Assessment of Blurring and Facial Expression Effects on Facial Image Recognition*

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Abstract. In this paper we present methods for assessing the quality of facial images, degraded by blurring and facial expressions, for recognition. To assess the blurring effect, we measure the level of blurriness in the facial images by statistical analysis in the Fourier domain. Based on this analysis, a function is proposed to predict the performance of face recognition on blurred images. To assess facial images with expressions, we use Gaussian Mixture Models (GMMs) to represent images that can be recognized with the Eigenface method, we refer to these images as "Good Quality", and images that cannot be recognized, we refer to these images as "Poor Quality". During testing, we classify a given image into one of the two classes. We use the FERET and Cohn-Kanade facial image databases to evaluate our algorithms for image quality assessment. The experimental results demonstrate that the prediction function for assessing the quality of blurred facial images is successful. In addition, our experiments show that our approach for assessing facial images with expressions is successful in predicting whether an image has a good quality or poor quality for recognition. Although the experiments in this paper are based on the Eigenface technique, the assessment methods can be extended to other face recognition algorithms.

Keywords: Face recognition, Image Quality Assessment, Facial expressions, Blurring Effect, Gaussian Mixture Model.

1 Introduction

Face recognition has become one of the most important applications of image analysis and computer vision in recent years. Nowadays, the use of face recognition systems for biometrics is considered by many governments for security in important buildings such as airports and military bases. The performance of biometric systems such as *fingerprint*, *face*, and *iris* recognition highly rely on the quality of the captured images. Thus, the demand for a preprocessing

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module to assess the quality of input images for the biometric systems is obvious. The quality measures of a captured image can then determine whether the image is acceptable for further processing by the biometric system, or another image needs to be captured. The importance of the facial image quality and its effects on the performance of the face recognition systems was also considered by Face Recognition Vendor Test (FRVT) protocols [1]. For example, FRVT2002 [2] consists of two tests: the High Computational Intensity (HCInt) test and the Medium Computational Intensity (MCInt) test. The HCInt test examines the effect of changing the size of the database on system performance. On the other hand, the MCInt measures the performances on different categories of images that include images with different effects such as changes in illumination, and pose variations.

In the literature, few researchers have addressed the performance of face recognition systems with lower quality images [3]. In [4], Draper *et al.* built two statistical models to examine how features of the human face could influence the performance of three different face recognition algorithms: principle components analysis (PCA), an interpersonal image difference classifier (IIDC), and an elastic bunch graph matching (EBGM) algorithm. They examined 11 features: race, gender, age, glasses uses, facial hair, bangs, mouth state, complexion, state of eyes, make up use, and facial expressions. Their study, based on two statistical models, showed that images with certain features are easier to recognize by certain methods. For example, subjects who close their eyes are easier to recognize using PCA than EBGM. Considering the results in their paper, it is obvious that there is a need for systems to assess the quality of facial images for face recognition.

In this paper, we develop novel algorithms for assessing the quality of facial images with respect to the effects of blurring and facial expressions. These algorithms can be used in developing a facial image quality assessment system (FIQAS) that works as a preprocessing module for any face recognition method. The idea of FIQAS is to assess the quality of facial images and either reject or accept them for the recognition step. We focus on assessing the effect of blurring and facial expressions on facial images. In order to develop the algorithms for assessing the quality of facial images, the challenge is to measure the level or the intensity[1] of the factors that affect the quality of the facial images. For example, a facial image could have an expression with intensity in a range starting from neutral to maximum. Obviously, the recognition of a facial image with exaggerated expressions is more difficult than the recognition of a facial image with a light expression. For blurring effect, measuring the level of blurriness is possible. On the other hand, measuring the intensity of face expression is difficult because of the absence of the reference neutral face image.

Considering the issues discussed above, we take two different strategies to assess the quality of facial images: one strategy for blurring effect and another strategy for facial expressions. For blurring effect, we develop a function for predicting the performance rate of the Eigenface recognition method on images

[1] In this paper, the word intensity is synonymous with the word level.

with different levels of blurriness. In case of facial expressions, where measuring the intensity of an expression is difficult, we classify the images into two different classes: "Good Quality" images, and "Poor Quality" images; and then model the images based on Gaussian Mixture Models (GMMs). The GMMs are trained using the Cohen-Kande face database, where the class assignment of the training images is based on whether the Eigenface method succeeds or fails in recognizing the face. The results are encouraging and can be easily extended to assess quality for other face recognition methods.

The rest of this paper is organized as follows: Section 2 introduces the algorithms for assessing the quality of facial images affected by blurring and facial expressions. Section 3 presents experimental results. Conclusions and the future works are discussed in Section 4.

2 Algorithms for Quality Assessment of Facial Images

We assume that the facial images do not have illumination problem. In fact, illumination is one of the important factors that could affect the performance of a face recognition system, but in this paper we assume that the images are only affected either by blurring or by facial expressions. Following, we will present our algorithms for assessing the facial images with respect to blurring and expressions.

2.1 Blurring Effect Assessment

To assess the quality of facial images with respect to blurring, we measure the intensity of blurriness. Based on this measure, we define a function to predict the recognition rate of the Eigenface method. An image with sharp edges and without blurring effects has more energy at the higher spatial frequencies of its Fourier transform than the lower spatial frequencies. In other words, an image with fine details and edges has flatter 2-D spatial frequency response than a blurred image.

There are different techniques to measure the energy of the high frequency content of an image. One technique is to analyze the image in the Fourier domain and calculate the energy of the high frequency content of the image by statistical analysis. One statistical measure that can be used for this purpose is the Kurtosis. In the following subsection, we review this measure and discuss the advantages and disadvantages of it. Then in the last subsection, we introduce the function that predicts the performance rate of face recognition on a given image based on the blurriness of the image.

Image Sharpness Measurement Using the Kurtosis. An elegant approach for image sharpness measurement is used in electron microscope [5]. This approach is based on the statistical analysis of the image using Fourier transform. Kurtosis is a measure of the departure of a probability distribution from Gaussian (normal) distribution. For a one dimensional random variable x with mean μ_x and statistical moments up to the fourth degree, the Kurtosis is defined by Kotz and Johnson [6]:

$$\kappa = m_4/m_2^2 \tag{1}$$

where m_4 and m_2 are the fourth and second moments respectively. For a normal distribution, the value of the $\kappa = 3$. Therefore, the value of κ can be compared with 3 to determine whether the distribution is "flat-topped" or "peaked" relative to a Gaussian. In other words, the smaller the value of the Kurtosis, the flatter the distribution. For a multi-dimensional random variable, Y, the Kurtosis is defined as:

$$\kappa = E[(Y - \mu_Y)^t \Sigma^{-1} (Y - \mu_Y)]^2 \tag{2}$$

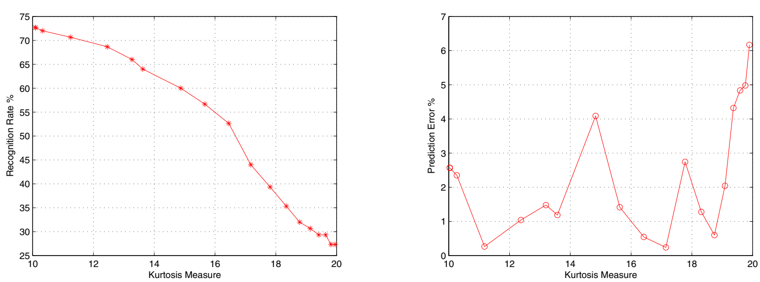
where Σ is the covariance matrix and μ_Y is the mean vector.

In this work, we use the value of Kurtosis (Eq. 2) for predicting the face recognition rate. Our experiments show that this measure has a linear response within a wide range of blurring. In our experiments the facial images were blurred using a Gaussian mask with different values of the σ. The average value of the Kurtosis for facial images without blurring is 10 and it increases with larger values of σ.

Face Recognition Performance Prediction. Figure 1(a) shows the recognition rate of the Eigenface method versus the Kurtosis measure. The figure shows that the recognition rate decreases with larger values of the Kurtosis measure (higher blurriness). To assess the quality of an unknown face image degraded by blurring, we define a function that predicts the recognition rate of the Eigenface from the Kurtosis measure. This function is obtained by linear regression of the data in Figure 1(a):

$$R(\kappa) = R_{max} + a_1 * (\kappa - 10) + a_2 * (\kappa - 10)^2 \tag{3}$$

where R_{max} is the maximum recognition rate of the specific face recognition system (e.g. Eigenface in our work), and the parameters a_1 and a_2 can be determined by linear least mean square error regression. As shown in the experiments Section, this function is capable of predicting the recognition rate of the Eigenface method on images affected by blurring. The same procedure can be used to develop quality measures and prediction functions for other face recognition methods.



(a) (b)

Fig. 1. (a) Recognition rate of the Eigenface method versus Kurtosis measure. (b)Prediction error versus Kurtosis measure.

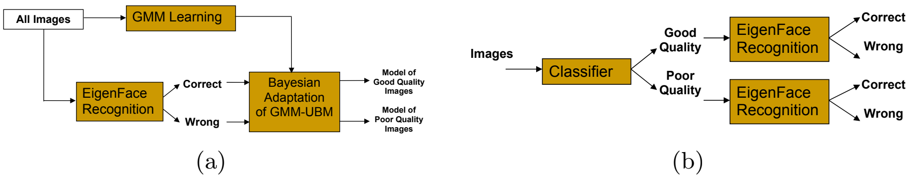


Fig. 2. System diagram for assessing the quality of facial images with expressions: (a) Training the GMM-UBM models, (b) Testing the models for classification

2.2 Facial Expression Effect Assessment

In facial expression analysis, the temporal dynamics and intensity of facial expressions can be measured by determining either the geometric deformation or the density of wrinkles that appear in certain regions of the face [7]. For example the degree of smiling is proportional to the magnitude of the cheek movement and the rise of the corners of the mouth. Since there are interpersonal variations with regard to the amplitudes of the facial actions, it is difficult to determine the absolute facial expression intensity for a given subject without referring to an image of the neutral face of the subject. In this work, we assume that we do not have the image of the neutral face of the subject during the operation of the system, as a result, we follow a different approach from the one we use in the blurring effect. Figure 2(a) shows a block diagram of our algorithm. In order to train the system, we use a database of facial images that contains for each subject an image with neutral face and images with different expressions with varying intensities.

During training, we use the Eigenface recognition method, for recognizing these facial images. The result of this step would be two subsets of facial images: one set that could be recognized correctly, called "Good Quality" images, and the other set that could not be recognized correctly, called "Poor Quality" images. Next, we adapt the Gaussian Mixture Model (GMM) based on Universal Background Model (UBM) to model these two classes of facial images. During the image assessment phase, for a given test image, we use the GMM-UBM models to classify the facial image into one of the two classes, i.e., good quality or poor quality image for face recognition. For a review of the GMM-UBM models, we refer the readers to the work in [8] that has been successfully applied in speaker verification. During testing, as shown in Figure 2(b), given a test image, we test if the image belongs to the class of images with good quality or poor quality. This is achieved using the *Maximum Likelihood* decision rule. We applied this approach to the Cohn-Kanade database [9]. Our experiments show that the accuracy of the system is 75% in discriminating between the images with good quality and the images with poor quality.

3 Experiments and Results

We use the images in the FERET gallery [1] to evaluate our algorithm for predicting the recognition rate of the Eigenface method on images with blurring

Table 1. Classifier performance: (a) Different expressions. (b) Total performance.

		Correct Classification (%)	Incorrect Classification (%)
Good Quality	Joy	73.66	26.34
	Anger	67.68	32.32
	Fear	81.25	18.75
	Disgust	67.05	32.95
	Surprise	33.58	66.41
	Sadness	61.46	38.54
Poor Quality	Joy	25.00	75.00
	Anger	33.33	66.67
	Fear	0.00	100.00
	Disgust	37.50	62.50
	Surprise	6.45	93.55
	Sadness	0.00	0.00

(a)

	Classifier performance%
True Positive	75.67
False Positive	29.03
True Negative	70.97
False Negative	24.33

(b)

effect. The FERET gallery includes 600 images for 150 different subjects. Each subject has four images, one is frontal with no expression, one is frontal with joy expression, and two are near frontal. In our experiments we only use the frontal images. To apply the Kurtosis measure to a facial image, we first detect the face and normalize the illumination in the images. For face detection, we use boosted face detector [10] which is implemented by OpenCV library [11]. Then, we normalize the size of the detected face area to 128×128 pixels. To test this measure, we use a Gaussian filter to blur the neutral face images in the FERET gallery and the Kurtosis to measure the intensity of blurring effect. We split the gallery into two separate sets of equal sizes for the training and the testing phases. We experiment with different values for σ, of the Gaussian filter, to obtain images with different levels of blurriness. We estimate the coefficients of Equation 3 by applying regression to the data in Figure 1(a). Figure 1(b) shows the error in predicting the recognition rate of the Eigenface method for the images in the test set.

To evaluate our approach for assessing the quality of facial images with facial expressions, we use the Cohn-Kanade face database which includes 97 subjects with different facial expressions captured in video sequences. Each sequence starts with a neutral face expression and the expression's intensity increases toward the end of the sequence. We split the database into two separate sets of equal sizes for the training and the testing. For training the classifiers, we need two sets of facial images. The first set includes images that are correctly recognized by the Eigenface recognition method. The second set includes images that the face recognition system fails to recognize. The two sets are obtained by applying the face recognition to all the images in the training set.

To train the GMM-UBM model, we select the frames of the neutral faces and the frames with high intensity expression for both training and testing the GMMs. Table 1(a) shows the performance of the classification for assessing the quality of facial images with different expressions. Table 1(b) shows the total performance of the system. The surprise expression is the expression that highly degrades the performance of the face recognition system. This is due to the fact that for the surprise expression the muscles in the upper and the lower parts of the face are deformed. In other words, the change in face appearance with surprise expression is more than the change for the other expressions.

4 Conclusion

In this paper, we presented methods for assessing the quality of facial images affected by blurring and facial expressions. Our experiments show that our methods are capable of predicting the performance of the Eigenface method on the images. In the future, we will work on finding a measure for assessing the quality of facial images with respect to illumination. We will also integrate the different measures of image quality to produce a single measure that indicates the overall quality of a face image.

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