Pilot Fatigue Detection Using BP Neutral Networks

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Abstract

The main purpose of this paper, is to ensure the safety of pilots by monitoring fatigue degree. To evaluate fatigue level, BP neural network method is adopted to collect data features, and three physiological parameter data ---- SDNN of heart rate variability (HRV), blink rate and body temperature are collected. The human heart rate variability and body temperature are collected at the pilot's earlobe through the photoplethysmography (PPG method). The blink rate is collected via a head-mounted device. According to the subjects' subjective fatigue level and objective operation performance, a BP neural network classification model can be established to achieve the discrimination effect . The paper "Automatic Detection of Driver Impairment Based on Pupillary Light Reflex" [1]indicates that the blink rate is strongly correlated with human fatigue level. The paper "Study on Fatigue and Recovery of Engineering Vehicle Drivers Based on HRV" has proved that both HRV and heart rate are associated with human fatigue level. The paper "Control of Liquid Cooling Garments: Technical Control of Mean Skin Temperature and its Adjustments to Exercise" also presents the relationship between body temperature and fatigue value. In this paper, three indicators data are carefully analyzed and integrated via artificial intelligence BP neural network, and a fatigue detection model is successfully built. In this way, the model can classify the fatigue degrees efficiently and serve as a warning function.

Keywords: Physiological parameters; BP Neutral Network; Fatigue Detection; Blink

1. Introduction and Motivation

With the increasing workload of pilots, fatigue phenomenon is becoming more and more prominent, and fatigue detection has become a key subject that needs long-term research. Although fatigue detection technologies are emerging in an endless stream, most of them are aimed at the field of automobile drivers, few studies are targeted on the real-time fatigue detection of pilots. Moreover, most papers can only indicate that some physiological parameters of the human body are related to fatigue value, but there is no way to classify different degrees of fatigue directly. The results of current research on fatigue detection are mainly divided into three categories: 1) Methods based on physiological signals, such as electromyographic signals and electrocardiographic signals. 2) Methods based on driver behavior, such as aircraft steering angle, flight attitude, etc. 3) Methods based on driver facial features, such as eye closure degree, head deviation angle, etc.

The vast majority of studies related to fatigue are applied to the automotive field. Taking into account the actual situation, the driver has no way to detect physiological signals during driving. Thus, the mainly used technology in those situations is to capture the face area through the camera for feature extraction, so as to determine fatigue degree. However, since the pilot's face is covered by helmet, sunglasses and mask, the camera is not easy to capture facial information. PPG method is adopted to fit the pilot's earlobe, collect heart rate data, and combine the blink rate to obtain more accurate physiological information, which makes the physiological signal detection technology better applied.

Therefore, this paper focuses on the pilot fatigue detection method based on physiological signals. Firstly, the heart rate variability, blink rate, and body temperature data are obtained, and then the BP neural network model is constructed. Through artificial intelligence, fatigue level classification is performed eventually.

1.1 Theoretical Basis

The characteristic indicator of heart rate variability (HRV) is the rr interval, which is the interval between two adjacent heartbeats and varies with different heartbeats. Changes in heart rate are influenced by changes in the sympathetic and parasympathetic nerves. Sympathetic nerve excitement will increase the heart rate, while parasympathetic nerve excitement will slow down the heart rate. Heart rate and rhythm are largely regulated by the autonomic nervous system. Fatigue is mainly divided into physical fatigue and psychological fatigue[2]. Physical fatigue is considered to be fatigue of the nervous system, which is mainly manifested by insufficient release of acetylcholine in the anterior membrane of the neuromuscular junction, resulting in the inability of skeletal muscle cells to contract. At the same time, lactic acid accumulation and glycogen depletion lead to decreased muscle tension and reduced exercise endurance. Psychological fatigue is a mental fatigue phenomenon caused by long-term monotonous, repetitive work or continuous high-intensity load work. Changes in the activity of the central nervous system are an important factor which lead to the status of fatigue. When fatigue occurs, the activity of the Sympathetic Nervous System (SNS) increases and the activity of the Vagus Nervous System (VNS) decreases, both of which are related to fatigue of the central nervous system.

When the human body is in a state of fatigue, the eyes will be sensitive to light and the pupil will shrink[1]. Therefore, the diameter of the pupil can be used to evaluate the fatigue state of the eyes. However, the pilot's helmet is too close to their eyes. If infrared light is directly exposed to their eyes, it will cause strong stimulation. Therefore, the blinking frequency is used, instead of infrared light, to judge the fatigue state.

Research from Shanghai Institute of Physical Education has confirmed that branched-chain amino acids are related to human metabolism[3], and when the human body is exercising, the body temperature will rise by 1 degree Celsius for every 13% increase in basal metabolism. Therefore, the degree of exercise fatigue can be reflected by body temperature.

2. Correlation Analysis

The existing equipment collected 9 different physiological parameters, including heart rate, heart rate variability, blink rate, body temperature, electromyography, respiratory rate, blood pressure, blood oxygen saturation, and EEG. As a practical matter, EEG is not currently available for use on airplanes, so it is not used as a physiological parameter input model. So far, the data volume is close to 10 million sets, more than 50 gigabytes.

2.1 Correlation between physiological parameters and fatigue

Correlation analysis refers to the analysis of using two or more correlated variables to measure the closeness of two factors. The correlation coefficient is an indicator that reflects the degree of linear correlation between two variables. The following two methods are used: Pearson correlation coefficient analysis and Spearman correlation coefficient analysis.

Pearson correlation coefficient: it used to measure the correlation coefficient between two continuous random variables;

Spearman correlation coefficient: it ranks correlation coefficient, it is solved according to the rank order of the original data, it is also known as the Pearson correlation coefficient between rank variables.

The value range of the above two coefficients is [-1,1]. When it is close to 1, it means that the two have a strong positive correlation; when it is close to -1, it means that there is a negative correlation; when the value is close to 0, it means that the correlation is very low.

2.2 Code analysis results

Heart rate and heart rate variability

According to the Pearson correlation coefficient analysis, the absolute value of the correlation coefficient between heart rate and heart rate variability reached 91.45, and the significance coefficient reached 1.06, that is, the two affect each other and cannot be used as different features to input the model.

According to the Spearman correlation coefficient analysis, the absolute value of the correlation coefficient between heart rate and heart rate variability is 92.26. Similarly, it cannot be used as different features to input the model.

In summary, heart rate and heart rate variability can only be selected as input physiological parameters for fatigue assessment. Since heart rate variability represents the change of heart rate, heart rate variability is selected as the corresponding indicator.

Correlation of other parameters with fatigue

physiological parameters	Pearson correlation coefficient	Spearman correlation coefficient
Heart rate variability	0.79	0.8069
Blink	0.316	0.2951
Body temperature	0.53	0.4886
Respiratory rate	0.0506	0.3086
Electromyography	0.5052	0.4118
Blood oxygen saturation	0.3693	0.4722
High blood pressure	0.1151	0.2469
Low blood pressure	0.0000	0.02

Table 1

Correlation between heart rate variability and fatigue

According to the data in Table 1, the Pearson correlation coefficient between heart rate variability and fatigue is 0.79, and the Spearman correlation coefficient is 0.8069, which proves that heart rate variability and fatigue are strongly correlated.

Correlation between blinking and fatigue

According to the data in Table 1, the Pearson correlation coefficient between blinking and fatigue is 0.316, and the Spearman correlation coefficient is 0.2951, which proves that blinking and fatigue are weakly correlated.

Correlation between body temperature and fatigue

According to the data in Table 1, the Pearson correlation coefficient between body temperature and fatigue is 0.53, and the Spearman correlation coefficient is 0.4886, which proves that body temperature and fatigue have a low correlation.

Correlation between respiratory rate and fatigue

According to the data in Table 1, the Pearson correlation coefficient between respiratory rate and fatigue is 0.0506, and the Spearman correlation coefficient is 0.3086, which proves that respiratory rate and fatigue are weakly correlated.

Correlation between electromyography and fatigue

According to the data in the table, the Pearson correlation coefficient between electromyography and fatigue is 0.5052, and the Spearman correlation coefficient is 0.4118, which proves that electromyography and fatigue have a low correlation.

Correlation between blood oxygen saturation and fatigue

According to the data in the table, the Pearson correlation coefficient between blood oxygen saturation and fatigue is 0.3693, and the Spearman correlation coefficient is 0.4722, which proves that blood oxygen saturation and fatigue have a low correlation.

Correlation between high and low blood pressure and fatigue

According to the data in the table, the Pearson correlation coefficient between high blood pressure and fatigue is 0.1151, and the Spearman correlation coefficient is 0.2469, which proves that high blood pressure and fatigue are weakly correlated.

According to the data in the table, the Pearson correlation coefficient between low blood pressure and fatigue is close to 0, and the Spearman correlation coefficient is 0.02, which proves that low blood pressure and fatigue are not correlated.

Combining high and low blood pressure proves there is no correlation between blood pressure and fatigue.

Conclusion

In summary, the correlation between the eight physiological parameters and fatigue is ranked from high to low as follows: heart rate variability = heart rate > electromyography > blood oxygen saturation > body temperature > blinking > respiratory rate > blood pressure.

At the same time, since heart rate variability basically has no difference from heart rate, and according to correlation analysis, the significant coefficient of the two reaches 1.06, and the absolute value of the correlation exceeds 92%, that is, the two affect each other and cannot be used as different features to input the model.

Finally, according to actual needs, heart rate variability, body temperature, and blink rate are selected as input parameters of the neural network model.

3. Data processing

3.1 Obtaining data

The device synchronously collects ECG signals to ensure the synchronization and stability of the data during the experiment, as well as recording the original data of HRV, body temperature, blink rate and corresponding time in real time during the experiment (see Figure 1).

```
          Time(s)    Value(ms)
0         1.190240   690.429688
1         1.868950   678.710938
2         2.549615   680.664062
3         3.246880   697.265625
4         3.959771   712.890625
...            ...          ...
5231   3675.153130   656.250000
5232   3675.813286   660.156250
5233   3676.475396   662.109375
5234   3677.134575   659.179688
5235   3677.797661   663.085938

[5236 rows x 2 columns]
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Figure 1

The blink data collected by the ErgoLAB device is shown in Figure 2.

Start Time [ms]	End Time [ms]	Blink Start [ms]	Blink Duration [ms]	Blink End [ms]	Eye L/R	Number
0	1265276	299	119	419	Left	1
0	1265276	1338	120	1458	Left	2
0	1265276	3156	139	3296	Left	3
0	1265276	5294	139	5433	Left	4
0	1265276	5933	139	6073	Left	5
0	1265276	7191	119	7311	Left	6
0	1265276	9029	139	9169	Left	7
0	1265276	10348	159	10507	Left	8
0	1265276	10787	119	10907	Left	9
0	1265276	11526	159	11686	Left	10
0	1265276	12825	139	12965	Left	11
0	1265276	14003	99	14103	Left	12
0	1265276	15362	99	15462	Left	13
0	1265276	16101	139	16241	Left	14
0	1265276	16820	139	16960	Left	15
0	1265276	18199	119	18319	Left	16
0	1265276	19058	139	19198	Left	17
0	1265276	20796	159	20956	Left	18
0	1265276	21915	119	22034	Left	19
0	1265276	23373	140	23513	Left	20
0	1265276	25610	119	25730	Left	21
0	1265276	28028	139	28167	Left	22
0	1265276	30465	139	30605	Left	23

Figure 2

3.2 Data preprocessing

Due to the instability of the equipment, it is necessary to pre-process the data to avoid data packet loss and to check whether there are outliers. Through the IQR method, we set upper and lower boundaries and delete outliers to obtain more accurate data. It is shown in Figure 3.

```
             Time(s)   Value(ms)
0           1.190240  690.429688
1           1.868950  678.710938
2           2.549615  680.664062
3           3.246880  697.265625
4           3.959771  712.890625
...              ...         ...
5231     3675.153130  656.250000
5232     3675.813286  660.156250
5233     3676.475396  662.109375
5234     3677.134575  659.179688
5235     3677.797661  663.085938

[5217 rows x 2 columns]
```

Figure 3

4. Neural networks

4.1 BP neural network

Since the collected pilot physiological data is structured and linear, a BP neural network method is selected for classification. Give a sample D, $x = [x_1 \ldots x_3]^T$, the linear model is:

$$f(x, w) = w_1 x_1 + w_2 x_2 + w_3 x_3 + b$$

x_1, x_2, x_3 represent blink rate, body temperature, and heart rate variability respectively. $w_1 \sim w_3$ are the corresponding weights, and b is the bias.

BP (Back Propagation) neural network is a multi-layer feedforward network which is trained according to the error back propagation algorithm. Its learning rule is to use the gradient descent method to continuously adjust the weights and thresholds of the network through back propagation, so as to minimize the sum of square errors of the network. It contains an input layer, a hidden layer, and an output layer. The input layer is the physiological parameters (blink rate, body temperature, heart rate variability); the hidden layer contains the ReLU activation function, the loss function optimizer Adam and the loss function cross entropy; the output layer includes the fatigue classification (such as awake state, moderate fatigue state and severe fatigue state), and contains the softmax activation function. The structure of the BP neural network is shown in Figure 4:

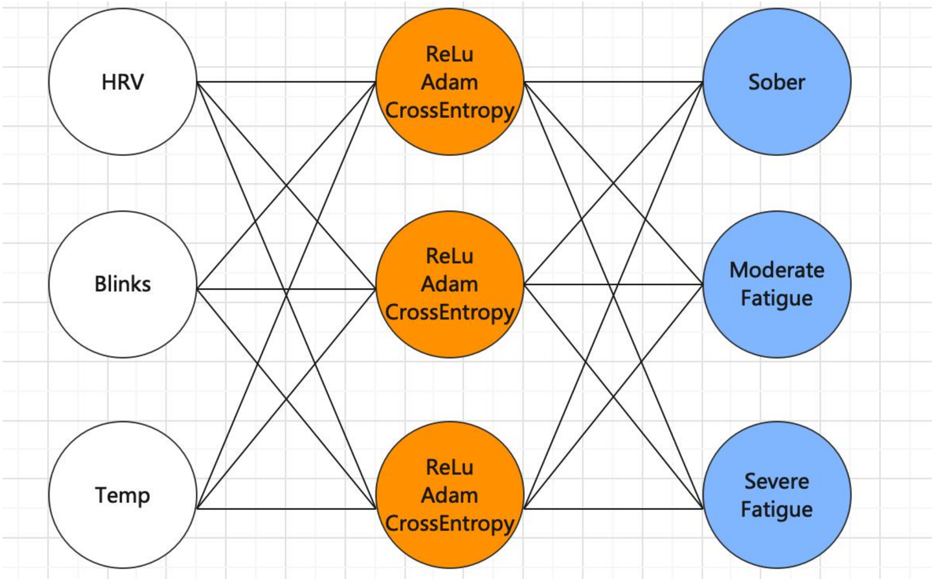

Figure 4

4.1.1 Input layer

The pilots' physiological parameters, namely body temperature, heart rate variability and blink rate, were collected and divided into a training set (80%) and a testing set (20%). The training set was used for feature extraction, iteration and loss optimization of the data, and the testing set was used to test the model's accuracy.

4.1.2 Hidden layer

The role of the hidden layer is to extract the features of the input data into another dimensional space to present its more abstract features, which can be better linearly divided. The training data is passed through the Relu activation function, cross entropy and Adam loss function optimizer to get the minimum error, and then the error is backpropagated, iterated continuously, and the weights and thresholds are updated. After a large number of iterations, the weights tend to stabilize, and finally, the testing set is passed into the model for accuracy calculation.

ReLU activation function: In the fatigue classification task, since the output target fatigue level y is a discrete label, and the value range of the pilot's physiological parameters is a real threshold, it cannot be used directly for prediction, so it is necessary to add a nonlinear function ReLU to predict the output target.

$$\mathrm{ReLU}(x) = \max(x, 0)$$

ReLU function image:

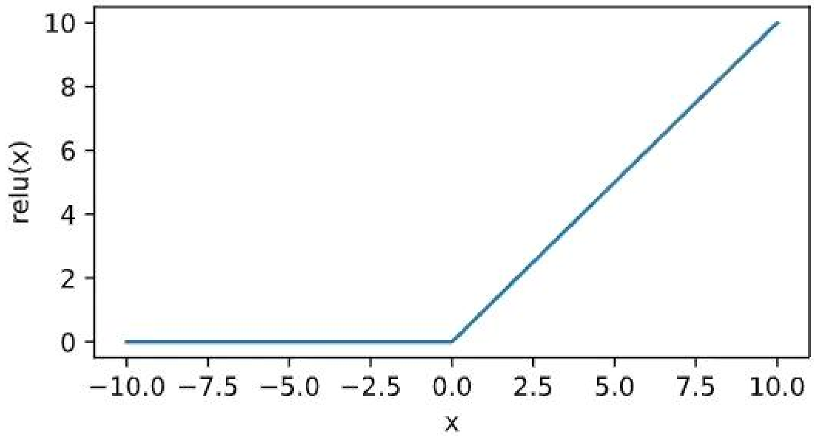

Figure 5

Cross Entropy Loss: A prediction result will be obtained after the pilot's physiological parameters are passed through the model. Due to the reasons including equipment instability, data packet loss, etc., there may be errors and deviations between the determined fatigue level and the actual situation, that is, losses. The loss function is essentially a function that calculates the difference between the two and minimizes the error between the two so that the predicted value is infinitely close to the true value. Cross entropy can measure the difference between true and predicted probability. The formula is as follows:

$$H(p, q) = -\sum p(x_i) \log(q(x_i))$$

$p(x_i)$ is the true probability, $q(x_i)$ is the predicted probability. The smaller the cross entropy value, the better the prediction model effects.

Adam loss function optimizer: According to the above loss function principle, in order to minimize the loss, it is necessary to calculate the gradient of the weight and bias b of the i-th training data relative to the loss function. Then the minimum value of the objective function is finally found by updating the weight value and deviation value iteratively, which is called gradient descent. The Adam loss function optimizer can make the gradient descent faster, and reduce the training time of physiological parameter samples, as well as updating the neural network parameters according to the gradient information so that the predicted value of the pilot's physiological parameters is closer to the true value. The Adam optimizer update rules are as follows:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2$$

$$\hat{m}_t = \frac{m_t}{1-\beta_1^t}$$
$$\hat{v}_t = \frac{v_t}{1-\beta_2^t}$$
$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\hat{v}_t}+\epsilon}\hat{m}_t$$

Where g_t is the gradient, β_1 and β_2 are the decay coefficient of the two exponentially weighted averages, $\hat{m}_t$ and $\hat{v}_t$ are the moving average corrected by the gradient deviation, θ_{t+1} is the updated parameter, η is the learning rate, ϵ is a small constant used to avoid division by 0.

Error back propagation: In a neural network, it is difficult to obtain the best regression effect through the network with the initialized parameters. Therefore, it is necessary to continuously reduce the error, update the weight, and iterate again to minimize the loss, so as to optimize the model. The formula is as follows:

Output value

$$y(n) = [v_j^1, v_j^2 .. v_j^j]$$

Expected output is

$$d(n) = [d_1, d_2 ... d_n]$$

The error at the nth iteration is

$$e_j(n) = d_j(n) - y_j(n)$$

The total error is

$$e(n) = \frac{1}{2}\sum_{j=1}^{j} e_j^2(n)$$

Assume that the weight between the hidden layer and the output layer is w_{ij}, calculate the gradient of the error to the weight, and then adjust it in the opposite direction:

$$\Delta w_{ij}(n) =- \eta \frac{\partial e(n)}{\partial w_{ij}(n)}$$
$$w_{ij}(n+1) = \Delta w_{ij}(n) + w_{ij}(n)$$

According to the chain rule:

$$\frac{\partial e(n)}{\partial w_{ij}(n)} = \frac{\partial e(n)}{\partial e_j(n)} * \frac{\partial e_j(n)}{\partial v_j^j(n)} * \frac{\partial v_j^j(n)}{\partial u_j^j(n)} * \frac{\partial u_j^j(n)}{\partial w_{ij}(n)}$$

Therefore, the weight correction is:

$$\Delta w_{ij}(n) = \eta \partial e_j(n) * \frac{\partial v_j^j(n)}{\partial u_j^j(n)} * \frac{\partial u_j^j(n)}{\partial w_{ij}(n)}$$

Since the transfer function is generally a linear function in the output layer, the derivative is 1, then $\frac{\partial v_j^j(n)}{\partial u_j^j(n)} = 1$

Substitute into the above formula, we get:

$$\Delta w_{ij}(n) = \eta \partial e_j(n) * \frac{\partial u_j^j(n)}{\partial w_{ij}(n)}$$

After calculating the reverse error, the corrected weight is only the weight between the hidden and output layers. When the network completes a complete update, it is necessary to update the weight between the input and hidden layers as well. Similarly,

$$\delta_I^i = f'\,(u_I^i(n)) \sum_{j=1}^{J} \delta_J^j w_{ij}$$

At this point, a round of weight adjustment of the three-layer BP neural network is completed.

4.1.3 Output layer

Softmax activation function: It is often used with the cross entropy loss function in classification problems. Softmax processes the output results so that the sum of the predicted values of multiple classifications is 1, and then the loss is calculated by cross entropy. Since the fatigue classification task is a kind of multi-classification, that is $y = \{1,2..C\}$, the conditional probability of softmax prediction is:

$$P(y = c|x) = \mathrm{softmax}(w_c^T x)$$

According to the characteristics of the softmax activation function, the function outputs a real number between 0 and 1, which represents the probability, that is, the possibility of classification of different fatigue levels. The formula is as follows:

$$yk = \frac{\exp\,(ak)}{\sum_{i=1}^{n} \exp\,(ai)}$$

$\exp\,(ak)$ is an exponential function. There are n neurons in the output layer. The output yk of the kth neuron is calculated. The numerator is the exponential function of a single input value, and the denominator is the sum of the exponential functions of all input information.

The BP neural network is used to extract features of the blink rate, body temperature, and heart rate variability data sets. The minimum gradient method is used, and the epoch is set to 100. The learning rate is 0.02. In this way, the loss function converges to the minimum value at an appropriate speed and the loss in the iterative process is minimized, with the aim of improving the final classification accuracy.

5. Test plan

5.1 Test design

In this experiment, the subjects were in a simulated cockpit. They wear personal protective equipment, simulating the actual wearing situation of pilots and actual working conditions to obtain test data. The independent variable was flight simulation operation; the dependent variables were subjective questionnaire survey, physiological indicators, and performance indicators.

Independent variables

The flight monitoring operation task is to simulate the pilot's dynamic monitoring of flight parameters, using a medium load simulation scenario. During the test, the test subject needs to monitor and respond to the simulated flight attitude parameters on the display interface: pitch angle, roll angle, heading angle, airspeed, pressure altitude, speed, and cylinder temperature. The specific operations are shown in Tables 2 and 3 below.

State parameters	Real operation in case of abnormality
Airspeed	Adjusting the throttle position
Barometric altitude	Push or pull the control lever/adjust the throttle
Pitch angle	Pushing or pulling the control lever
Roll angle	Left or right pressure control lever
Heading angle	Left or Right Hand Joystick
Engine speed	Adjusting the throttle position
Cylinder temperature	Adjusting the size of the air duct

Table 2 Real operation when state parameters are abnormal

State parameters	Normal numerical range	Increase	Reduce
Airspeed	90～130	Insert key	Delete Key
Barometric altitude	1200～1800	Page up Key	Page Down Key
Pitch angle	-20～+20	Direction keys ↑	Direction keys ↓
Roll angle	-30～+30	Direction keys←	Direction keys→
Heading angle	Course of the target ± 5	Mini keyboard 0	Mini keyboard Enter
engine speed	1800～2700	Mini keyboard 1	Mini keyboard 7
Cylinder temperature	120～200	Mini keyboard 2	Mini keyboard 8

Table 3 Operations in case of abnormal state parameters in the experiment

To study the fatigue of pilots during flight missions, this experiment adopted a repeated measurement display interface design.

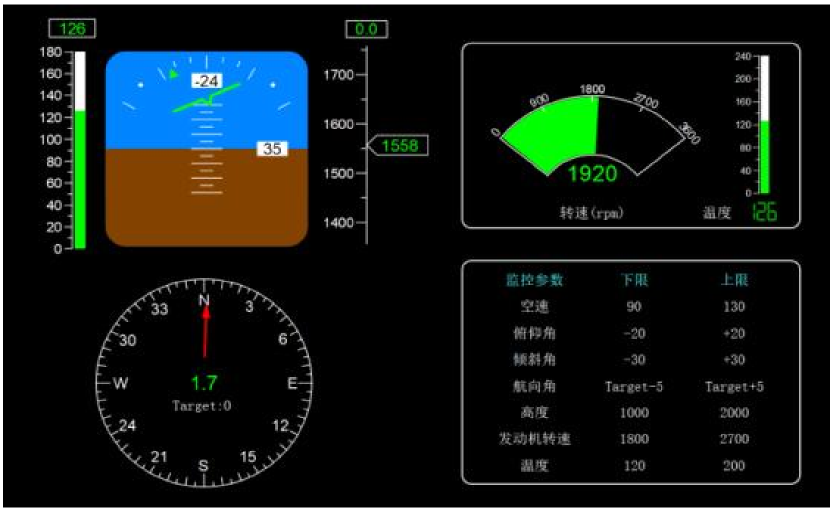

Figure 6 Flight Monitoring and Control Test

In the simulated monitoring task, no more than one abnormal information appears at the same time, and the probability of abnormality in each flight parameter is the same. The frequency of abnormal information is set to appear randomly every 10 to 30 seconds, and the subjects need to quickly complete the identification, judgment and response operations of abnormal information. The software background automatically records the subjects' operation and reaction time when they complete the driving task as the subjects' performance evaluation indicators.

5.2 Dependent variable

The dependent variables mainly include subjective questionnaire surveys, physiological indicators and performance indicators.

a) Subjective questionnaire survey

The subjective questionnaire survey uses the Karolinska Sleepiness Scale questionnaire.

To facilitate subsequent data integration and processing, the table mainly records the basic information such as the subject's name, age, gender, and whether he/she has flight experience in simulated flight.

1	Extremely alert
2	Vert alert

3	Alert
4	Rather alert
5	Neither alert nor sleepy
6	Some signs of sleepiness
7	Sleepy,but no effort to keep awake
8	Sleepy,but some effort to keep awake
9	Very sleepy,greater effort to keep awake,fighting sleep

Table 4 karolinska Sleepiness Scale

The Karolinska Sleepiness Scale is mainly used for test subjects to self-assess their current fatigue status during each test. It is divided into nine levels. The specific assessment criteria for each level are shown in Table 4.

b) Physiological indicators

Physiological indicators mainly include EEG, ECG, EMG, blood oxygen saturation, blink rate, ear pulse, body temperature and other physiological parameters. The physiological parameters of the test subjects are monitored in real-time throughout the test.

c) Performance indicators

Performance indicators mainly include reaction time and manipulation accuracy. The manipulation results are mainly divided into four situations: correct, wrong handling, normal state misjudged as fault, and no fault found. Among them, no fault found and normal state misjudged as fault can be used as indicators to judge cognitive accuracy; handling errors are used as manipulation accuracy indicators.

5.3 Test personnel

This experiment was conducted through public announcement recruitment, and selected according to the height and weight of the 50th percentile of fighter pilots in the military standards of the People's Republic of China. By statistically analyzing the basic information of the subjects, the average age of the sample was between 20 and 40 years old. The subjects had normal vision and hearing, no color weakness and color blindness, no cognitive impairment and hearing impairment, and they can correctly identify the prompt information set in the test and have no bad habits such as smoking. At the same time, 2 days before the start of the test, the subjects were required to rest normally, not stay up late, and not take any drugs or drinks that affect the central nervous system.

5.4 Test length

Each subject wore personal protective equipment and completed the test according to the display interface. Each test lasted 6 hours, with 1 hygiene and mealtime at 12 noon.

5.5 Test debugging

The test debugging phase is mainly the process of debugging the test instruments, test equipment, test environment and test platform. The debugging process is mainly aimed at flight monitoring and control tasks which last more than 6 hours, ensuring that the test platform will not experience any fluctuations and freezes within 6 hours, and the background data records are normal and complete.

5.6 Test process

aPre-train and instruct the subjects, so that they can understand the test process, clarify the test's purpose, know the test's safety requirements. Additionally, we also need to make them familiar with flight operations, subjective scale level perception and filling methods.

The subjects conduct 30 minutes to 1 hour of simulation exercises on the medium-difficulty test to learn and master the operation and use of the test equipment.

The test personnel adjust the test procedures and measuring equipment. The subjects fill in the fatigue scale and record the current status.

The subjects start to perform low-load boundary tests, and the test program displays the instrument monitoring page. The flight parameters on the interface will change randomly, and an abnormal parameter will appear randomly every 10s to 30s. The subjects need to monitor the changes in the parameters of the interface at all times, to identify abnormalities in time, and to make the prescribed corresponding operations. The specific operation methods are shown in Table 3. The program automatically records the accuracy and reaction time of the subjects. After the end of this test, the subjects fill in the KSS fatigue scale.

During the test, the subjects filled out the KSS scale every 20 minutes, and if fatigue changes occurred at non-specified times, the specific time and KSS scale level should also be stated.

5.7 Test results

The experimental data was put into the BP neural network, and after 100 iterations and weight updates, the final classification accuracy was as follows:

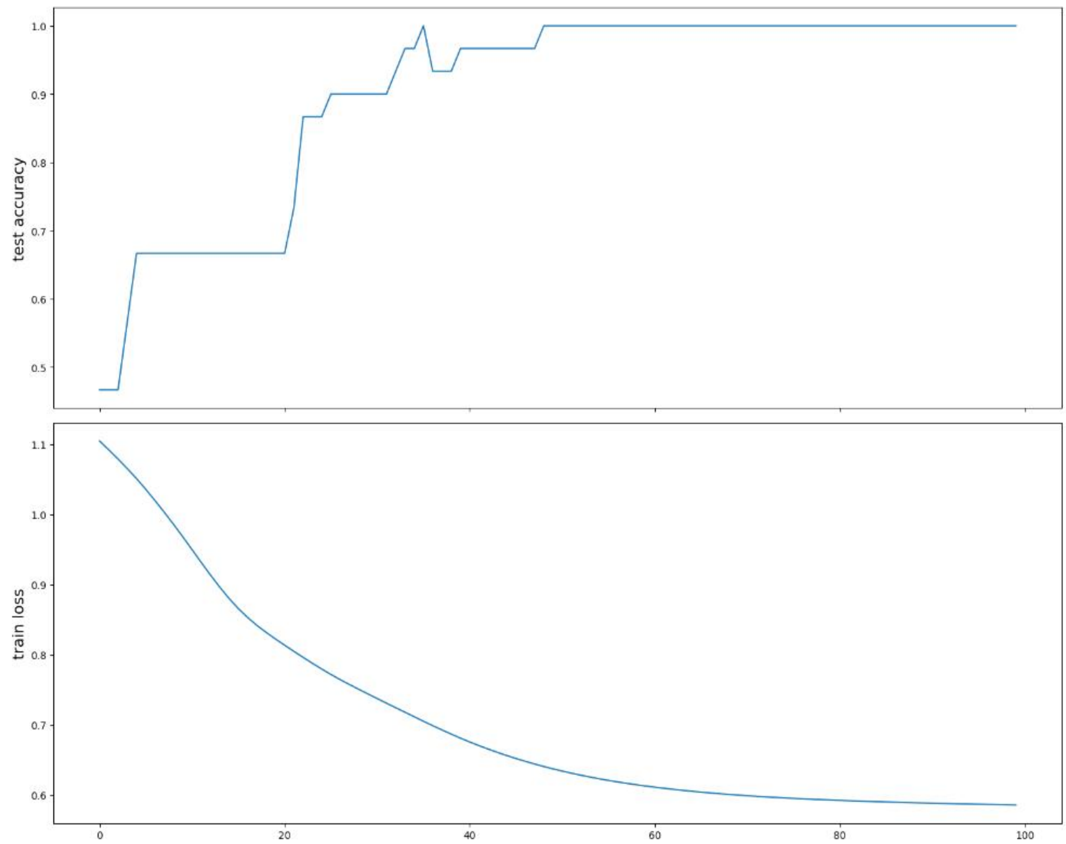

Figure 7

Test accuracy is the accuracy of model training, and train loss is the loss degree of the data set during training. As can be seen from the figure, the model's accuracy increases with the increase of iteration number and finally reaches 98%. The degree of training loss decreases with the increase of iteration number. Both illustrate that the model can achieve the expected fatigue assessment effect after continuous training.

6. Summary and application

Based on the data of human physiological parameters including hrv, body temperature and blink rate obtained in the experiment, a bp neural network model is built, and the accuracy of the model is improved through continuous iteration and loss degree optimization. Finally, the accuracy of the model is close to 100%, which meets the expectation. This technology can accurately assess the pilot's fatigue level by monitoring the pilot's physiological state and behavioral performance in real-time. Moreover, it can serve as an early warning to remind the pilot to take measures to relieve fatigue when necessary. At the same time, the system also provides a certain degree of demand for human-computer interaction technology. When the pilot is fatigued, the degree of automatic driving can be more in-depth, and more intelligent flight management can be achieved. For example, when the system detects pilot fatigue, it can automatically adjust the flight plan to reduce the pilot's workload; or communicate with the ground control center in real time to obtain more support and help. This integrated design not only improves the level of flight automation, but also enhances the flexibility and safety during the flight process. It helps to avoid operational errors or misjudgments caused by pilot fatigue, thereby significantly reducing the risk of flight accidents.

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