Robust Face Recognition using AAM and Gabor Features

Sanghoon Kim, Sun-Tae Chung, Souhwan Jung, Seoungseon Jeon, Jaemin Kim, and Seongwon Cho

***Abstract*—**In this paper, we propose a face recognition algorithm using AAM and Gabor features. Gabor feature vectors which are well known to be robust with respect to small variations of shape, scaling, rotation, distortion, illumination and poses in images are popularly employed for feature vectors for many object detection and recognition algorithms. EBGM, which is prominent among face recognition algorithms employing Gabor feature vectors, requires localization of facial feature points where Gabor feature vectors are extracted. However, localization method employed in EBGM is based on Gabor jet similarity and is sensitive to initial values. Wrong localization of facial feature points affects face recognition rate. AAM is known to be successfully applied to localization of facial feature points. In this paper, we devise a facial feature point localization method which first roughly estimate facial feature points using AAM and refine facial feature points using Gabor jet similarity-based facial feature localization method with initial points set by the rough facial feature points obtained from AAM, and propose a face recognition algorithm using the devised localization method for facial feature localization and Gabor feature vectors. It is observed through experiments that such a cascaded localization method based on both AAM and Gabor jet similarity is more robust than the localization method based on only Gabor jet similarity. Also, it is shown that the proposed face recognition algorithm using this devised localization method and Gabor feature vectors performs better than the conventional face recognition algorithm using Gabor jet similarity-based localization method and Gabor feature vectors like EBGM.

***Keywords*—** Face Recognition, AAM, Gabor features, EBGM.

I. INTRODUCTION

FOR safer society, interests in constructing a reliable access control system based on personal identification have been increasing [1]. Biometric based identification is more reliable than token based system (card, key, and etc.), and face recognition among biometric identification systems are natural and does not have less negative responses in using from peoples , and thus much more research efforts have been pouring into this area among biometric areas [2,3]. However, variations due to different environments in illuminations, poses, face expressions, and aging are so great that the correlation between two images of the same person under different environments can be smaller than that between two images of the different persons [4]. For these reasons, it is well known that developing a commercially successful face recognition algorithm robust to illuminations, poses, expressions and aging are very difficult.

Face recognition algorithms so far reported in the literatures can be classified as Image-based method using face image information and Feature vector based method using features extracted from face images [2,3]. PCA [5], LDA [6], ICA [7], Local Feature Analysis [8], template based method [9] belong to the first category, and EBGM (Elastic Bunch Graph Matching) [10,11], AAM (Active Appearance Model) [12,13], Morphable Model [14] belong to the second category. EBGM, AAM, and Morphable Model are called model based face recognition algorithms since it needs to construct model first.

Image-based face recognition algorithms usually utilize whole pixel information of images so that even a small local change in illuminations, poses, expressions affects the algorithms significantly and therefore they are not usually robust to illuminations, poses, expressions and aging. On the other hand, Gabor features are known to be more robust to small variations in scaling, rotation, distortion, illumination, poses, and expressions so that they are popularly employed as features for face recognition [15].

EBGM is the most prominent algorithm among face recognition algorithms using Gabor features. The facial feature localization method based on Gabor jet similarity employed in EBGM is known to be sensitive to initial values of the facial feature points [10, 11]. EBGM uses the average value of the same facial feature points in model face images used in constructing Model Bunch Graph as an initial value of the feature point for localizing the facial feature point in a new incoming face images. The average values in the constructed Model Bunch Graph may not provide good initial values for the localization of feature points when testing face images are under various illuminations, poses and expressions. Extraction of feature vectors at wrong facial feature points is well known to be a severe cause of deterioration of face recognition performance [16]. In localizing facial feature points, AAM (Active Appearance Model) is known to be relatively stable [12,13], but is affected by illuminations, poses, and expressions. Thus, if one first localizes facial feature points by AAM and refine facial feature point by Gabor jet similarity using the facial feature points obtained by AAM as initial values, one may achieve more stable localization of facial feature points.

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In this paper, we propose a face recognition algorithm using AAM and Gabor jet similarity in localizing facial feature points, and show improvement of face recognition rates.

The rest of the paper is organized as follows. Section 2 introduces facial feature localization method based on Gabor feature vectors, and Section 3 introduces AAM-based facial feature point localization method, and Section 4 presents our proposed face recognition algorithm. Experiment results are described in Section 5, and finally Conclusion comes in Section 6.

II. Localization of Facial Feature points based on Gabor Feature Vectors

A. Gabor Wavelet, Gabor Jet and Gabor Jet Similarity

The Gabor feature vectors at facial feature points of face images used in this paper are the ones obtained by convolving Gabor wavelet kernels with the intensity of the pixel at the facial feature points of the face images. The Gabor wavelet kernels used in this paper are as follows [11].

$$W(x, y, \theta, \lambda, \sigma) = e^{-\frac{1}{2\sigma^2}(\vec{x} \bullet \vec{x})} e^{i \vec{k} \bullet \vec{x}} \qquad (1)$$

where wave vector $\vec{k}$ is given as $\vec{k} = \left(\frac{2\pi \cos\theta}{\lambda}, \frac{2\pi \sin\theta}{\lambda} \right)^t$, and θ represents wavelet direction, λ represents wave length, σ in (1) represents the size of Gaussian, and is proportional to λ. In this paper, we consider 40 Gabor wavelet kernels obtained by $\theta \in \{0, \frac{\pi}{8}, \frac{2\pi}{8}, \frac{3\pi}{8}, \frac{4\pi}{8}, \frac{5\pi}{8}, \frac{6\pi}{8}, \frac{7\pi}{8}\}$, $\lambda \in \{4, 4\sqrt{2}, 8, 8\sqrt{2}, 16\}$ and $\sigma = \lambda$ in (1).

Let us denote the Gabor wavelet coefficient (Gabor feature vector) obtained by convolving j-th one among the above 40 Gabor wavelet kernels with $I(x, y)$ (intensity of image at (x, y)) as $J_j(x, y)$. Then, Gabor jet $J(x, y)$ at a pixel point (x, y) of an image is defined to be the set $J = \{J_i; j = 1,...,40\}$.

Each Gabor wavelet coefficient J_j can be represented as $J_j = a_j e^{i\phi_j}$ (magnitude a_j, phase ϕ_j).

Suppose $J_j^0 = a_j^0 e^{i\phi_j^0}$ is the j-th Gabor wavelet coefficient at (x_0, y_0), and the Gabor jet at (x_0, y_0) as $J^0(x_0, y_0) = \{J_j^0; j = 1,...,40\}$. Then, Gabor jet similarity $S_\phi(J, J^0)$ between J and J^0 is defined [10] as

$$S_\phi(J, J^0) \equiv \frac{\sum_{j=1}^{40} a_j a_j^0 \cos(\phi_j - \phi_j^0)}{\sqrt{\sum_{j=1}^{40} a_j^2 \sum_{j=1}^{40} (a_j^0)^2}} \qquad (2)$$

B. Model Bunch Graph

For M model face images, one detects faces, renders the detected face upright (if necessary) and normalizes the size of face images. For those M normalized model face images, one can locate v facial feature points manually and calculate Gabor jet at each manually located facial feature point. Then, we call {M Gabor jets, M coordinates, 'average coordinates'} for each facial feature point as Gabor Bunch at the facial feature point. The collection of Gabor Bunches at all v facial feature points is called 'Model Bunch Graph'. The concept of Model Bunch Graph is introduced by EBGM [10].

The model images should be randomly selected to reflect various poses, expressions, and illuminations so as for feature localization to work well on testing.

C. Localization of Facial Feature Points Based on Gabor Jet Similarity

Localization of facial feature points based on Gabor jet similarity is processed as follows. For a normalized new incoming face image, one first calculates Gabor jets at all positions around the initial estimated coordinates of the facial feature point. The initial estimated coordinates of the facial feature point is usually set by the average value of the corresponding facial feature point in Model Bunch Graph. Next, one try to find one of positions around the initial estimated coordinates of the facial feature point where the Gabor jet has the maximal Gabor jet similarity with a Gabor jet in Model Bunch Graph. Then the position is decided as the facial feature's coordinates. Localization of the rest of facial feature points are done in the same way. In order to enhance the precision rate of this feature point localization method, one may need to calculate Gabor jets at a larger neighborhood around each facial feature point. Calculating Gabor jets at all positions around the initial estimated coordinates of the facial feature point takes lots of computation time and thus localization of the facial feature points by calculating the maximal Gabor jet similarity between Gabor jets in Model Bunch Graph and all Gabor jets around the initial facial feature point is not appropriate for real-time processing. Thus, [10] proposed a faster computation method as follows.

Suppose we know Gabor jet $J^0(x_0, y_0)$ at (x_0, y_0). Then, the Gabor jet similarity between the Gabor jet $J'(x_0 + dx, y_0 + dy)$ at $(x_0 + dx, y_0 + dy)$, which is sufficiently near (x_0, y_0), and Gabor jet J^m can be approximately calculated without direct computation of Gabor jet $J'(x_0 + dx, y_0 + dy)$ at $(x_0 + dx, y_0 + dy)$ as

$$S_\phi(J^m, J') \cong \frac{\sum_{j=1}^{40} a_j^m a_j^0 \cos(\phi_j^m - (\phi_j^0 + \vec{d} \bullet \vec{k}_j))}{\sqrt{\sum_{j=1}^{40} (a_j^m)^2 \sum_{j=1}^{40} (a_j^0)^2}} \qquad (3)$$

where $\vec{d} = (dx, dy)^t$, $J_j^m = a_j^m e^{i\phi_j^m}$, $J^m = \{J_j^m; j = 1,...,40\}$

Also, (dx, dy) which maximizes (3), can be approximately calculated as in the below equation (4).

$$\begin{pmatrix} dx \\ dy \end{pmatrix} \cong \frac{1}{\Gamma_{xx}\Gamma_{yy} - \Gamma_{xy}\Gamma_{xy}} \begin{pmatrix} \Gamma_{yy} & -\Gamma_{yx} \\ \Gamma_{xy} & \Gamma_{xx} \end{pmatrix} \begin{pmatrix} \Phi_x \\ \Phi_y \end{pmatrix}$$
$$\Phi_x = \sum_j a_j^m a_j^0 k_{jx}(\phi_j^m - \phi_j^0), \Phi_y = \sum_j a_j^m a_j^0 k_{jy}(\phi_j^m - \phi_j^0)$$
$$\Gamma_{xx} = \sum_j a_j^m a_j^0 k_{jx} k_{jx}, \Gamma_{yy} = \sum_j a_j^m a_j^0 k_{jy} k_{jy} \tag{4}$$
$$\Gamma_{xy} = \sum_j a_j^m a_j^0 k_{jx} k_{jy}, \Gamma_{yx} = \sum_j a_j^m a_j^0 k_{jy} k_{jx}$$

Thus, one can calculate the positional variation (dx^m, dy^m) from the initial estimated facial feature point (x_0, y_0) which maximizes Gabor jet similarity between the Gabor jets around at (x_0, y_0) and Gabor jet $J^m (m = 1,...,n)$ in Model Bunch Graph. Then one can decide the final eye localization as

$$(\hat{x}, \hat{y}) \cong (x_0, y_0) + (dx^{\hat{m}}, dy^{\hat{m}}) \tag{5}$$

Where $(dx^{\hat{m}}, dy^{\hat{m}})$ is the positional variation which maximizes the Gabor jet similarity among the positional variation (dx^m, dy^m) for all $(m = 1,..., \mathrm{M})$.

Equations (3), (4) and (5) hold well only for small variation, so that the precision of the localization of a facial feature point based on (3), (4) and (5) decreases as the initial coordinates (x_0, y_0) of the facial feature point go away from the true eye coordinates.

However, we found that when one take the facial feature point obtained by AAM (Active Appearance Model), not the average value in Model Bunch Graph as the initial estimated coordinates of the facial feature point, one can localize the facial feature points more robustly.

III. AAM-Based Facial Feature Point Localization

In this section, we briefly explain the AAM-based feature point localization method. This explanation is based on [12]. As stated in [12,13], AAM consists of two stages: Modeling stage and Fitting stage.

A. AAM Modeling

We assume the number of facial feature points of face is v, and the number of face model images is M. Then, the shape vector X of each face is defined as the vector consisting of v feature points, that is, $X = (x_1, y_1, x_2, y_2, ..., x_v, y_v)^t$ where (x_i, y_i) is a coordinate of i-th facial feature point and 't' means the transpose of vector (and matrix).

Here we also assume that each shape vector X is already normalized by Procrutes analysis [17].

Applying PCA analysis into all shape vectors from M face model images, one can obtain a mean shape S_0, and n characteristic mode vectors S_i $(\mathrm{i} = 1, ..., \mathrm{n})$. Then, shape vector X of each model face or a new face can be represented as a linear combination of the mean shape S_0, and n characteristic shape mode vectors S_i $(\mathrm{i} = 1, ..., \mathrm{n})$ as follows,

$$X = S_0 + \sum_{i=1}^{n} S_i b_i = S_0 + P_s \vec{b}_s \tag{6}$$

(where $P_s = [S_1, ..., S_n]$, $\vec{b}_s = (b_1, ..., b_n)^t$)

In order to construct a statistical model of the gray-level texture, each model image is needed to be warped into the mean shape so as to let feature points match the mean shape using Delaunay triangulation algorithm [18]. After that, one samples gray-level information from the shape-normalized model images and normalizes it to remove global lighting effects and then forms a texture vector g. Likewise as in the shape vectors, PCA analysis is applied to all texture vectors from M face model images, and then one can obtain a mean normalized gray-level vector $\overline{T}$ and k characteristic texture mode vectors $T_i (i = 1,..., k)$.

Likewise as in the shape vectors, texture vector g of each model face or a new face can be represented as a linear combination of the mean normalized gray-level vector T_0 and k characteristic texture mode vectors $T_i (i = 1,..., k)$ as follows.

$$g = T_0 + \sum_{i=1}^{k} T_i c_i = T_0 + P_g \vec{b}_g \tag{7}$$

(where $P_g = [T_1, ..., T_k]$, $\vec{b}_g = (c_1, ..., c_k)^t$)

Combining (1) and (2) can be represented using a common parameter vector $\vec{c}$ as follows [12].

$$\begin{aligned} X &= S_0 + Q_s \vec{c} \\ g &= T_0 + Q_g \vec{c} \end{aligned} \tag{8}$$

Modeling shape and texture as in (8) is called (combined) AAM.

B. AAM Fitting

Fitting AAM model (8) into a new image is an optimization problem.

By finding parameter vector $\vec{c}$ minimizing the squared error between the texture of a modeled face as (8) and a new image, one can decide the face represented by (8) as the face to be aligned in the new image. And, facial feature points represented by $X = S_0 + Q\vec{c}$ are considered as the final feature points to be localized. How to find parameter vector $\vec{c}$ minimizing the squared error and how to set the initial parameter vector for fitting process depends on AAM algorithms. Usually, the initial parameter vector is set to match the mean shape.

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IV. Face Recognition based on AAM and Gabor Feature Vectors

The proposed face recognition algorithm based on AAM and Gabor feature vectors proceeds in three stages: modeling stage, registration stage, and recognition stage (refer to Fig. 1). In modeling stage (omitted in Fig. 1), Model Bunch Graph about M normalized face model images are constructed (refer to Section 2.2). In registration stage, the proposed algorithm first localizes the facial feature points from the normalized face images to be registered using AAM and refines the localization of facial feature points based on Gabor jet similarity. Next, it extracts Gabor feature vectors at all facial feature points and registers them into database.

In recognition stage, the algorithm locates facial feature points in the same way as in registration stage, that is, using AAM and Gabor jet similarity, and extracts Gabor feature vectors at the facial feature points. Next, it measures similarity between the extracted Gabor feature vector of a new coming face image and registered Gabor feature vectors in database, and finally decide whether pass or rejection, that is, whether the coming person is one of the registered persons or not. The decision for pass or rejection in our face recognition algorithm is basically based on the similarity between Gabor jets of a new incoming face image and Gabor jets in the registered database, but in order to reduce recognition failure rate (especially FAR), we devise ranking rule based on Gabor jet similarity and decide pass or rejection based on this ranking rule.

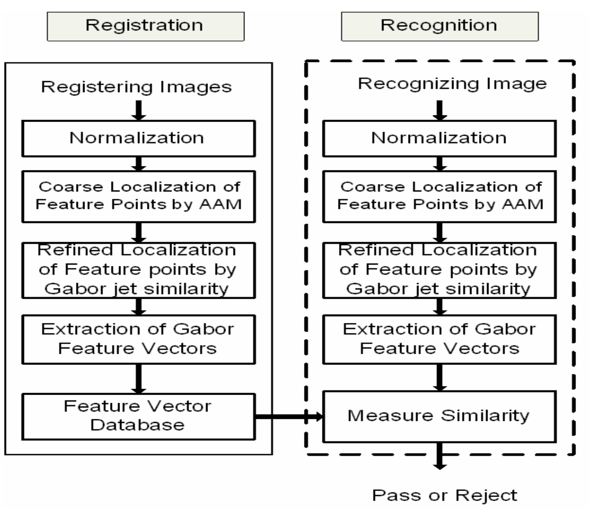

Fig. 1 The Proposed Face Recognition algorithm using AAM and Gabor Feature Vectors

In order to enhance the efficiency of localization of feature points, size normalization of images is necessary. Since eyes are one of the most prominent facial feature points which can be successfully used for face size normalization, eye localization is very important process before normalization [1,16]. We use Ada-Boosting algorithm [19] to detect face in a new incoming image. The faces detected by Ada-Boosting methods do not have regular size since the incoming images can be taken in different positions from the camera. Therefore, normalization process where face poses are rendered to be upright and face sizes are regularized is necessary for fair and efficient feature extraction. After we estimate tilt angle of face rotation in an image by using information about valleys and edges [20], we rotate the original image by the reverse tilt angle and render the face image upright. For the upright images, we detect faces and normalize the faces into size 256×256. For the normalized upright face image, all feature points are localized by combination of AAM and Gabor jet similarity, and feature vectors at the localized feature points are extracted by convolving Gabor wavelet kernels with the pixels of feature points. .

V. Experiments

A. Experiment Environments

In order to evaluate our proposed algorithm, we construct and use a domestic face databases in our experiments.

The domestic face database consists of 515 images of 76 persons with different poses and illuminations. Each image is JPEG with a resolution of 640×480. Some face images of our domestic face database are shown in Fig. 2.

Fig. 2 Some face images of the domestic face database

We use 245 images of 49 persons for registration, and 270 images of 54 persons for the test of recognition. In the test of recognition, 27 persons among 54 testing persons are selected from registered persons in order to see the FAR (False Acceptance Rate) and FRR (False Rejection ratio) at the same time.

B. Experiment Results

Table I shows the experiment results. Fig. 3 and Fig. 4 show the difference between two feature point localization methods: localization only by Gabor jet similarity and localization by combination of AAM and Gabor jet similarity. Fig. 3 shows that localization of facial feature points only by Gabor jet similarity does not work well for profiled face images while it works well for front view face images, but Fig. 4 shows that localization of facial feature points by combination of AAM and Gabor jet similarity relatively works well even for profiled face images. Table I shows that improvement in facial feature localization by combination of AAM and Gabor jet similarity decreases FRR.

TABLE I
COMPARISON BETWEEN THE PROPOSED FACE RECOGNITION ALGORITHM AND THE FACE RECOGNITION ALGORITHM BASED ON THE BASIC GABOR FEATURES ONLY

Algorithms	FRR (%)	FAR (%)
Gabor Features only	9.53	0
Proposed Algorithm	4.76	0

Fig. 3 Localization of facial feature points only by Gabor jet similarity

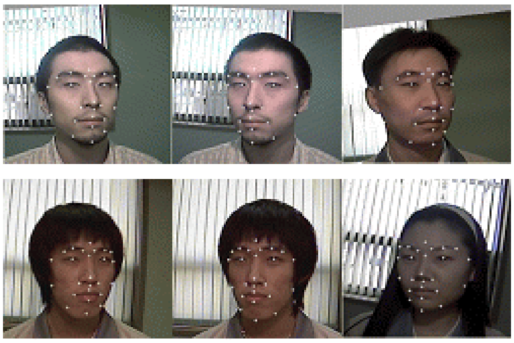

Fig. 4 Localization of facial feature points using AAM and Gabor jet similarity

VI. CONCLUSION

In this paper, we propose a robust face recognition algorithm using AAM and Gabor features. AAM is used for estimating initial values for localization of facial feature points by Gabor similarity.

Experiment results show the facial feature localization method using AAM and Gabor feature vectors is more robust to poses and illuminations than that using Gabor feature vectors only, and thus that the proposed face recognition algorithm using AAM and Gabor features performs better than that using Gabor features only.

Currently, we are testing our proposed algorithm for various face databases and real-time face recognition processing, and in the future will report the experiment results.

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