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Research article

Image processing effects on the deep face recognition system

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Abstract: Face recognition technology has become an important quantitative examination method in the field of forensic identification of human images. However, face image quality affects the recognition performance of face recognition systems. Existing research on the effects of face image denoising and enhancement methods on the face recognition performance are typically based on facial images with manually synthesized noises rather than the noises under natural environmental corruption, and their studied face recognition techniques are limited on the traditional face recognition algorithms rather than state-of-the-art convolutional neural network based face recognition methods. In this work, face image materials from 33 real cases in forensic identification of human images were collected for quantitative analysis of the effects of face image denoising and enhancement methods on the deep face recognition performance of the MXNet system architecture based face recognition system. The results show that face image quality has a significant effect on the recognition performance of the face recognition system, and the image processing techniques can enhance the quality of face images, and then improve the recognition precision of the face recognition system. In addition, the effects of the Gaussian filtering are better than the self-snake model based image enhancement method, which indicates that the image denoising methods are more suitable for performance improvement of the deep face recognition system rather than the image enhancement techniques under the application of the practical cases.

Keywords: face recognition; image enhancement; image denoising; forensic identification of human images; MXNet

1. Introduction

Currently, face recognition systems (FRS) [1,2] have play an important role in face recognition and face verification tasks. In the field of public security, we can use face images of perpetrators at crime scenes to obtain possible identification of suspects by searching and comparison through the FRS. And in the subsequent examination of forensic identification of human images, judicial experts can give professional judgment on whether the identity of the perpetrator and the suspect are the same. After that, the image materials can be better converted into court evidence to demonstrate the facts of crimes.

1.1. Forensic identification of human images

Forensic identification of human images (FIHI) is to make the professional judgment on whether human images captured in images or videos are from the same persons [3]. Usually, we name the human images in crime scenes as the questioned human images, and the suspect images as the known human images. In the process of giving expert opinions, the experts use both the qualitative and quantitative analysis methods. Currently, the face recognition technology is one of the most important quantitative examination methods for FIHI, which can carry out efficient and accurate quantitative inspection and analysis on face features of facial components and their spatial relationships [4]. The human image features in the field of FIHI consist of the head morphological features, facial components and their spatial relationship features, beard features, wrinkle features, facial dynamic features, body type features, special human body marking features, human dress features, body adornment features, and other human dynamic characteristics, such as gait [5]. Among them, the facial components and their spatial relationship features are one of the most important parts of the human image features, and they are usually the key features in most cases of FIHI.

However, the real problem is that in practical cases, the questioned face images, for example, captured in road monitoring systems are usually in poor quality due to long shooting distances or low image resolutions, which may have a great impact on the recognition performance of FRS [6]. What's more, in many cases, it even does not meet the minimum input requirement of FRS.

1.2. Image processing techniques in face recognition

The field of image processing research has a long history. Wealth of image processing techniques have been proposed. Image processing methods can be roughly divided into image denoising [7,8] and image enhancement techniques [9] according to the different usage purposes. Image denoising is mainly to remove image information that is useless or interfering with the target information, including from the traditional filter-based denoising methods [10] to current deep denoising techniques [11,12].

Image denoising is a classic problem and has been studied for a long time. So far, researchers have proposed various methods for image denoising. The state-of-the-art single image denoising techniques can be divided into filtering, sparse coding, classical external priors, low rank, deep learning and hybrid model based methods [13–16]. In addition, image denoising methods can be generally classified into spatial domain methods and transform domain methods [17]. Spatial domain based image denoising, for example Wiener filtering [18], relies on an assumption that noises occupy the higher region of the frequency spectrum, and they make use of low pass filtering on pixel groups. Its disadvantage is the negative effect on image blurring, which in turn loses sharp edges [10]. In the transform domain based image denoising, it first transforms images to specific domain, such as the discrete cosine transform domain, and then different denoising strategies are applied in transformed images with the statement that noise features are different in the transform domain. For example, the wavelet transform [19] decomposes images into scale-space representation, and then removes noises while preserving image features regardless of frequency content. The 3DDCT based image denoising [20] was to enlarge non-zero DCT coefficients in high frequency parts which would enhance the image texture and edge information while denoising.

The image enhancement techniques are mainly used to highlight useful information in images, such as the edge-preserving self-snake model based methods [21]. These technologies can more or less improve people's visual perception experiences of images. Additional, some methods were proposed to specialize in face image super-resolution [22,23]. Among them, the learning-based image super-resolution techniques [24–26] are one of the hotest solutions for increasing the spatial resolution of low-resolution images. Especially, recent years have witnessed remarkable progress of deep learning based image super-resolution methods. However, in the field of forensic science, it requires the submitted data with the features of the authenticity, relevance, and legality. In the field of FIHI, more emphasis is placed on the authenticity of data sources. Therefore, the image processing should not change substantive contents of original face images. This requires us to hold a cautious attitude in face image processing with regard to the additional data introduced in image processing.

Several literatures [27–29] existed on face image quality assessment via deep convolutional neural network based face recognition techniques. The studied quality factors of face images comprised the illumination [27], contrast, blurriness, occlusion, pose [28], low-resolution, noise [29] etc. For the research of the effects of image quality or image processing methods on the recognition performance of FRS, the effects of the covariate of lighting conditions on the recognition precision of face recognition algorithms was studied in [30], in which the results showed that poor lighting conditions dramatically decreased the face recognition performance. Bharadwaj et al. [6] studied the effects of the BayesShrink denoising techniques on the local binary patterns [31] based texture recognition method for face recognition. The BayesShrink technique [32] was wavelet based soft thresholding technique for image denoising, and the experiments were carried out by using the AR face database [33]. The influence of different denoising methods on the recognition performance of seven holistic 3D face recognition algorithms was studied in [34], in which six denoising algorithms were evaluated which consisted of Gaussian, mean and median filtering, multi-scale wavelet denoising, adaptive Wiener filtering and non-linear diffusion. And the seven 3D face recognition algorithms were studied, which comprised multi-class support vector machine, principal component analysis, kernel Fisher's analysis, probabilistic neural network, KNN-classification, bootstrap aggregation decision trees and linear discriminant analysis methods. The experiments were conducted by using the Face Recognition Grand Challenge v2.0 dataset [35].

The existing research on the face image quality assessment methods [28,29] was aimed to select optimal face images with high quality for face recognition in FRS, and considered the image quality factors comprised noises and others. However, they were very different with our work, in which we wanted to study the effects of the image processing on the recognition performance of the deep face recognition system. In addition, in our studied topic, similar literature [6,34] focused on the FRS with traditional face recognition algorithms, such as the local binary patterns and support vector machine, which had substantial performance differences compared with currently widely used deep learning based face recognition techniques [37,38]. Furthermore, their studied noises were manually synthesized and added in the face images [6,29] rather than using noises under natural environmental corruption. The state-of-the-art face recognition technology are typically based on convolutional neural network based methods [37,38], on which the effects of varieties of image processing techniques are still unknown, especially in the field of real case studies. We aimed to study the effects of image denoising and enhancement techniques on the deep face recognition system under the application of FIHI. In order to enhance the validity and practical applicability of the results, the face image materials were all derived from real cases in FIHI. We collected 33 real cases which all happened in recent years. In these cases, the initial information of the suspects was found out through the recognition of the perpetrators' face images in FRS. And in the subsequent examination of FIHI, the authors served as the judicial experts giving the expert opinions that the perpetrator and the suspect were the same persons in each cases. Furthermore, the above expert opinions were all accepted by courts. The practical case study could guarantee the research results more suitable for practical application in FIHI. Our contribution could be summarized as follows:

(1) Understanding the effect of the image processing techniques on the state-of-the-art neural network based FRS under the real cases of FIHI, including the image denoising and enhancement techniques.

(2) Quantitative analysis of the effect of the image processing methods on the FRS. Investigating how many effects of the image processing techniques can bring on the recognition performance of FRS.

(3) Statistical comparative analysis of the effects of the Gaussian filtering based image denoising and the self-snake model based image enhancement techniques on the face recognition system.

The rest of the paper was organized as follows: Section 2 comprised the basic information of the tested face image materials, including their source, image quality, etc. The detailed experimental methods also presented in this section. The experimental results were shown in section 3, in which the statistical effects of the tested image quality and the image processing methods were described. The discussions and conclusions were given in the last section.

2. Materials and methods

In order to guarantee the generalization and applicability of the results in practical case applications, the used face image materials were all from real cases in the field of forensic identification of human images. The state-of-the-art deep face recognitin system was used and tested to study the effects of different image processing techniques. The Gaussian filtering based image denoising method and the self-snake model based image enhancement method was studied which were commonly used in the field. In order to evaluate the effects of the image processing methods, the original face images without processing were used as a control point, and were compared with the processed ones. The processing operation was only applied to the questioned face images and the known face images were directly used without image processing. Their effects were measured by the recognition precision in the face verification tasks of the studied FRS. The main steps of our study were shown in Figure 1.

Thirty three pairs of the questioned face images and the known face images were collected from the 33 real cases of the FIHI. The size distribution of the questioned face images captured by the face detection method was shown in Figure 2, in which the smallest face image size was 30*28 pixels and the largest one was 175*174 pixels. The known face images were from the photos of the suspects' identity card or the front faces of the suspects taken when they were captured, which generally had better image quality. We studied the effect of the image processing methods applied to the questioned face images on the state-of-the-art neural network based FRS. The factor of the known face images processing was not considered in this paper.

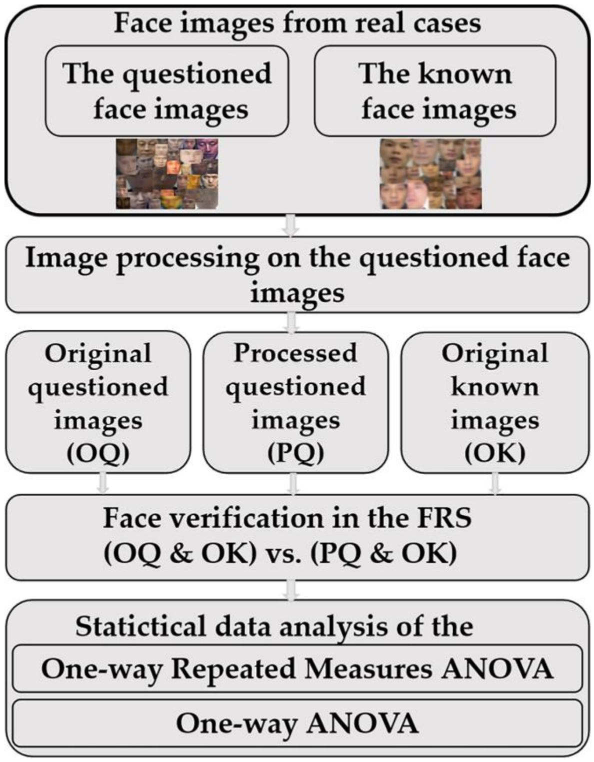

Figure 1. The schematic diagram of the proposed method.

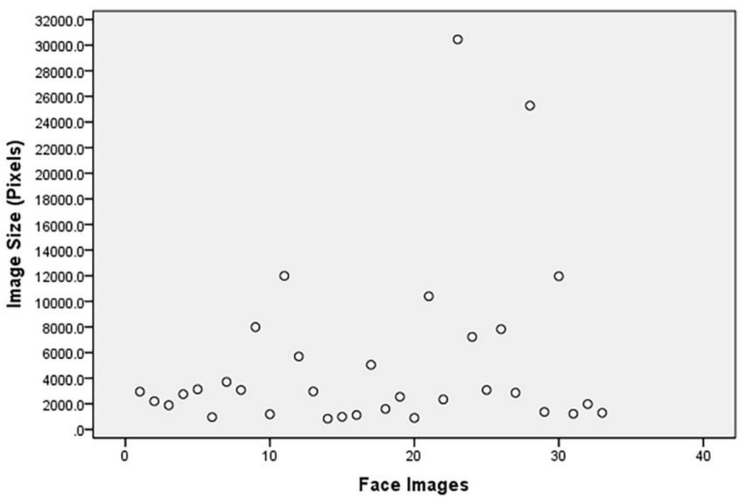

Figure 2. Image size distribution of the questioned face images.

We used the face recognition system which was based on the MXNet system architecture to quantify the similarity between the 33 pairs of the questioned and the known face images. In the used FRS, the scores of the face verification task were between 0 and 100. The higher score meant the more similar between the compared face images. In order to study the effect of the image processing techniques. The similarity values were computed between the known face images and the questioned face images before and after image processing respectively. The statistical data analysis techniques were used to compute the effect of the image processing methods on the FRS.

The simplest Gaussian filtering method [10] was selected to denoise face images, and the self-snake based method [39] was used to enhance face images which was a most basic and important image enhancement method based on Partial Differential Equation [39,40]. The selected two image processing methods were very common and popular in the field of the FIHI. In the Gaussian filtering based image denoising, the parameters of the Gaussian blur radius were set to 0.5, 1.0 and 2.0 pixels respectively. We set the zoom ratio of the face images to 200% in the self-snake based face image enhancement. We used the JC(i)(i = 1,...,33) and YB(i)(i = 1,...,33) to represent the sets of the questioned face images and the known face images in the cases. GB0.5(i)(i = 1,...,33), GB1(i)(i = 1,...,33), GB2(i)(i = 1,...,33) were used to represent the JC(i)(i = 1,...,33) denoised by the Gaussian filtering with blur radii of 0.5, 1.0, and 2.0 pixels respectively. SS(i)(i = 1,...,33) meant JC(i)(i = 1,...,33) processed by the self-snake model based image enhancement method. The similarity scores between JC(i)(i = 1,...,33) and YB(i)(i = 1,...,33) calculated in the FRS were marked as SM(i)(i = 1,...,33). The SM1(i)(i = 1,...,33), SM2(i)(i = 1,...,33), SM3(i)(i = 1,...,33), SMs(i)(i = 1,...,33) respectively were used to represent the similarity scores of the GB0.5(i)(i = 1,...,33), GB1(i)(i = 1,...,33), GB2(i)(i = 1,...,33), and SS(i)(i = 1,...,33) compared with YB(i)(i = 1,...,33) in the face verification tasks.

Considering the experimental design methods, the repeated measurement analysis of variance method was used to analyze the effect of different image processing methods on the FRS. The influence of the face image size on the recognition performance of the FRS was tested by means of one-way analysis of variance.

3. Results

3.1. The effects of the face image sizes

In order to facilitate data analysis, we divided the face image sizes into three categories, ie, the width and height of the face images were less than 50 pixels, between 50 and 70 pixels, and more than 70 pixels, marked as Size1, Size2, and Size3. The one-way ANOVA analysis was carried out to analyze the effect of the face image size on the FRS. The results were shown in Table 1.

Table 1. The effect analysis of the face image size on the FRS by using one-way ANOVA.

SizeNo	Mean	Std. Deviation	N
Size1	80.142	4.8286	12
Size2	84.255	4.7798	11
Size3	86.440	6.1661	10
Total	83.421	5.7417	33

The homogeneity test of variance showed that the variance was homogeneous (F(2,30) = 0.812, P = 0.453). Our results showed that there were significant differences in the means ($F(2,30) = 4.132$, $P = 0.026$). The pairwise comparison test among the image sizes found that compared with the Size 1 face images, the Size 3 obtained higher face verification scores in the FRS ($F = 6.298$, $P = 0.026$). The scores of the Size 2 were not significantly different from the Size 1 ($P = 0.070$) and Size 3 ($P = 0.348$). The results showed that the bigger sizes of face images, the higher scores the face verification results could be obtained. Generally, the larger face image sizes meant the higher image quality which then could obtain the higher scores in verification tasks of the FRS.

3.2. The effects of the different image processing methods

In order to study the effects of the different image processing methods on the recognition performance of the FRS, we selected the highest scores of the Gaussian filtering based methods with different parameter setting as the final effects of the denoising method, labelled as SMg(i)(i = 1,...,33). Namely, SMg(i)(i = 1,...,33) = Max{SM1(i), SM2(i), SM3(i)}(i = 1,...,33). We used the repeated measurement analysis of variance method to compare the mean differences among the SM(i)(i = 1,...,33), SMg(i)(i = 1,...,33) and SMs(i)(i = 1,...,33). The descriptive statistics information were shown in Figure 3.

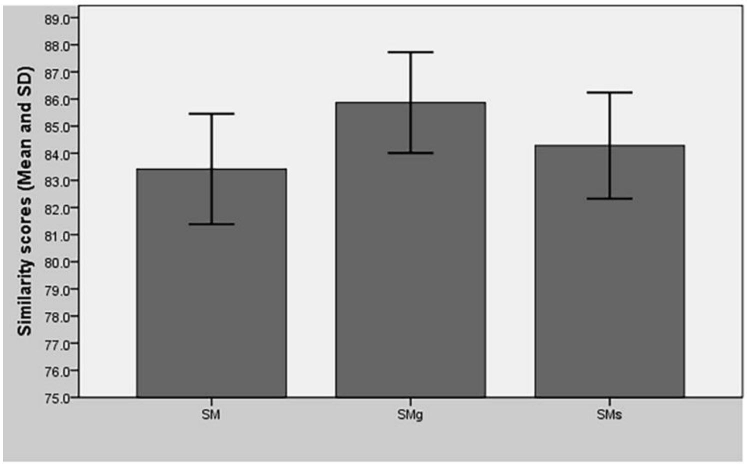

Figure 3. Effects of the different image processing methods on the recognition performance of the FRS.

The Greenhouse-Geisser method ($P = 0.797$) was used to analyze the tested data since they did not meet the Mauchly's Test of Sphericity ($P = 0.010$). The results showed that there were significant differences among the SM(i)(i = 1,...,33), SMg(i)(i = 1,...,33) and SMs(i)(i = 1,...,33) ($F(1.593, 50.977) = 40.986$, $P = 0.000$). The subsequent pairwise comparison examinations were further carried out, and the results were described as follows.

3.2.1. SM(i)(i = 1,...,33) vs. SMg(i)(i = 1,...,33) and SMs(i)(i = 1,...,33)

The comparison results between SM(i)(i = 1,...,33) vs. SMg(i)(i = 1,...,33) and SMs(i)(i = 1,...,33) were shown in Table 2.

Table 2. The comparison results between SM(i)(i = 1,...,33) vs. SMg(i)(i = 1,...,33) and SMs(i)(i = 1,...,33).

A	B	Mean Difference (A-B)	Std. Error	Sig 1	95% Confidence Interval for Difference 1	
					Lower Bound	Upper Bound
SM	SMg	−2.445 *	0.309	0.000	−3.226	−1.665
	SMs	−0.864 *	0.193	0.000	−1.351	−0.377

*Note: 1 Adjustment for multiple comparisons: Bonferroni.
* The mean difference is significant at the 0.05 level.

The results showed that there was significant difference between SM(i)(i = 1,...,33) and SMg(i)(i = 1,...,33), which meant that comparing to the original face images, the face images with the Gaussian filtering based image denoising could obtain higher similarity scores in the FRS. The effect of the Gaussian filtering based image denoising was 2.445. Although the Gaussian filtering processing reduced the image sharpness, it improved the recognition performance of the FRS. There was significant difference between SM(i)(i = 1,...,33) and SMs(i)(i = 1,...,33), that was, comparing to the original face images, the face images with the self-snake based image enhancement could improve the recognition performance of the FRS, and their mean differences was 0.864. The results showed that the self-snake model based image enhancement not only enhanced the visual display result of images, but it also improved the recognition precision of the FRS.

3.2.2. SMg(i)(i = 1,...,33) vs. SMs(i)(i = 1,...,33)

The comparison results between SMg(i)(i = 1,...,33) and SMs(i)(i = 1,...,33) were shown in Table 3.

Table 3. The comparison results between SMg(i)(i = 1,...,33) and SMs(i)(i = 1,...,33).

A	B	Mean Difference (A-B)	Std. Error	Sig 1	95% Confidence Interval for Difference 1	
					Lower Bound	Upper Bound
SMg	SM	−2.445 *	0.309	0.000	−3.226	−1.665
	SMs	1.582 *	0.304	0.000	0.813	2.350

*Note: 1 Adjustment for multiple comparisons: Bonferroni.
* The mean difference is significant at the 0.05 level.

The results showed that there was significant difference between SMg(i)(i = 1,...,33) and SMs(i)(i = 1,...,33), which meant that comparing to the self-snake based image enhancement method, higher similarity scores were obtained in the Gaussian filtering based image denoising. Their effect difference was 1.582, which might show that the image denoising would be more effective than the image enhancement methods for the performance improvement of the FRS.

3.3. The effects of the gaussian filtering based image denoising under different parameters

In order to study the effects of the Gaussian filtering based image denoising on the recognition performance of the FRS under the conditions of different parameter settings. The repeated measurement analysis of variance method was carried out to compare the mean differences among the SM(i)(i = 1,...,33), SM1(i)(i = 1,...,33), SM2(i)(i = 1,...,33) and SM3(i)(i = 1,...,33). The descriptive statistics information were shown in Table 4.

Table 4. The effect comparison among SM(i)(i = 1,...,33), SM1(i)(i = 1,...,33), SM2(i)(i = 1,...,33) and SM3(i)(i = 1,...,33).

Effect	Mean	Std. Deviation	N
SM	83.421	5.7417	33
SM 1	85.021	5.4986	33
SM 2	85.097	5.3577	33
SM 3	81.709	7.2233	33

The Greenhouse-Geisser method (P = 0.464) was used to analyze the tested data since they did not meet the Mauchly's Test of Sphericity (P = 0.000). The results showed that there were significant differences among SM(i)(i = 1,...,33), SM1(i)(i = 1,...,33), SM2(i)(i = 1,...,33) and SM3(i)(i = 1,...,33) (F(1.392, 44.536) = 15.096, P = 0.000). The subsequent pairwise comparison examinations were further carried out, and the results were shown in Table 5.

Table 5. The effect comparison among SM(i)(i = 1,...,33), SM1(i)(i = 1,...,33), SM2(i)(i = 1,...,33), SM3(i)(i = 1,...,33).

A	B	Mean Difference (A-B)	Std. Error	Sig 1	95% Confidence Interval for Difference 1	
					Lower Bound	Upper Bound
SM1	SM	1.600*	0.258	0.000	0.875	2.325
	SM2	−0.076	0.281	1.000	−0.867	0.715
	SM3	3.312*	0.816	0.002	1.016	5.608
SM2	SM	1.676*	0.347	0.000	0.701	2.650
	SM1	0.076	0.281	1.000	−0.715	0.867
	SM3	3.388*	0.724	0.000	1.351	5.425

*Note: 1 Adjustment for multiple comparisons: Bonferroni.
* The mean difference is significant at the 0.05 level.

The results showed that there were significant differences between SM(i)(i = 1,...,33) vs. SM1(i)(i = 1,...,33) (P = 0.000) and SM2(i)(i = 1,...,33) (P = 0.000), which indicated that comparing to the original face images, the face images with the Gaussian filtering based image denoising with the Gaussian blur radius of the 0.5 and 1.0 pixels could both improve the recognition performance of the FRS, and their effects were 1.600 and 1.676 respectively. Nevertheless, the means between SM(i)(i = 1,...,33) and SM3(i)(i = 1,...,33) had no significant difference (P = 0.190).

Comparing to the Gaussian blur radius of the 2.0 pixels, the Gaussian filtering based image denoising with the parameter setting of the 0.5 and 1.0 pixels both gained the better recognition performance in the FRS, and their mean differences were 3.312 ($P = 0.002$) and 3.388 ($P = 0.00$) respectively. Nevertheless, the means between SM1(i)(i = 1,...,33) and SM2(i)(i = 1,...,33) had no significant difference ($P = 1.000$). The results indicated the Gaussian filtering based image denoising techniques could improve recognition performance, provided the correct parameters were applied. In our study, the quality of the questioned face images was dramatically worsened in the Gaussian filtering with the parameter setting of 2.0 pixels, as shown in Figure 4.

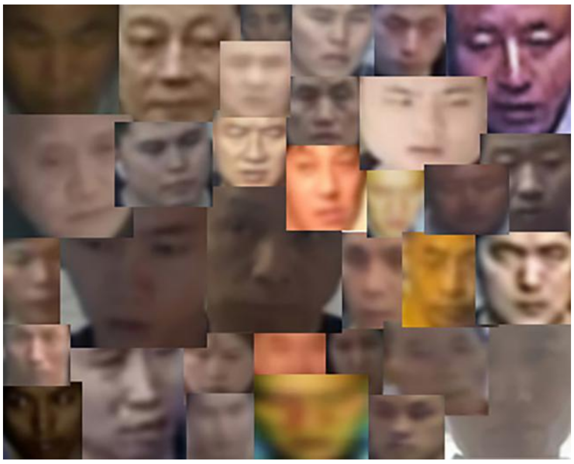

Figure 4. The questioned face images processed by the Gaussian filtering with radii setting of the 2.0 pixels.

3.4. The effects of the different image denoising methods

In order to study the effects of the different image denoising methods on the recognition performance of the FRS, we compared the effects of the image denoising methods among the Gaussian filtering (GF), the Wiener filtering (WF) [18], and the wavelet transform (WT) [19] based methods, which were all common used single-image denoising techniques in the FIHI. Considering the effects of different parameter settings on image denoising performance, we selected different combination of parameters for each used image denoising methods. The maximum scores of the face verification results under different parameters were served as the final scores of the corresponding denoising methods. In the Wiener filtering based image denoising, the parameters of the filtering window radius were set to 3.0 and 5.0 pixels, and the noise variances were set to 25 and 50 respectively, which finally resulted in four groups of denoising images in the Wiener filtering method. In the wavelet transform based method, the noise variances were specified as 0.2, 1.0, 2.0 and 4.0 respectively.

The repeated measurement analysis of variance method was applied to analyze the effects of the above image denoising methods on the recognition performance of the FSR. The means among the SMg(i)(i = 1,...,33), WF(i)(i = 1,...,33), WT(i)(i = 1,...,33) were compared and the descriptive statistics information were shown in Table 6.

The pairwise comparison among SMg(i)(i = 1,...,33), WF(i)(i = 1,...,33), WT(i)(i = 1,...,33) showed that the significant differences were found between SMg(i)(i = 1,...,33) and WT(i)(i = 1,...,33) ($P = 0.001$), and mean difference was 1.552, which meant that comparing to the wavelet transform based image denoising method, the Gaussian filtering could significantly improve the recognition performance of the FSR. In addition, there was significant difference between WF(i)(i = 1,...,33) and WT(i)(i = 1,...,33) (P = 0.049), and mean difference was 1.012. No significant difference was observed between SMg(i)(i = 1,...,33) and WF(i)(i = 1,...,33) (P = 0.227).

Table 6. The descriptive statistics information of the effects of the three studied image denoising methods on the recognition performance of the FSR.

Effects	Mean	Std. Deviation	Number
SMg	85.897	5.257	33
WF	85.358	5.011	33
WT	84.345	5.361	33

4. Discussion and conclusions

In this paper, face images materials from 33 actual cases in forensic identification of human images were collected. The statistical effects of the image denoising and enhancement methods on face recognition were studied. The Gaussian filtering based method was used for image denoising. For the image enhancement, the self-snake model based technique was applied. The studied image processing methods are common and popular in the FIHI. The statistical data analysis techniques were used to quantitatively compute the effects of the different image processing methods on the recognition performance of the state-of-the-art neural network based face recognition system.

Our results found that both the Gaussian filtering based image denoising and the self-snake based image enhancement methods could improve the recognition performance of the used FRS. However, the effects of the Gaussian filtering based method were better than the later. This might be attributed to the facts that the image enhancement method improved the visual display quality of images, at the same time, it also partially augmented the image noises. In our study the questioned face images were all collected from the real cases. The image noises not only existed in the high frequency information of the images, but the face contour information might also partially be contaminated in the real cases. Furthermore, in order to be more robust to the variations of image quality, face angles, etc. Current neural network-based FRS have been paid more attention to the face overall outline information which mainly exists in the low frequency part of images. The face local detail information has relatively little effects on the recognition performance of the FRS. For example, in one of our studied cases, the suspect has a large spot on his right cheek. We removed this face spot by using image processing techniques. The similarity score in our used FRS between the original face and the face after removing the spot is still up to 99.999%. Our used Gaussian filtering based image denoising is a typical image smoothing method, which erases the contaminated high frequency information of images and then highlights the outline information of faces.

In addition, among our studied three image denoising methods, the effects of both the filtering based image denoising methods, i.e. the Gaussian filtering and the Wiener filtering based methods, were better than the wavelet transform based method which is a typical transform domain image denoising technique. Generally, spatial domain filters remove noises to a reasonable extent but at the cost of losing image sharp edges. However, the transform techniques in image denoising usually have the features that they remove noises while still preserving image characteristics, such as edges. The different effects of the spatial domain and transform domain image denoising techniques might be attributed to the fact that, in our study, the tested face images were all from real cases in the FIHI, which largely encountered the environmental corruption of noise, blur, and bad illumination. The high frequency components, such as edges and textures of face images, usually corrupted by noises. The Gaussian filtering and the Wiener filtering based methods removed noises in the spatial domain without specially focusing on image characteristic existing in the high frequency domain. The above features might be the key for the maximum effects of the spatial domain filters based denoising techniques on the performance improvement of the FRS.

To sum up, we found that face image quality could play a significant effect on the recognition performance of the face recognition system, and the image processing techniques could improve the recognition precision of the face recognition system. In addition, the effects of the Gaussian filtering were better than the self-snake model based image enhancement method, which indicated that the image denoising methods were more suitable for performance improvement of the deep face recognition system rather than the image enhancement techniques in the application of the practical cases. Our results have important guiding roles in the selection of image processing methods for deep face recognition applications in real cases of FIHI. The correct parameters for image processing are important in practical application. An automatic parameter selection framework will be valuable for performance improvement of the FRS. However, in the real cases of the FIHI, the traversing method of the parameters in a certain range will be very useful despite its simplicity, which will be studied in future work. Furthermore, we only studied the effects of the two representative image processing techniques, other state-of-the-art denoising and enhancement techniques, such as current hot methods of deep denoising, etc., would be further studied under real case applications in future work. In addition, the number of the tested face image materials from real cases of the FIHI was relatively few when compared with the public face databases. The face image set would be further extended in future work for more precise data analysis.

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Conflict of interest

The authors declare there is no conflict of interest.

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