Intelligent Fatigue Detection Method in Industrial System Based on Facial Multi-feature Fusion

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Abstract. With the development of science and technology, the complexity of industrial production system has been significantly improved, and higher requirements have been put forward for human safety. Aiming at the contradiction between the intrusiveness and the accuracy of fatigue behavior detection in human factor safety, a multi-feature fusion intelligent fatigue state detection method was proposed. Firstly, the image recognition algorithm was used to accurately obtain the information of facial expression feature points. By analyzing the dynamic characteristics of all the feature points, the facial fatigue features were extracted. Secondly, an experimental scheme was designed to collect and process facial expression feature data, and a dynamic marker model of fatigue characteristics was constructed to form a fatigue index that directly reflected the fatigue degree of the working process. Finally, the neural network regression model was established to fit the characteristic data. Through the comparative analysis of different schemes and various evaluation indexes, the rationality of the fitting results of this method was proved. The experimental results show that this method can reasonably quantify the fatigue index of people under different conditions, and realize the intelligent detection of facial fatigue state.

1. Introduction
With the development and progress of science and technology, the reliability of industrial technical system has been significantly improved. However, this improvement has not prevented major disasters such as the gas leak at the Bhopal chemical plant in India, the Chernobyl nuclear power plant accident, the Three Mile Island nuclear power plant accident, and the Air France 447 disaster. It is not difficult to find that human safety and reliability in complex industrial scenes is also one of the important reasons that affect system accidents. Therefore, the accurate detection of human behavior for safety has extremely important practical significance and theoretical research value for ensuring the safety of personnel and industrial system [1].

Fatigue behavior, as a kind of human safety behavior, is very important in many complex industrial scenes. Accurate and effective detection of fatigue behavior is still a hot and difficult point in this field. Markus et al. used an electrocardiogram sensor to detect heart rate variability data and analyze the internal relationship between heart rate variation and fatigue [2]. Since the detection of physiological signals requires wearing devices, it is an invasive detection, which affects the normal work and is not conducive to promotion. Fatigue detection based on visual features. For example, Mehrdad Sabet et al. used Haar feature and Adaboost classifier to detect facial and eye states [3]. Anjali Ku et al. used
OpenCV to detect faces and eyes, and sent out reminders when fatigue was found. The algorithm has good real-time performance and still has some room for optimization [4]. As can be seen from the above studies, due to the subjectivity, complexity and instability of fatigue measurement, there are contradictions among the intrusive, accurate and real-time performance of fatigue detection [5]. In order to carry out quantitative transformation on these problems and coordinate the relationship between them, a more suitable fatigue detection method can be formed [6].

This paper proposes a feature fusion from face the fatigue status of intelligent detection method, key feature points on face recognition, on the basis of the analysis and extraction of personnel reflect fatigue behavior and process of multidimensional fatigue characteristics of fusion on the basis of establishing the comprehensive evaluation model of fatigue, improve the accuracy of fatigue behavior.

2. Detection of facial fatigue characteristics

2.1. Detection of facial feature points

Facial feature points refer to the locations of key points reflecting facial features, such as eyes, mouth and facial contour. In this paper, the facial feature point recognition model based on Dlib is used to obtain the feature points required for fatigue feature recognition [7], and their distribution is shown in Figure 1.

![Figure 1. Location distribution of facial feature points](image)

Through the annotation and training of the data feature points, the model of 68 facial feature points was obtained in this paper. The 68 facial feature points started from the left cheek and distributed along the edge of the cheek and the main facial organs successively.

2.2. Eye feature extraction

When a person is tired, the blink duration and number of blinks will change significantly, and the change of the eye state, as an important feature reflecting the person's state, is also the main feature required in the fatigue detection process [3]. In this paper, the ratio of the height to the width of the feature points in the eye feature area is taken as the eye closure. From the opening to the closing of the eyes, the height of the characteristic area of the eye drops significantly, but the width changes less, so this ratio decreases rapidly. The ocular feature points are shown in Figure 2.

![Figure 2. Distribution of related feature points in the left eye](image)
Taking the left eye as an example, the feature points related to the left eye are 36-41. By obtaining the coordinate information of the feature points, the aspect ratio of the eye can be calculated. The calculation method is shown in Formula (1).

$$d_{eye} = \frac{(p^{40} + p^{41}) - (p^{37} + p^{38})}{2(p^{39} - p^{36})}$$  (1)

where $p$ is the coordinate value of the corresponding feature points $(x, y)$.

At present, there is no unified threshold of aspect ratio in the existing research of blink detection, so the threshold is determined by experimental data in this paper. Part of the experimental results are shown in Figure 3.

![Figure 3. Data of eye aspect ratio](image)

Among them, the horizontal axis represents the sequence of frames, and the vertical axis represents the aspect ratio of the eyes. As can be seen from the figure, the aspect ratio of the eyes concentrates between 0.175-0.280 in the normal state of opening eyes. When the eyes are closed, the aspect ratio of the eyes decreases rapidly, and the experimental data show that the ratio is mainly below 0.150, but some singular values are close to or slightly higher than 0.150. Therefore, 0.160 is considered as the threshold value in this paper. When the aspect ratio is less than 0.160, the eyes are in a closed state, and when the aspect ratio is greater than 0.160, the eyes are in an open state.

2.3. Mouth feature extraction

Yawning is also an obvious feature of fatigue in the assessment of fatigue state. In the normal working process, the tester relieves drowsiness by persistent yawning, which is judged to be a high degree of fatigue. The yawning state is a dynamic process in which the mouth opens rapidly and continues for a while before closing, which makes it easy to detect with strong reliability in terms of computer vision technology [8-9]. The mouth feature points are shown in Fig. 4.

![Figure 4. Distribution of mouth related feature points](image)

The feature points related to the mouth are No. 60-67. The aspect ratio can be calculated by obtaining the coordinate information of the feature points, and the calculation method is shown in Formula (2).
where $p$ is the coordinate value of the corresponding feature points $(x,y)$.

At present, there is no unified threshold of aspect ratio in yaw detection research, so this paper determined the threshold based on experimental data. Part of the experimental results are shown in Figure 5.

According to the experimental data, in the normal closure state, the aspect ratio of the mouth is concentrated between 0 and 0.1. In the speaking state, the aspect ratio of the mouth has obvious changes and the frequency of changes is fast. The value distribution range is wide, the time is relatively short, and the aspect ratio concentrates between 0 and 0.3. In the yawning state, the ratio of the mouth to the aspect is relatively high, and the experimental data show that the ratio is mainly concentrated above 0.45 and will persist for a period of time. Therefore, when the mouth aspect ratio is greater than or equal to 0.45, it can be considered as yawning, and when the mouth aspect ratio is less than 0.45, it can be considered as non-yawning.

3. Fatigue measurement index experiment and analysis

3.1. Design of fatigue measurement experiment scheme

In this paper, Python was used to design a data acquisition program based on facial feature recognition algorithm. The resolution of the video recorded in the experiment was 640*480, the frame rate was 29, and the length of a single video data was set to 30 seconds, that is, the total frame number of a video was 870 frames. This test required the test personnel to work normally and study, and the head could rotate slightly. But make sure the camera can get a picture of the face.

A total of 3500 data samples were measured in the experiment, which were divided into training samples and test samples according to 4:1, namely, 2800 training samples and 700 test samples. The training samples were used for the generation and training of the neural network model, and the test samples were used to test the training results and the accuracy of the neural network. According to the identified features, the blink frame number, blink number, yawning frame number and yawning number were collected as the basis for fatigue judgment. The Fatigue state was evaluated by expert rating method, and the range of Fatigue index (FI) was set at 0-1. The larger the number, the higher the Fatigue degree. The classification of different Fatigue degrees was based on:

1) Awareness (0-0.35). Focused on the present, focused, not blinking too much, alert, fully alert and able to react quickly.

2) Mild fatigue (0.35-0.7). Slight increase in the number and duration of blinking, reactive but less alert, lethargy, and occasional drowsiness.
3) Severe fatigue (0.7-1). Slow reaction times, difficulty staying awake, drowsiness, frequent yawning, and inability to concentrate.

Some experimental data are shown in Table 1.

| No. | Close your eyes frames | Times of blinking | The number of yawning frames | Times of yawning | Total video frames | Fatigue index |
|-----|------------------------|-------------------|------------------------------|------------------|-------------------|---------------|
| 1   | 140                    | 22                | 104                          | 1                | 870               | 0.75          |
| 2   | 56                     | 9                 | 0                            | 0                | 870               | 0.1           |
| 3   | 101                    | 15                | 97                           | 1                | 870               | 0.7           |
| 4   | 165                    | 12                | 0                            | 0                | 870               | 0.4           |
| 5   | 101                    | 15                | 0                            | 0                | 870               | 0.3           |
| 6   | 99                     | 5                 | 50                           | 1                | 870               | 0.35          |
| 7   | 123                    | 14                | 194                          | 3                | 870               | 0.8           |
| 8   | 263                    | 19                | 135                          | 2                | 870               | 0.95          |
| 9   | 131                    | 5                 | 0                            | 0                | 870               | 0.25          |
| 10  | 51                     | 8                 | 5                            | 1                | 870               | 0.1           |

The division of the fatigue index can reflect the degree of fatigue tester, can be seen from the table, when fatigue index is low, people are awake, usually yawn, even if it does, it can rapidly response, not long time continued the behavior, with the increase of fatigue index, testers status into mild fatigue, usually show the blink of an eye time longer. When the fatigue index is higher, it becomes a state of severe fatigue, which is mainly manifested in the obvious increase of the duration and number of yawns, and the total duration of blink is usually higher.

3.2. Experimental feature processing

In order to eliminate the influence of sampling time and sampling frame rate on different feature sizes, data features were processed, and the ratio of eye closing time to total time was taken as the average Blink index (BI), and the ratio of Blink times to sampling time was taken as the Blink frequency (BF). The ratio of Yawn duration to total duration is taken as the Yawn index (YI), and the ratio of Yawn frequency to sampling time is taken as the Yawn frequency (YF). Through data processing, characteristic data and the fatigue index (FI) are shown in Table 2.

| N   | BI     | BF     | YI   | YF   | FI   |
|-----|--------|--------|------|------|------|
| 1   | 0.087  | 0.167  | 0    | 0    | 0.1  |
| 2   | 0.105  | 0.633  | 0    | 0    | 0.3  |
| 3   | 0.114  | 0.167  | 0.057| 0.033| 0.35 |
| 4   | 0.141  | 0.467  | 0.223| 0.1  | 0.8  |
| 5   | 0.169  | 0.667  | 0.025| 0.033| 0.55 |
| 6   | 0.302  | 0.633  | 0.155| 0.067| 0.95 |
| 7   | 0.151  | 0.167  | 0    | 0    | 0.25 |
| 8   | 0.097  | 0.4    | 0.066| 0.033| 0.4  |
| 9   | 0.272  | 0.467  | 0.122| 0.133| 0.9  |
| 10  | 0.04   | 0.1    | 0    | 0    | 0.05 |

As shown in Table 2, the influence of sampling time on the result is eliminated through feature processing, so as to make a good preparation for the subsequent training of the model.
4. Multi-feature fusion fatigue index calculation model

4.1. Subjective and objective fatigue evaluation method based on neural network

In this paper, a multi-feature fusion fatigue state intelligent detection method is proposed. The method is regression fitting through MLP, so as to reflect the contribution of different parameters to the evaluation results. In order to make the algorithm have better adaptability, multi-scale feature parameters are introduced to expand the features of the data set through multi-scale features, to establish a direct relationship between different features, to train the data in a higher dimension, and to improve the accuracy of the model.

4.2. The introduction and application of multilayer perceptron

Multi-layer Perceptron (MLP) is an algorithm model based on deep neural network. Its basic structure includes input Layer, hidden Layer and output Layer. Each input node is connected to the output node through multiple weighted chains, so as to simulate the connection between neurons. The training process of multi-layer perceptrons is the process of constantly adjusting the weight, and finally the input-output relationship can be better fitted [10]. In order to improve the efficiency of data training, the parameters of the regression model are shown in Table 3. The \( n_{\text{feature}} \) is the number of features of a data input.

| Name    | Parameter | Name    | Parameter |
|---------|-----------|---------|-----------|
| input   | n_feature | output  | 1         |
| hidden1 | 32        | activation | ReLU     |
| hidden2 | 64        | Dropout  | 0.3       |
| hidden3 | 128       | learning_rate | 0.005   |
| hidden4 | 64        | optimizer | Adam     |
| hidden5 | 32        | Loss_function | MSE     |

As shown in Table 3, the hidden layer using the ReLU activation function is built in the architecture of the model, and the batch training method is selected, that is, all the recorded information in the training data set is used to minimize the total error. Since the method needs to adjust the weights continuously before meeting any conditions for ending the training, there is the possibility of passing the data several times. After adjustment, the adaptive motion estimation algorithm (Adam) was selected as the optimization algorithm, and the mean square error loss function was selected as the loss function. Dropout was added to each layer to improve the generalization ability of the model.

4.3. Analysis of experimental results

By replacing the data into the neural network for training, in order to better verify the performance under different features, the structure of the training model is unchanged in this paper, and the combination of different features is used for experimental comparison. After the training of different feature models, the detection results are evaluated. The results of each evaluation index are shown in Figure 6.
Figure 6. Comparison of evaluation results of various schemes

Among them, the horizontal axis represents different feature models, and the vertical axis represents the evaluation results of each feature model in the test data. The experiment adopts the Mean Squared Error (MSE), Mean Absolute Error (MAE), and root Mean Square Error (RMSE). Root Mean Squared Error and R score are the evaluation criteria of the regression model. As can be seen from the figure, CI (Comprehensive index) has the lowest result on each Error index, and it is closest to 1 on the goodness of fit. It shows that CI model has obtained the best evaluation results in each index.

By analyzing the fatigue degree of the tester through feature fusion, the fatigue degree can be determined by different fatigue characteristics from a variety of perspectives, so as to effectively improve the effectiveness and stability of the intelligent monitoring system.

The correlation data of CI features were substituted into the traditional machine learning model for calculation, and compared with the MLP regression method in this paper. The results of each evaluation index are shown in Figure 7.

Figure 7. Comparison of evaluation results of different algorithms
As can be seen from the comparison in the figure, among the three loss calculations, the MLP regression model has the lowest loss value, while it has the best evaluation result in goodness of fit. Therefore, it can be considered that the regression model used in this paper is reasonable to some extent, and the trained model can be used to conduct intelligent detection of facial fatigue state.

5. Summary
Aiming at the contradiction between accuracy and real-time performance of human fatigue state detection in complex industrial scenes, a multi-feature fusion fatigue detection method is proposed in this paper. The fatigue information presented by the video sequence in a period of time is transformed into multi-dimensional key fatigue features, and the fatigue index analysis model is fused to realize the comprehensive evaluation of the fatigue state. Compared with the traditional method, the new method has advantages in non-contact and real-time performance and higher identification accuracy, which is of great significance for reducing the cost of industrial supervision and ensuring the safety of personnel and industrial system.

The experimental sample data set was used to verify the method, which showed that the method in this paper can identify a variety of fatigue characteristics under different states more accurately, and the fatigue evaluation results can be obtained accurately. Compared with the single feature identification method, its identification accuracy can be greatly improved. In addition, a fatigue index analysis model with automatic updating mechanism is established. When there is a big difference between the predicted value of the model and the current sample, the new sample will be automatically transformed into a new sample input model according to the evaluation results of the relevant parameters among the samples, and the model will be reconstructed, which provides a new quantitative analysis method for the accurate perception of fatigue behavior in complex industrial scenes. Since the actual fatigue state of human body is not only related to the fatigue features extracted in this paper, but also has a certain correlation with other features, we should consider deeper fatigue features in further research.

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