Application of Blind Deblurring Algorithm for Face Biometric

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ABSTRACT
Face recognition is one of the most important abilities which we use in public security and for identity verification for physical and logical access. It is well known that many image-based face recognition algorithms perform well, when constrained (frontal, well illuminated, high-resolution, sharp, and full) face images are acquired. However, their performance degrades significantly when the test images contain variations that are not present in the training images.

Face recognition in constrained acquisition conditions is one of the most challenging problems that have been actively researched in recent years. There are many factors low resolution, poor illumination, pose variation, occlusion and relative motion between the sensor and objects in the scene to substantially degrade performance more than the other quality. The work described in this paper is interested in Motion Blur.

Motion Blur is often present in real-world images and significantly affects the performance of face recognition systems. This paper proposes a novel application for recognizing faces degraded by blur using deblurring of facial images using fast TV-l1 deconvolution model.

Experiments on a face database (FERET) artificially degraded by motion blur show that the faces recognition accuracy was better than that when using debluring algorithms.

General Terms
Pattern Recognition, Biometrics.

Keywords
Face Recognition, Motion blur, Deconvolution.

1. INTRODUCTION
Face recognition, as one of the major biometric technologies, has improved significantly since the first automatic face recognition system was developed by Kanade [16] and has become more and more important owing to rapid advances in technologies such as digital cameras, mobile devices and increased demands for higher security. Face recognition has several advantages over other biometric technologies: It is natural, nonintrusive, and the most important advantage of face is that it can be captured at a distance and in a covert manner.

Although face recognition has been actively studied over the past decade, the recognition systems yield satisfactory performance only under controlled scenarios and recognition systems degrade significantly when confronted with unconstrained situations.

Examples of unconstrained conditions [8-18] include illumination, pose variations, expressions, aging, and so on. Recently, researchers have begun to investigate face recognition under unconstrained conditions. For example, complex outdoor lighting is still a major area of research, despite the great deal of progress during the recent years [14 - 15].

Other factors which also affect the performance of face recognition systems include blur which may cause significant image degradations, blur is usually originated from camera motion or misfocused optics. It affects the appearance of faces in images, causing two main problems for face recognition : (i) the facial appearance of an individual changes due to blur; (ii) and different individuals tend to appear more similar when blurred [7].

The Face image will appear blurry which can reduce face recognition. The focus of the article is to achieve a quality edge preserving image restoration using Total Variation (TV)-L1 regularization technique [23]. L1 norm based approaches do not penalize edges or high frequency contents in the restored image.

In this paper we have used Viola-Jones algorithm [5] to detect people's faces (face detection) and PCA (principal component analysis) algorithm [1] to generate feature vector of face images (face recognition) using EigenFace method in which we recognize an unknown test image by comparing it with the known training images stored in the database as well as give information regarding the person recognized.

PCA is a classical dimensionality reduction method which has been applied in many applications. It is a linear transformation that searches for an orthonormal basis of a low dimensional subspace, so-called the principal components subspace, which explains the variability of the data as much as possible. PCA’s utility and success stem from the simplicity of the method that calculates the eigenvectors and eigenvalues of the sample covariance matrix of the data set.

In this paper, a new application is proposed to deblurring face image using fast TV-l1 deconvolution model [23]. The algorithm is fast and accurate to restore the clear image. The rest of this paper is organized as follows:

In section 2 we present the image quality assessment for face biometric in terms of motion blur and a new method is proposed to restore (blind deconvolution) face image; finally the experimental results and conclusion are show in section 3 and 4.

2. IMAGE QUALITY ASSESSMENT

2.1 Motion Blur Assessment Method

Image quality assessment plays an important role in automated biometric systems for two reasons: (i) system performance, and (ii) interoperability. In this paper we assess image quality from the face biometric. There are many factors out-of-focus lens, atmospheric turbulence, and relative motion between the sensor and objects in the scene to substantially degrade performance more than the other quality. There are many researches on face recognition under pose and illumination changes but the problems caused by blur still mostly overlooked. The work described in this paper is interested in Motion Blur.

The blurring process is modeled as the following convolution:

$$\mathrm{I}(\mathrm{x},\mathrm{y}) = (M \circledast P)(x,y) + n(x,y) \qquad (2.1)$$

Where $\circledast$ is the convolution operator, M is the original image, I is the degraded image and P is the blurring kernel (Point Spread Function), and n is the noise.

The motion-blur kernel is very different from the kernels of other types of blurring (e.g. out-of-focus blurring, Gaussian-type optical blurring), as there exist not simple parametric forms to represent motion-blur kernels.

The Blur kernel can be presented on function the two parameters θ and S , where θ is a continuous curve of finite length in R_2 which denotes the camera trajectory and S is the speed function which varies along θ.

There are two main approaches in existing techniques for face recognition under blur and can be classified as: (i) inverse methods based on deblurring, and (ii) direct methods based on invariants.

In general, recovering the latent image M from the blurry observation I is a deconvolution problem. Even with complete knowledge of the blur kernel P, inverting (2.1) to obtain M is an ill-posed problem due to the unknown nature of Blur. Techniques for performing image restoration have been actively studied by the image processing community [4], which is further separated into the non-blind and blind cases. In the non-blind case, the blur kernel P is assumed to be known or estimated, and the task is to recover the clear image M by reversing the effect of convolution on the blurred image I. There have been extensive studies on robust non-blind deconvolution algorithms for examples learning priors on clean image statistics [9- 19], Regularization methods based on total variation [27] and Tikhonov regularization [25]. Such ideas have also been applied for recognizing faces across blur [17- 22- 21- 29]. In the case of blind deconvolution problem [20], that does not assume any knowledge of the blur kernel and attempts to solve an under constrained problem of estimating both P and M from I which is a more challenging task.

In contrast to this, direct methods [11- 12- 13- 10- 28] based on invariants search for those properties of the original image that are preserved across blur. This is suited for applications where the goal is not to recover the clean image, but to extract features invariant to blur that can be used for subsequent tasks such as recognition or retrieval objects/ faces in distorted images [3- 24].

Motion deblurring is a typical blind deconvolution problem, because the motion between the camera and the scene always varies for different images.

The blind deconvolution is formulated as a joint minimization problem with regularizations:

$$M^*, P^* = \|M \circledast P - I\|_2 + \Theta_P(P) + \Theta_M(M) \ (2.2)$$

Here $\|\mathrm{M} \circledast \mathrm{P} - \mathrm{I}\|_2$ is the data fitting term. To overcome the inherent ambiguities between the blur kernel P and the clear image M, certain regularization terms on both P and M have to be added in the minimization ($\Theta_\mathrm{P}(\mathrm{P})$ and $\Theta_\mathrm{M}(\mathrm{M})$ are the regularization terms on the blur kernel and the latent image). In this section, a two phase method is introduced for PSF estimation. The first stage aims compute a coarse version of the kernel. In the second phase non-convex optimization is employed.

2.2 Sparse Kernel Estimation

2.2.1 Salient Edges Prediction

The work in [23] has discussed the usefulness of edge information and demonstrated that the edges of large-scale objects are significant to the kernel estimation. The sharp edges are firstly selected using the blurred image. For each pixel i in the blurred image I_i, we form a local window $W_{h(i)}$ centered at it with size h * h, which is the same as that of the corresponding blur kernel at scale l. The usefulness of the edges is measured as:

$$r(i) = \frac{\left\|\sum_{j\in w_h(i)} \nabla I(j)\right\|_2}{\sum_{j\in w_h(i)} \|\nabla I(j)\|_2 + \kappa} \qquad (2.3)$$

Where $\nabla \mathrm{I} = (\partial_\mathrm{x}\mathrm{I}, \partial_\mathrm{y}\mathrm{I})$ is the image gradient. A large value r implies that the image structure is strong in the local window. When the local region is flat or has fine texture, the gradients will be neutralized by each other, so that the value of $\left\|\sum_{\mathrm{j}\in \mathrm{w_h(i)}} \nabla \mathrm{I(j)}\right\|$ is small. κ serves to prevent producing a large r in flat regions. We construct a matrix L_r as a binary mask using a unit step function

$$\mathrm{L}_r(\mathrm{i}) = \eta_{\tau_r}(r(i) - \tau_r) = \begin{cases} 0, & r(i) < \tau_r \\ 1, & r(i) \geq \tau_r \end{cases} \qquad (2.4)$$

For each pixel, $\mathrm{L_r(i)} = 1$ if the r-value is larger than the threshold τ_r, and $\mathrm{L_r(i)} = 0$ is otherwise.

The further selection of sharp edges is determined by the gradient magnitude of shock filtered image. Shock filter [30] is an effective tool to restore strong edges from the blurred signals. In $\mathrm{M_t}$ denote the Shock filter image recovered from the blurred image. The final selected edges for kernel estimation are determined as:

$$\nabla M^s = \nabla M_\mathrm{t} \circ L_s \qquad (2.5)$$

$$L_s(i) = \eta_{\tau_S}((\|\nabla M_t\|_2 \circ L_r) - \tau_S)$$

Where ∘ is the element-wise multiplication operator.

2.2.2 Estimating the Blur Kernel

The initial kernel estimation is obtained by iteratively performing the salient edges selection, kernel estimation and image deconvolution at each level l. Based on the salient sharp edges $\nabla \mathrm{M_l^s}$; we rewrite the function with a Gaussian regularized term as:

$$\widehat{P^\mathrm{l}} = \left\|\nabla M_l^s \circledast P - \nabla I^l\right\|_2 + \lambda_P \|\mathrm{P}\|_2 \quad (2.6)$$

Where λ_P is a weight and the regularizer $\|P\|_2$ is similar to [23– 31- 32]. Eq. (2.6) can be calculated efficiently in the Fourier domain by:

$$\widehat{P^l} = \mathcal{F}^{-1}\left(\frac{\overline{\mathcal{F}(\partial_x M^s)}\mathcal{F}(\partial_x I^l)+\overline{\mathcal{F}(\partial_y M^s)}\mathcal{F}(\partial_y I^l)}{\mathcal{F}(\partial_x M^s)^2+\mathcal{F}(\partial_y M^s)^2+\lambda_k}\right) \quad (2.7)$$

Where $\mathcal{F}(\cdot)$ and $\mathcal{F}^{-1}(\cdot)$ represent the FFT and inverse FFT respectively. $\overline{\mathcal{F}(.)}$ is the complex conjugate operator.

2.2.3 Corse Image Estimation

In the image deconvolution, we use the sharp edge gradient ∇M^S as a spatial prior in order to guide the recovery of a coarse version of the latent image. We rewrite the function as:

$$\widehat{M^l} = \|M \circledast \widehat{P^l} - I^l\|_2 + \lambda_M\|\nabla M - \nabla M_l^S\|_2 \quad (2.8)$$

Where λ_M is the regularization Weight. The frequency domain the solution of Eq. (2.8) can be expressed as:

$$\widehat{M^l} = \mathcal{F}^{-1}\left(\frac{\overline{\mathcal{F}(\widehat{P^l})}\mathcal{F}(I^l)+\lambda_M\overline{\mathcal{F}(\partial_x)}\mathcal{F}(\partial_x M^s)+\overline{\mathcal{F}(\partial_y)}\mathcal{F}(\partial_y M^s)}{\overline{\mathcal{F}(\widehat{P^l})}\mathcal{F}(\widehat{P^l})+\lambda_M\left(\overline{\mathcal{F}(\partial_x)}\mathcal{F}(\partial_x)+\overline{\mathcal{F}(\partial_y)}\mathcal{F}(\partial_y)\right)}\right) \quad (2.9)$$

2.2.4 ISD-Based Kernel Refinement

To enhancing the sparsity of the kernel, the ISD method is applied to refine it. In [33], the implementation of ISD, called threshold-ISD, is as fast as L1-minimization but requires fewer measurements. The algorithm forms a partial support $S = \{j|\ P(j) > \tau\}$ based on the current estimation. The regularization term is replaced in Eq. (2.6) by $\sum_{j\in\bar{S}}|P(j)|$ and get:

$$\widetilde{P} = \|\nabla M_l^s \circledast P - \nabla I^l\|_2 + \beta\sum_{j\in\bar{S}}|P(j)| \quad (2.10)$$

Then the large-value elements of kernel are preserved, while the insignificant elements are iteratively suppressed to reduce the noise. Interested readers can refer to [33] for more details.

2.3 Fast TV l1 Deconvolution

Given the estimation $\widetilde{\mathbf{P}}$ of the kernel, to compute the final deblurred result, a TV l1 model is proposed in deconvolution, which is written as:

$$\widetilde{M} = \|M \circledast \widetilde{P} - I\|_2 + \gamma\|\nabla M\|_1 \quad (2.11)$$

The deblurred image is recovered by the deconvolution technique proposed in [34]. The final result shown the small edges and textures are restored well and few artifacts are introduced.

3. EXPERIMENTAL RESULTS

There are many standard faces databases that could be employed in faces researches. The FERET [6] database was used in this study to evaluate the performance of the proposed method, but the database does not include many motion blurred faces images. Therefore, the motion blurred faces images were artificially produced using MATLAB (Fig.1).

The FERET database was the first data set available to researchers. In terms of the number of people, it is the largest data set that is publically available. The images in the database were initially acquired with a 35 mm camera and then digitized. The database contains 13 539 face images from 1565 subjects, with varying pose, facial expression and age.

The database includes two subsets: 'FA' (Regular facial expression) and 'FB' (Alternative facial expression) having 50 images, respectively. Each subset contains a single image per person. Subset 'FA' is used as a training set. We evaluated the recognition accuracy on the 50 images. The identification target set is 'FA' and the query set is 'FB'.

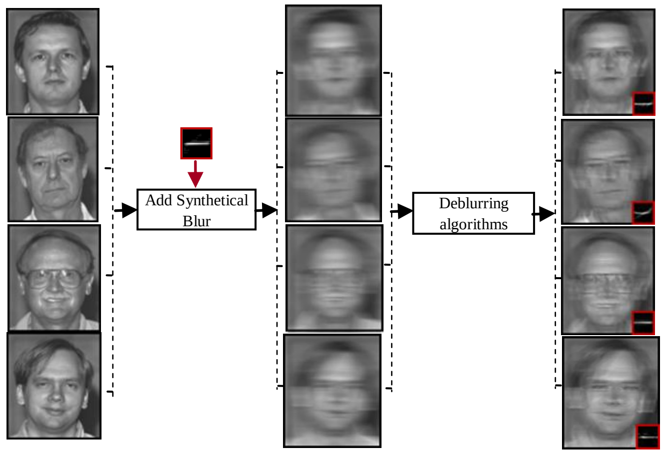

Fig.1: (a) The left image shows the input faces images (FERET); (b) the Middle images show the blurring result. (c)The Right images shows the deblurring faces images and Motion blur kernel

The faces should be recognized to identify the persons in the face images. Viola-Jones algorithm is used to find position of the faces in a given image (Fig.2).

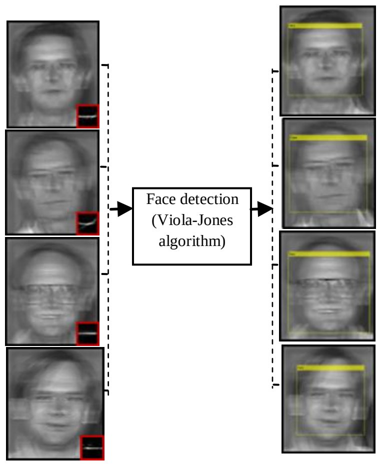

Fig.2: (a) The left images shows the deblurring faces images and Motion blur kernel; (b) The Right images shows face detection images using Viola-Jones algorithm

After face detection, feature extraction is performed to provide effective information that is useful for distinguishing between faces of different persons (Fig.3).

In the experiment [Fig.1 (a), Fig.2 (b)], we artificially produced motion blurred Faces images from 50 persons, the synthetic blurry images were generated by convolving the faces images with a 15 × 15 synthetic kernel to authenticate via identification (one-to-many template matching). A Feature vector created by imaging the face is compared to a stored value template in a database (Fig.3).

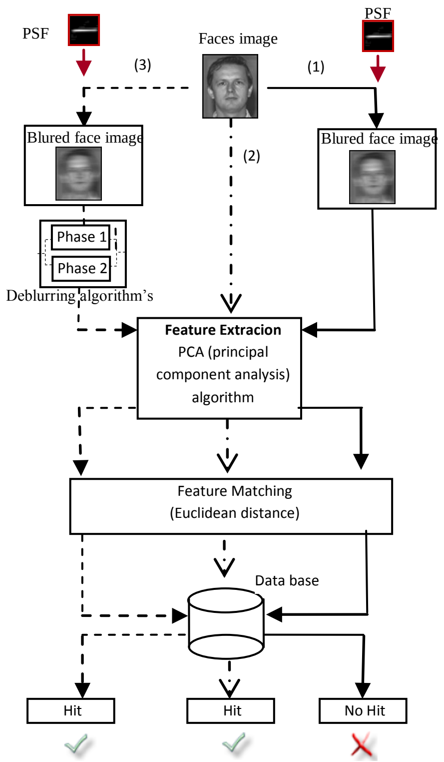

Fig.3: (1) Authenticate blurred faces image with synthetic blur (2) Authenticate faces image without Blur (3) Authenticate faces image (first the image is blurred with synthetic blur and deblurred)

The motion blur can be in the form of a translation, a rotation, or some combinations of these. It's characterized by the direction θ and size of blur S which varies along θ. In this work only the important case of a global translation and variations of S will be considered (Fig.4).

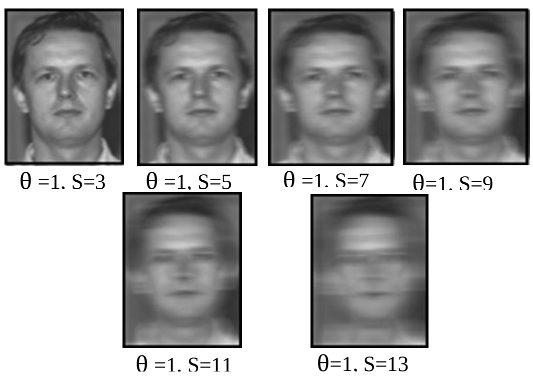

Fig.4: Examples of motion blurred faces images with different values of size of blur S

The proposed deblurring algorithm is based on a mathematical idea introduced in [23]. This method restored blurred images in terms of visibility, but we restored them in terms of recognition, generally allow using the default or automatically adapted parameter values. Matlab implementation spends about 1.07 seconds to estimate a debluring image from a 512×786 face image (Gray scale) with an Intel Core2Quad CPU Q8400@ 2.66G.

For face matching, the extracted feature vector of the input face is matched against those of enrolled faces in the database; the result of face authentication was determined by the Euclidean distances (Fig.3).

As shown in Fig.5, we can notice that PCA (principal component analysis) algorithm is sensitive to blur although it is one of the state of- the-art methods in face recognition. We also notice that the blur-invariant descriptor approach (PCA) works very well with small amount of blur but its performance deteriorates when the amount of blur increases.

After deblurring the experimental results showed that the FRR was decrease when using the proposed method.

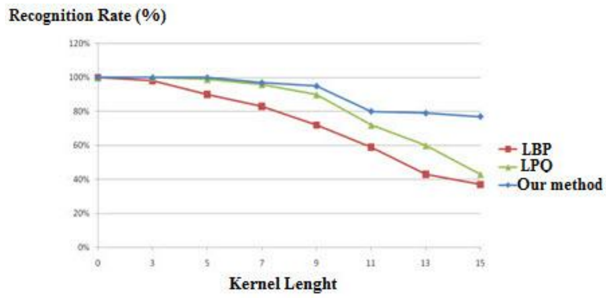

Fig.5: Recognition results for synthetically generated motion –Blurred images

To compare the change of euclidean distance by motion blurring, we measured the difference between face image without and with motion blurring. If S varied between 0 and 3, the user was accepted and the face recognition has a good accuracy without using the deblurring algorithm, but if *S* is greater than S = 3 the FRR (False Rejection Rate) is increase (The FRR refers to an error that rejects the genuine person enrolled in the recognition system) to overcome this problem, the proposed deblurring algorithm is used to restore the motion-blurred face images.

Finally, we compare our methods with other algorithms such as Local Phase Quantization "LPQ" [26] and binary patterns (LBP) [2] the results in Fig.3shown that our algorithm gives the best performance followed by LPQ and LBP.

4. CONCLUSIONS

In this article, a novel restoration method of motion-blurred face images is proposed. Therefore, face recognition accuracy was better than that when using debluring Algorithms. However, a suggestion for future work is to study motion restoration method for nonlinear motion blurred (The variations of both direction θ and size of blur S) face images.

After deblurring the experimental results showed that the FRR was decrease when using the proposed method.

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