RESEARCH ON FUZZY LOGIC PIO DETECTOR

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Abstract

PIO detector is a kind of pattern-recognition method, which generally consists of data acquisition, data preprocess, feature extraction and classifying decision. Using SFTF and wavelet transform to extract the features of PIO events, and then optimize the membership functions of fuzzy PIO detector with fuzzy clustering algorithm. The detector results show this method is effective.

1 Introduction

Aircraft and pilot coupling (APC) is a form of interaction in pilot-vehicle system (PVS). In certain circumstance, this adverse coupling produces unintended oscillations or divergences when the pilot attempts to precisely maneuver the aircraft. If the PVS instability takes the form of an oscillation, the APC event is called “pilot-involved oscillation” (PIO). Recently the research about PIO focused on the criteria of aircraft design, the prediction technology for PIO, and source of category Ⅲ PIO events. Although these researches are deeply, the PIO events still can not be avoided. At the end of last century, the detection technology for PIO has been developed.

The PIO detector uses some methods in the theory of pattern recognition, such as data processing, feature extracting and classification. This paper uses four distinguishing characteristics of PIO event to identify the normal flight and oscillation state. The identification model is fuzzy logic PIO detector. [1] Different type aircrafts have different kind of PIO events. And the characteristics of these PIO events are different. So the by clustering the flight data of certain kind of aircraft could find the feature of flight data distribution between normal and oscillation. Then using the clustering results could optimize the membership function of fuzzy logic PIO detector.

2 The Characteristics of PIO

For an understanding of PIO, McRuer introduced the three PIO categories. These three PIO categories can be de as follows:
Category Ⅰ: Essentially linear pilot-vehicle system oscillations;
Category Ⅱ: Quasi-linear pilot-vehicle system oscillation with rate or position limiting;
Category Ⅲ: Essentially non-linear pilot-vehicle system oscillation with transitions.

The main effects causing Category Ⅰ PIO is excessive lags caused by time delays and various filters in the FCS. This category of PIO can be identified and predicted by the frequency domain criteria. Most severe Category Ⅱ PIO events were caused by actuator position or rate limiting, such as JAS39. The nonlinear Category Ⅲ PIO is more complex. The nonlinear properties in Category Ⅲ PIO can cause sudden changes in the effective aircraft dynamics that result in the abrupt (sometimes referred to as “cliff-like”) onset of PIO events, such as YF-22 in 1992.

3 Feature extraction algorithms

The early study of PIO features extraction algorithm was based on Fourier transform method. Now the method based on wavelet transform has been developed to extract the features. This kind of wavelet transform can extract the features more precisely than Fourier transform, but this arithmetic needs more time. The two feature extraction algorithms will be introduced briefly as follows.

3.1 Short Time Fourier Transform (STFT)

STFT is a kind of linear transform based on Fourier Transform, and a powerful tool in analysis of the nonstationary signals. The kernel idea of STFT if to use a size-fixed and moving "window" to analyze the nonstationary signals, so STFT is also called Windowed Fourier Transform (WFT).

The nonstationary signal is $s(t)$, and defined a window function as $h(t)$

$$s_t(\tau) = s(\tau)h(\tau - t) \qquad (3.1)$$

$s_t(\tau)$ is the function with variable τ which bound is t . Using Fourier transform to transform $s_t(\tau)$, the result is

$$\begin{aligned} S_t(\omega) &= STFT[s(t)] \\ &= F_\tau[s_t(\tau)] = \frac{1}{\sqrt{2\pi}} \int s(\tau)h(\tau - t)e^{-j\omega\tau} d\tau \end{aligned} \qquad (3.2)$$

The mark τ means that the Fourier operator's integral variable is τ .

Then the discrete Fourier transform of signal $s(t)$ is

$$S(t,k) = \sum_{m=-\infty}^{+\infty} s(m)h(n-m)e^{-j\frac{2\pi}{N}km}, \quad k = 0,1,\cdots,N-1 \qquad (3.3)$$

In this function

$$\omega_k = \frac{2\pi}{N}k, \quad k = 0,1,\cdots,N-1 \qquad (3.4)$$

3.2 Wavelet Transform

In this paper, the wavelet transform based on reference [2]. The mother wavelet is hyperbola-Gaussian complex wavelet. Establish a mother wavelet function as

$$\psi(t) = \frac{1}{2\sqrt{\pi}} e^{-\left(\frac{t}{2}\right)^2 + j\mu t} \qquad (3.5)$$

Hence that its corresponding continuous wavelet function will be

$$\hat{\psi}_{a,b}(\omega) 2a\sqrt{\pi} e^{-\left(\frac{\omega - \frac{1}{a}\mu}{\frac{1}{a}}\right)^2 - jb\omega} \qquad (3.6)$$

Because of the request for detecting PIO in time, a kind of hyperbola-Gaussian complex transform was generated through the time domain transform from (-∞, 0) to (-∞,∞).

$$\psi_{a,b}(t) = \begin{cases} |4\pi a\sigma|^{-\frac{1}{2}} e^{-\left(\frac{b-t-\frac{c}{b-t}}{2a\sigma}\right)^2 + j\mu\left(\frac{b-t-\frac{c}{b-t}}{a}\right)} & t < b \\ 0 & t \ge b \end{cases} \qquad (3.7)$$

Fig. 1 illustrates the shape and its spectrum of hyperbola-Gaussian complex wavelet as the changing of scale a (b=50). The application verified that it is available to extract characters of PIO.

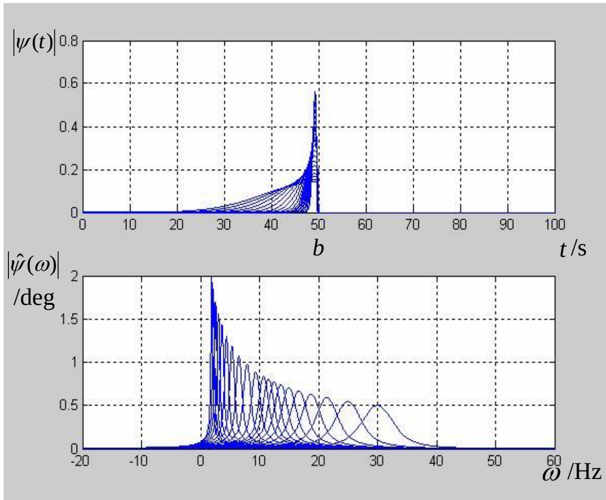

Fig. 1 Time Wave Pattern and Spectral Shape of Hyperbola-Gaussian Complex Wavelet

Both kinds of extraction algorithm can extract the features of PIO events. STFT is easy and count quantity is small. But the result is delay the real time. This is the inherence shortcoming of STFT algorithm. Wavelet transform can overcome this shortcoming, but the count quantity is very large, now it does not fit the computer onboard.

Fig. 2 shows the instantaneous frequencies extracted by STFT and wavelet transform. Compared with the results of STFT, Wavelet transform has smoother and less peaks.

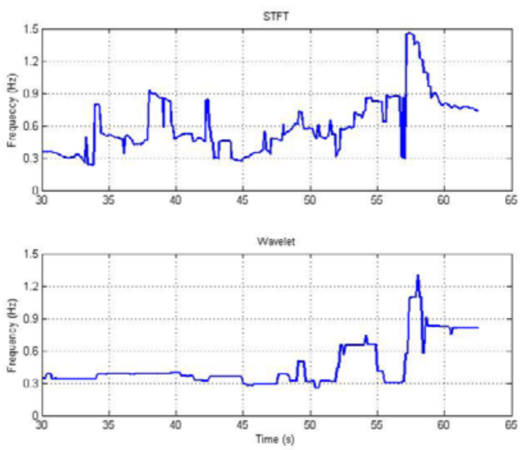

Fig. 2 Results of Transform

4 Fuzzy logic detector

The fuzzy logic detector in this paper refers to the reference [1]. This fuzzy logic detector uses four feature parameters as the input, the by the Mamdani fuzzy inference system detects and distinguished the normal oscillation and PIO events. The four feature parameters are main frequency, the stick amplitude, cosine of phase lag and actuator speed. These four parameters could represent the difference between normal oscillation and PIO events. According to the reference [3] [4], the main frequency varies from 0.3 Hz to 1.5 Hz. The lag between stick and flight response is large, nearly 180°. When systemic lags from any sources abruptly stretch the aircraft response to this degree, the pilot loses an accurate mental concept for aircraft control and may even suspect a control system malfunction. The actuator rate exceeds 40% of the maximal deflection rate. Pilot stick commands have very large amplitudes, when the pilot fails to recognize the changed nature of the aircraft response, pilot may increase gain through the cockpit stick.

These four feature parameters make up the input and fuzzy variables of Mamdani fuzzy inference system, and these fuzzy variables was fuzzified by a set of membership functions. These membership functions show their range and regularities.

1. Main frequency variable has three membership functions. The Nominal membership function is a bell curve centered at 0 Hz. This represents steady state trimmed flight or slow maneuvering. The APCrange membership function is a trapezoidal membership function that encompasses the 0.3 Hz to 1.5 Hz. The Over-controlling function represents high frequency movements beyond the bandwidth of PVS.

2. Main stick amplitude variable has only two bell cure membership functions. The Low function covers amplitudes less than about 50% of the stick radius of movement. The High function covers amplitudes over 50% of the radius of movement.

3. Cosine Phase lag has two bell curve membership functions. The Nolag function covers the values from -0.5 to 1 where the state nearly synchronizes with the stick or with the normal rate command systems. The Log180 function is a bell curve centered at -1 Hz.

4. Actuator speed function has two trapezoidal membership functions. The SpeedSaturated function cover the range more 40% radius of deflection rate, and the Nominal function covers the left range.

The bell curve formula $f(x,a,b,c)$ is

$$f(x,a,b,c)=\frac{1}{1+\left|\frac{x-c}{a}\right|^{2b}}.$$

The coefficients a, b, c decide the curve's position and shape.

The fuzzy inference system uses these four fuzzy variables and fuzzy rule sets to detect is there PIO happens or not. The rule surface of this fuzzy detector could represent fuzzy variable contribution to the PIO estimate. The fuzzy inference system in this paper is shown in Fig. 3. The membership functions represent each feature's regularities, so the form of membership functions determines the performance of the fuzzy detector. Now the design of membership function based on experts' experience and the research conclusion. The types of aircrafts are different and their FCSs are different too. Because these difference, the distribution of flight parameters when PIO events happen are not same. The membership functions of fuzzy variables for each aircrafts must be adjusted. In this paper, use clustering analysis to deal with flight data and according to cluster results design or adjust membership functions.

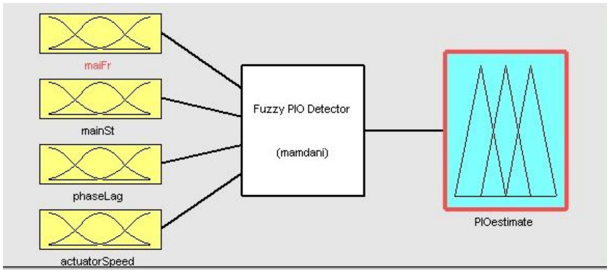

Fig. 3 Fuzzy Inference System

5 Fuzzy clustering

Fuzzy clustering is kind of unsupervised clustering method, and fuzzy clustering analysis is a clustering method with fuzzy theory. Because the fuzzy clustering defines the membership degree of sample belonging to the each category, and establish the fuzzy description, and the theory of Fuzzy C-Mean clustering algorithm which based on object function is perfect. So this paper uses this method optimize membership functions with clustering results and membership degree.

Fuzzy C-Mean (FCM) clustering is developed from Hard C-Mean (HCM) clustering. It allows one piece of data to belong to two or more clusters by minimizing the following objective function:

$$\begin{cases} J_1(U,P) = \sum_{K=1}^{N}\sum_{I=1}^{C} \mu_{IK}(d_{ik})^2 \\ s.t. \quad U \in M_{hc} \end{cases} \qquad (5.1)$$

Where $U = [u_{ik}]_{c\times n}$ is membership matrix with μ_{IK} as the degree of object in fuzzy cluster c, and d_{ik} is the Euclidian distance measure between x_k and p_i.

(1) FCM algorithm is as follows:

Define cluster c, $2 \le c \le n$, the count number of sample; set iterative threshold ε, initialize clustering prototype matrix $P^{(0)}$,. Iteration counter $b = 0$.

Step 1: calculate or flash the membership matrix $U^{(b)}$,

If $\exists d_{ik}^{(b)} > 0, \forall i,k$, then

$$\mu_{ik}^{(b)} = \left\{\sum_{j=1}^{c}\left[\left(\frac{d_{ik}^{b}}{d_{jk}^{b}}\right)^{\frac{2}{m-1}}\right]\right\}^{-1} \qquad (5.2a)$$

If $d_{ir}^{(b)} = 0$ and $\exists i,r$, then

$$\mu_{ir}^{(b)} = 1 \text{且对 } j \ne r, \mu_{ir}^{(b)} = 0 \qquad (5.2b)$$

Step 2: calculate cluster center matrix $P^{(b+1)}$ with formula (5.3):

$$p_i^{(b+1)} = \frac{\sum_{k=1}^{n}\left(\mu_{ik}^{(b+1)}\right)^m \cdot \mathbf{x}_k}{\sum_{k=1}^{n}\left(\mu_{ik}^{(b+1)}\right)^m}, i = 1,2,\cdots c \qquad (5.3)$$

Step 3: If $\left\|P^{(b)} - P^{(b+1)}\right\| < \varepsilon$, the iterating will stop, we get membership matrix $\mathbf{U}$ and cluster center $\mathbf{P}$; If not turn to Step 1. This procedure converges to a local minimum or a saddle point of $J_1(U,P)$.

Based on FCM, some similar algorithms were built up as Fuzzy C-Line (FCS), Fuzzy C-Spherical Shell (FCSS). These methods achieve clustering the sample which distribution like line, hyperplane or shell.

(2) Fuzzy C-Spherical Shell clustering algorithm

Fuzzy C-spherical Shell clustering algorithm [5] has the same basic theory, but difference is the definition of distance d_{ik}.

The distance of x_k and p_i can been defined as different type according to sample distribution. In FCM d_{ik} is Euclidian distance, and in FCSS the sample is spherical shell. So we define the distance d_{ij} as follows:

$$d(x_i, p_j) = (\|x_i - p_j\|_A^2 - r_j) \qquad (5.4)$$

Where r_j is the radius of the spherical shell, r_j is

$$r_j = \sum_{i=1}^{n} u_{ij}^m \|x_i - p_j\| \Big/ \sum_{i=1}^{n} u_{ij}^m \quad , \quad \forall j \qquad (5.5)$$

6. Application of clustering result

Before clustering analysis, we must normalize the flight data. Then the some data ranges are from -1 to +1, such as the stick displacement.

Clustering input is a flight data matrix that is made up of actuator deflection rate stick displacement and roll rate. These three flight data are all vary from -1 to 1, and exhibit difference between normal flight and PIO events. The time history flight data and the data of PIO event part are shown in Fig. 4. The input of fuzzy detector is shown in Fig. 5. It can be seen that the distribution of flight is spherical analogously, and the center is near zero point. This figure also shows the clustering result of input data. In this figure, we use different color and marks distinguish membership degree above 0.5 or not.

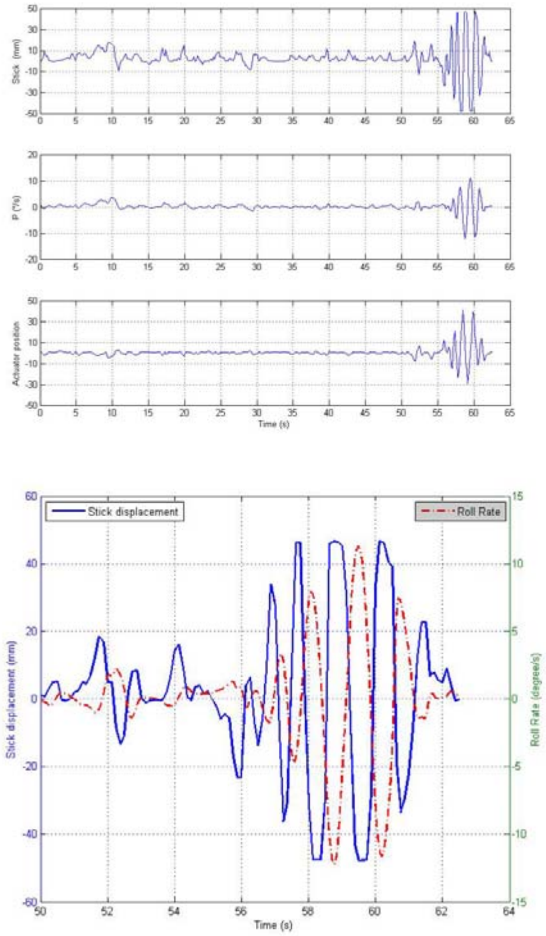

Fig. 4 Time history of Flight data

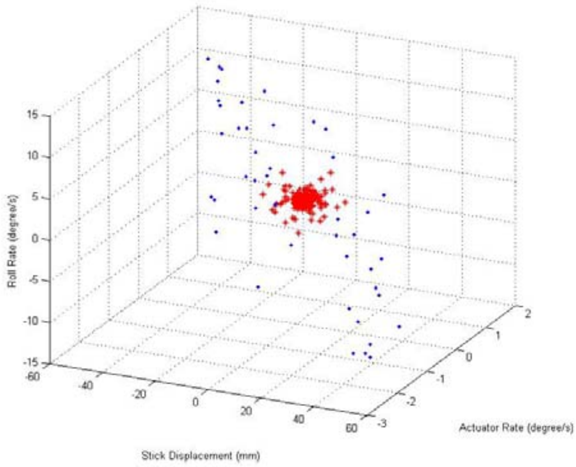

Fig. 5 Flight data distribution and Clustering Results

The clustering results are membership degree matrix, clustering center and object function. For each row of input, there is a membership degree and each line with membership degree can buildup a membership degree curve for certain flight data. The Fig. 6 is stick displacement data and membership degree curve. This curve represents the stick displacement distribution range and feature. By this curve, we can optimize the membership function in main stick amplitude variable.

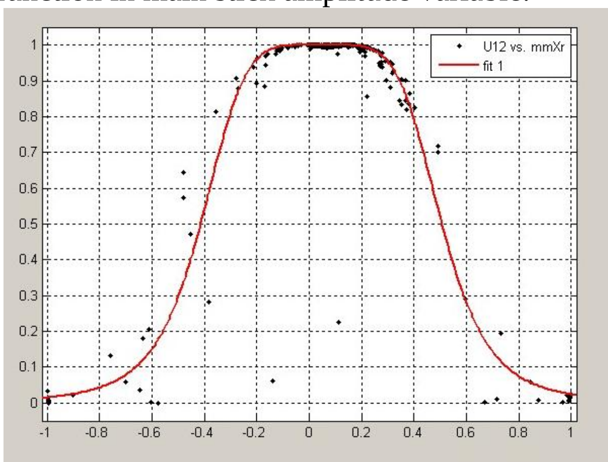

Fig. 6 Stick and Membership Degree Curve

In Table 1 there are the original coefficients of every membership functions correspondingly in Table 2, the coefficients are optimized with membership curves generated from clustering results. In this table some membership functions is trapezoid functions which need four coefficients.

Table 1 Original coefficient of Membership functions

	a	b	c	d
Nominal	0.3	2.4	0	/
APCRange	0.2	0.5	0.8	1.1
StickLow	0.5	5.4	-0.1	/
StickHigh	0.632	5.4	1	/
Lag180	0.5	1.5	-1	/
Nolag	1.5	6	1	/
Norminal	0	0.1	1	1.5
Saturated	0.25	0.5	2.5	2.5

Table 2 Improved Membership Functions

	a	b	c	d
Nominal	0.3	2.4	0	/
APCRange	0.2	0.3	0.6	1.3
StickLow	0.5	3.5	0	/
StickHigh	0.5	3.5	1	/
Lag180	0.5	1.75	-1	/
Nolag	1.5	6	1	/
Norminal	0	0.1	0.75	1.25
Saturated	0.75	1	2.6	2.7

Fig. 7 and 8 show the fuzzy PIO detector result. In Fig. 7 the fuzzy variables use the coefficients in Table 1. From the detecting result, we can see that this fuzzy PIO detector can identify the PIO event. But the PIO estimation is not steady. Fig. 8 shows the detection results which use improved the membership functions with the coefficients in Table 2. Compared two detecting results, the FCSS could cluster the flight data effectively, and the clustering results also could improve the performance of fuzzy PIO detector.

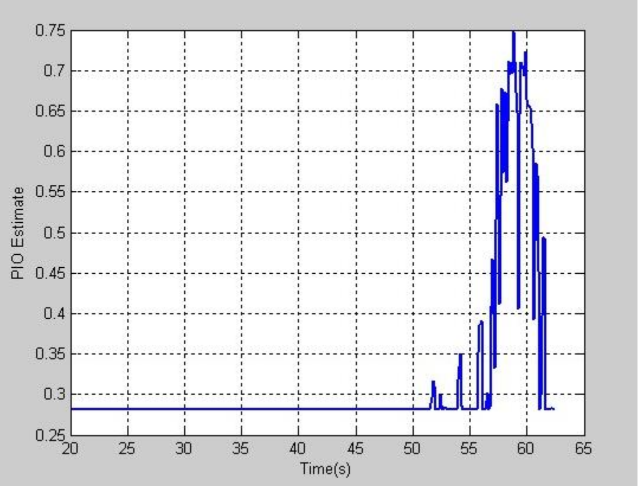

Fig. 7 Detecting Results

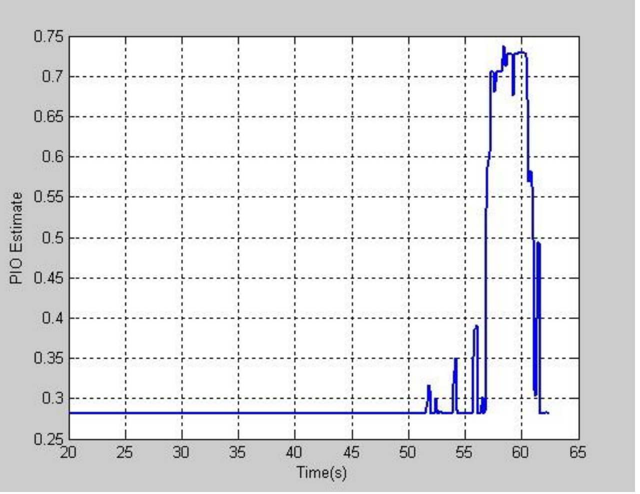

Fig. 8 Improved Detecting Results

5 Conclusion

This paper discussed the feature extraction algorithm of flight data in PIO events, and fuzzy PIO detector with these features. Then introduce Fuzzy C-mean clustering method and its other form Fuzzy C-Spherical Shell clustering algorithm. By using the clustering algorithm process the flight data, we can get the distribution features and improve the membership function by clustering results. From the result of PIO detector, we can see that this method for optimizing membership functions is effective.

Fuzzy clustering is a kind of unsupervised clustering method. This clustering method analyzes the data, based on internal discipline of data. And there is not any priori knowledge and manual intervention in this process. So maybe we could use this method detect PIO events.

Because the PIO events are rare and the investigation is hard, so we just have several flight data which have PIO information before writing this paper. Therefore the fuzzy clustering apply to PIO detection will need more tests and experiments.

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