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# Face Recognition on Linear Motion-blurred Image

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***Abstract***

*Most face recognition algorithms are generally capable to achieve a high level of accuracy when the image is acquired under wellcontrolled conditions. The face should be still during the acquisition process; otherwise, the resulted image would be blur and hard for recognition. Enforcing persons to stand still during the process is impractical; extremely likely that recognition should be performed on a blurred image. It is important to understand the relation between the image blur and the recognition accuracy. The ORL Database was used in the study. All images were in PGM format of 92 × 112 pixels from forty different persons, ten images per person. Those images were randomly divided into training and testing datasets with 50-50 ratio. Singular value decomposition was used to extract the features. The images in the testing datasets were artificially blurred to represent a linear motion, and recognition was performed. The blurred images were also filtered using various methods. The accuracy levels of the recognition on the basis of the blurred faces and filtered faces were compared. The performed numerical study suggests that at its best, the image improvement processes are capable to improve the recognition accuracy level by less than five percent.*

***Keywords***: *face recognition; image blurring; laplacian filter; singular value decomposition*



## 1. Introduction

Face recognition has been widely used in the area of computer vision and machine learning. It is being used for criminal identification, credit card verification, security, forensic, monitoring system, and many more[1]. It is a means for a better biometric-based identification [2]. In addition, the facial features identified in the face recognition can provide high compatibility in a machine readable travel documents [3]. Not only in practical applications, face recognition has also undergone the theoretical development in a great extent [4]. Despite of those developments, the success of the face recognition is still strongly affected by many internal and external factors. For example, occlusion and poor illumination can drastically degrade the accuracy of the face recognition [5]. Blur image due to motion also has significant impact to the accuracy. Such an image is a result of relative movement between the camera and the scene during the image integration [6], and four conditions may exist on the process: moving object captured by a static camera, static object captured by a moving camera, motion of both object and camera, and the shutter movement [7].

For the reasons, a number of studies has been conducted to investigate motion blur and its effects on the face recognition. For example, Yitzhaky et al. [8] proposed a method to estimate the blur function from a motion-blurred image. Vageeswaran and Mitra [9] formulated the motion-blurred image problem into a convex optimization problem and proposed a blur-robust algorithm to rectify the image. The restoration of the blurred image is also an issue occurred in the medical imaging in which Kalotra and Sagar [10] has proposed the use of the improved Lucy-Richardson technique. Punnappurath et al. [11] proposed MOBILAP method that allows the face recognition to be performed on the basis of the blurred image due to poor illumination and pose. The method was demonstrated to be accurate at the level of 76 percents.

Moghaddam and Jamzad [12] proposed a novel algorithm to estimate the direction and length of motion blur using Radon transform and fuzzy set. The algorithm was evaluated using images blurred with artificial movement in various directions (between 0 and 180 degrees) and

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lengths (between 10 and 50 pixels). Their results suggested the method is still effective when the signal to noise ratio is slightly higher than 22 dB. The current study is focused on the face recognition of blurred images, particularly due to a linear motion. In addition, the focus is also directed to the effect of a number of image enhancement techniques on the accuracy of the face recognition.

## 2. Research Method

The procedure of this research is graphically shown in Figure 1. Firstly, face images were obtained from ORL database (website with the url: http://www.cl.cam.ac.uk/research/dtg/attarchive/facedatabase.html). This database has face images of 40 different persons with 10 images per persons. Those images were taken at various lighting conditions, facial expressions (open/closed eyes, smiling/not smiling) and facial details (glasses/no glasses). Each image has 92×112 pixels in gray scale. The image file format is portable gray map (pgm). These images are then divided into two groups (training and testing datasets) with the composition of 50-50.

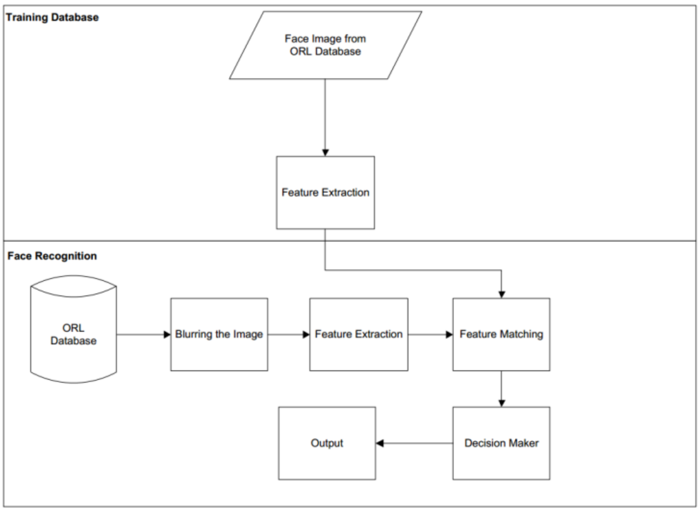


Figure 1. The research procedure.

Secondly, the images in the training dataset are extracted for their features using the singular value decomposition (SVD) method. This process provides the basis functions and their associated weights. In the testing phase, any given face image is projected to the above SVD basis functions. It results in a coefficient vector which should be compared to the weight vector obtained in the training phase. The comparison is evaluated with respect to the Euclidian distance.

The above procedure is repeated for artificially blurred images. The blurred image is obtained via a convolution process with a kernel function resembling a linear motion. The blurred images are also enhanced using various filters and face recognition. The various filters are Laplacian filter, median filter, Wiener filter and Richardson-Lucy algorithm.

## 3. Theory

In this research, singular value decomposition (SVD) is used to extract the feature components of face images. Assuming that we have $N$ images where each has the size of $m \times n = M$ pixel. The training process subsequently is: Represent each image in a vector $\mathbf{f}_i$, where $i = 1, \cdots, N$; Calculate the image average $\bar{\mathbf{f}} = \sum \mathbf{f}_i / N$; Subtract each image with the image average: $\mathbf{a}_i = \mathbf{f}_i - \bar{\mathbf{f}}$; Arrange the vectors $\mathbf{a}_i$ into a matrix: $\mathbf{A} = [\mathbf{a}_1\, \mathbf{a}_2 \cdots \mathbf{a}_N]$; Decompose the matrix into its singular vectors and values: $\mathbf{A} \rightarrow \mathbf{U}\Sigma\mathbf{V}^T$. The matrix $\mathbf{U}$ contains the eigen-face vectors $\mathbf{u}_1, \mathbf{u}_2, \cdots, \mathbf{a}_M$; Select some of the first eigen-face vectors to become the base-face: $\mathbf{u}_1, \mathbf{u}_2, \cdots, \mathbf{a}_r$ where $r < M$; and finally, project each training image to the base-face: $\mathbf{w}_i = [\mathbf{u}_1\ \mathbf{u}_2 \cdots\ \mathbf{u}_r]^T \mathbf{a}_i$. The projection completes the training process, which results the base-faces $\mathbf{u}_1\ \mathbf{u}_2 \cdots\ \mathbf{u}_r$ and the weighting vector of each image in the database $\mathbf{w}_i$.

During the face recognition process, we subtract a given face $\mathbf{f}^*$ with the face average, $\mathbf{f}^* - \bar{\mathbf{f}}$, and project the face into the base-faces: $[\mathbf{u}_1\ \mathbf{u}_2 \cdots\ \mathbf{u}_r]^T(\mathbf{f}^* - \bar{\mathbf{f}}) \to \mathbf{w}^*$. The face is reconized as the $j$-person, if $\|\mathbf{w}_j - \mathbf{w}^*\|_2$ is the smallest among$\|\mathbf{w}_i - \mathbf{w}^*\|_2, i \neq j$. In the current research, the blur on the face images is introduced artificially with the following procedure. The image degradation process is achieved via a convolution process:

$$g(x,y) = h(x,y) \otimes f(x,y), \tag{1}$$

where $g(x,y)$ is the degraded image, $h(x,y)$ is the point spread function (PSF) for image blurring due to a linear motion, $f(x,y)$ is the original image, and $\otimes$ is the convolution operator. The PSF represents the degree that an image spreads around a point [13]. The PSF for image blurring due to a linear motion is written

$$h(x,y) = \begin{cases} \dfrac{1}{L} & \text{if } (|x\cos\theta + y\sin\theta| \leq L/2) \\ 0 & \text{Otherwise} \end{cases}, \tag{2}$$

where $L$ is the blur level in pixel and $\theta$ is the motion direction. The motion blur occurs when an object or a camera moves during light 80 exposure. Motion blur can be in the form of translation, rotation, and sudden change of the scale or some combination of these forms. When the recorded scene translates relative to the camera at a constant velocity under an angle of α with respect to the horizontal axis during the exposure interval. Figure 2 shows the effects of the motion blur of various blur levels $L$.

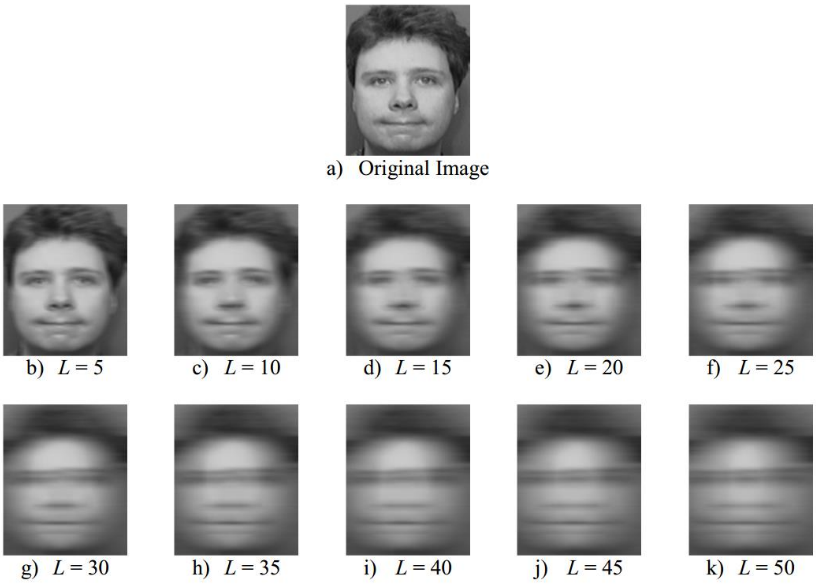


Figure 2. Effect of the blur level/length $L$ to a face image.

Four image enhancement methods are discussed in the current work: Laplacian filter, median filter, Richardson-Lucy algorithm, and Wiener filter. The Laplacian filter is widely used to emphasize texture and image viewer focus and to enhance image contrast [14]. The Laplacian filter has a $3 \times 3$ kernel matrix. The matrix has three types: 4, 8, and 9 cores. The kernel matrices of the three types are respectively:

$$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}, \begin{bmatrix} 1 & 1 & 1 \\ 1 & -8 & 1 \\ 1 & 1 & 1 \end{bmatrix}, \text{and} \begin{bmatrix} -1 & -1 & -1 \\ -1 & 9 & -1 \\ -1 & -1 & -1 \end{bmatrix}. \quad (3)$$

The first two types is implemented via:

$$f = g - (g \otimes L_k), \quad (4)$$

where $f$ is the enhanced image, $g$ is the degraded image, and $L_k$ is the Laplacian kernel. The last type is implemented via:

$$f = g \otimes L_k. \quad (5)$$

The second filter is median filter. The filter is best known as order-statistic filter. It is one of the powerful non-linear order-statistic filter [15]. The median filter replaces the center pixel of the window with the media of all pixel values in the window [16]. The median filter is given by:

$$f(x, y) = \mathrm{median}_{(s,t)\in S_{xy}} g(s, t), \quad (6)$$

where $S_{xy}$ is the sliding window. For certain types of random noise, media filter provides excellent noise reduction capabilities, with considerably less blurring than that of the linear smoothing filters of similar size [17].

The third filter is Richardson-Lucy algorithm. This algorithm is well-known as non-blind deconvolution algorithm, which is good at image de-blurring. However, if the used PSF does not exactly match with the PSF of the blurring process, the enhanced image will have undesired ringing artifacts at the smooth region around edges [18]. The formulation of Richardson-Lucy algorithm can be defined as the superscript $t$ denotes the iteration index, and $k$ is the PSF value [18].

$$f^{t+1} = \left(k \frac{g}{f^t \otimes k}\right) f^t, \quad (7)$$

The last considered filter is Wiener filter. The use of this filter is popular in many signal enhancement methods [19]. Wiener filter could be applied to a wide variety of problems, such as for signal processing, image processing, image deconvolution, or noise reduction. The input of Wiener filter is an image degraded by noise, while the output is calculated by using

$$f = g \otimes (f^0 + n), \quad (8)$$

where $f^0$ is the original image and $n$ is the noise and $g$ is the response of Wiener filter [20-23]. Finally, the accuracy of the face recognition is calculated by

$$\text{Accuracy} = \frac{\text{The Number of Correct Recognition}}{\text{The Number of All Cases}} \times 100. \quad (9)$$

In the current numerical trials, the number of all cases is 200.

## 4. Results and Analysis

Firstly, we discuss the baseline case where the face recognition is directly applied to images in the testing dataset. This results is essential for two reasons. First, to understand to which extend the use of blur image reduces the level of accuracy. Second, to understand to which extend the use of standard image enhancement methods is capable to improve the quality of the blurred image in the context of face recognition.

The baseline of the level of accuracy is shown in Figure 3. This results means that at its best, the utilized recognition method is capable only to correctly identify nine out of ten persons. However, this result is affected by the number of singular value components, as expected. For the cases where the number of SVD components are below 30, the accuracy is strongly affected by the number of the SVD components. Above that threshold, the effect is small; and above 50, the effect is negligible.

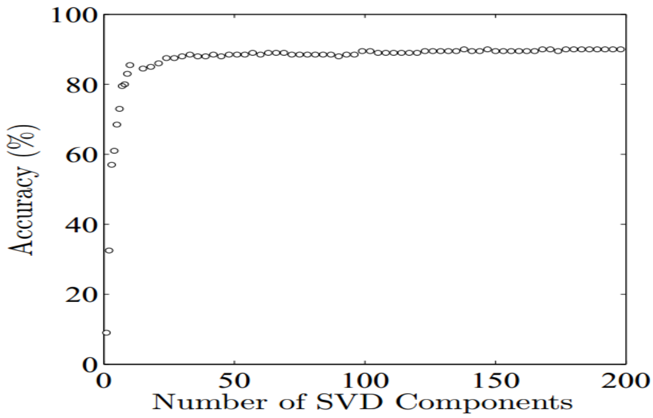


Figure 3. The level of the accuracy of face recognition as a function of the number of singular value decomposition components.

When the face image is blur, for example, due to linear motion, we would expect that the accuracy would drop. The higher blur level would result the lower accuracy. Numerical results, as depicted in Figure 4 and Table 1, strongly support the hypothesis with high coefficient determination $R^2$ values within the range of 0.963 and 0.987. These results show that the blur level is inversely proportional with the accuracy level. The regression model: $y \sim \beta_0 + \beta_1 \cdot x$ is statistically significant with $p$-Value much lower than the significance level $\alpha = 5\%$. What interesting is that the accuracy drops at higher rate when the face recognition is performed using more SVD components. However, this relationship is well maintained for the blur level in the range of 0 and 40 pixels. Above 40 pixels, the accuracy is relatively not affected by the blur level.

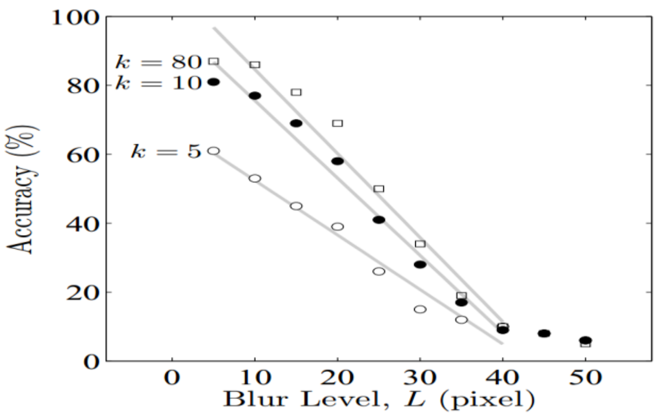


Figure 4. The effects of the blur level to the face recognition accuracy for the number of SVD components of 5, 10, and 80. The regression model is depicted as solid line. The model coefficients are provided in Table 1

Traditionally, we rely on image enhancement methods prior applying face recognition algorithms when dealing with blurred face images. The improvement in the level of accuracy by this approach is discussed the following. We only evaluate four image enhancement methods, namely, Laplacian, median, Richardson-Lucy, and Wiener filters. The numerical experiments indicate that only the Laplacian filter is able to provide a visible improvement in the level of accuracy. The improvements by the remaining filters are negligible. The improvement on the level of accuracy is about 4% when the image recognition is performed using 80 SVD components for images with blur level in the range of 0 to 40 pixels as shown in Figure 5. The average improvement is very small for 5 SVD component case. The relation between the level of improvement and the number of SVD components is rather strong at 0.87 with respect to the Pearson's correlation coefficient. There is no conclusive relation between the accuracy improvement and the blur level.

Table 1. The results of the simple regression analysis for the blur level (independent variable) and the level of accuracy (dependent variable). The regression model is: Accuracy = $\beta_0 + \beta_1 \cdot$ Blur Level. The blur level is limited to the range of 0 and 40 pixels. The number of SVD components $k$ is varied as 5, 10, 20, 40, and 80. $R^2$ denotes the coefficient of determination

| | Estimate | SE | $t$-Stat | $p$-Value | $R^2$ |
|---|---|---|---|---|---|
| $k = 5$ | | | | | |
| (Intercept) | 68.250 | 2.729 | 25.012 | 2.689E-07 | 0.973 |
| $x_1$ | -1.583 | 0.108 | -14.651 | 6.350E-06 | |
| $k = 10$ | | | | | |
| (Intercept) | 98.071 | 3.111 | 31.528 | 6.765E-08 | 0.982 |
| $x_1$ | -2.248 | 0.123 | -18.244 | 1.747E-06 | |
| $k = 20$ | | | | | |
| (Intercept) | 100.680 | 2.715 | 37.076 | 2.569E0-08 | 0.987 |
| $x_1$ | -2.302 | 0.108 | -21.408 | 6.777E-07 | |
| $k = 40$ | | | | | |
| (Intercept) | 108.360 | 3.924 | 27.616 | 1.491E-07 | 0.977 |
| $x_1$ | -2.471 | 0.155 | -15.903 | 3.923E-06 | |
| $k = 80$ | | | | | |
| (Intercept) | 109.040 | 4.899 | 22.258 | 5.379E-07 | 0.963 |
| $x_1$ | -2.441 | 0.194 | -12.579 | 1.546E-05 | |

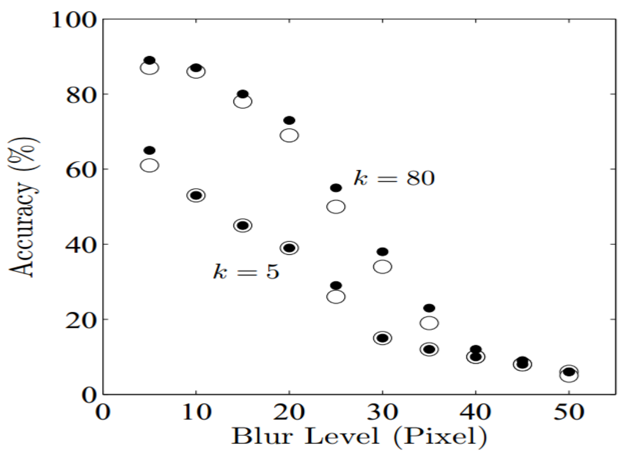


Figure 5. Improvement of the accuracy level by using Laplacian filter: 'O' without filter and '●' with filter

## 5. Conclusion

An acceptable level of accuracy of face recognition is achievable only on well controlled environment. The accuracy level degrades quickly when the face image is taken on moving object, bad illumination, bad face position, or from improper distance. This study intends to quantify how the accuracy level drops when the image acquisition is performed on faces undergoing linear motion. This work is important for some areas of applications. The face recognition is performed using the SVD method and the linear motion is introduced artificially. The results suggest that the accuracy level drops linearly with increasing the blur level. Applying an image enhancement method prior face recognition does not improve much the accuracy level.

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