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Pose-tolerant Non-frontal Face Recognition using EBGM

Kin-Wang Cheung, Jiansheng Chen, *Member, IEEE*, and Yiu-Sang Moon

***Abstract*— Traditional automatic face recognition methods focus on handling frontal or near frontal face images. Therefore, they cannot be directly applied to the pose-varied or non-frontal face images captured by non-intrusive video surveillance systems. In this paper, a non-frontal face recognition algorithm based on Elastic Bunch Graph Matching (EBGM) is proposed. The proposed method measures face similarity using facial features which are more robust to pose variation. Experimental results show that the proposed method can achieve a verification accuracy of 97% on face images with 30° pan-angle. Also, the proposed method can reasonably tolerate ±10° variation in the pan-angle, indicating its robustness in tolerating errors in pose estimation. This method can be easily extended to provide non-frontal face recognition up to half profile.**

I. Introduction

Traditionally, images captured by non-intrusive video surveillance systems were mainly used as evidences in prosecution after crimes had been committed. Recent advances in the personal authentication technology, however, have made it possible for using video surveillance systems to help preventing crimes by identifying "suspects" beforehand. One natural way of realizing such an intelligent surveillance system is to employ the automatic face recognition technology. However, face images captured by typical static surveillance cameras often suffer from low resolution, motion blurring, and pose variation problems. Multi-camera surveillance systems have been proposed to solve the low resolution problem [7], [8]. In these systems, Pan-Tilt-Zoom (PTZ) cameras are directed and zoomed into the target person for capturing high resolution images. Also, the multi-shot de-blurring technique proposed in [9] can be applied to solve the motion blur problem. The pose variation problem, however, is more challenging because it is essentially originated from the variation of user behaviors, which cannot be controlled or intervened by the intelligent surveillance system under the basic assumption of user non-intrusiveness.

Traditional face authentication algorithms such as Principal Component Analysis (PCA) [1], Linear Discriminant Analysis (LDA) [3], and Elastic Bunch Graph Matching (EBGM) [2] are initially designed to recognize human faces using frontal face images. Therefore these methods may not be suitable to be directly applied to the pose varied face images captured by the surveillance systems. Fig. 1 shows two sample non-frontal face images captured by the dual camera surveillance system proposed in [8]. Also, in most existing face authentication systems, the registered face images in the databases are frontal or near-frontal. Comparing the captured non-frontal face image with the frontal image in the database is itself a difficult problem considering that most face features are distorted due to the pose inconsistency.

Fig. 1. Face images captured by surveillance cameras can be varied in both pan (left and right) and tilt (up and down) directions. The distortion of face images in pan-direction is more severe than tilt-direction, since the face images are no longer symmetric when the faces are rotated from frontal-view in pan-direction. Therefore, this paper will concentrate on how pose variation in pan-direction affects face recognition.

There are mainly two kinds of approaches for solving this problem. Blanz et. al. used a 3D morphable model to estimate the frontal face image from the captured non-frontal face image [4]. Then traditional frontal face authentication algorithms can be applied for recognition. However, this method requires a computationally intensive frontal face reconstruction process for each captured face image, and therefore is not suitable for real-time implementations. Also, the reconstruction result depends a lot on the training process and thus the artifacts introduced during reconstruction may affect the reliability of the face recognition algorithm significantly.

Alternatively, we can rotate the corresponding frontal face image in the database accordingly so that it has the similar pose as that of the captured face image. Then the two face images with similar poses can be matched. In fact, such a solution can be implemented with high efficiency. Suppose during the registration, face images with different poses are captured so that the 3D model of the user's face can be established offline using software such as FaceGen [18]. Such an assumption is reasonable since it is always safe to allow more requirements on the registration process for biometric systems. During the surveillance process, when a face image, possibly non-frontal, is captured, we only need to estimate the pose of the captured face image [19], [20] and then rotate the 3D models in the databases to get the corresponding face projections. Then we can compare these non-frontal face images with similar poses. The pose estimation and 3D model

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K. W. Cheung, J. S. Chen and Y. S. Moon are with the Department of Computer Science and Engineering, The Chinese University of Hong Kong, Hong Kong (e-mail: {kwcheung, jschen, ysmoon}@cse.cuhk.edu.hk).

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transformations can be performed with high efficiency and can be implemented in real time. However, the traditional face authentication algorithms have to be modified so that they can be applied to the non-frontal face images.

In this paper we will investigate the feasibility of applying the EBGM face recognition algorithm for solving such a non-frontal face recognition problem. We will modify the baseline EBGM algorithm so that it can be applied to non-frontal face recognition. The EBGM algorithm is selected because as a local feature based method, it is believed to be able to tolerate more pose variations than global methods such as PCA and LDA [5]. To cope with the possible errors in the face pose estimation, we will also investigate the pose tolerance of the proposed modified EBGM algorithm.

The rest of this paper is organized as follows: Section II gives an overview of the EBGM algorithm and explains how it is modified for non-frontal face images. Section III describes the experimental setup and the face database used. Experimental results are also shown in this section. Section IV presents some further discussion on the proposed method as well as the experimental results. Advantages and limitations of the proposed method are discussed in Section V, together with the future work.

II. EBGM FOR SIDE-VIEW FACE IMAGES

A. *Overview of the baseline EBGM algorithm*

The original EBGM algorithm was proposed by Wiskott et. al. in 1997 [2]. An implementation of EBGM, modified from the original algorithm [11], was made public by CSU in 2003 [10]. This implementation was designed for frontal-view face recognition; however it is possible to extend it for non-frontal face images.

The basic idea of EBGM is to locate and extract local facial features, such as eyes, noses and mouth corners, for face matching. The geometric locations of the facial features are represented as a face graph (Fig. 2). Meanwhile, Gabor responses of the extracted facial features are stored in the wavelet form called Gabor jets.

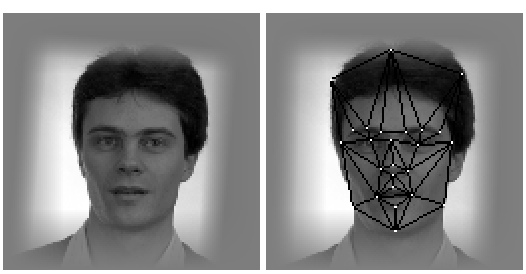

Fig. 2. EBGM locates and extracts facial features ("landmarks") using Gabor wavelets.

To locate facial features, EBGM first initializes features' locations using the model bunch graph which is trained using no less than 70 face images of different persons [11]. After initialization, the features' locations are refined using local search to maximize the similarity between each facial feature and the corresponding feature stored in the model bunch graph. Local regions around the refined feature locations are then extracted using multi-scale and multi-directional Gabor wavelets. Gabor wavelets are chosen because their responses are similar to human visual perception [6], [11]. The face graph and its Gabor jets are combined as the template of the face and will be used for face matching.

Finally, EBGM calculates the similarity score between two face images by comparing their EBGM templates. It has been shown that the authentication performance of EBGM depends significantly on how accurate facial features are located [16].

B. *Modified EBGM for non-frontal face matching*

Non-frontal face images are different from their frontal-view counterparts in mainly two aspects. Firstly, feature locations are noticeably shifted; and the relative geometric distances among features points are also changed. Second, facial features are distorted and even occluded in non-frontal face images (Fig. 3). Directly applying the baseline EBGM algorithm to non-frontal face images adopting the model bunch graph trained on frontal face images will lead to severe inaccurate feature localization [16]. Therefore, the baseline EBGM algorithm has to be adjusted specifically to handle non-frontal face images.

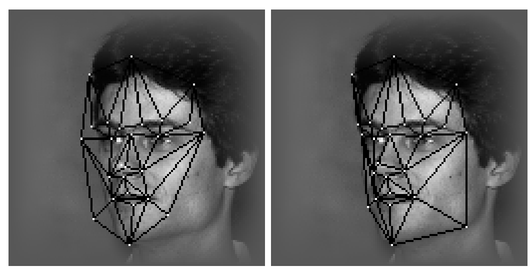

Fig. 3. a) Directly applying the baseline EBGM algorithm to non-frontal face images will lead to severe inaccurate feature localization. b) The manually selected feature point locations.

The proposed non-frontal EBGM is modified from the baseline frontal-view EBGM implementation developed in CSU [11]. There are two major changes. Firstly, a new model bunch graph is trained using non-frontal face images. Second, local facial features are weighted in similarity measure in the face template matching. Features which are more stable over pose variation will weight more in the face matching.

Before building the new model bunch graph, we have to decide the poses of the face images in the training set. Liu et. al. suggested that the "¾ view", or 32 degrees varied from frontal-view in pan-direction, was an optimal pose for training pose-robust face recognition models [15]. The ¾ view is also a popular choice because government photographs, such as travel visas and arrest photographs often require a ¾ profile to be submitted. Moreover, face images with poses around the "¾ view" are commonly captured in surveillance systems, such as the system proposed in [8] which was launched in a corridor environment. Therefore, the "¾ view" has been chosen as the pose for the new model bunch graph training.

The new model bunch graph was trained using 70 non-frontal face images selected from the CAS-PEAL face database [12]. Since CAS-PEAL does not have face images exactly in the "¾ view", images with 30° rotation were chosen. The feature locations of the selected face images were manually marked by human experts. The new model bunch graph was then trained using the training algorithm in the CSU EBGM implementation [10].

In the non-frontal face images, some of the local features are no longer suitable for the face recognition due to serious distortion and occlusion. For example, in Fig. 3, the feature points on the left hand side of the face are obviously distorted. These features can be given less weights or even discarded during face matching. Similarly, local features that are more robust to pan-angle rotation should be emphasized in the face similarity measurement. Based on these observations, we empirically weighted the facial features as shown in Fig. 4.

Suppose now we study a specific case in which the faces are 30°-rotated towards the right hand side of the person, as shown in Fig. 4. Facial features around the left face edge are occluded. These features are also difficult to be located and matched due to their significant distortions over pose variation. Thus these features are discarded. On the other hand, features around the right eye are more invariant to this specific face rotation. As a result, these features weight more in the face similarity measurement.

With the above modifications, the EBGM algorithm can now be extended to the non-frontal face image matching. In the next section, we will show, using experiments, the reliability, authentication performance and post tolerance of the proposed modified EBGM face authentication algorithm.

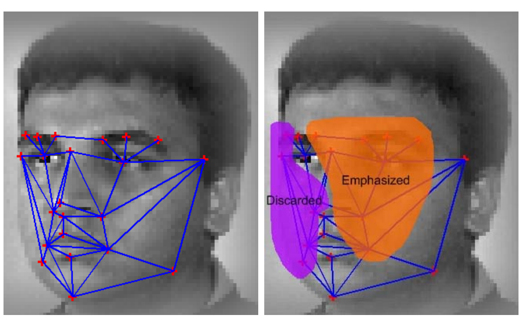

Fig. 4. a) An example of a "30°-rotated face towards the right hand side of the person" is shown. The person turns his face leftwards from our perspective. The three facial features at the top of the head are removed. b) The emphasized and discarded features are shown.

III. Experiments

A. Experimental Setup

The experiments to be presented in this section are intended to validate the effectiveness of the proposed modified EBGM algorithm in non-frontal face authentication. We will also evaluate to what extend can the proposed method tolerate the inaccuracy in the pose estimation.

The CUbiC FacePix database [17], [21] was chosen in this experiment because the face images are varied solely in pan-direction. Other factors, such as the illumination and the background are kept unchanged among images. This characteristic allows us to focus on validating the effectiveness of the proposed method over the pose variation only. Also, FacePix provides face images with precisely measured pose angle with a granularity of 1 degree so that we can evaluate the pose tolerance of the proposed method in a delicate manner. In contrast, other large-scale face databases with varied face poses are often sampled with granularities of 10-20 degrees [12], [13], [14].

The FacePix database consists of face images of 30 people. For each people, there are 181 face images captured. These face images are ranged from left profile to right profile with a granularity of one degree in pan angle, as is shown partially in Fig. 5.

Fig. 5. Face images of a person in FacePix database from frontal to left profile. Images are shown with an interval of 10 degrees.

In the experiment, five face image groups were selected from the FacePix database. Their pan angles are centered at {20°, 25°, 30°, 35°, 40°} leftwards. Considering the possible error in measuring the pan angle, face images within two degrees variation from the central pan angle are included in the same group and are considered to share the same pose. For example, for each person, the 30-degree group contains five face images with their pan angles vary from 28° to 32°. In the following descriptions, we use {N°} to represent the face image group with central pan-angle equals N degrees.

The following five sets of one to one verification experiments were performed: {30°} vs. {20°}, {30°} vs. {25°}, {30°} vs. {30°}, {30°} vs. {35°}, and {30°} vs. {40°}. In the experiment {30°} vs. {30°}, the cases in which the two matching face images have exactly the same pan angle are excluded. The underlying rationale of such an experimental setting is closely related to the application scenario we have described in the last two paragraph of section I. The image group {30°} can be seen as the images retrieved from the database through 3D face model rotation and projection. Therefore, the rotation angle can be accurately controlled. Other image groups are used to simulate the non-frontal face images captured by the surveillance system and their poses can only be estimated with certain errors. For example in [19], the pose estimation problem was handled by classifiers with 10° quantization. In the next section, we will compare the verification performance of two feature weighting strategies.

We also conducted the same verification test on {0} vs. {0} using the baseline EBGM algorithm. The baseline EBGM algorithm includes more features (e.g. hair features) than the modified EBGM algorithm and thus the former method should be more accurate in verifying faces.

B. Experimental Results

The verification results of the modified EBGM algorithm on non-frontal view face images are shown below. Two feature weighting strategies were employed and compared. The first weighting strategy set all facial features and their intermediate points as equally important (which is equivalent to "without weighting"). The second strategy emphasized (double) and discarded (set zero) facial features according to their robustness against pose variation (i.e. "with weighting") as described in section II.

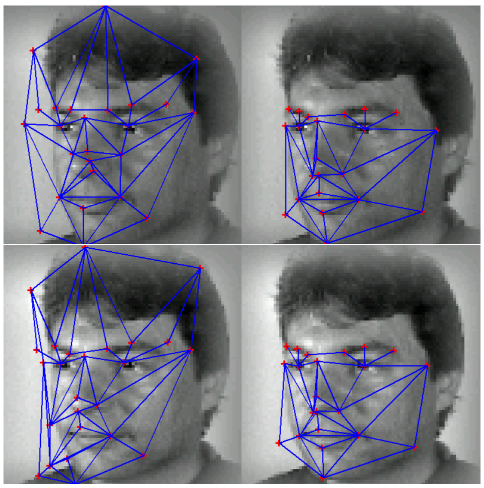

Fig. 6. (Left) The baseline EBGM algorithm using frontal training images fails to locate some facial features (e.g. features around the nose). (Right) Using non-frontal training images can help improve the accuracy of feature localization.

From Fig. 6 we can see that the baseline EBGM algorithm designed for frontal face matching cannot locate some facial features accurately on the non-frontal face images. However, our modified EBGM algorithm is able to locate these features and achieve verification accuracy comparable to the frontal face verification. A verification test for the baseline EBGM algorithm was conducted by [22] using The Facial Recognition Technology (FERET) database [23]. The equal error rates (EER) for 4 frontal probe sets were measured, as shown in Table 1.

Probe Category	Evaluation Task	Gallery Size	EER
FB	Facial Expression	1196	**0.05**
dup1	Aging of subjects	1196	**0.18**
fc	Illumination	1196	**0.10**
dup2	Aging of subjects	1196	**0.18**

Table 1. Performance of baseline EBGM algorithm on FERET verification test

Database	Probe	EER (without weighting)	EER (with weighting)
{30}	{20}	0.14	0.07
{30}	{25}	0.07	0.05
{30}	{30}	0.04	0.03
{30}	{35}	0.08	0.06
{30}	{40}	0.12	0.08
{30}	All	**0.11**	**0.06**

Table 2. The equal error rates of the proposed EBGM algorithm on verification test using the FacePix database.

From Table 2, the overall equal error rates of the proposed algorithm are comparable to the results in Table 1. The EER of the baseline EBGM algorithm on {0} vs. {0} was 0.02, which is comparable to the EER of the proposed algorithm on {30} vs. {30} as well.

Also we can observe from Fig. 7-12 that the second weighting strategy can generally improve the authentication performance. And this kind of improvement is more noticeable for the cases of large pose differences between the two image groups for matching, indicating an enhancement in the pose variation tolerance. Generally speaking, the experimental results show that our proposed method can tolerate ±10 degrees of pose variation by being able to achieve reasonable face authentication accuracies.

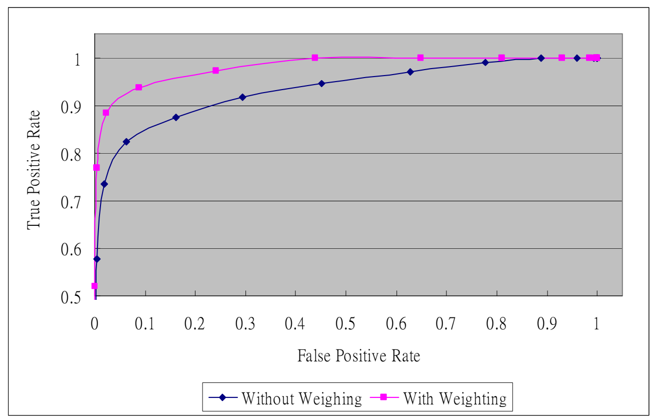

Fig. 7. ROC curve of {30°} vs. {20°} using modified EBGM

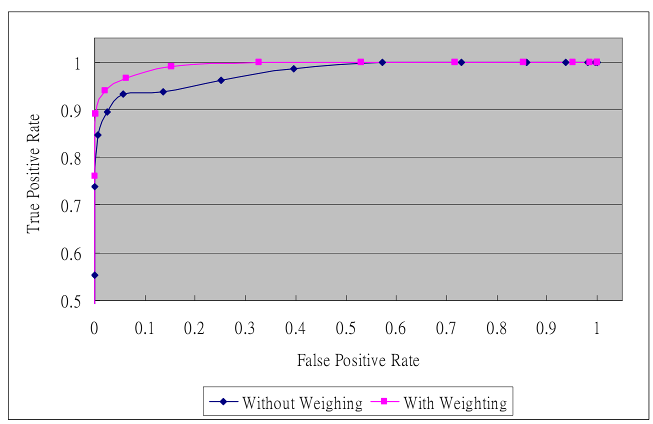

Fig. 8. ROC curve of {30°} vs. {25°} using modified EBGM

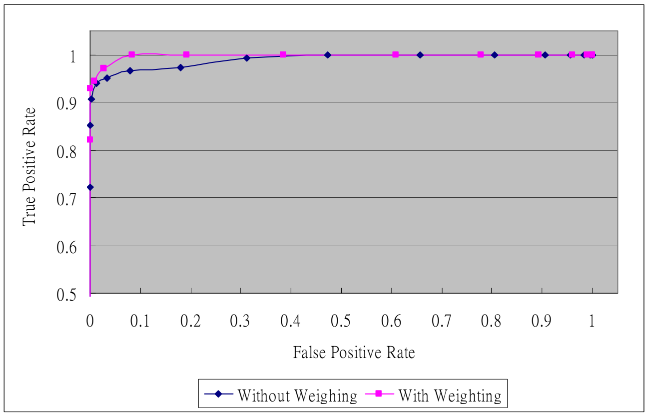

Fig. 9. ROC curve of {30°} vs. {30°} using modified EBGM

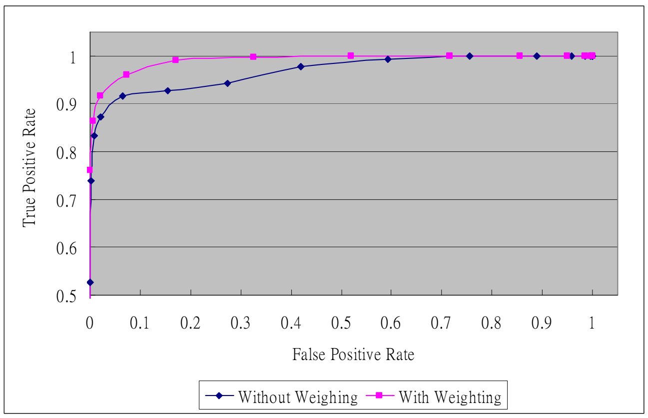

Fig. 10. ROC curve of {30°} vs. {35°} using modified EBGM

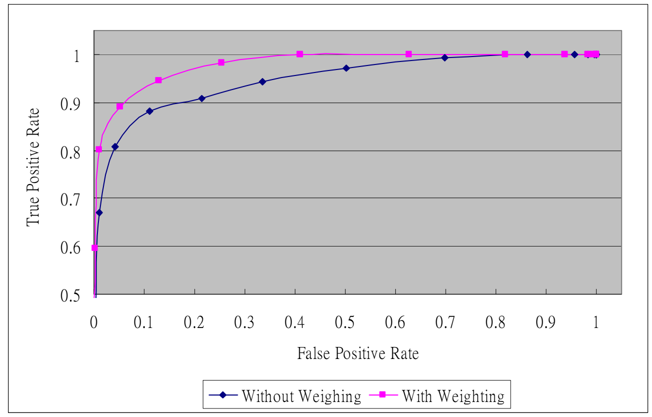

Fig. 11. ROC curve of {30°} vs. {40°} using modified EBGM

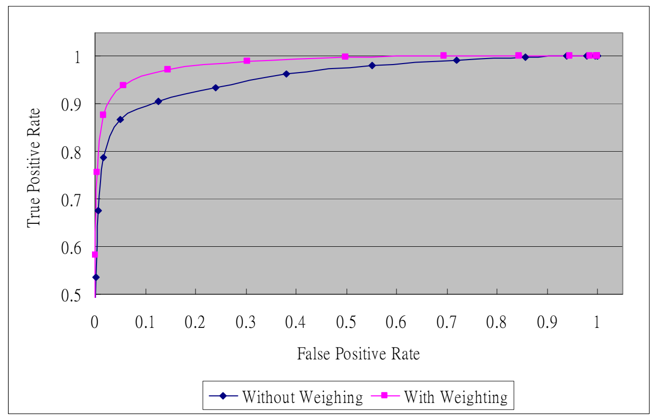

Fig. 12. ROC curve of the overall authentication i.e. {30°} vs. {20°, 25°, 30°, 35°, 40°} using modified EBGM

IV. Discussions

The experiments show that the proposed modified EBGM can effectively handle non-frontal face images around 30° with a tolerance of ±10° in pan-direction. This method may facilitate the intruder detection in video surveillance systems especially when frontal face images are hard to be captured. One possible way of further improving the proposed method is to adopt more flexible feature weighting strategies. This can be achieved by quantitatively modeling the robustness of facial features over pose variation. For example, when the probe face image is estimated to be 30°-rotated leftwards (from our perspective), the left eye should be weighted much less than the right eye in the proposed method since the local region around the left eye will be distorted and partially occluded by the nose. However, if the proposed method is applied to another probe face image, which is 20°-rotated leftwards, the left eye should have more weighting because the distortion of the left eye is less severe.

Poses beyond half profiles differ from the poses we have studied so far. Because half of the face is occluded, new facial points instead of two eyes should be used for face normalization and alignment. Also, an alternative set of facial features should be extracted for face representation and matching. Further studies are necessary for applying EBGM to handle poses beyond half profiles.

The selection of training images will also affect the performance of EBGM noticeably. In our experiments, all training images were selected randomly from the CAS-PEAL Chinese face database. This kind of random selection, however, may not cover all representative types of face appearances. An example is shown in Fig. 13, in which the modified EBGM failed to locate features around nose and mouth due to the moustache. Close examination of the training set used in our implementation reveals that no face with moustache is included. This is not surprising since the CAS-PEAL was collected in the north part of China where very few people would grow a moustache. This indicates that a better way of constructing the training set is to deliberately select representation face images diversifying in terms of gender, age, race, facial appearance, etc.

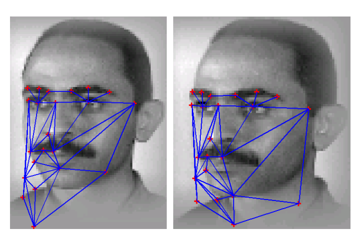

Fig. 13. Facial Features around nose and mouth fail to locate properly for the person with a moustache on the upper lip, since this case is not included in our training set. Therefore, training images have to be carefully chosen to include all possible face appearances.

V. CONCLUSIONS

In this paper we proposed a non-frontal face recognition algorithm modified from the baseline EBGM. A non-frontal model was trained to locate facial features in non-frontal face images. Moreover, a selective weighting strategy was proposed to measure face similarity using features which are more robust to pose variation. The selective weighting strategy was compared with uniform weighting strategy for non-frontal face verification. The experimental result shows that this simple weighting approach can allow the proposed non-frontal EBGM on 30° to handle face images with ±10 degrees of toleration. This result encourages us to design a multi-view face recognition system which can handle pose variation up to half profile for video surveillance systems.

Intuitively, when local feature-based face recognition methods are applied to non-frontal face images, the results should be less discriminative than using frontal face images. One reason is that in frontal face images, prominent facial features [6], such as eyes, eyebrows, and month, are concentrated on the central of the faces. Therefore, their corners are easy to detect and their patterns can be compared directly to distinguish human faces. However, in non-frontal face images these prominent facial features could be significantly distorted or even occluded. Furthermore, facial features which can be clearly observed in non-frontal face images, such as cheekbones and jaws, are hard to be located automatically. Features around ears are usually covered by hair as well. As a result, discriminative facial features which can be extracted from non-frontal face images are fewer than frontal face images. Further studies are required to quantitatively estimate the discriminative power of the facial features extracted from non-frontal face images.

It is interesting that similar approaches have been suggested to deal with frontal face images under different illuminations. In [6], Zou et. al. suggested to exclude facial features (e.g. the nose region) which vary significantly when the lighting condition is changed. The robustness of other facial regions over illumination changes were also quantitatively studied in [6]. It could be a valuable reference for us to conduct more comprehensive studies over pose variation in the future.

ACKNOWLEDGMENT

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