Type-II Fuzzy Neural Networks for Image Stabilization of the Airborne Camera

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Abstract. The vibration rule of the airborne camera was studied to solve the image vibration in aerial photography of the Micro Aircraft Vehicle. A method based on the ability of function approximation of type 2 fuzzy neural networks with self-organizing recurrent intervals (SRIT2FNN) to simulate the vibration rule of airborne camera in the MAV and predict the vibration displacement vectors during image stabilization was proposed. The SRIT2FNN has no initial rules, which are generated from the simultaneous on-line parameter and structure learning. The results show that SRIT2FNN control system is more stable and the higher precision, and good real-time performance than combined BP neural networks.

Keywords: Type-II fuzzy neural networks; real-time image stabilization; airborne camera in micro aircraft vehicle.

1. Introduction

The electronic imaging equipment used in the micro-air vehicle airborne system requires a long operating distance, a long focal length of the optical system, and a large attitude change of the aircraft used in the camera system. The aircraft body vibrates violently, which is easy to cause image shaking and instability, resulting in image quality reduction and resolution reduction. In order to overcome this phenomenon in the past, optical methods and optical, mechanical and electrical methods are generally used to stabilize the image sequence, so as to improve the quality of the output image. However, these methods often increase the power consumption and weight of the system, and the accuracy of the stable image is not ideal. In recent years, image stabilization technologies are mainly divided into two categories in terms of implementation methods: optical image stabilization technology and electronic image stabilization technology [1-2]. Both technologies have been well developed due to their respective advantages. Optical image stabilization is to take measures in the optical system to achieve the goal of image stabilization. Electronic image stabilization technology is a method that combines electronic equipment and digital image processing technology. By detecting the motion vector of the reference image and the compared image and using it to compensate the compared image, the instability between frames of video image sequence can be eliminated or reduced to obtain a clear and stable video image sequence. Electronic stabilization is like a new image sequence stabilization technology, because of its high stabilization accuracy, small size, light weight, low power consumption and real-time processing. Traditional electronic image stabilization techniques (grayscale projection, feature matching) are all based on motion estimation, that is, the relative displacement between adjacent frames of image sequence is calculated first, and then compensation is implemented. However, motion estimation occurs before shooting, and the biggest difference between it and motion prediction is that motion prediction occurs after shooting. The key to the realization of the prediction lies in the simulation of the motion law,
and the camera vibration has certain regularity due to airflow, engine and other reasons. The investigation results show that this vibration movement can be regarded as the synthesis of several simple harmonic vibrations. Then it can predict the position of the on-board camera at the next moment and implement the compensation.

Fuzzy neural network combined with the characteristics of the fuzzy theory to deal with uncertainty and neural network learning ability, can approximate any nonlinear and has good generalization ability, has been successfully applied to application systems [3-5]. However, all of these analyses and applications are based on type 1 fuzzy neural networks. Type 2 fuzzy set [6-8] is an extension of the model of fuzzy sets, the concept of it is the fuzzy subordinate function value of fuzzy, and the second type fuzzy logic as the previous part, the neural network as the late part of type ii fuzzy neural network, because the conventional type 2 fuzzy neural network [9] in the rating from type ii type to the type of extremely large amount of calculation. Therefore, an interval type 2 fuzzy neural network is proposed to simplify the computation. Type ii fuzzy neural network by interval type 2 fuzzy language, as a former parts, the process of neural network with three layers of interval as after a while, from type 2 a set of fuzzy rules set by multilayer networks for type ii fuzzy inference system, it has the advantages of the second type fuzzy system and neural network, which can be used to any approximation nonlinear function, strong generalization ability. In this paper, a self-organizing recursive interval 2-type fuzzy neural network is constructed and trained to predict the vibration vector of an airborne camera.

2. The Self-organized Recursive Interval 2 Fuzzy Neural Network is Used to Predict the Vibration of Airborne Camera

The generalization ability of neural network refers to the adaptability of the network trained with known samples to new unknown data. If the J(t) of the network is very small when the training stops, but the prediction error with the new data is very large, then the generalization ability of the network is considered to be poor. The causes of this phenomenon is called overtraining, excessive training is to point to in the case of a limited sample size, if the build of the network is too complicated, so network to simulate the motion law of history than the actual as sophisticated function expression, the expression for the sample data error is very small, but when to use it for the unknown data, error might be larger, in the case of a limited sample size how to build an appropriate scale of the network, to find a balance to the training and generalization of q is not an easy thing, to solve the problem of the traditional methods are: enlarge the sample size, the larger the sample size, sampling is representative, The less likely it is to occur; Early stopping algorithm is adopted, that is, a part of the sample is taken out to form the test set, and the network is tested continuously while training. If there is no overtraining, the test error will decrease with the increase of training times. If the test error increases after a certain training, it indicates that the overtraining should be stopped in time. However, the pre-stopping algorithm can not always make the network reach the expected error accuracy, so the stability of the network is poor.

In view of the poor generalization ability of the above neural networks, the self-organizing recursive interval two-type fuzzy neural networks in this paper evolve all the two-type fuzzy rules online through simultaneous learning of structure and parameters of front and rear parts, so as to improve the generalization ability and prediction accuracy of the self-organizing recursive interval two-type fuzzy neural networks.

In the process of image stabilization, \( U(t) \) is used to represent the position of camera vibration at time \( t \). Since the acquisition and feedback of image stabilization equipment are discrete signals, \( U(t) \) can be written as equal time interval sequence \( U_{l_0+n\Delta t} \), where \( l_0 \) represents the time in fact and \( \Delta t \) represents the interval, \( n = 0,1,2,\ldots \). Since the image stabilizer will constantly collect data, as long as the data of the self-organizing recursive interval type 2 fuzzy neural network is constantly adjusted, continuous prediction can be made. The prediction method can be expressed mathematically as follows:

\[
Y_{l_0+(k+n+1)\Delta t} = \text{SRIT} - IIFNN (X_{l_0+k\Delta t}, X_{l_0+(k+1)\Delta t}, \ldots, X_{l_0+(k+n)\Delta t})
\]
In the formula, \( Y_{n+k+(t+n-1)\Delta t} \) represents the predicted result, \( m, n \) is an integer constant, and \( k = 0, 1, 2, \ldots \), the whole formula represents the data after the time interval of \( n \) is predicted with \( m \Delta t \) consecutive known points.

### 3. Structural Learning

The purpose of structural learning algorithm is to realize the rule generation through online learning, so as to modify the network structure. The spatial activation intensity is taken as the standard to determine whether fuzzy rules are generated. Since the spatial activation intensity is interval bounded, its central value is:

\[
f^t_c = \frac{1}{2} (f^1 + f^2)
\]  

(1)

The spatial activation intensity center value \( f^t_c \) is used as the rule generation standard. The new data \( x \) is input into the network, and the change produces a new rule. The uncertainty mean of each new type 2 fuzzy set is expressed as follows:

\[
m^j_{1(i, j)} + m^j_{2(i, j)} = [x_j - 0.1, x_j + 0.1], \quad j = 1, \ldots, n_u + n_o
\]

The center value of each new binary fuzzy set is preset (set \( \sigma_j = 0.5 \) in this paper), which will determine the width of the fuzzy set. The input of each block after the new data \( x(t) \) represents:

\[
I = \arg \max_{1 \leq i \leq M(t)} f^t_c (\tilde{x})
\]

(2)

Where, \( M(t) \) represents the number of existing rules at time \( t \), and if \( f^t_c \leq f_{th} \), a new rule will be generated, and \( f_{th} \in (0, 1) \) is the pre-set initial value. After the new rule is generated, the uncertainty mean and width of the corresponding new type 2 fuzzy set are calculated as follows:

\[
[m^j_{1(i, j)}^{M(t)+1}, m^j_{2(i, j)}^{M(t)+1}] = [x_j(t) - 0.1, x_j(t) + 0.1]
\]

(3)

\[
\sigma_j^{M(t)+1} = \beta \left( \sum_{j=1}^{n_u+n_o} \left| x_j - \left( \frac{m^j_{1(i, j)} + m^j_{2(i, j)}}{2} \right) \right|^2 \right)^{0.5}
\]

(4)

In the structural learning algorithm, the uncertain range is firstly preset, and all membership functions share a range. Through the following membership function parameter learning algorithm, the uncertain mean range of membership functions is automatically adjusted to make them different.

### 4. Parameter Learning Algorithm

Parameter learning and structural learning are carried out simultaneously. For each new input data, whether new rules are generated or not, all parameters in the self-organizing recursive interval type 2 fuzzy neural network need to be adjusted. The purpose of parameter learning is to reduce errors:

\[
E = \frac{1}{2} \sum_{q=1}^{n_q} [y_q(t+1) - y_d(t+1)]^2
\]

(5)

Among them, \( y_q(t+1), y_d(t+1) \) represents the output and expected output values of self-organizing recursive interval type 2 fuzzy neural network respectively. Gradient descent algorithm is used to learn and modify the antecedent parameters:
\[ \lambda_q^t(t+1) = \lambda_q^t(t) - \eta \frac{\partial E}{\partial \lambda_q^t(t)} \]  

(6)

Where, \( \eta \) is the learning variable and the value of \( \eta = 0.03 \) in this paper, then:

\[ \frac{\partial E}{\partial \lambda_q^t} = \frac{\partial E}{\partial y_q^t} \left( \frac{\partial y_q^t}{\partial y_q^t} \frac{\partial y_q^t}{\partial \lambda_q^t} + \frac{\partial y_q^t}{\partial \lambda_q^t} \right) \]

(7)

\( w^j \) represents the parameter \( x^j \) of the input variable \( i \) in the second type fuzzy set in the \( \tilde{A}_j \) interval.

The formula for updating the parameter \( w^j \) is as follows:

\[ w^j(t+1) = w^j - \eta \frac{\partial E}{\partial w^j(t)} \]

(8)

In the process of parameter learning, if the trailing value \( \tilde{y}_{lq}, \tilde{y}_{rq} \) is changed, the corresponding rule sequence will also change. Therefore, before updating the parameters, it is necessary to determine the exact location of the antecedent/afterpiece parameters. In the learning time of each step, the fuzzy rules change sequentially, so it is difficult to determine the exact location of the antecedent/afterpiece parameters. To solve this problem, the orderly regular kalman filtering algorithm is adopted, which ensures that the original order of rules is guaranteed in the process of parameter learning:

\[ y^l_{lq} = \Phi^T_{lq} \tilde{y}_{lq} \]

\[ \Phi^T_{lq} = \frac{\sigma^T Q^T_{l} E^T_{l} E_1 Q_1 + \psi^T Q^T_{l} E^T_{l} E_2 Q_1}{p^T_f Q_1 \sigma + g^T_f Q_1 \psi} \in \mathbb{R}^{M \times 1} \]

(9)

\[ y^r_{rq} = \Phi^T_{rq} \tilde{y}_{rq} \]

\[ \Phi^T_{rq} = \frac{\sigma^T Q^T_{r} E^T_{r} E_3 Q_r + \psi^T Q^T_{r} E^T_{r} E_4 Q_r}{p^T_r Q_r \sigma + g^T_r Q_r \psi} \in \mathbb{R}^{M \times 1} \]

(10)

Among them, \( p^T_f \) is the l-dimensional unit column vector; \( g_r \) is the m-l dimension unit column vector; \( p^T_r \) is the unit column vector of R dimension; \( g_r \) is the m-l dimension unit column vector. \( E_1 \) is the l-dimensional error column vector; \( E_2 \) is the M-L dimension error column vector; \( E_3 \) is the R-dimensional error column vector; \( E_4 \) is the M-R dimension error column vector. Therefore, the output \( y^t_q \) can be rewritten as:

\[ y^t_q = \frac{1}{2} (y_{lq}^t + y_{rq}^t) - \frac{1}{2} (\Phi^T_{lq} \tilde{y}_{lq} + \Phi^T_{rq} \tilde{y}_{rq}) = \begin{bmatrix} \tilde{y}_{lq} \\ \tilde{y}_{rq} \end{bmatrix} \]

(11)

Through the above structure and parameters of online learning, to construct the network structure. In fact, the steps of the vibration prediction algorithm for the micro-air vehicle airborne camera are as follows: 1) The initial network structure of the self-organizing recursive interval type 2 fuzzy neural network is zero. When the collected sample data set is input into the network, the self-organizing recursive interval type 2 fuzzy neural network trains the network through structural learning and parameter learning, and adjusts the network structure at the same time.
2) The data buffer with a length of \( n \) is set as buffer, and the newly collected continuous data are placed in the buffer successively. After each prediction, \( k \) is added 1, and the buffer is shifted automatically. When the buffer is full, the data \( U_{t_0 + k \Delta t}, U_{t_0 + (k+1) \Delta t}, \ldots, U_{t_0 + (k+n) \Delta t} \) of the whole buffer buffer is input into the self-organizing recursive interval type ii fuzzy neural network. Then the camera vibration data of the micro air vehicle is predicted by the self-organizing recursive interval type 2 fuzzy neural network.

5. Simulation and Experiment

In the MATLAB environment, the self-organizing recursive interval type 2 fuzzy neural network in this paper is simulated and compared with the double-bp neural network in literature [10] to verify the superiority of the scheme in this paper. Literature [10] uses two BP neural networks to predict the vibration vector of airborne camera, and Levenberg-Marquardt algorithm to train the network. This method improves the stability and calculation accuracy of the network, but this method uses two BP neural networks and does not perform network prediction in parallel, which wastes time and makes it difficult to achieve the real-time performance of image processing. The self-organizing recursive interval type 2 fuzzy neural network uses the structure learning algorithm and parameter learning algorithm in this paper to modify the network rules and adjust the network structure, so as to achieve the final prediction accuracy. In order to facilitate differential BP neural network and the self-organizing recursive interval type 2 fuzzy neural network, select the same sample, choose the training sample capacity is 200, in the MATLAB environment, repeated 15 times experimental results as shown in figure 2-3, diagram: the line of sight said airborne camera vibration signals, "○" said the real value,"×" said predicted, vibration signals are expressed as:

\[
U = 30 \sin(2\pi t) + 40 \sin(\pi t + \frac{\pi}{6}) + 85 \sin(3\pi t + \frac{\pi}{7}) + 55 \sin(5\pi t + \frac{\pi}{8}) + 60 \sin(9\pi t + 12.3)
\]

(12)

![Figure 1. Curve of forecasting results.](image)

(a) By using combined BP neural networks (b) By using proposed method.

![Figure 2. Displacement error comparison of worst forecasting results.](image)

(a) By using combined BP neural networks (b) By using proposed method.

From the simulation results, it can be seen that the double-BP neural network is not enough to support the network to fully simulate the inherent law of data due to the insufficient number of samples. Therefore, after repeating the experiment for 20 times, the predicted maximum displacement error floats...
between 0 and 4 pixels, which is stable but not accurate enough. The self-organizing recursive interval type 2 fuzzy neural network has good stability, and the predicted maximum displacement error is less than 0.15 pixels, and the operation speed is fast enough to meet the needs of image stabilization.

![Frame 40](image1.png) ![Frame 120](image2.png) ![Frame 200](image3.png)

**Figure 3.** Original image sequence.

![Frame 40](image4.png) ![Frame 120](image5.png) ![Frame 200](image6.png)

**Figure 4.** Original image sequence after vibration compensation.

Using 100 frames of 640*480 continuous micro air vehicle aerial photography dynamic image sequence shown in Fig.3, through VC++ programming on the computer simulation experiment, using self-organizing recursive interval type 2 fuzzy neural network can be more accurately predicted the motion vector of airborne camera vibration, and the motion vector prediction speed block, the time used is only 8ms. By compensating the motion vector of airborne camera vibration predicted by the motion compensation unit, the image sequence can be stabilized as shown in Fig.4.

6. Conclusion

One self-organizing recursive interval type 2 fuzzy neural network for airborne camera vibration vector forecasting method was proposed. Realizing the prediction and motion compensation unit on the forecast to the airborne camera vibration motion vector according to the feedback signal input, and the stability of the image sequence can be realized. Finally, the prediction process of camera vibration vector is compared between the proposed method and the double BP neural network. The experimental results show that the proposed method is more accurate and more stable.

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