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The Landing Safety prediction model by integrating pattern recognition and markov chain with flight data

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Abstract: This paper aims to predict the landing state during the landing phase to ensure landing safety and reduce the accidents loss. Some past researches have demonstrated the landing phase is the most dangerous phase in flight cycle and fatal accident. The landing safety problem has become a hot research problem in safety field. This study concentrates more on the prediction and advanced warning for landing safety. Firstly, four landing states are divided by three flight parameter variables including touchdown, vertical acceleration and distance to go; Subsequently, pattern recognition based on BP neural network is used to established the landing state prediction model; the genetic algorithm is used to initialize the model parameter; the Markov chain is proposed to revise and improve the model for higher prediction precision. Finally, in comparison of pattern recognition and the Markov chain revision results, the Markov chain revision method is demonstrated to be practical and effective.

Key Words: Landing safety; flight data; pattern recognition; Markov Chain

1. Introduction

Aviation accident has the characteristics of small occurrence probability, great economic loss and high casualty rate. Once the aviation accident happened, it will not only damage the aircraft and the personnel, but also bring a very negative impact on society. There were 11 mishaps in which the cost of damage including destroy or missing is one million and more in the US navy in the landing process during 2011 and 2012. Therefore, landing safety is the focus that people concentrate on and urgent to be solved for the serious consequence [1][2]. In addition, the fatal accidents data demonstrates there are about 23 percent of all fatal accidents take place in the landing phase from 2003 to 2012, though this phase just accounts for about 1% proportion in flight cycle [3]. The landing state of landing phase is closely related to many factors including operation, environment and human factor which could be recorded and shown by QAR data. QAR data is widely used to store data and analysed to monitor the flight states [4].

Flight data is monitoring data to record the states of flying and equipment, which has significant implications for developmental, train, security monitoring and control and maintenance. The objective of someone is to present an evaluating method for irregular deviations of flight control surface deflected angles based on flight data through the post flight analysis. The lift-to-drag (L/D) model for an aging twin-jet transport will be established through the fuzzy-logic model (FLM). The irregular deviations of flight control surfaces can be examined by the L/D model-predicted results through sensitivity analysis. If the irregular deviations of flight control surfaces are not rigged before the flight, the flight control system may not work properly and it may have flight safety concerns in flight [5]. Someone presents the flight test results of forced landings involving a UAS, in a controlled environment, and which was conducted to ascertain the performances of previously developed (and published) path planning and guidance algorithms. These novel 3-D nonlinear algorithms have been designed to control the vehicle in both the lateral and longitudinal planes of motion. These algorithms have hitherto been verified in simulation. HITL simulations were conducted prior to the flight tests and displayed good landing performance, however, due to certain identified interfacing errors, the flight results differed from that obtained in simulation[6]. In order to use flight data more effectively, some research about QAR data was based on improved association rules to mine the relation between variables and the proposed algorithm was capable of discovering meaningful and useful association rules in an effective manner[7]. To reduce landing mishap risk, the hybrid landing safety method based on support vector machine (SVM) and rough set theory (RST) was applied in carrier landing of aircraft to do an earning of landing accidents[8]. In reality, the research on landing safety of flight parameter is not mature and there is rare study about the visual landing variables forecasting in advance for adjusting to valid accidents from the perspective of pattern recognition. This paper aims at predicting the states of touchdown speed, vertical acceleration and distance to go for pilots to make decisions by flight data analysis. This paper could make an accurate prediction of landing state before landing. Once the prediction model identify that the landing state is not suitable for landing, the polite can take proper measures in a timely manner, which can reduce the frequency of occurrence of events in a certain extent, so as to improve the safety of aircraft landing.

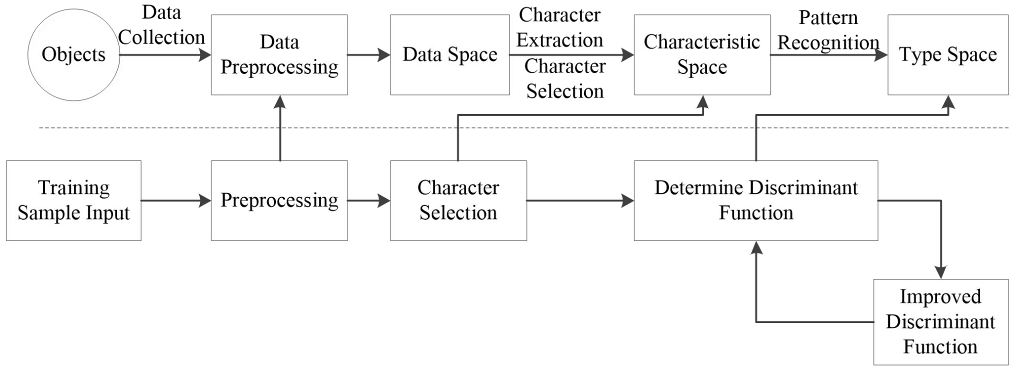

Figure. 1 Pattern recognition process.

Pattern recognition [9]is aimed to classify and descript the physical objects named "model" to make the recognition results consistent with the practical objects under the condition of minimum error probability. The process of pattern recognition is as Figure. **1**. The pattern recognition process consists of the recognition process and the learning process. The upper part of the dotted line indicates the recognition process and the lower part of the dotted line indicated the learning process. According to the nature and description of the object, the traditional pattern recognition method is mainly divided into two methods, statistical pattern recognition and syntactic pattern recognition. In recent years, the method of fuzzy pattern recognition and neural network have become more and more popular.

Artificial neural network[10] (ANN) is important ways in pattern recognition. In the practice of pattern recognition, there is noise interference and the missing of input and output information. The distributed information storage characteristics of artificial neural network makes it good fault tolerance and robustness. Artificial neural network is also dominant to be used to settle the non-linear problems. Landing states is related to many factors, which can be reflected by recorded flight data, while the flight data is not simple linear relation with each other. So it's difficult to directly discuss their relation and the way about artificial neural network is useful to deal with the linear and nonlinear relation together for training the data and find the optimal output. Artificial neural network has more advantages in large sample data analysis, self-adaption and self-learning ability and nonlinear problems [11], which can be used to forecast the landing states of aircraft.

In order to guarantee the stable operation of shearers and promote construction of an automatic coal mining working face, Jing Xu et al. proposed an online cutting pattern recognition method with high accuracy and speed based on Improved Ensemble Empirical Mode Decomposition (IEEMD) and Probabilistic Neural Network (PNN)[12].

G Wang et al. discussed the problem of characterization for uncertain multichannel digital signal spaces, propose using fuzzy n-cell number space to represent uncertain n-channel digital signal space, and put forward a method of constructing such fuzzy n-cell numbers. Further, based on the metrics or difference values appropriately defined, they put forward an algorithmic version of pattern recognition in an imprecise or uncertain environment[13].

YM Liu et al. proposed a recognition method for quality abnormal pattern of dynamic process with PCA-SVM, and proposed a feature selection technique that employs a principal component analysis, Then, the extracted features were treated as input vector for SVM classifier, following a particle swarm optimization algorithm is proposed[14].

Markov chain model was firstly presented by Markov in 1906[15]. It's random process for states transition, which means the present states are only related the near previous states and independent of others. The related theory has been completed so far, which was a random process of discrete state and one of the most important branches. Markov model obtained the prediction value by interval with discrete time series. Among that, the state transferring matrix was changing with data information, which was a period of time series recently. So Markov model had accuracy advantage for short-term prediction. At present, Markov[16] was widely used in communication and computer, economy management, biochemistry and physics research, education, weather forecasting and so on. Also, Hidden Markov Model (HMM)[17] is developed and used to describe the model including hidden unknown parameters, which is a statistic model. The flight has different state when flying and landing, so it's possible to predict the landing state by state transferring before touchdown.

Flight data is record in time series, which is foundation of forecasting. Mining the potential rules and combining with current or future's conditions are the premise of predicting the objects' developments. Flight states are influenced by all kinds of factors including operation, environment and mans. Many factors can be shown by flight data directly or indirectly. So the prediction variables are more or less linear or nonlinear to other variables, while the relation is difficult to confirm. Traditional multivariate regression analysis, GM(1,n) may not settle the complicated relation. Considering the complex relationships between flight variables and the large capacity of samples, artificial neural network is used as a pattern recognition to forecast the landing state. The error between prediction value and actual value is as a standard to evaluate the accuracy of the prediction model. The initial parameters of artificial neural network can be given by genetic algorithm, which is easy to obtain the optimal initial parameters. The Markov chain is applied to revise the prediction result for higher prediction accuracy, which is conductive to the realization of the advanced warning of landing safety.

2. Preliminary

2.1 Least-Mean Square Algorithm

Least-Mean square algorithm[18] is a model of neural network which the output units are based on linear relation. The output y_i for the unit i is:

$$y_i = \sum_j W_{ij} x_j \tag{1}$$

Where W_{ij} is the weight for the input x_j, j is the number of the input. The sum of error can be expressed by error function:

$$E = \sum E_p = \sum_p \sum_i \left(t_i^p - y_i^p\right)^2 \tag{2}$$

Where p is a set of input mode, y_i^p is the expected value of node i when inputting mode p, and t_i^p is the actual value. The goal of the model is finding a set of weight by training the data to make the error function minimum.

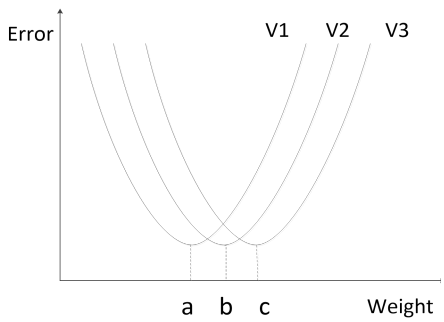

Figure. 2 The relation curve of weight and error.

When the other variables remain unchanged, the relationship between the weight of a single variable and the total error is shown as Figure 2. In order to avoid the influence of randomness, 3 single variables, namely V1, V2 and V3, are used to find the relationship. It's obvious that error could be minimum when the weight is taking a certain value. Different variable might have different weight value and the weights are mostly concentrated in the middle of the range. However, it is not practical to keep the constant of other variables in actual process, but the existence of this kind of relation provides the basis for the determination of the weight of each variable.

Gradient descent is used to select and test the optimum weight for minimum error, which the increment of weight is proportional to negative derivative of error.

$$\Delta W_{ij} = -k \frac{\partial E_p}{\partial W_{ij}} \tag{3}$$

Where k is the proportionality coefficient. The derivation of the equation (2) is:

$$\Delta W_{ij} = 2k\left(t_i^p - y_i^p\right)x_j^p \tag{4}$$

And the increment of weight is proportional to the difference between expected value and actual value and relative input.

2.2 BP artificial neural network

BP artificial neural network algorithm[19][20]is development of LMS algorithm, which is the product of the combination of non-linear multilayer perceptron and LMS to make the error function minimum. BP artificial neural network algorithm usually chooses Sigmoid function as the input function:

$$f(x) = \frac{1}{1+e^{-(x-\theta)}} \tag{5}$$

Where θ is threshold.

BP artificial neural network consists of input layer, hidden layer and output layer and its kernel is adjusting the network parameters by transporting error backwards and correcting error at the same time to achieve or approach the expected relation between input and output[21]. The three layers' structure is enough to settle most of questions. So this paper chooses this as the model. The BP artificial neural network is mainly self–learning process and reducing error by revising the transferring error. The structure of BP artificial neural network is as Figure 3. The process of BP artificial neural network is as Figure 4.

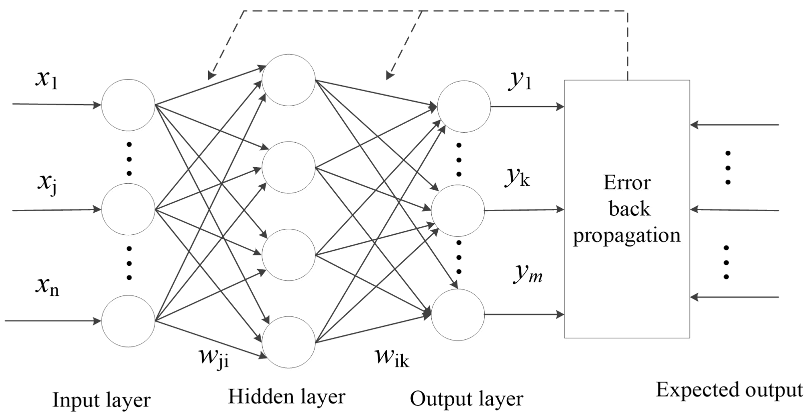

Figure. 3 The structure of BP neural network.

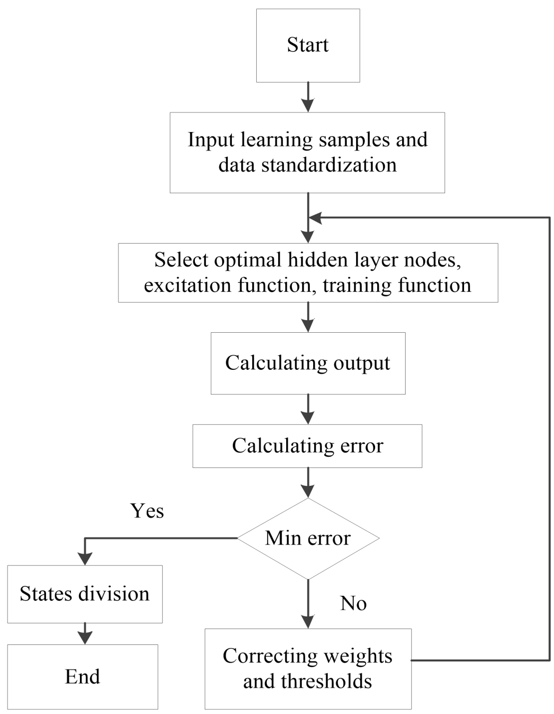

Figure. 4 The process of the BP algorithm.

The BP algorithm process is followed:

When flight data is used to analyze landing safety, multiple variables need to be taken into consideration. On the one hand, different variables have different units; on the other hand, different variables may have large differences in magnitude. For example, the speed of aircraft is 34.34 m/s at a certain moment, while the corresponding pitch angle is 0.79 degrees. It is hard for the prediction model to compare the results between variables without the standard. Therefore, it's necessary for flight data to be standardized.

Step1: The data standardization.

$$x_{ij}^{*} = \frac{x_{ij} - \bar{x}_j}{\sqrt{\sum_{i=1}^{n}\left(x_{ij} - \bar{x}_j\right)^2 \Big/ n-1}} \tag{6}$$

x_{ij}^{*} is the standardization value, x_{ij} is the original data for variable j at i flight. $\bar{x}_j$ is the average of variable j, n is the number of flight.

Step2: Determine the nodes, weights and thresholds of input.

The initial weights and thresholds is given by genetic algorithm and the value region is $[-1,1]$. While the weights and thresholds of hidden layer nodes are respectively followed.

The input s_j of hidden layer at i node:

$$s_i = \sum_{j=1}^{n} w_{ij} x_j + \theta_i \tag{7}$$

x_j is the input of input layer at j node, w_{ij} is the weight from j node of input layer to i node of hidden layer. θ_i is the threshold of i node of hidden layer.

The output l_j of hidden layer at i node:

$$l_i = \phi\left(s_i^n\right) \tag{8}$$

ϕ is the excitation function of hidden layer.

The input s_k of output layer at k node:

$$s_k = \sum_{i=1}^{q} w_{ki} l_k + a_k \tag{9}$$

w_{ki} is the weight from i node of hidden layer to k node of output layer, a_k is threshold of k node of output layer, q is node number of neurons .

The output l_k of output layer at k node:

$$l_k = \varphi(s_k) \tag{10}$$

φ is the excitation function of output layer.

Step3: Error back propagation.

The error is calculated in every layer from input layer and revised by gradient descent with the weight and threshold of every layer to make the final output close to expected value.

For sample p, the quadratic error criterion function E_p is:

$$E_p = \frac{1}{2}\sum_{k=1}^{q}\left(T_k - l_k\right)^2 \tag{11}$$

T_k is original value for k node.

The total error criteria function is:

$$E = \frac{1}{2}\sum_{p=1}^{n}\sum_{k=1}^{q}\left(T_k^p - l_k^p\right)^2 \tag{12}$$

The correction of weight and threshold can be give based on this.

2.3 Genetic algorithm

Genetic algorithm[22][23] was proposed by Professor Holland in American university of

Michigan. Genetic algorithm is a random search method according to biological natural selection and natural genetic mechanism to simulate the evolutionary process from lower grade to higher in nature. The main steps of genetic algorithm are as follows:

Step1: Determine the initial population of potential solutions to the problem.

Step2: Calculate the fitness function value of each individual.

Step3: Determine the operator and parameters of the algorithm. Genetic operator is the rule of genetic algorithm, and it has selection operator, crossover operator and mutation operator. The parameters include cluster, group size, crossover probability, mutation probability, which have great influence for genetic algorithm.

Step4: Determine the algorithm criterion to stop running. The criterion for stopping operation is generally expressed as the form of an algorithm that performs the maximum algebra. If the optimal solution is identified in the running process, it can be set to stop when the individual is found. When the genetic algorithm stops running, the best individual in the current generation is designated as the solution of the problem to be solved.

The process of genetic algorithm can be shown as figure 5. The genetic algorithm starts from the initial population which is randomly generated. The optimal solution could not be found until the population finish evaluating from generation to generation by selection, crossover and mutation operation. Genetic algorithm does not directly function in the problem space, but in the coding space. The major advantage of genetic algorithm is that the genetic operation is relatively simple and the algorithm is general and with good robustness.

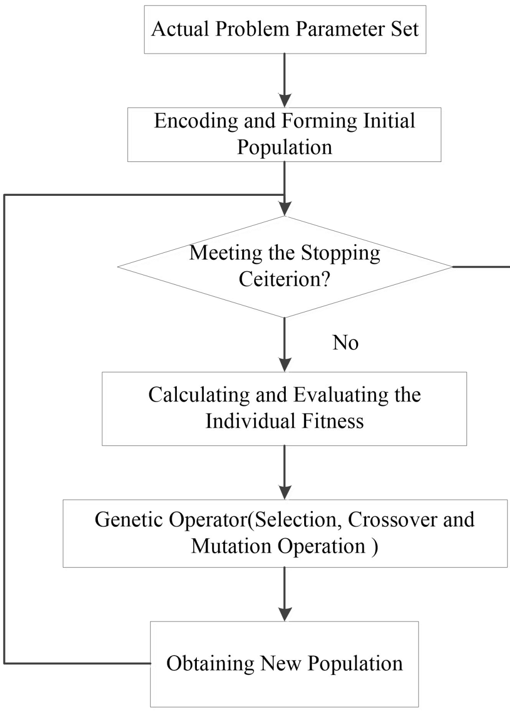

Figure. 5 Process of genetic algorithm.

2.4 Markov chain

Markov chain[24]is the random process with parameters and discrete states, whose definition is assuming the random process:

$$\{X_n, n \in N\}$$

for arbitrary conditions $i_0, i_1, \cdots, i_n \in I$, the state space is $I = \{i_0, i_1, \cdots, i_n, \cdots\}$, the time parameter set is $N = \{0,1,2,\cdots,n,\cdots\}$, there is $P\{X_0 = x_0 . X_1 = x_1, \cdots, X_n = x_n\} > 0$ and

$$P\{X_{n+1} = i_{n+1} | X_0 = x_0, X_1 = x_1, \cdots, X_n = x_n\} = P\{X_{n+1} = x_{n+1} | X_n = x_n\} \tag{13}$$

so the random process $\{X_n, n \in N\}$ is called Markov chain.

Above the formula, the status of the random variable X_{n+1} is only related to the previous status X_n and has nothing to do with the earlier status, which is defined non-aftereffect property, or Markov property.

The following conclusions can be obtained from the definition of Markov property.

Theorem 1(the definition of equivalence): Assuming $\{X_n, n = 0,1,2,\cdots\}$ is random variable sequence. C is a countable set of real number, $X_n \in C, n = 0,1,2\cdots$. The following conclusions are equivalent.

(1) $\{X_n, n = 0,1,2,\cdots\}$ is a countable state Markov chain.

(2) For arbitrary $n \ge 1$, $i_{0,}i_{1,}i_{2,}\cdots,i_{\mathrm{n}-1,}i_{\mathrm{n}} \in C$, formula 13 can establish.

(3) For arbitrary $n \ge 1$, any strict rise to a non-negative integer sequence $n_0, n_1, n_2, \cdots, n_n$, any $i_{0,}i_{1,}i_{2,}\cdots,i_{\mathrm{n}} \in C$ all meets

$$P\{X_{n_n} = i_{\mathrm{n}} \mid X_{n_{n-1}} = i_{\mathrm{n}-1}, \cdots, X_{n_1} = i_{1,} X_{n_0} = i_0\} = P\{X_{n_n} = i_{\mathrm{n}} \mid X_{n_{n-1}} = i_{\mathrm{n}-1}\}.$$

(4) For arbitrary $n \ge 1$, any strict rise to a non-negative integer sequence $n_0, n_1, n_2, \cdots, n_n$, any $i_{0,}i_{1,}i_{2,}\cdots,i_{\mathrm{n}} \in C$ all meets

$$P\{X_{n_0} = i_0, X_{n_1} = i_{1,} \cdots, X_{n_n} = i_{\mathrm{n}}\}$$
$$= \sum_{k\in C} P\{X_0 = k\} P\{X_{n_0} = i_0 \mid X_0 = k\} P\{X_{n_1} = i_1 \mid X_{n_0} = i_0\} \cdots P\{X_{n_n} = i_n \mid X_{n_{n+}} = i_{n+}\}$$

(5) For arbitrary $n \ge 1, m \ge 1$, any strict rise to a non-negative integer sequence $n_0, n_1, n_2, \cdots, n_n, n_{n+1}, \cdots, n_{n+m}$, any $i_{0,}i_{1,}i_{2,}\cdots,i_{\mathrm{n}}, i_{\mathrm{n}+1}\cdots, i_{\mathrm{n+m}} \in C$ all meets

$$P\{X_{n_0} = i_0, X_{n_1} = i_{1,} \cdots, X_{n_{n-1}} = i_{\mathrm{n}-1}, X_{n_{n+1}} = i_{\mathrm{n}+1} \cdots, X_{n_{n+m}} = i_{\mathrm{n+m}} \mid X_{n_n} = i_{\mathrm{n}}\}$$
$$= P\{X_{n_0} = i_0, \cdots, X_{n_{n-1}} = i_{\mathrm{n}-1} \mid X_{n_n} = i_{\mathrm{n}}\} \bullet P\{X_{n_{n+1}} = i_{n+1}, \cdots, X_{n_{n+m}} = i_{\mathrm{n+m}} \mid X_{n_n} = i_{\mathrm{n}}\}$$

(6) For arbitrary $n \ge 1, m \ge 1$, any strict rise to a non-negative integer sequence $n_0, n_1, n_2, \cdots, n_n, n_{n+1}, \cdots n_{n+m}$, any $i_{0,}i_{1,}i_{2,}\cdots,i_{\mathrm{n}}, i_{\mathrm{n}+1}, \cdots, i_{\mathrm{n+m}} \in C$ all meets

$$P\{X_{n_{n+1}} = i_{\mathrm{n}+1} \cdots, X_{n_{n+m}} = i_{\mathrm{n+m}} \mid X_{n_n} = i_{\mathrm{n}}, X_{n_{n-1}} = i_{\mathrm{n}-1}, \cdots, X_{n_0} = i_0\}$$
$$= P\{X_{n_{n+1}} = i_{\mathrm{n}+1}, \cdots, X_{n_{n+m}} = i_{\mathrm{n+m}} \mid X_{n_n} = i_{\mathrm{n}}\}$$

Markov property is widely used in automatic control, genetic, market forecast and so on. Markov property is its basic characteristic. Therefore, Markov chain can't be applied to forecasting field unless it meets Markov property test requirement, which could ensure the accuracy of prediction.

It's also obligatory to estimate whether the random process have Markov property, which is the prerequisite of using the Markov model. The way is to apply χ^2 statistics to test the Markov property of discrete series.

The assumption is that there are q states, n_{ij} is the numbers changing from the state i to state j, $\hat{P}_{ij}$ is the frequency transferring from state i to state j, $\hat{P}_j$ is the ratio of the total value of rank j in $(n_{ij})_{q\times q}$ and the total of all lines and rows,

$$\hat{P}_j = \frac{\sum_{i=1}^{q} n_{ij}}{\sum_{i=1}^{q}\sum_{j=1}^{q} n_{ij}} \tag{14}$$

$$\hat{P}_{ij} = \frac{n_{ij}}{\sum_{i=1}^{q} n_{ij}} \tag{15}$$

so statistics

$$\chi^2 = 2\sum_{i=1}^{q}\sum_{j=1}^{q} n_{ij} \left| log\left(\hat{P}_{ij} / \hat{P}_j\right) \right| \tag{16}$$

are submitted to χ^2 distribution which degree of freedom is $(q-1)^2$. Choosing the confidence level α, checking the table of χ^2 value to obtain $\chi^2_\alpha\left((q-1)^2\right)$. If $\chi^2 > \chi^2_\alpha\left((q-1)^2\right)$, it's reasonable that X_k is suited for Markov property.

It's obvious whether states distribution is satisfying the Markov property is influenced by number

n_{ij} and states number q.

To evaluate the model, prediction results should be noted and divided: true positive (TP), false positive (FP), true negative (TN), false negative (FN), which the sum of them is the samples' number. The precision rate (P)[25] stands for the forecasting results are corresponding to the actual results, which the equation is P=TP/(TP+FP). And the recall rate stands for how many the actual results are forecasting accurately, which the equation is R=TP/(TP+FN).

3. Research on landing states prediction with pattern recognition and Markov chain

As is known to all, flight data is recorded as a type of time series, which is a multi-stage time domain data and difficult to predict landing states according to traditional time series. Therefore, it is necessary for further processing of the data. The original flight data includes multiple landing sorties and multiple flight variables, which needs to eliminate abnormal data and redundant data, such as the data recorded after landing. The remaining data is disposed and sliced according to same height from 9m to 2m with the interval of 0.5m so that there are 15 sets for every flight. And there are 47 flight sorties and 40 of them are used as training data sets of the model while others are t as testing data sets.

Flight data is recorded as time series at a certain frequency. The flight states are influenced by many factors and the recorded data is changeful, which is different from financial data for lack of smoothness. So the data must be disposed to meet the input condition for pattern recognition.

In this paper, the division of landing states is based on the values of three variables at the landing time, so the landing time must be determined. This paper takes a certain flight sort as an example to show how to find the landing time. The determination of landing time is shown as Figure 6.

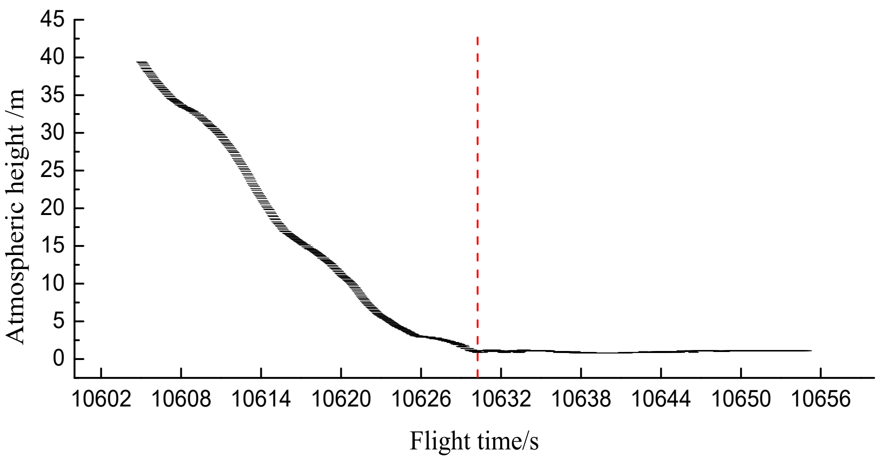

Figure. 6 The determination of landing time.

As the red line in the figure 5 shows, the landing time is the corresponding time at which the atmospheric height is lowest. Landing times of other flight sorties can be found like this. After the landing time is determined, the values of touchdown, vertical acceleration and distance to go can be obtained and landing states can be divided. Every variable can be divided into good zone and bad zone. If three variables' values are all in good zone, it is the best landing state. So the landing states is divided into four levels, the superior is that three variables are in the good zone, the second level is that two variables are in the good zone, the third level is that only one variable is in the good zone, and the forth level is that three variables are in the bad zone. Next, the data is collected at the same height for different flight. According to some research based on flight data, the flight state is similar at the same height. So this paper chooses flight data at the same height to input the model to forecast the landing states. After pre-processing, 47 sets of flight data are the foundation of research of this paper. And 40 sets of flight data are the training sample and the rest are the test samples.

The flight data is collected and proposed to meet the demands based on slicing data according to the same height for different flight. Of course, the flight state is similar at the same height for some related research based on the data. The method is made up of the following steps:

Step 1. The landing states reflected by three variables are forecasted one by one based on artificial neural network optimized by genetic algorithm. States division could be finished according to this.

Step 2. Three variables are directly calculated by artificial neural network optimized by genetic algorithm. Of course, the relevant states division is also obtained.

Step 3. Comparing the two results and Markov chain prediction is used to discuss the states transition for landing states forecasting.

Step 4. The model evaluation should be done for the states prediction, which is a standard for practicability of the model precision.

4. Numeric case

For forecasting the landing states, the flight data including touchdown speed, vertical acceleration and distance to go needed to be collected. Flight data is recorded by quick access recorder with time series. The variables at every height include angle of pitch (ap), angle of pitch rate (apr), roll angle (ra), roll angle rate (rar), true heading (th), yaw rate (yr), aileron displacement (ad), lifting speed (ls), forward acceleration (fa), vertical acceleration (va), lateral acceleration (la), distance to go (dtg), engine speed (es), atmospheric height (ah), airspeed (a), side offset (so) and ground speed (gs). They are all real-time and numeric.

Touchdown speed, vertical acceleration and distance to go when landing can be obtained and divided to the different levels. For touchdown speed, the threshold at landing time is set as 29.6 m/s. When touchdown speed is exceeding the value, the flight is easy out of control and the landing state is bad.

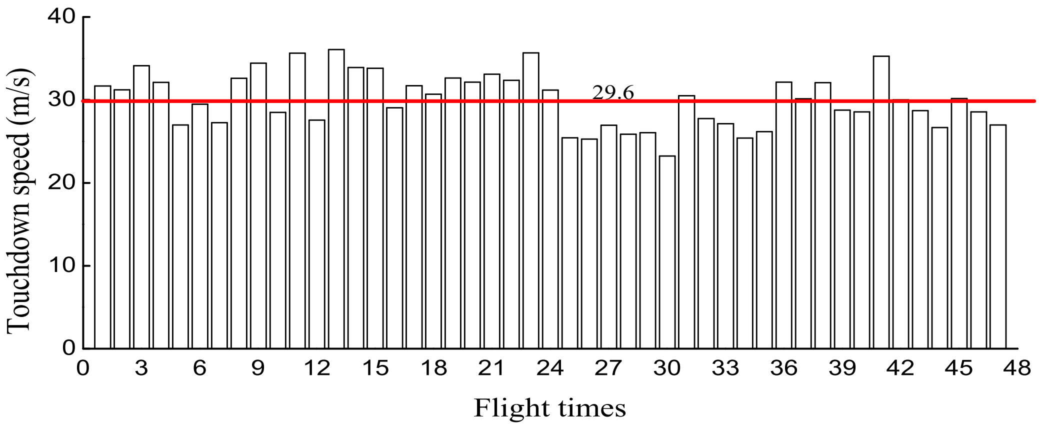

Figure. 7 Touchdown speed of 47 times flight.

From Figure 7, it's obvious that there are 24 flight sorties exceeding the threshold of touchdown speed at the landing time.

For vertical acceleration, the threshold at landing time is set as 18.2 m/s2. When landing acceleration is exceeding the threshold, the landing state is bad. From Figure 8, there are 22 flight sorties exceeding the threshold of vertical acceleration at the landing time.

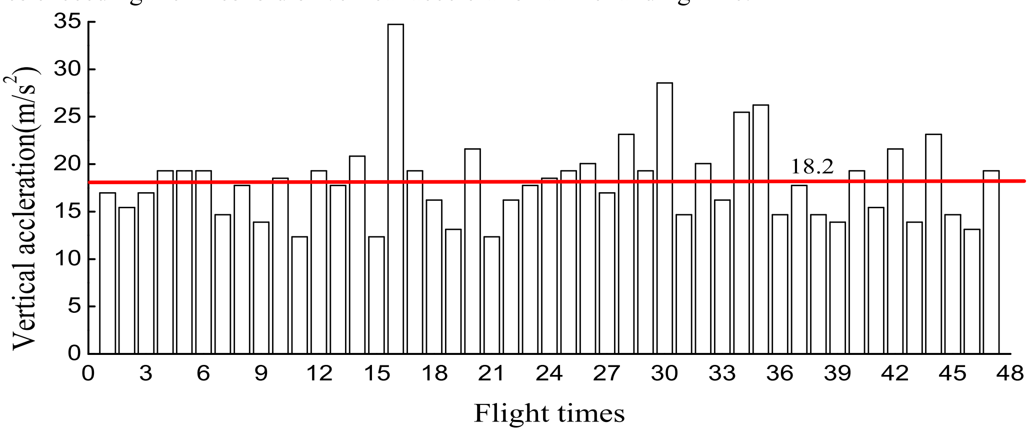

Figure. 8 Vertical acceleration of 47 times flight.

For distance to go, the distance is for the scheduled landing site, so it's relative value interval that variable gets suitable value and landing states is good as Figure. . There are 18 flight sorties exceeding the threshold of distance to go at the landing time.

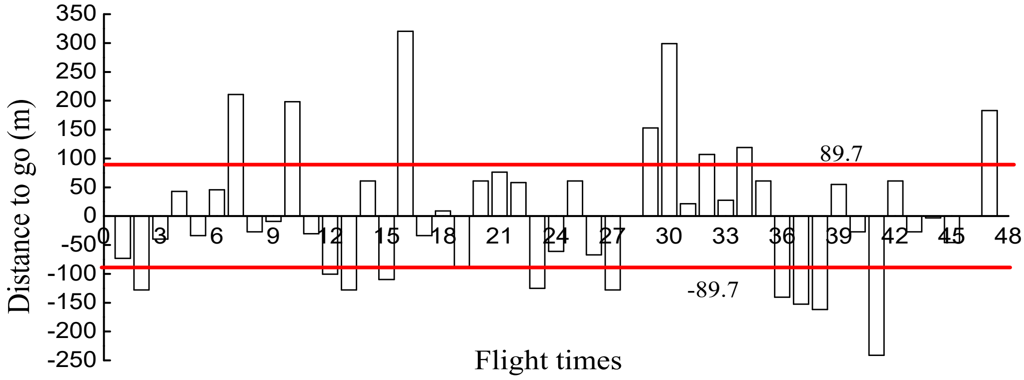

Figure. 9 Distance to go of 47 times flights.

So it's clear that each landing state level can be divided based on above.

While all variables will be the input of BP artificial neural network for training to fit the best function, some parameters must be set for pattern recognition. For example, the hidden layer's node must be determined at the height of 9m. According to Kolmogorov theory, if the number of input layer is m , the number of node of hidden layer is $2m+1$. With this, forecasting results by increasing or decreasing the number are given and found quickly the best node number. The results are as Figure. .

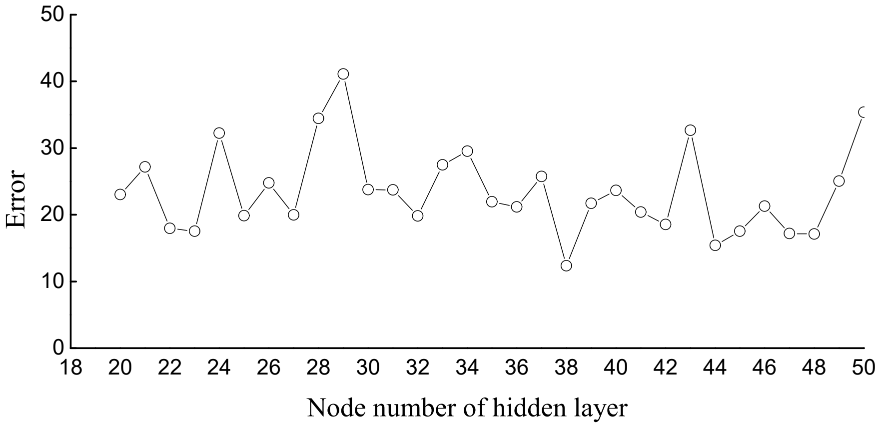

Figure. 10 The error for different nodes.

It's obvious that the error is smallest when the number is 38. So the node number of hidden layer is 38. Of course, the weight and threshold must be confirmed when training the data, while the excitation function is chosen as 'tansig' and the training function is 'trainlm'. Genetic algorithm can find the best weight and threshold from input layer to hidden layer. Of course, the software can solve the process of genetic algorithm. Once finished, the BP neural network can operate and change the weight and thresholds by itself until the minimum error is found. The basic parameters of network model consist of training number, parameters epochs, learning rate, minimum mean square error, excitation function and training function. In this paper, the number of training is set as 1000, the epochs are 1000, learning rate is 0.1, the minimum mean square error is 0.005, the training function is LM algorithm, while the excitation function needs to be chosen from logarithmic sigmoid transfer function and hyperbolic tangent sigmoid transfer function.

The landing states reflected by three variables are forecasted as Table 1 one by one based on artificial neural network optimized by genetic algorithm at the height of 9m.

Table 1 Prediction of landing variables

No.	Actual Landing States			Prediction Landing States		
	Vertical Acceleration	Distance To Go	Touchdown Speed	Vertical Acceleration	Distance To Go	Touchdown Speed
1	15.43	-241.09	35.26	14.18	-239.14	34.79
2	21.61	61.04	29.99	23.2	69.63	29.95
3	13.89	-27.47	28.71	13.32	-27.85	28.14

4	23.15	-3.05	26.66	24.69	31.31	26.49
5	14.66	-45.78	30.18	16.25	8.29	29.32
6	13.12	0	28.57	11.18	11.91	29.1
7	19.29	183.11	26.97	18.87	158.92	26.89

It can be seen from Table 2 and Table 3 and Table 4 that the prediction error ratios of touchdown speed and distance to go are much lower, indicating that BP artificial neural network can better describe the relationship between velocity and other variables. we can see that compared with the prediction of normal acceleration, BP neural network has better efficiency and accuracy and is more suitable for touchdown speed prediction. Different from the prediction of touchdown speed and vertical acceleration, the range of the distance to go varies more and is positive and negative. However, the prediction results of the BP neural network are also smaller, which is more instructive for actual flight.

Table 2 Vertical Acceleration results comparison

Actual value	Regression prediction	Error ratio	BP artificial neural network prediction value	Error ratio
15.43	10.54	31.70%	14.18	8.10%
21.61	17.23	20.30%	23.2	7.36%
13.89	21.56	55.20%	13.32	4.10%
23.15	17.23	25.60%	24.69	6.65%
14.66	16.9	15.30%	16.25	10.80%
13.12	19.71	50.20%	11.18	14.80%
19.29	18.88	2.13%	18.87	2.18%

Table 3 Distance To Go results comparison

Actual value	Regression prediction	Error ratio	BP artificial neural network prediction value	Absolute error
-241.09	-234.31	6.78	-239.14	1.95
61.04	-2.73	63.77	69.63	8.59
-27.47	-32.16	4.69	-27.85	0.38
-3.05	-12.42	9.37	31.31	34.36
-45.78	-66.55	20.77	8.29	54.07
0	-62.644	62.644	11.91	11.91
183.11	219.14	36.03	158.92	24.19

Table 4 Touchdown Speed results comparison

Actual value	Regression prediction	Error ratio	BP artificial neural network prediction value	Error ratio
35.26	33.2	5.90%	34.79	1.40%
29.99	24.82	17.30%	29.95	1.35%
28.71	38.99	35.80%	28.14	1.98%
26.66	20.4	23.50%	26.49	0.66%
30.18	32.33	7.10%	29.32	2.84%
28.57	35.49	24.20%	29.1	1.84%
26.97	5.4	79.90%	26.89	0.30%

Above the Table 1, the prediction value of three variables based on pattern recognition one by one is shown and compared with the actual landing value. It's obvious that the value of prediction model is close to the actual value and the errors between prediction values and actual values are all within 5 percent, which means the prediction accuracy of landing states at the height of 9 m is high and has practical reference value.

What's more, the landing states could be classified according to the prediction results as followed Table .

Table 5 Classification of landing states

Actual States	**Prediction States**			
	1	2	3	4
1	24	6	0	0
2	2	28	0	0
3	0	6	37	2
4	0	0	0	0

The classification results of landing states prediction model is shown in Table , in which the precision rate $P = 91.8\%$ and recall rate $R = 91.8\%$. It' obvious that the prediction is relatively accurate while there are several prediction mistakes for the variables prediction one by one. But the shortcoming of the model is a little cumbersome and not convenient.

It's well-known that the flight states can be reflected by flight data and the prediction states are also potential map of landing states. As for the prediction one by one, this is not suitable for Markov chain because of little states changes and high prediction precision.

While the landing states are directly reflected by three variables including vertical acceleration, distance to and touchdown speed, it' s necessary and straightforward that the prediction result for landing states is calculated together and the results at height of 7m are as Table .

Table 6 Prediction results

No.	Actual Landing States			Prediction Landing States		
	Vertical Acceleration	Distance To Go	Touchdown Speed	Vertical Acceleration	Distance To Go	Touchdown Speed
1	15.43	-241.09	35.26	16.34	-207.82	33.19
2	21.61	61.04	29.99	21.60	61.03	29.99
3	13.89	-27.47	28.71	12.01	1.35	26.20
4	23.15	-3.05	26.66	15.09	155.84	25.63
5	14.66	-45.78	30.18	20.55	-222.17	30.68
6	13.12	0	28.57	16.52	-3.99	28.92
7	19.29	183.11	26.97	16.31	228.27	29.96

From the above Table , there are seven groups that the prediction results are shown. To actual landing states, some prediction results are becoming worse which the error is large while several prediction variables based on BP artificial neural network at height of 7m is good and close to the actual value. Of course, there are many factors effecting the prediction results of three variables at the same time. A high correlation between variables may affect the outcome of the prediction. For example, the correlation coefficient between distance to go and touchdown speed is 0.84.

Table 7 — Classification results of flight times

Actual States	Prediction States			
	1	2	3	4
1	7	13	10	0
2	2	17	9	3
3	3	5	33	3
4	0	0	0	0

It's apparent that the precision rate and recall rate could be solved that $P = 85.1\%$ and $R = 60\%$. From the Table , there are 23 sets wrong prediction for level 1 while it's more accurate for level 2 and level 3, which demonstrates that pattern recognition based on BP artificial neural network is suitable for QAR data analysis to forecast the landing states. According to our research, the best forecasting height based on the results is 7m or 3m for higher precision.

For Markov chain prediction, the state transferring matrix is:

$$P=\begin{bmatrix}7 & 13 & 10 & 0\\ 2 & 17 & 9 & 3\\ 3 & 5 & 33 & 3\\ 0 & 0 & 0 & 0\end{bmatrix}$$

The Markov property is $\chi^2(9)=29.43>\chi^2_{0.01}(9)=21.666$, which means the state division meet the demands. It's obvious that the probability of prediction for level 1is less than that for level 2 and level 3, which means the way of prediction is lower precision for level 1 and the prediction accuracy of level 2 and level 3 for actual landing states is higher than forecast error rates. According to the practical results, the transition matrix is:

$$T=\begin{bmatrix}2 & 5 & 2 & 0\\ 5 & 12 & 9 & 3\\ 3 & 11 & 24 & 2\\ 0 & 1 & 5 & 0\end{bmatrix}$$

It's obvious that when the prediction states for level 2 and 3 the following states are also themselves, while as the prediction for level 1 the following states is easy to be forecasted level 2. So when the prediction state is level 2, it's necessary to check out which variable is out of the threshold and in-time to adjust the flight status by operating the flight. In practical engineering application, the expected result is level 1. There is something to revise the prediction model for state level 1.

If the continuous prediction state is level 1, the prediction value should be revised for the variables out of threshold by the function $V_a=V_p-\frac{5}{9}\overline{V}$, which V_a is the final value, V_p is the prediction value and $\overline{V}$ is the error between the value of last height and the value of current height. The precision of level is $\frac{2}{9}$ and the error rate is $\frac{7}{9}$.

At the height of 7m, the third group landing prediction result is level 1 while the state is level 2 at 6.5m which the ground speed (30.02 m/s) is out of threshold. The revised result is that the prediction value of ground speed is 29.49 m/s, which the prediction state is level 1. Of course, the subsequent revision could be done like this. The research result indicates that the process of revision is effective and the prediction results are more close to the actual values. However, it is worth to note that the modified function is summarized by a large number of results of data calculation. Different application data has a different function. The modified function is not universal.

5. Conclusion

This paper discusses the landing_safety based on the flight data and builds the pattern recognition based on BP neural network to predict landing state indicated by touchdown speed, vertical acceleration and distance to go. The Markov chain is applied to revise the prediction result. Conclusions can be drawn as follows.

According to the results of pattern recognition,_we can see that prediction value's errors are unstable and some status' prediction precision is not high, which means the application of pattern recognition in flight data analysis is suitable but needs to be improved.

It's remarkable and effective for pattern recognition to predict the_variables one by one.

For landing states prediction with three variables together, it's obvious that the error is little big but the Markov chain is suitable for this and is also used to revise the error for subsequent level 1 prediction. According to their precision and recall rate, it's high and accurate that the prediction model is applicable for landing states.

This paper builds pattern recognition and Markov chain to realize the advanced prediction of landing state before landing, which can ensure landing safety, thus greatly reduce the accidents and losses. The division of landing states depends largely on experience, which for sure calls for more researches. The prediction of landing state is a relatively new field of landing safety with more mining space.

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Conflicts of Interest

The authors declare no conflict of interest.

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