Blurred Face Image Authentication for Enterprise Attendance Using Adaptive Light Adjustment and GAN-CNN Architecture

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This paper combined the adaptive light adjustment algorithm and the generative adversarial network (GAN) deblurring algorithm with a convolutional neural network (CNN) algorithm for blurred face image recognition. First, the adaptive light adjustment algorithm and the GAN algorithm were used to perform deblurring operations on blurred face images, and then the CNN algorithm was used to recognize them. Then, simulation experiments were conducted. In the experiments, the adaptive light adjustment-combined GAN deblurring algorithm was compared with the Gaussian filter method and traditional GAN algorithm. The proposed face authentication algorithm was compared with the support vector machine and traditional CNN algorithms. The results showed that the adaptive light adjustment-combined GAN algorithm could effectively deblur the face image, with a peak signal to noise ratio of 32.08 and a deblurring time of 0.29 s. Moreover, the proposed face authentication algorithm could effectively recognize the identity of the blurred face image, with a precision of 0.987, a recall rate of 0.986, and an F value of 0.986, and it consumed 0.31 s for recognition.

Povzetek: Ta članek predstavlja algoritem za avtentikacijo zamegljenih obrazov za evidenco delovnega časa, ki združuje prilagoditev svetlobe, izostritev s GAN (Generative Adversarial Network) in prepoznavanje s CNN.

1 Introduction

In today's rapidly developing digital age, the enterprise attendance management as an important part of human resource management is experiencing a significant transformation, shifting from traditional manual processes to intelligent and automated systems [1, 2]. Traditional attendance methods include paper-based attendance and card-based attendance. Although they can meet the basic requirements of enterprises to a certain extent, they have defects such as easy to forge, easy to lose, and inconvenient to manage. With the rapid development of biometric technology, facial recognition technology has become a solution due to its unique characteristics of non-contact, high accuracy, and difficulty in replication [3]. But in the process of actual use, face recognition technology is also faced with many challenges. Especially under the impact of complex and changeable attendance environment, facial images can become blurred due to factors such as changes in light, interference from obstructions, shooting angles, or resolution [4]. Processing blurry face images to reduce their blurriness or extract key facial features can effectively improve the accuracy of face authentication. Related works are reviewed in Table 1. Those studies have all analyzed aspects such as faces and fuzzy classification. Some of them focused on face recognition, while others placed the research emphasis on fuzzy classification. This paper, however, focuses on the recognition of blurred faces for enterprise attendance purposes. The innovation of this paper lies in combining the clarification of blurred faces with face image recognition. In the process of clarifying blurred faces, an adaptive light adjustment algorithm was used to reduce the influence of environmental light in the image, and the generative adversarial network (GAN) algorithm was utilized to clarify the blurred faces. Finally, the advantages of the convolutional neural network (CNN) algorithm in image recognition were exploited to identify face images. Moreover, during the CNN training process, in order to avoid the rigidity brought about by manually annotating features of face images, triplet samples were adopted for training. This paper combined the adaptive light adjustment algorithm for blurred face images and the GAN algorithm for deblurring with the CNN algorithm for the recognition of blurred face images. Then, simulation experiments were carried out. The contribution of this paper lies in combining the adaptive light adjustment algorithm and the GAN algorithm to deblur blurred face images and using the CNN algorithm trained with triplet samples to recognize face images, providing an effective reference for the security and efficiency of enterprise attendance. The limitation of this paper is that the scale of face samples used in the test is limited, resulting in insufficient generalization of the experimental results. The future research direction is to expand the sample scale to improve the generalization of the face recognition algorithm.

Table 1: Related works

Author	**Research content**	**Research results**
Balovsyak et al. [5]	They implemented a face recognition in system by using the Viola-Jones method and fuzzy logic.	The results showed that the method can improve the accuracy of face and mask recognition.
Khan et al. [6]	They proposed a layered classifier based on fuzzy rules for the forensic field.	The results showed that this method can play an important role in the forensic field.
Zhang et al. [7]	They proposed a new method of face recognition that incorporates fuzzy set theory.	The experimental results verified that this method can effectively identify blurred faces.

2 The algorithm for recognizing blurred face images

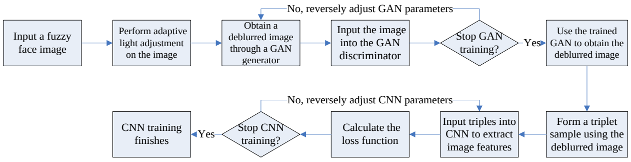

Figure 1: The algorithm training flow of blurred face image recognition

When human face is used as a biometric authentication for attendance [8], it has the advantages of non-contact, high accuracy, and difficult to copy [9]. To improve the accuracy of face recognition authentication, this paper first performs the adaptive adjustment processing on the blurred face image, then uses a GAN to deblur it, and finally uses a CNN to extract face features for identity authentication [10]. The specific flow is as follows.

① A blurred face image with a specified size is input and processed by light adaptive adjustment, including image defogging and Gamma correction:

$$\begin{cases} J(x) = \dfrac{I(x) - A}{\max(t(x), t_0)} + A \\ f(x) = (N(x))^{2K(x) + K'(x) - 0.5} \end{cases}, (1)$$

where $I(x)$ is the pixel of the original image, A is the global atmospheric light component, which is an empirical formula, $t(x)$ is the transmission function of scattered light, which is an empirical formula, t_0 is the minimum of $t(x)$, $J(x)$ is the image after defogging, $N(x)$ is the image after the normalization of $J(x)$ pixel values, $K(x)$ is the mean luminance of $J(x)$, and $K'(x)$ is the standard deviation of the luminance of $J(x)$ [11].

② The face image processed by adaptive light adjustment is input into the GAN generator to generate a deblurred image [12], and the size of the generated image is the same as the input size.

③ The generated image is taken as the negative sample, and the corresponding clear original face image is taken as the positive sample. The two samples are input to the GAN discriminator for forward calculation. Finally, the judgment result of whether the sample is the original clear face image is output to the softmax layer of the discriminator.

④ Whether the training of the GAN is terminated is determined. The termination condition is that the training times reach the threshold or the loss function converges to stability. If the training termination condition is met, proceed to the next step; otherwise, the loss function is used to reversely adjust the weight parameters in the GAN generator and the discriminator [13]. The loss function is:

$$\begin{cases} L_{cont} = \dfrac{\sum_{x=1}^{W}\sum_{y=1}^{H}(I_{x,y}^{s} - G(I_{x,y}^{b}, w_i))^2}{WH} + \beta\sum_{i=1}^{n} w_i^2 \\ L_{adv} = E_{I^s}[\log D(I^s)] + E_{I^b}[\log(1 - D(G(I^b)))] \end{cases}, (2)$$

where L_{cont} refers to a content loss, L_{adv} refers to an adversarial loss, (x, y) refers to image pixels, W and H are the width and height of the image, $I_{x,y}^{s}$ is the (x, y) pixel in the original clear face image, $I_{x,y}^{b}$ is the (x, y) pixel in the original blurred face image, $G(I_{x,y}^{b}, w_i)$ is the (x, y) pixel of the simulated clear image processed by the GAN generator, w_i is the weight parameter in the GAN generator, β is the regularization term coefficient of $I_{x,y}^{b}$, E_{I^s} and E_{I^b} are the mathematical expected distribution of the original clear and blurred face image, $D(I^s)$ is the probability that the original clear face image is judged as a clear image by the GAN discriminator, and $D(G(I^b))$ is the probability of $G(I^b)$ being recognized as a clear image. After the GAN is trained, it is applied to the subsequent training of the CNN.

⑤ The trained GAN is employed to deblur the blurred face image in the training set, and then a triplet sample is constructed using the deblurred image [14]. The triplet sample consists of two positive samples and one negative sample. The two positive samples are the face images of the same person, and the negative samples are the face images of the other person.

⑥ The triplet sample is input into the CNN. Convolutional features are extracted and compressed for each face image in the triplet through convolutional layers and pooling layers.

⑦ The loss function of the CNN for the triplet sample is calculated:

$$loss = \sum_{i}^{N} \left[\left\| f(x_i^a) - f(x_i^p) \right\|_2^2 - \left\| f(x_i^a) - f(x_i^n) \right\|_2^2 + \alpha \right]_+ , \quad (3)$$

where $f()$ refers to the CNN, x_i^a and x_i^p are two positive samples in the i -th triple, x_i^n is the negative sample in the i -th triple, and α is the margin of the feature vector between the x_i^a, x_i^p group and the x_i^a, x_i^n group.

⑧ Whether CNN training can be terminated is determined. The training termination condition is also that the number of training reaches the prescribed number or the triplet loss function converges to stability. If the condition is satisfied, the training of CNN is completed; otherwise, the parameters in CNN are reversely adjusted according to the triplet loss. When the above algorithm is trained, and it is applied to the blurred face identity authentication for enterprise attendance, the basic process is as follows. First, the blurred face image of an employee is processed through the adaptive light adjustment algorithm, and then it is input into the GAN algorithm to generate a clear face image. After that, the clear image is input into the CNN algorithm. The face features are obtained from the last convolutional layer of the CNN algorithm. Finally, the face features extracted by the CNN algorithm is compared with the face features stored in the database to achieve identity authentication. The face features stored in the database are also extracted through the CNN algorithm.

3 Simulation experiment

3.1 Experimental environment

The simulation experiment was carried out in the laboratory server, which was configured as Windows11 system, I7 processor, 16 G memory, and RTX4060 graphics card. Python was used for programming.

3.2 Experimental data

The open-source Columbia University Public Figures Face Database (m6z.cn/5DlIR9) was used as the dataset for the simulation.

3.3 Experiment setup

The relevant parameters of the face identity authentication algorithm used for attendance are shown in Table 2. The GAN and CNN algorithms were both trained 500 times, with a learning rate of 0.02. The group convolution and squeeze-and-excitation (Group-SE) module in the GAN generator is a composite structure, which is composed of the standard convolutional layer, the grouped convolutional layer, the nonlinear activation layer, the SE layer, the standard convolutional layer, and the feature fusion layer in sequence.

Table 2: Relevant parameters of the proposed algorithm.

	Structure	Parameter setting	Structure	Parameter setting
GAN generator	Input layer	200×250	The first convolutional layer	Eight 7×7 convolution kernels, a step size of 2, and a sigmoid activation function
	Group-SE module	12	Deconvolution layer	Eight 7×7 convolution kernels, tahn activation function
GAN discriminator	Input layer	200×250	Convolutional layer 1	Eight 3×3 convolution kernels, a step size of 2, and a sigmoid activation function
	Convolution layer 2	16 3×3 convolution kernels, a step size of 2, and a sigmoid activation function	Pooling layer	3×3 mean pooling box, a step size of 2
	Fully connected layer	Softmax function	Output layer	1 node
CNN for extracting facial features	Input layer	200×250	Convolutional layer 1	32 3×3 convolution kernels, a step size of 2, and a sigmoid activation function
	Convolutional layer 2	64 3×3 convolution kernels, a step size of 2, and a sigmoid activation function	Pooling layer 1	3×3 mean pooling box, a step size of 2
	Convolution layer 3	64 3×3 convolution kernels, a step size of 2, and a sigmoid activation function	Pooling layer 2	3×3 mean pooling box, a step size of 2
	Output layer	128 nodes		

The SVM and traditional CNN algorithms were used for verification and comparison. The principle of the SVM algorithm for face identity authentication was to train using the training samples according to the identity corresponding to the face and then use it to classify the identity of the input face image to achieve identity authentication. The relevant parameters of the SVM algorithm are as follows. A linear kernel function was used, and the penalty parameter was set to 1. The principle of the traditional CNN algorithm for face authentication was to store feature vectors extracted from face images by the CNN algorithm, extract feature vectors from an image to be authenticated using the CNN algorithm, and compare them with the stored feature vectors. The relevant parameters of the traditional CNN algorithm were consistent with the CNN part of the proposed algorithm.

In addition, an ablation experiment was conducted on the GAN algorithm. The GAN algorithm without the Group-SE module was tested and compared with the complete GAN algorithm.

3.4 Evaluation criteria

In the algorithms employed, the GAN algorithm was used to deblur blurred face images, and the evaluation criteria for the deblurring effect are:

$$\begin{cases} PSNR = 10\lg\left(\dfrac{(2^n-1)^2}{MSE}\right) \\ MSE = \dfrac{\sum_{i=1}^{H}\sum_{j=1}^{W}(X_{i,j}-Y_{i,j})^2}{H\times W} \end{cases}, \quad (4)$$

where $PSNR$ is the image distortion index (the larger the value, the smaller the distortion), $X_{i,j}$ and $Y_{i,j}$ are the deblurred image pixel and original clear image pixel, and MSE is the average error between $X_{i,j}$ and $Y_{i,j}$.

The performance of the proposed algorithm for face identity authentication was measured by the commonly used precision, recall rate, and F value. The equations are:

$$\begin{cases} P = \dfrac{TP}{TP+FN} \\ R = \dfrac{TP}{TP+FP} \\ F = \dfrac{2\cdot P\cdot R}{P+R} \end{cases}, \quad (5)$$

where P denotes the precision, R denotes the recall rate, F is the combined value of the precision and recall rate, TP is the number of true positive samples, FP is the number of false positive samples, FN is the number of false negative samples, and TN is the number of true negative samples.

3.5 Test results

The partial deblurring results of three deblurring algorithms for blurred face images are shown in Figure 1. It can be seen that the face image processed by the adaptive light adjustment-combined GAN algorithm was the clearest, followed by the face image processed by the traditional GAN algorithm. Although the face image processed by Gaussian filtering was clearer than the original image, the blurriness was still visible to the naked eye. The objective deblurring effects of the three deblurring algorithms are shown in Table 3. It can be seen that the adaptive light adjustment-combined GAN algorithm had the largest $PSNR$ and the shortest deblurring time, followed by the traditional GAN algorithm with a medium $PSNR$ and deblurring time, and the Gaussian filter algorithm had the smallest $PSNR$ and the longest deblurring time.

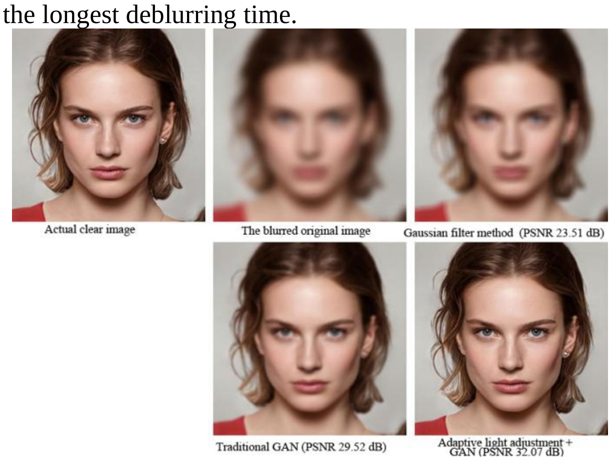

Figure 1: Partially blurred face images and images deblurred by three deblurring algorithms.

Table 3: The deblurring effect of the algorithms.

	Gaussian filtering method	Traditional GAN	Adaptive light adjustment +GAN
PSNR /dB	23.45	29.54*	32.08*+
Deblurring time/s	1.25	0.97*	0.29*+

Note: * indicates that the p value in the difference with the Gaussian filtering method is smaller than 0.05; + indicates that the p value in the difference with the traditional GAN algorithm is smaller than 0.05.

The recognition performance of the three authentication algorithms is shown in Table 4 and Figure 2. It can be seen that for blurred faces, the proposed algorithm combining adaptive light adjustment, GAN, and CNN had the highest recognition accuracy and the shortest recognition time. The accuracy and recognition time of the traditional CNN algorithm for blurred faces were in the middle among the three algorithms, while the SVM algorithm exhibited the worst recognition accuracy and the longest recognition time. The receiver operator characteristic (ROC) curves also showed that the proposed algorithm had the best human face recognition performance, followed by the traditional CNN algorithm, and the SVM algorithm was the worst.

Table 4: Recognition performance of three authentication algorithms.

	Precision	Recall rate	F value	Recognition time consumption/s
SVM algorithm	0.712	0.711	0.712	2.36

Traditional CNN algorithm	0.875*	0.876*	0.875*	1.12*
Adaptive light adjustment +GAN+CNN	0.987*+	0.986*+	0.986*+	0.31*+

Note: * indicates the p value in the difference with the SVM algorithm is smaller than 0.05; + indicates the p value in the difference with the traditional CNN algorithm is smaller than 0.05.

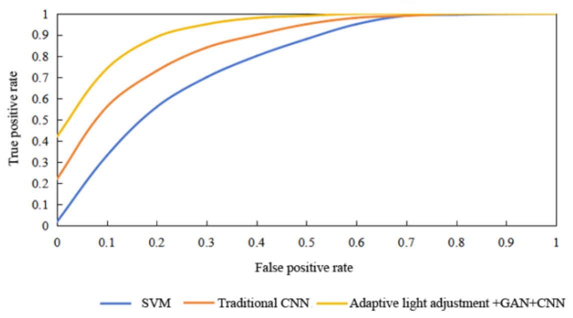

Figure 2: The ROC curves of three algorithms.

An ablation experiment was conducted on the GAN algorithm to verify the contribution of the Group-SE module in the GAN algorithm. The results are shown in Table 5. After removing the Group-SE module, although there was no significant change in the deblurring time, the deblurring effect of the GAN algorithm on blurred face images was significantly reduced, which verified that the Group-SE module made a significant contribution in the GAN algorithm.

Table 5: The ablation experiment for the GAN algorithm.

	The GAN algorithm without Group-SE	**GAN algorithm**
PSNR /dB	22.56	32.08*
Deblurring time/s	0.28	0.29

Note: * indicates the p value in the difference is smaller than 0.05.

4 Discussion

In today's digital age, attendance management, which is part of human resource management, has gradually shifted from traditional manual execution to digital and automated execution, greatly enhancing the efficiency of human resource management. The attendance management in the daily operations of enterprises needs to be efficient and accurate enough, and the traditional attendance methods are gradually failing to meet the requirements. Face recognition technology has the advantages of being non-contact, highly efficient, and difficult to replicate, but it still faces problems such as light interference, obstructions, and low camera resolution in practical applications, all of which can cause blurring of images and reduce the accuracy of recognition and authentication. This paper used the adaptive light adjustment algorithm combined with GAN algorithm to deblur the blurred image and then used the triplet sample constructed by the deblurred image to train the CNN algorithm.

When the blurred face recognition algorithm proposed in this paper is applied to enterprise attendance management, its overall process can be divided into the entry and verification of employee face information. When entering the image, a camera is first used to collect the employee's face image, the adaptive light adjustment algorithm and GAN algorithm were used to deblur the collected face image, the trained CNN algorithm was used to extract the face features from the face image, and the extracted face features are stored. During verification, the system similarly captures the employee's facial image via the camera, applies an adaptive light adjustment algorithm and GAN-based deblurring algorithm for preprocessing. Subsequently, a CNN is employed to extract facial features. The extracted features are then compared against the stored template. If the discrepancy between them is below a predefined threshold, authentication is granted; otherwise, it is rejected.

In the process of face identity authentication using the above-mentioned algorithm, the accuracy of the blurred face recognition algorithm is of crucial importance. In this paper, the proposed recognition algorithm was tested in simulation experiments. First, the deblurring effect of the adaptive light adjustment algorithm combined with the GAN algorithm was tested, and then the face recognition performance of the CNN algorithm was tested. Compared with the Gaussian filter and the traditional GAN algorithm, the adaptive light adjustment algorithm combined with the GAN algorithm exhibited the best deblurring effect. The reason is that the Gaussian filter can effectively deal with the noise that follows the normal distribution in the image, but in the blurred image, the factors that cause the face to blur are not all the noise that conforms to the normal distribution. The traditional GAN algorithm generates a "clear image" based on the input "blurred image". Although the GAN algorithm adjusts the parameters within the algorithm by using the confrontation between the generator and the discriminator during training, the "clear image" is always generated based on the "blurred image" and is affected by the "blurred image". The deblurring algorithm used in this paper first preprocessed the blurred image using an adaptive light adjustment algorithm and then generated a "clear face image" through the GAN algorithm, so the deblurring effect was better. In the face recognition and authentication part, this algorithm used triplet samples to train the CNN algorithm. There is no need to annotate the identity category of the face image; instead, it only needs to extract the face features in the image to obtain more comprehensive features, so its recognition performance was the best.

5 Conclusions

This paper combined the adaptive light adjustment algorithm and the GAN deblurring algorithm with a CNN algorithm for blurred face image recognition and carried out simulation experiments. In the experiments, the adaptive light adjustment-combined GAN deblurring algorithm was compared with the Gaussian filter method and the traditional GAN algorithm. Moreover, the proposed blurred face authentication algorithm was compared with the SVM and traditional CNN algorithms. The adaptive light adjustment-combined GAN algorithm had the best deblurring effect on the face. In terms of objective deblurring indicators, the adaptive light adjustment-combined GAN algorithm had the largest *PSNR* and the shortest deblurring time. The proposed authentication algorithm had the highest recognition accuracy and the shortest recognition time for blurred face images.

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