layer is μ_{ij} .

The third-layer is an input fuzzed layer. It computes membership functions of inputs which match each language value. By choosing suitable membership functions, accuracy values of inputs can be converted into fuzzy membership function values and then input the network. The fuzzy set is a Gaussian function as in (11).

$$f = \exp\left(\frac{-(x-c)^2}{2\sigma^2}\right) \quad (11)$$

The fourth-layer is a fuzzy regulation layer. Each node stands for a regulation, which can achieve the computing function of fuzzy set, and output the applicable degree of each regulation. In the network, the input X_1 and X_2 separate define five fuzzy sub-sets as PL, PS, Z, NS, and NL. The corresponding fuzzy regulation base is showed at the Table Ⅰ. There are twenty-five regulations.

TABLEI FUZZY REGULATION BASE

Regulation	NL	NS	Z	PS	PL
NL	VL	L	M	L	VL
NS	L	M	H	M	L
Z	M	H	VH	H	M
PS	L	M	H	M	L
PL	VL	L	M	L	VL

The fifth-layer realizes defuzzification. Gravity method is adopted.

$$\bar{y} = \frac{[\sum_{i=l}^{l} y_i \mu_B(y_i)]}{\sum_{i=l}^{l} \mu_B(y_i)} \tag{12}$$

2) Adjustment of weighted values of models

Neural network can adjust parameters according to training sample data, so as to achieve precise tracking. Using BP algorithm can adjust variable parameters: μ_{ij} , θ_i and W_{ij} , as mentioned in [12].

D. Combination of Interacting Multiple Model and Fuzzy Neural Network

In the network, state variables of maneuvering target input fuzzy neural network. The matching degree of each model can be obtained and replace mode probability computing in IMM algorithm. The fuzzy regulation and membership degree function, which are constructed by neural network, can adjust themselves according to self-learning and association of neural network. So, the complexity of computing can be reduced and the precision of tracking can be improved.

The structure of the network is shown as figure 2.

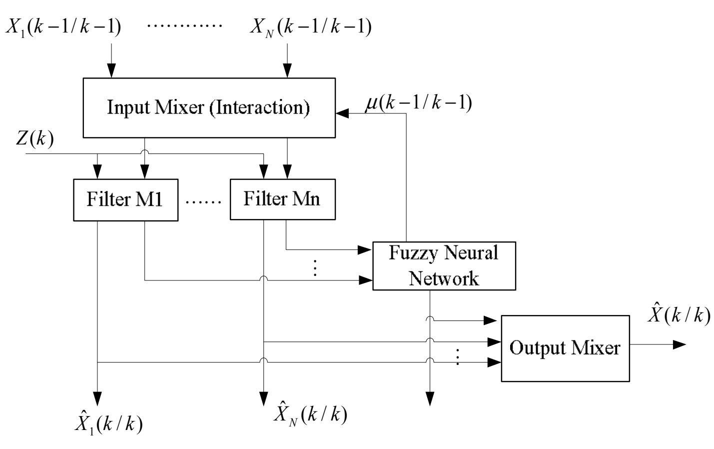

Figure2. Network Structure of Improved IMM algorithm

III. SIMULATION RESULTS

A. Simulation scene

Supposing scanning period T is 1s, initial velocity is 300m/s, enter angle is 300°.In scan period [61,105] and [151,195], the turn rate is 3.74°/s and -3.74°/s respectively. It makes a constant-speed movement in rest times. The position measurement standard error of each dimension in Cartesian Grids σ equals 100m. Suppose that the measurement values of X axis and Y axis are irrelevant. The max turn rates of CT model are 4°/s and -4°/s.The Markov transfer probability matrix is as follows.

$$P_{ij} = \begin{bmatrix} 0.8 & 0.2 \\ 0.2 & 0.8 \end{bmatrix}$$

B. Simulation result analysis

In order to verify the validity of the algorithm, 100 times Monte-Carlo simulation are done and a comparison with traditional IMM algorithm is given. The filtering error of X axis is shown as figure 3.

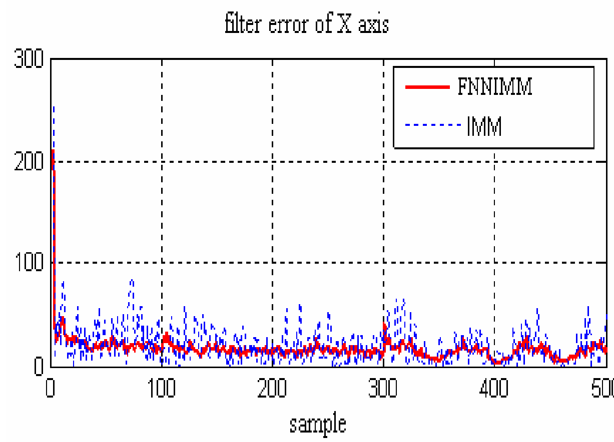

Figure3. Filter errors of X axis

The simulation results indicate that the algorithm which only uses two models to interact has the advantages of simple structure, the max turn rate needn't be pre-established, self-learning and self-adjusting by fuzzy neural network. Therefore, it has a great tracking effect for the target which has unknown turn rate or fast-variety turn rate.

IV. CONCLUTIONS

Fuzzy neural network is introduced into maneuvering target tracking, which means people's fuzzy judgments are introduced into the maneuvering target tracking field. The precision of position estimation can be improved and have good abilities of anti-disturbance and fault tolerant.

In the fuzzy neural network, the choice of membership functions of input variables has little effect to the target tracking. The accuracy of regulations and the choice of inference composed algorithms play an important role on results. Generally speaking, the more minute fuzzy sub-sets compartmentalizes, the more accuracy regulations are. With the increase of fuzzy regulations, precision of position estimation can be improved, but the time of learning can be increased at the same time. It results in larger computing and lower real-time of system.

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