Face fatigue detection method based on convolution neural network

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Abstract. In order to monitor the fatigue state of the face, a state detection algorithm based on a variety of facial fatigue parameters is proposed. Firstly, convolution neural network is used to enhance the edge information of eyes and mouth for accurate positioning. Then, a rotation invariant LBP pyramid feature is used to describe the eyes, and a linear SVM classifier is trained to distinguish the open and closed state of eyes. The open and closed state of mouth is judged according to the open area and aspect ratio of mouth. At the same time, the vertical movement of eyes is counted to determine changes in head position. Finally, based on the state of eyes and mouth and the position of head, four fatigue parameters which can describe the state are calculated, and the final fatigue state is obtained by convolution neural network. The experimental results show that the detection and state discrimination algorithms have high accuracy.

Keywords: Convolution neural network; face detection; fatigue state detection.

1. Introduction

In the process of facial fatigue detection, due to the continuous changes of the spatial position and head posture of the subject, the monitoring equipment may not be able to capture effective facial information [1]. To solve this problem, a multi device monitoring fusion scheme based on convolutional neural network is used to monitor the subject's face. Then, the fusion method based on the minimum judgment of face rotation angle is used for data fusion [2]. Finally, the optimal data set of facial feature points is obtained, and the fatigue feature sample database is constructed. Fatigue features are extracted based on the optimal facial feature points set, and the effectiveness of these features is analyzed and verified by statistical analysis. Aiming at the problem that shooting distance and shooting angle are constantly changing, feature compensation methods based on convolution neural network and Euler angle are proposed. Experiments show that this method can effectively reduce the influence of shooting distance and shooting angle on the size of feature value [3]. Finally, taking the detection rate of single kernel support vector machine as the evaluation index, the optimal kernel function is selected, and the single branch decision tree and support vector machine are fused to construct the job fatigue detection model. The experimental results show that this model has higher detection rate than the single kernel support vector machine model [4]. The server encapsulates the above detection algorithm through data monitoring layer, data calculation layer and data storage layer to realize data collection, calculation and storage, so as to ensure the accuracy of facial fatigue detection.
2. Detection method of facial fatigue state

2.1. Facial fatigue information collection

Facial feature points are the coordinate points set describing the contour of face and organ, and it is the premise of extracting facial fatigue features. In this chapter, firstly, the common face detection algorithm is introduced and the feature point detection method is introduced[5]. Then, the face feature point data acquisition scheme using multiple monitoring equipment is introduced. Then, the optimal sample data is obtained by using the target level data fusion method based on the minimum decision of head rotation angle. Finally, the above scheme is used to simulate the industrial production environment, and the data of facial feature points in fatigue and non fatigue operation are collected and integrated to construct the fatigue sample database[6]. Most of the traditional fatigue testing researches have many behavioral limitations on the tested. Specifically, in fatigue testing research, the action will be limited by many factors, such as the limitation of moving space, and the head posture will not produce a large angle change and spatial offset[7]. But in industrial production workshops, the situation is often more complex. The behavior limit of workshop workers is less, the activity space is relatively large and the behavior is difficult to predict[8]. In this way, the monitoring equipment can not collect effective data when sampling and testing. In order to avoid such a situation, multi monitoring equipment is used to monitor human face. After a series of investigation and research, it is found that, in general, the range angle that a single monitoring device can capture depends on the size of the monitoring lens used[9]. Taking 4mm lens as an example, the monitoring angle is 69.9 degrees by looking up the table. Assuming that the monitoring distance always meets the requirements of the farthest monitoring distance, the number of monitoring equipment used is positively related to the angle of the monitoring area, such as formula.

\[ N = \frac{C}{n} \] (1)

Among them, \( N \) represents the minimum number of required monitoring devices, \( n \) represents the maximum monitoring angle of a single monitoring device, and \( C \) represents the angle of monitoring area. On the premise of meeting the basic regional monitoring conditions, the following formula is used to simply represent the relationship between performance, cost performance and the number of monitoring equipment [10]. The data fusion method based on the minimum judgment of head rotation angle is used to fuse the monitoring data. The algorithm belongs to the target level fusion method, which is more efficient and robust than the data level fusion method. The basic idea is that each monitoring device gives the detection results of each frame image, uses the fusion algorithm to make a comprehensive judgment on the result set, and outputs the most reasonable result[11]. The monitoring video streams generated by each monitoring device are collected, and the initial frames of these video streams are aligned.

\[ F = \begin{bmatrix} f_{11} & f_{12} & L & f_{1n} \\ f_{21} & f_{22} & L & f_{2n} \\ M & M & O & M \\ f_{m1} & f_{m2} & L & f_{mn} \end{bmatrix} \] (2)

Firstly, the facial feature points are collected and fused. In the process of acquisition, because the spatial position and head posture of the subjects are constantly changing, the monitoring equipment may not be able to capture effective facial information[12]. In order to solve this problem, the multi device monitoring fusion scheme is used to monitor the subjects' faces. First, the data collected by each device is used to recognize the facial feature points. Then, the fusion method based on the minimum judgment of facial rotation angle is used to fuse the data. Finally, the optimal facial feature points data set is obtained, and the fatigue feature sample database is constructed[13]. The algorithm is as follows:
Furthermore, the image with the smallest head rotation angle in each group is selected as the standard image of this group, and other images are discarded. Fatigue features are extracted based on the optimal facial feature points set, and the effectiveness of these features is analyzed and verified by statistical analysis. Then, aiming at the problem of changing shooting distance and shooting angle, the feature compensation method based on distance mapping and Euler angle are proposed. The detection rate of single kernel support vector machine is taken as the evaluation index, the optimal kernel function is selected, and the single branch decision tree and support vector machine are fused to construct the job fatigue detection model.

In the field of image processing, filter is a linear filter commonly used in edge detection. In spatial domain, a two-dimensional filter is the product of a sine plane and a Gaussian kernel function. The definition of two-dimensional filter is as follows:

$$g(x, y, \lambda, \theta, \varphi, \sigma_x, \sigma_y) = \exp \left( -\frac{1}{2} \left( \frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2} \right) \right) \cdot \exp \left( i2\pi \frac{x}{\lambda} + \varphi \right)$$

The key work of the research on fatigue detection is to extract the effective fatigue characteristics based on the above algorithm. Based on the optimal facial feature set obtained in chapter two, two aspects of research are carried out, one is fatigue feature extraction, the other is fatigue feature compensation [14]. In the aspect of feature extraction, we extracted several eye features and mouth features for statistical analysis to verify their effectiveness. In feature compensation, the paper first introduces the reasons for the change of shooting distance and shooting angle when facial data acquisition, and expounds the influence of these two changes on the feature value.

2.2 Feature recognition of facial fatigue data based on convolutional neural network

As an important branch of machine learning technology, deep learning technology has been developed rapidly in recent years. The deep learning technology extracts the original data layer by layer through the layered processing mechanism, and through training a large number of sample data, a more comprehensive target feature expression model is obtained[15]. Compared with the traditional machine learning method, when training the deep learning model, it can directly train a large number of data training samples. The whole training process does not need the manual participation and automatically adjusts the parameters of the model. In addition, compared with the traditional machine learning method, the method of deep learning is more robust and accurate. A typical convolutional neural network is composed of convolution layer, reduced sampling layer and full connection layer, and its specific structure is as follows:
Multi device monitoring fusion scheme is used to collect the data of facial feature points. First, the data collected by each device is used to recognize the facial feature points. Then, the data fusion method based on the minimum judgment of head rotation angle is used to fuse the data, and finally the optimal set of facial feature points is obtained[16]. The optimal feature points are labeled and the fatigue feature sample database is established. In this paper, we only use multiple monitoring devices in the data acquisition stage, and all subsequent data processing uses the optimal feature point set after data fusion[17]. On the basis of facial optimal feature points set, the eye fatigue feature and mouth yawn feature are extracted, and the statistical method is used to intuitively show the change rule of eye movement behavior curve and mouth behavior curve of subjects in different fatigue states[18]. Using the method of variance analysis, the significant differences of each characteristic parameter in different fatigue states were analyzed. Finally, scientific and reasonable eye movement features and mouth features were selected. In the process of detection, the original input image is firstly processed through several convolution layers and downsampling layers to obtain multiple low-scale feature vectors (one-dimensional vectors), which are the feature expression of the original input image in the high-level layer[19]. Then, these low-scale eigenvectors are used as the input of traditional neural network to form a deep convolution neural network model. Face detection is an important application field of object detection. Object detection can be roughly divided into three processes: candidate region generation, image feature extraction and image feature classification. The calculation formula of LBP eigenvalue centered on any pixel \((x, y)\) in the image is as follows.

\[
LBP_{p,r}(x, y) = g(\lambda(x, y), \theta, \phi, \sigma_x, \sigma_y) \sum_{p=0}^{P-1} S\left(f(x, y) - f\left(x_p, y_p\right)\right)2^p
\]  

(6)

The investment of less monitoring equipment in the industrial workshop can reduce the cost, but it also means that the fatigue detection performance and accuracy are reduced. Because the less monitoring equipment, it means that each device is responsible for the larger angle of the region, the larger the angle of the region, the larger the error of facial feature point detection will be, and even the situation of missing detection may appear. Five four lens monitoring devices are used to monitor the subjects at o-point[20]. The angle of each monitoring device is 70 degrees. In the best case, the face plane of the subjects at o-point is perpendicular to the central axis of the monitoring device, but in the worst case, the head posture of the subjects may rotate 35 degrees. Although the facial feature point detection algorithm can detect the features of the face sub image rotated at a certain angle, the detection error will increase with the increase of the angle. Therefore, the appropriate increase in monitoring equipment can improve the performance and accuracy of fatigue detection, but too much investment in monitoring equipment is meaningless. Too many devices will bring the following two problems: first, too many monitoring devices will bring waste of cost and computing resources. Secondly, with the increase of the number of monitoring equipment, the improvement of fatigue detection performance will be less and less obvious, and even drag down the whole performance. In a word, the distribution and quantity selection of monitoring equipment is a trade-off problem.
monitoring conditions, the following formula is used to simply represent the relationship between performance, cost performance and the quantity of monitoring equipment.

$$S = \text{perf} \propto LBP_{p,R}(x,y) \log \frac{N}{(\alpha + \mu) \times N}$$

The extraction performance of facial feature points is tested in three cases of naked eyes, wearing glasses and wearing sunglasses, and the eye mouth feature points are visualized. The experimental results show that ERT algorithm can extract the key points from the facial region, especially in the naked eye state, and the positioning accuracy of the feature points is high. In the case of wearing sunglasses, if the head posture is adjusted in the horizontal direction, the feature point error may be large. In view of this phenomenon, this paper finds that the change of head posture leads to the deviation of dstt algorithm in tracking the driver's face area, which can not accurately track the driver's head posture. Therefore, intermittent face location strategy is used to detect and track the face region, that is, every SS, mtcnn face detection algorithm is used to relocate the driver's face region, and the initial tracking target of dstt target tracker is updated, so that dstt can always track the driver's face region in real time and accurately. Especially when the driver's head posture changes dramatically in the horizontal direction, the proposed intermittent face detection strategy performs well, which can accurately track the face region and ensure the accuracy of ERT facial feature points extraction. Combining image feature extraction and image feature classification, the process of face detection is: candidate region generation process and candidate region discrimination process. Generally, the sliding window method is used to segment the image and generate candidate regions. The traditional sliding window method will use the multi-scale sliding window method. This method uses different scales of sliding windows to slide on the whole image with equidistant steps to generate candidate region images. The advantage of the traditional sliding window method is that it has low miss detection rate, but the disadvantage is that it needs to consume huge search space and time in the detection process, and the detection efficiency will be greatly affected. The figure shows the process of generating candidate region image based on traditional sliding window method.

![Fig. 2 Candidate image generation based on sliding window method](image)

In order to solve the problem of different PERCLOS parameter values, this paper proposes an online real-time updating PERCLOS coefficient conversion model. When detecting different eye regions, the eye region of the first N frames is extracted by preprocessing, and the corresponding PERCLOS conversion coefficient is obtained after morphological processing. Further, the PERCLOS conversion coefficient extracted by preprocessing is used to transform the follow-up eye feature parameters. Finally, the fatigue state can be distinguished according to the criterion. Through the development of a scientific fatigue assessment scale for fatigue testing. The evaluation scale was filled in by the workers directly, and the fatigue was evaluated according to the subjective feelings of the workers. The key point of self rating scale method is to develop a scientific and reasonable evaluation scale, which is directly related to the scientificity and reliability of fatigue test results. Convolution neural network is widely used
because it is simple, easy to operate, economical, and can correctly reflect the physical and psychological fatigue of workers. It has a good guiding role for the production planning of enterprises. Objective response to the physical state of workers, objective, judge the fatigue situation of workers, avoid the interference of subjective factors of individual workers, is a reliable method to study and detect the fatigue state of workers.

Convolution neural network is used to extract eye feature parameters, which mainly extract two states of closed and open eyes. When the eye is open, the label value is 1, and when the eye is closed, the label value is 0. When using convolutional neural network to extract eye feature parameters, sigmoid function is used in the last layer, and the range of output function is 0-1. In general, the distribution pattern and geometric shape of human facial organs are basically the same, and in computer vision, human face contains a lot of feature information such as gray, color, texture and so on. In the knowledge-based detection method, researchers try to use the prior knowledge of facial skin color, facial geometry, facial texture information to build face region detection model, so as to realize face detection. In color space, human skin color has strong clustering characteristics, which is the theoretical basis of face detection based on skin color. First, the skin color information is gathered in a small range by clustering, then the skin color distribution model is constructed, and the input image is compared with it, and finally the detection region in the image is obtained. In the research, based on the skin color model detection method, combined with and using the geometric relationship between facial organs (eyes and mouth) to confirm the detection results, the method has good robustness for face detection with pose changes. The face detection algorithm combined with face shape and skin color information is suitable for the situation that the light environment does not change. The knowledge base of facial information is constructed by using the edge and gray information of facial image, and the multi-level detection method is used to improve the detection speed. The advantage of convolution neural network detection method is simple and intuitive, easy to understand and apply.
2.3. Realization of face fatigue detection

Human face is a very important biological feature, which contains rich information. Through the detection and recognition of human face, we can analyze the corresponding gender, age, identity, expression and other information. The research and application of face region detection and recognition plays an important role in the field of computer vision and pattern recognition. For the research of face fatigue expression recognition based on machine learning, face detection is the most basic and first step. The purpose of face detection is to detect and recognize the specific features of the face in the image. Face detection has attracted more and more attention of researchers at home and abroad in recent years because of its broad application fields and important application value. Therefore, more and more face detection algorithms are proposed and applied by researchers in various fields at home and abroad. The existing face detection and location methods can be divided into four categories, they are: face detection algorithm based on template matching, face detection algorithm based on statistical learning, face detection algorithm based on knowledge and face detection algorithm based on feature points.

Nowadays, with the rapid development of information technology, the use of computer extends to more and more fields. In the research of artificial intelligence, making the computer or computer-based robot have the same thinking ability as human beings, and be able to recognize and deal with things correctly through their own algorithms, has been the direction of people's efforts, and also the thing that people hope. With the rapid development of computer, the direction of computer recognition related to face image is also booming. Using the knowledge of computer vision and pattern recognition, through the analysis of face image, the face fatigue expression recognition based on machine learning is realized. After a lot of literature reading and research analysis, comprehensive domestic and foreign related research in various fields, it is found that the research on fatigue detection is mainly concentrated in the field of transportation and medicine, while the research on fatigue detection in the field of industry and manufacturing is relatively less. But even so, these research results also bring great inspiration. On the basis of in-depth investigation and analysis of the relevant research results in various fields at home and abroad, the core task is to establish a fatigue detection model suitable for the factory workshop, and the goal is to improve the detection rate of the algorithm. The research focuses on the core issues of data acquisition and fusion, fatigue feature extraction, fatigue feature compensation, detection model training and so on. The research of this paper is of great significance for fatigue detection and early warning of workers in industrial workshops. Job fatigue is a complex psychological and physiological phenomenon, which is difficult to judge by simple statistical analysis. The distribution characteristics of eye mean closure under different fatigue levels are shown in the figure.

![Box plot of average eye closure](image)

**Fig. 4** Box line diagram of eye closure
The unit of vertical axis is pixel, and the scale represents the number of pixels. It can be seen from the figure that under the condition of job fatigue, the average eye closure of workers is significantly reduced and fluctuates greatly. Under the normal condition, the average eye closure is significantly greater than the upper quartile under the condition of job fatigue. This shows that the average eye closure of workers is significantly reduced under the condition of work fatigue. Based on the eye feature points set and mouth feature points set of facial feature points, the fatigue detection model is constructed, so as to carry out scientific and efficient fatigue detection. The face detection method based on feature point detection is also a classic face detection method. This method uses image processing, pattern recognition and other technologies to analyze and recognize the key points of the face in the image. These key point sets describe most of the features of the face, such as the face contour and the location of various organs (eyes, nose, mouth, etc.). Feature point detection method can quickly and directly obtain the subject's facial information in the image. It is one of the important means in the field of facial organ detection, facial posture analysis, facial expression recognition and analysis. Some eye features and mouth features are studied, and fatigue feature vectors are constructed through them. The fatigue feature vector is optimized, and then the kernel function is selected through experiments. Finally, the single branch decision tree and support vector machine are fused to build a fatigue detection model with better detection effect. The process of facial fatigue expression recognition algorithm is optimized, as shown in the following figure.

![Fig. 5 Optimization of facial fatigue state recognition steps](image)

In order to adapt to the complex and changeable behavior of workers in industrial workshops, multiple monitoring devices are used to monitor workers' faces in parallel. The key of this scheme is to solve the problem of distribution of multiple monitoring equipment in the workshop and the problem of information fusion of multi-source data. The whole fatigue detection is equivalent to a large-scale computing platform. The platform collects data through monitoring equipment, and inputs the collected image and video information to the computing module. The computing module gathers and processes the data, and finally obtains the optimal feature input vector, and transmits the feature input vector to the fatigue detection model, and finally gives the fatigue detection results. In order to ensure the rapid and accurate detection, the structural framework of face recognition model equipment is further optimized as follows:
The whole architecture tries to modularize all the functions, decouple all the functions, reduce the dependence between the modules, so as to improve the stability and maintainability of the system. Modularization idea decomposes each function module of the software, at the same time, it also greatly enhances the maintainability of the software, which is convenient for troubleshooting or upgrading optimization in the follow-up work. The modules call each other in synchronous or asynchronous mode based on a certain protocol, which can better guarantee the effect of facial fatigue state detection.

3. Analysis of experimental results

The data collected in the experiment include face feature data, eye feature data and mouth feature data. In order to conduct secondary analysis and calculation of facial feature data, eye feature data and mouth feature data, it is necessary to build a facial behavior database. The most important facial behavior data is eye feature data, followed by mouth feature data. In this study, although the facial contour data of workshop workers are also extracted, only the eye feature data and mouth feature data are calculated and analyzed twice. The main reason for adopting this strategy is that eye feature data and mouth feature data have obvious objective changes in fatigue state detection. On the one hand, the feature data of both eyes can represent a lot of information. For example, when the fatigue is too high, the feature parameters such as blink frequency, eye closure speed, eye closure time and so on will change significantly. On the other hand, when workers enter fatigue state, if yawning occurs, the mouth characteristic data will change significantly. In the experiment, two 4mm lens monitoring devices were used to monitor the subjects according to the way shown in Figure 2-2. For each subject, two groups of simulation experiments were conducted: face data acquisition in normal state and face data acquisition in fatigue state. The subjects were tested in the same environment at the same time every day, and the interval between the two groups was one week. The preparation work before the experiment was started 2 days before the experiment. Experience shows that the human body is very energetic in the morning, and is more prone to fatigue between 14 and 16 in the afternoon. Therefore, we choose to collect facial data in normal condition from 10:00 to 12:00 in the morning and fatigue condition from 14:00 to 16:00 in the afternoon. In the experiment, more than 1 million face images are obtained by sampling the surveillance video at a sampling rate of 30 frames per second. According to the standard of 10s time window, the specific results are shown in the table.

| Table 1. Data sampling results |
|-------------------------------|
| Fatigue sample               | Non fatigue sample | Number of samples |
| 1199                         | 1901               | 3100              |
In this experiment, we collected facial videos of 5 students, and randomly selected 30 consecutive frames from each video as experimental samples. The number of training samples is 45000, the learning rate is $e = 0.001$, and the number of training batch samples is 18000 iterations. After training, the figure below shows the training error of convolutional neural network.

![Facial recognition error curve](image)

**Fig. 7** Facial recognition error curve

Based on the test results above, it can be seen that the error of the fatigue test method under this method is significantly lower in the actual test process, which is basically lower than the standard curve, which proves that this method has high effectiveness. The fatigue parameters are calculated according to the state discrimination results, and the fatigue state coefficient is obtained by fuzzy reasoning method, so as to judge whether early warning is needed.

| Experimental group | Eye closure (frame) | Continuous eye closure (frames) | Mouth open (frame) | Head high (frame) |
|--------------------|--------------------|---------------------------------|--------------------|------------------|
| 1                  | 5(5)               | 3(3)                            | 3(4)               | 1(3)             |
| 2                  | 11(12)             | 7(6)                            | 12(12)             | 6(6)             |
| 3                  | 4(4)               | 1(1)                            | 6(6)               | 6(4)             |
| 4                  | 8(7)               | 6(5)                            | 7(6)               | 7(6)             |
| 5                  | 3(3)               | 2(2)                            | 2(3)               | 3(4)             |

**Table 2.** Statistics of facial feature state

| Experimental group | BlinkFreq | ClosureDura | YawnFreq | NodFreq | DC      | Early warning or not |
|--------------------|-----------|-------------|----------|---------|---------|----------------------|
| 1                  | 0.200(0.177) | 0.100(0.100) | 0.133(0.100) | 0.000(0.100) | 0.188(0.223) | No (yes)               |
| 2                  | 0.400(0.457) | 0.200(0.231) | 0.366(0.366) | 0.166(0.167) | 0.428(0.492) | Yes (yes)              |
| 3                  | 0.133(0.133) | 0.066(0.066) | 0.166(0.166) | 0.132(0.201) | 0.219(0.233) | Yes (yes)              |
| 4                  | 0.247(0.300) | 0.166(0.132) | 0.200(0.231) | 0.200(0.222) | 0.310(0.352) | Yes (yes)              |
| 5                  | 0.067(0.064) | 0.032(0.32) | 0.100(0.066) | 0.100(0.100) | 0.182(0.169) | No (no)                |
It can be seen from the table that both state discrimination and reasoning results have high accuracy, and the error with the calibrated real value is within the controllable range, which can meet the needs of fatigue early warning.

4. Conclusions
A face state detection algorithm based on convolution neural network and fusion of multiple fatigue parameters is proposed. The experimental results show that according to the state of eyes and mouth and the position of head, calculating four fatigue parameters, using fuzzy reasoning to judge the state has high accuracy and robustness, and using a rotation invariant LBP pyramid to judge the state of eyes, the feature is not accurate. It only has a strong description ability, and solves some interference judgment problems such as skew in the process. At the same time, because the feature dimension is very low, the discrimination speed is very fast.

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