Face Recognition Using Face-ARG Matching

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Abstract—In this paper, we propose a novel line feature-based face recognition algorithm. A face is represented by the *Face-ARG* model, where all the geometric quantities and the structural information are encoded in an Attributed Relational Graph (ARG) structure, then the partial ARG matching is done for matching Face-ARG's. Experimental results demonstrate that the proposed algorithm is quite robust to various facial expression changes, varying illumination conditions and occlusion, even when a single sample per person is given.

Index Terms—ARG matching, face recognition, structural representation, stochastic analysis.

1 Introduction

Face recognition has been one of the most challenging and active research issues in computer vision for several decades [1]. A great deal of effort has been devoted to robustly identifying individuals under several facial variations including expression, pose, illumination changes, and occlusion. Facial features in a face image can be severely distorted and sometimes disappear due to some facial variations. Many appearance-based face recognition techniques based on the conventional component analysis techniques such as PCA [2], LDA [17], ICA [19], Kernel PCA [3], and NMF [14] have difficulty in administering substantial amount of facial variations as well as the new class sample analysis. Recently, the face recognition techniques using the generative subspace analysis or the generic face model were recently introduced in order to cope with illumination and pose changes [5], [8], [18]. Belhumeur and Kriegman [4] claimed that the set of images of an object taken under all possible illumination conditions with a fixed camera pose forms a convex illumination cone in the space of images and it can be reproduced by only a few images. Georghiades et al. [5] proposed a face recognition method based on the illumination cone robust to light changes. However, the discrimination capability for large database has not been tested and furthermore, the recognition process is very complex. And Gross et al. [9] used the Fisher light-fields to recognize faces across both pose and illumination simultaneously. On the other hand, a generic morphable 3D face model was introduced to estimate the shape and texture parameters of a face [8]. Although this method is somewhat robust to the pose and illumination changes, it is applicable only when the approximate pose and illumination conditions are given or estimated. Facial expression variation is another factor that makes face recognition difficult [27]. Martinez [24], [25] coped with this problem by directly estimating the deformation of a face caused by expression. In his scheme, the processes of identification and facial expression recognition are connected by a feed-forward like relation.

Aside from above distortions, other facial information loss, such as occlusion of faces by scarfs or digression of faces due to shadows and specular reflections, also affects the face recognition performance severely. Recently, several methods have been proposed to cope with partially corrupted faces. Hwang and Lee [13] reconstructed damaged regions by interpolating or extrapolating them in the linear subspace. Leonardis and Bischof [11] rejected outliers and dealt with occlusion through a hypothesize-and-test paradigm using subsets of image points. Black and Jepson [12] calculated the coefficients by a conventional robust M-estimator to eliminate outliers.

In general, most face recognition techniques seem to be inadequate when small and nonrepresentative training sets are given. Martinez [7] proposed a probabilistic face recognition approach that could compensate for the imprecise localization, partial occlusion, and extreme expressions with a single training sample. However, the recognition performance is severely affected by the illumination changes. Recently, the LEM (Line Edge Map) face recognition approach together with the generic LHD (Line segment Hausdorff Distance) [6] achieved a relatively high recognition rate under the pose, illumination and size variations with only one training face image per individual. However, it showed weak performance under severe distortions such as screaming and occlusion.

In this paper, we propose a novel face recognition algorithm not only comparable to [7] in the presence of occlusions and expression changes but also as good as [6] for illumination variations, even when only a single sample per person is available. Psychological studies [20], [21] indicate that a set of simple lines characterizing the structure of an object are sufficient to identify its shape and recognizable as gray-level images since the line drawings preserve most important feature information. The line segments are less sensitive to illumination changes and local variations since they integrate the inherent local structural characteristics with spatial information of a face image [6]. In this paper, being motivated by these psychological findings, a face is encoded by the Face-ARG, which consists of a set of nodes (line features) and binary relations between them, then the partial ARG matching algorithm [16] is employed in order to match Face-ARGs. Since the Face-ARG represents not only the local structural information but also the whole structure of a face, it improves upon the simple local characteristics of LEM [6]. Moreover, since the Face-ARG can be constructed using only a single face image, the proposed method has the same advantages as [6] and [7]. The proposed algorithm consists of two-phases. In the first stage, the correspondence graph of the reference Face-ARG and the test Face-ARG is constructed using the partial ARG matching algorithm [16] through the stochastic analysis of the feature correspondence in the relation vector space. Then, in the second stage, the stochastic distance between the corresponding relation vector spaces of the extracted subgraphs is evaluated and compared for the identification of a face.

The paper is organized as follows: In Section 2, the Face-ARG is described in detail. Section 3 defines the correspondence graph. The subsequent section develops the similarity measure and the face recognition process. Section 5 presents the experimental results. The concluding remarks are drawn in Section 6.

2 The Description of the Face-ARG

The Face-ARG consists of a set of nodes and binary relations between them (Fig. 1). In order to enhance the robustness of the representation to noise and occlusion, the relation vector space is employed in encoding the ARG [16]. A face can be described by an ordered triple Face-ARG model defined as

$$Face - ARG : \mathcal{G} = (\mathcal{V}, \mathcal{R}, \mathcal{F}), \tag{1}$$

where $\mathcal{V} = \{v_1, \ldots, v_N\}$ is the set of nodes of the graph, $\mathcal{R} = \{r_{ij} | v_i, v_j \in \mathcal{V}, i \neq j\}$ is the set of binary relation vectors between the nodes, and $\mathcal{F} = \{\mathcal{R}_i | i = 1, \ldots, N\}$ is the set of relation vector spaces of the nodes. The relation vector space $\mathcal{R}_i = \{\mathbf{r}_{ij} | j = 1, \ldots, N, j \neq i\}$, for $i = 1, \ldots, N$, represents the set of relation vectors between the node v_i and other nodes in $\mathcal{V}$. These relation vector spaces enable the Face-ARG to effectively describe the structural information of a face centered at a specific feature. Now,

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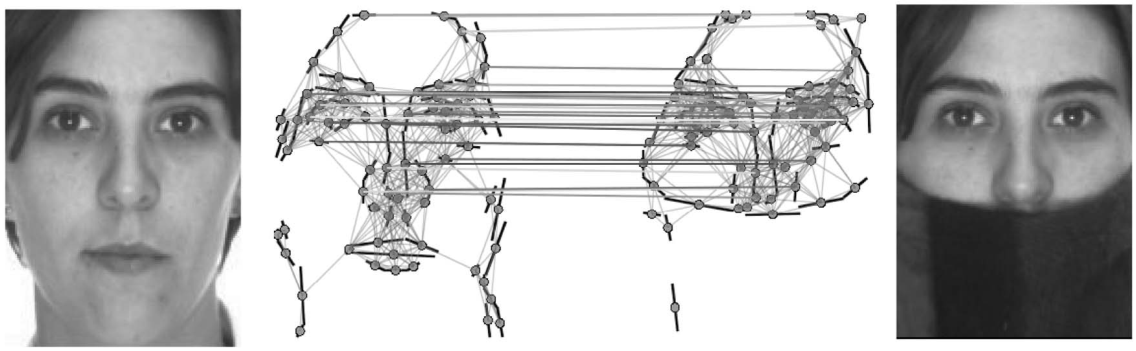

Fig. 1. An example of the Face-ARG representation and partial matching, in which a line segment is assigned as a node. Circles and thin lines in the figure denote the nodes and the edges of the Face-ARG, respectively.

it can be argued that if two faces are similar, then the relation vector spaces of corresponding features in their Face-ARG models should also be similar. Thus, by comparing the relation vector spaces of the features of two faces, we can establish the correspondence between features and then detect occlusion and finally evaluate the similarity between two faces.

In this paper, straight line segments are employed as face features, i.e., the nodes of a Face-ARG and the Nevatia-Babu algorithm was used for the line extraction [26]. To encode the mutual relations between a pair of line features (v_i, v_j), following six different types of measure are defined and used.

$$\begin{aligned} &r_{ij}(1) = \theta, r_{ij}(2) = \theta_c, r_{ij}(3) = \theta_m, \\ &r_{ij}(4) = DR, r_{ij}(5) = m_{ij,x}, r_{ij}(6) = m_{ij,y}, \end{aligned} \tag{2}$$

where, $r_{ij}(k), k = 1, \ldots, 4,$ are the same as defined in [16], which are RTS (Rotation, Translation, and Scale) invariant binary relations. $r_{ij}(5)$ and $r_{ij}(6)$ are the coordinates of the mean position vector $\mathbf{m}_{ij}$, which is the midpoint of two midpoints, $\mathbf{m}_i$ and $\mathbf{m}_j$ of v_i and v_j.

The Face-ARG model is similar to LEM in that a face is represented by a set of line segments. However, LEM only includes pixel-based local structural characteristics without considering the global structure in a face. A good deal of modern cognitive researchers have suggested that face features are perceived by human in a holistic (or configurational) manner with some kind of interactions between them [22], [23]. Provided that the binary relations are sufficient enough to describe the interrelation between line segments, the interferences between features of a face can be accommodated by employing the relation vector space representation. So, the proposed Face-ARG representation will be in accordance with these cognitive psychological findings. Due to this property, as will be discussed in the experimental section, the proposed Face-ARG algorithm outperforms LEM method, especially under global changes between facial features.

3 The Correspondence Graph

3.1 Definition of the Correspondence Graph

Assume that two Face-ARGs, $\mathcal{G}_1$ and $\mathcal{G}_2$ are given by

$$\mathcal{G}_k = \{\mathcal{V}^{\mathcal{G}_k}, \mathcal{R}^{\mathcal{G}_k}, \mathcal{F}^{\mathcal{G}_k}\}, k = 1, 2. \tag{3}$$

Let us define the directional correspondence between two nodes as follows:

Definition 1. *The* ith *feature in the Face-ARG,* $\mathcal{G}_1$ *has* directional correspondence *to the* lth *feature in the Face-ARG,* $\mathcal{G}_2$ *in terms of conditional probability, if* $|p(v_i^{\mathcal{G}_1} = v_l^{\mathcal{G}_2} | \mathcal{G}_1) - 1| \ll \epsilon$ *for small* $\epsilon > 0$ *and it is denoted by* $v_i^{\mathcal{G}_1} \rightarrow v_l^{\mathcal{G}_2}$.

Note that $v_l^{\mathcal{G}_2} \rightarrow v_i^{\mathcal{G}_1}$ is not guaranteed for $v_i^{\mathcal{G}_1} \rightarrow v_l^{\mathcal{G}_2}$. So, let us define *one-to-one correspondence* as the extension of the *directional correspondence*.

Definition 2. *The* ith *feature in the Face-ARG,* $\mathcal{G}_1$ *and the* lth *feature in the Face-ARG,* $\mathcal{G}_2$ *have* one-to-one correspondence *in terms of conditional probability, if* $|p(v_i^{\mathcal{G}_1} = v_l^{\mathcal{G}_2} | \mathcal{G}_1) - 1| \ll \epsilon_1$ *and* $|p(v_l^{\mathcal{G}_2} = v_i^{\mathcal{G}_1} | \mathcal{G}_2) - 1| \ll \epsilon_2$ *for small* $\epsilon_1 > 0$ *and* $\epsilon_2 > 0$*, and it is denoted by* $v_i^{\mathcal{G}_1} \leftrightarrow v_l^{\mathcal{G}_2}$.

Now, let us define *a correspondence graph* between $\mathcal{G}_1$ and $\mathcal{G}_2$ by

$$\mathcal{G}^{\mathcal{G}_1 \leftrightarrow \mathcal{G}_2} = \left(\mathcal{V}^{\bar{\mathcal{G}}_1}, \mathcal{V}^{\bar{\mathcal{G}}_2}, \mathcal{R}^{\bar{\mathcal{G}}_1}, \mathcal{R}^{\bar{\mathcal{G}}_2}, \mathcal{F}^{\bar{\mathcal{G}}_1}, \mathcal{F}^{\bar{\mathcal{G}}_2}, \mathcal{C}^{\mathcal{G}_1 \leftrightarrow \mathcal{G}_2}\right), \tag{4}$$

where $\bar{\mathcal{G}}_k \subseteq \mathcal{G}_k, k = 1, 2$ are subgraphs of the original graphs, in which all nodes have the one-to-one correspondence to each other, such that $v_i^{\bar{\mathcal{G}}_1} \leftrightarrow v_i^{\bar{\mathcal{G}}_2}$. $\mathcal{C}^{\mathcal{G}_1 \leftrightarrow \mathcal{G}_2}$ is the set of node pairs, which have the one-to-one correspondence, given by

$$\mathcal{C}^{\mathcal{G}_1 \leftrightarrow \mathcal{G}_2} = \left\{ \left(v_i^{\mathcal{G}_1}, v_l^{\mathcal{G}_2}\right) | v_i^{\mathcal{G}_1} \leftrightarrow v_l^{\mathcal{G}_2} \right\}. \tag{5}$$

In Fig. 2, an example of a correspondence graph construction is shown. In this figure, we note that $v_2^{\mathcal{G}_1} \rightarrow v_2^{\mathcal{G}_2}$ is true, but $v_2^{\mathcal{G}_2} \rightarrow v_2^{\mathcal{G}_1}$ is not, thus the two nodes $v_2^{\mathcal{G}_1}$ and $v_2^{\mathcal{G}_2}$ don't have the one-to-one correspondence relationship. So, the final correspondence graph, $\mathcal{G}^{\mathcal{G}_1 \leftrightarrow \mathcal{G}_2}$ does not include them.

3.2 Generation of the Correspondence Graph

The directional correspondences between two Face-ARGs can be obtained by using the partial ARG matching technique [16], which consists of two-phases, "Selection of candidate subgraphs" and "Occlusion detection," as shown in Fig. 3. In the first stage,

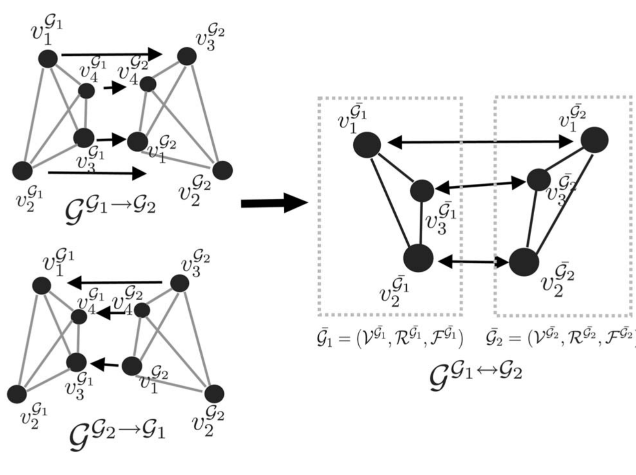

Fig. 2. A correspondence graph between $\mathcal{G}_1$ and $\mathcal{G}_2$.

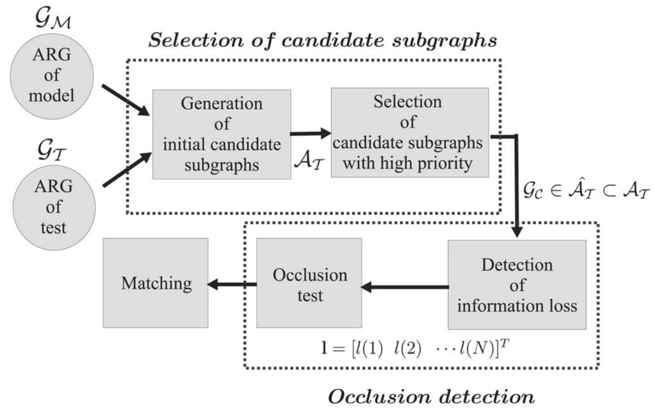

Fig. 3. Block diagram and data flows for the partial ARG matching process. $\mathcal{A}_\mathcal{T}$ is the total set of initial candidate subgraphs and $\hat{\mathcal{A}}_\mathcal{T}$ is the subset of $\mathcal{A}_\mathcal{T}$, which consists of candidate subgraphs, $\mathcal{G}_\mathcal{C}$s, with high priority [16].

candidate subgraphs for the reference model matching are extracted by the stochastic analysis in the relation vector spaces. Then, the missing features are detected by employing the error detection inequality and the voting schemes repeatedly until no more feature is found to be lost [16]. So, two directional correspondences between two Face-ARGs, $\mathcal{G}_1$ and $\mathcal{G}_2$ can be obtained as,

$$\begin{aligned}\mathcal{C}^{\mathcal{G}_1\rightarrow\mathcal{G}_2} &= \left\{\left(v_i^{\mathcal{G}_1}, v_l^{\mathcal{G}_2}\right)|v_l^{\mathcal{G}_2} \in \mathcal{V}_2^{\mathcal{G}}, v_i^{\mathcal{G}_1} \rightarrow v_l^{\mathcal{G}_2}\right\},\\ \mathcal{C}^{\mathcal{G}_2\rightarrow\mathcal{G}_1} &= \left\{\left(v_l^{\mathcal{G}_2}, v_i^{\mathcal{G}_1}\right)|v_i^{\mathcal{G}_1} \in \mathcal{V}_1^{\mathcal{G}}, v_l^{\mathcal{G}_2} \rightarrow v_i^{\mathcal{G}_1}\right\}.\end{aligned} \tag{6}$$

Then, by examining (6), we can easily establish the one-to-one correspondences between features in the reference face model and the test face as follows:

$$\mathcal{C}^{\mathcal{G}_1\leftrightarrow\mathcal{G}_2} = \left\{\left(v_i^{\mathcal{G}_1}, v_l^{\mathcal{G}_2}\right)|v_i^{\mathcal{G}_1} \leftrightarrow v_l^{\mathcal{G}_2}\right\}. \tag{7}$$

The correspondence graph between two Face-ARGs can be constructed by the definition in (4). An example of established correspondences by the proposed method is shown in Fig. 1, in which the corresponding features are connected by solid lines. Note that, in contrast to [16] in which matching is done using the directional correspondences, since the proposed algorithm employs the one-to-one correspondences, the false correspondence matching rate decreases drastically and it results in much higher recognition rate than [16].

4 Similarity between Two Face-ARGs and Face Recognition

4.1 Similarity between Two Face-ARGs

Given the correspondence graph, $\mathcal{G}^{\mathcal{G}_1\leftrightarrow\mathcal{G}_2}$ of two Face-ARGs, $\mathcal{G}_1$ and $\mathcal{G}_2$, with N corresponding node pairs, the similarity [16] between them can be measured by

$$\mathcal{S}\left(\mathcal{G}^{\mathcal{G}_1\leftrightarrow\mathcal{G}_2}\right) = \sum_{i=1}^{N}\mathcal{D}(\mathcal{R}_i)\cdot\omega_i = \sum_{i=1}^{N}\omega_i\cdot\left[\prod_{j=1,j\neq i}^{N} p(\mathbf{r}_{ij}^{\bar{\mathcal{G}}_2} - \mathbf{r}_{ij}^{\bar{\mathcal{G}}_1})\cdot\gamma_{ij}\right], \tag{8}$$

where $\mathcal{D}(\mathcal{R}_i)$ is a function that measures the difference between the relation vector spaces $\mathcal{R}_i^{\bar{\mathcal{G}}_1}$ and $\mathcal{R}_i^{\bar{\mathcal{G}}_2}$. $p(\mathbf{r}_{ij}^{\bar{\mathcal{G}}_2} - \mathbf{r}_{ij}^{\bar{\mathcal{G}}_1})$ is the probability of error in the relation vector space and ω_i and γ_{ij} are the weighting factor of the feature v_i and the weighting factor for the binary relation between feature v_i and v_j, respectively. In this paper, we assume that the error of the relation vector is Gaussian and the elements are statistically independent. As for $r_{ij}(5)$ and $r_{ij}(6)$, they are modeled by clipped Gaussian distribution as follows:

$$\begin{aligned}&p(\Delta = |(r_{ij}(5), r_{ij}(6)) - (\tilde{r}_{ij}(5), \tilde{r}_{ij}(6))|)\\ &= \begin{cases}\frac{1}{\sqrt{2\pi}\sigma_e}\cdot exp\left(-\frac{\Delta^2}{2\sigma_e^2}\right), & \text{if } |\Delta| < D_{thres},\\ P_c = \frac{1}{\sqrt{2\pi}\sigma_e}\cdot exp\left(-\frac{D_{thres}^2}{2\sigma_e^2}\right), & \text{otherwise.}\end{cases}\end{aligned} \tag{9}$$

4.2 Face Recognition

For the identification of a given test face, the test face $\mathcal{G}_\mathcal{T}$ is matched to all the reference faces $\mathcal{G}_\mathcal{M}$s in the face database ($\mathcal{FDB}$). Then, we select the best matched identity among the database which gives the highest similarity value above some prespecified threshold as the final recognition.

$$Face - ID = \arg\max_{\mathcal{G}_\mathcal{M}\in\mathcal{FDB}} S(\mathcal{G}^{\mathcal{G}_\mathcal{M}\leftrightarrow\mathcal{G}_\mathcal{T}}). \tag{10}$$

5 Experimental Results

For the evaluation of the proposed algorithm's performance, it was tested on the AR face DB, which is composed of color images of 135 people (76 men and 59 women) [10]. The AR face DB includes frontal view images with different facial expressions, illumination conditions, and occlusion by sunglasses and scarf; examples are presented in Fig. 4. All images used for experiments were normalized to face images of 120 by 170 pixels using the same warping method described in [7].

5.1 Analysis on the Effect of the Imprecise Line Extraction

In general, imprecise line extraction or noise can affect the overall performance of the line feature-based face recognition algorithms such as ours. There are usually three kinds of distortions: 1) position error, 2) loss of line segments, and 3) broken line segments. In order to investigate the robustness to the imprecise feature extraction, we evaluated the recognition rates of the proposed algorithm and LEM [6] method for those three kinds of distortions. In this experiment, 135 neutral frontal images in Fig. 4a were used for the gallery. They were also synthetically corrupted by three kinds of variations and used for test images as shown in Fig. 5. We added Gaussian noise to the end points of the line segments to impose the position error. For the realization of the lost line segments, some line segments were randomly eliminated. For the broken lines, random line segments were broken and Gaussian noise was added to the end points. The recognition results are summarized in Fig. 6, where the loss rate and

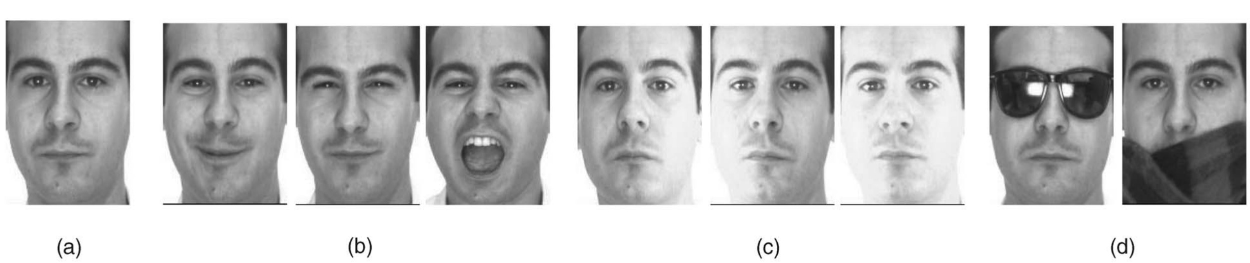

Fig. 4. The AR face database: Frontal faces (a) in normal, (b) under expression variations, (c) under illumination changes, and (d) with occlusion.

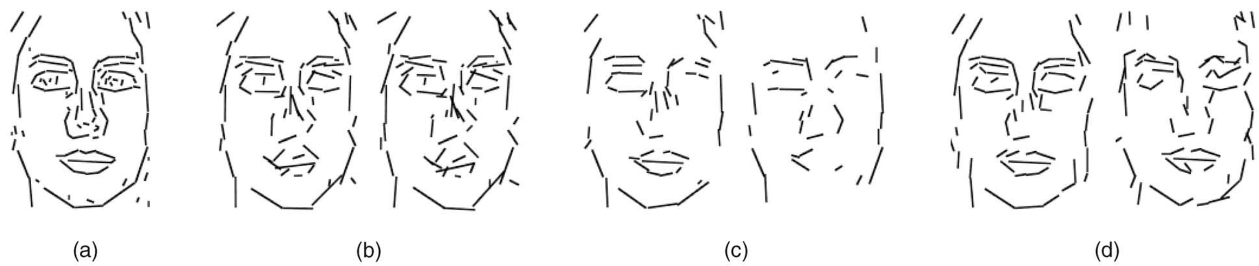

Fig. 5. Examples of feature variations due to the imprecise line extraction. (a) Original facial lines. (b) Lines with position error. (c) Lines with missing lines. (d) Lines with broken lines.

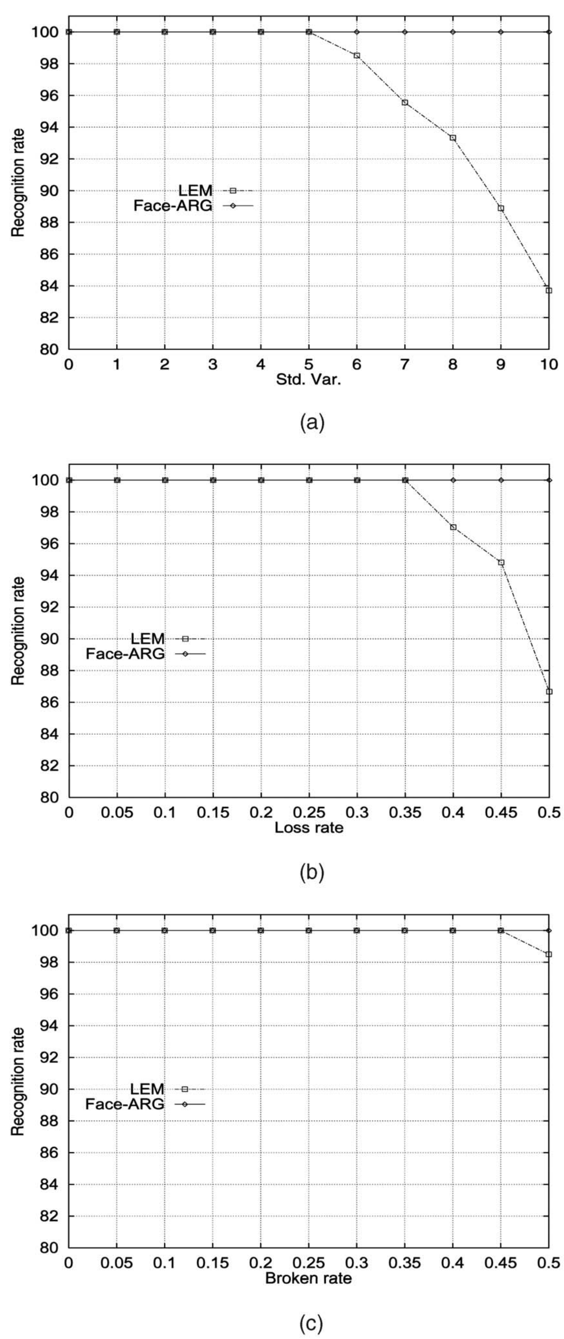

Fig. 6. The recognition rates of the proposed approach and LEM according to three kinds of variations.

the broken rate are the ratio of the number of missing lines and broken lines to the number of all line segments, respectively. The results show that the performance of the proposed algorithm is quite robust to those three kinds of distortions caused by the imprecise line extraction. In contrast, performance of LEM degraded severely especially for the position error and missing line segments when the variations became large.

We also conducted an experiment on other types of test images with different facial variations as shown in Figs. 4b, 4c, and 4d. In this experiment, 30 percent of line segments were broken, 10 percent of them were excluded, and Gaussian noise with $\sigma = 5.0$ was added on all the test images. The recognition result is presented in Fig. 7. The average recognition rate of the LEM method was severely degraded from 75 percent to 37.3 percent due to the imprecise line extraction, while the recognition rate of the proposed algorithm decreased only 21.6 percent (from 89.1 percent to 67.5 percent).

5.2 Analysis on the Effect of Parameter Setting

Here, let us list a few parameters that are involved in the proposed algorithm including,

- σ_ks, $k = 1, \ldots, 4,$ for the Gaussian error model of the four binary relations in (2).
- σ_e and D_{thres} in (9).
- Threshold value (f) for detecting the information loss in partial ARG matching [16].

As with many other vision algorithms, the optimal values of these parameters depend on the types of images. Especially, in case of σ_ks since the binary relations represent widely different types of physical quantities between two line features, the distributions and dynamic ranges become very different from each other. Thus, we could not theoretically optimize these parameters, but we can determined each one empirically. In our experiments, $\sigma_k, k = 1, 2, 3,$ were set to $\pi/6$, and σ_4 to the standard deviation of the binary relation value in the reference model. σ_e was set to $D_{thres}/\sqrt{2}$. We observed that setting of these parameters was not sensitive to a wide range of variations [16]. However, the choice of the other two parameters, D_{thres} and f, had important effect on the overall performance of the proposed algorithm since a high D_{thres} value makes the Face-ARG model have more interference between nodes, and a high f enforces the partial ARG matching to detect the missing features more rigorously. In order to investigate the effect of each parameter, we evaluated the recognition rate according to them. Fifty subjects were randomly selected from the AR face DB. For each subject, we used one neutral face image for a model and other images of smile, anger, and occlusion by sunglasses and scarf were used for the test. Fig. 8 represents the recognition results. When f is above 0.9 and D_{thres} is below $10\sqrt{2}$, the recognition rate was very low, especially for the occluded face images. It reveals that the global structure and the number of interrelations between nodes are important factors in face recognition robust to severe facial distortions. When $D_{thres} = 15\sqrt{2}$, the proposed algorithm showed good results regardless of the value of f. However, we found that $(D_{thres}, f) = (10\sqrt{2}, 0.7)$ were the optimal parameters that produces the best average recognition rate of 95 percent.

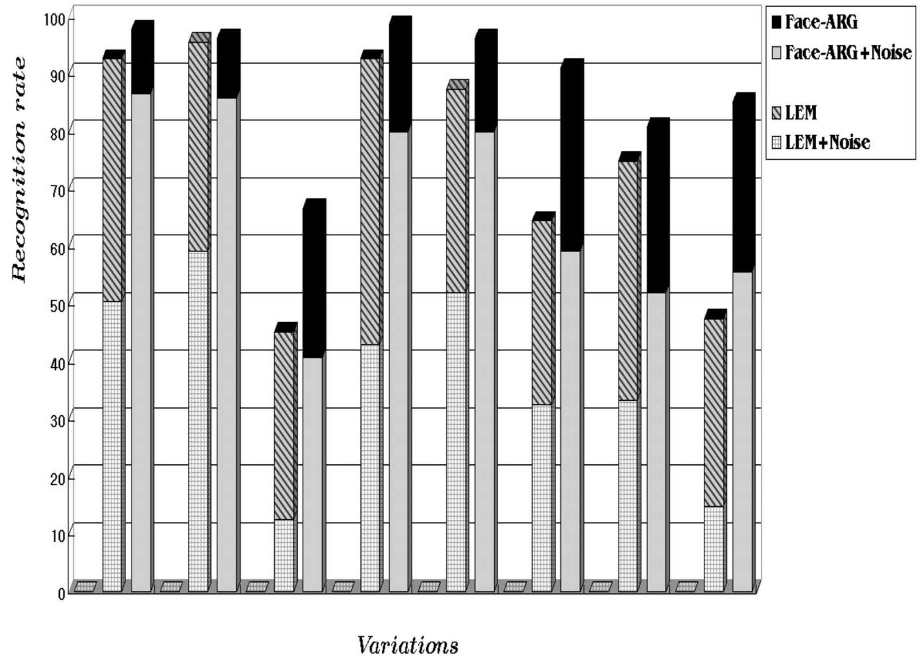

Fig. 7. The recognition rates of the proposed approach and LEM with/without noise due to the imprecise line extraction.

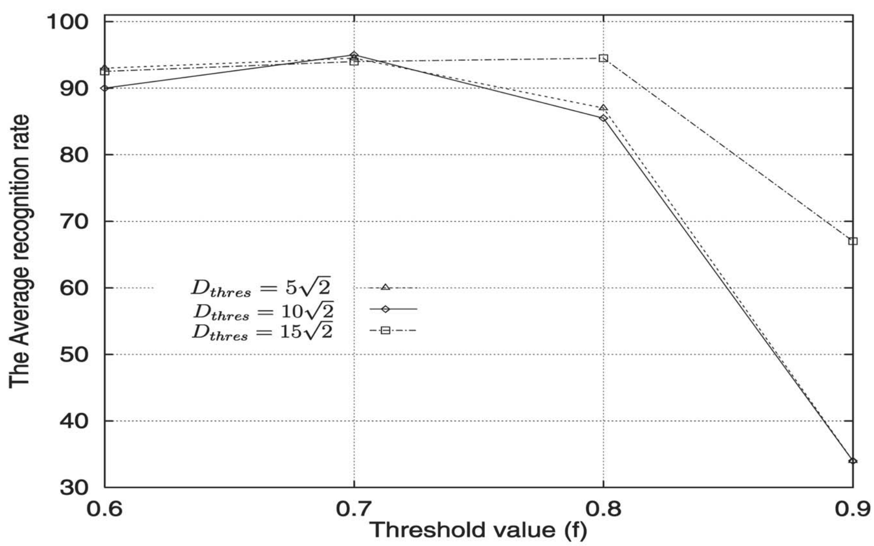

Fig. 8. The recognition results of the proposed approach according to the parameters, (D_{thres}, f).

5.3 Recognition Results on the Real Face DB

The performance of the proposed algorithm (Face-ARG) was compared with several conventional face recognition approaches including 1-NN, PCA [2], and NMF [14] method. In contrast to PCA which imposes orthonormal and orthogonal constraints for the bases and coefficients, respectively, NMF enforces nonnegativeness constraint on both bases and coefficients [14]. These different types of constraints during the learning phase result in different representations of faces. Unlike the basis images of PCA which are holistic, those of NMF are localized and part-based. Due to this sparse and local encoding characteristic, the face recognition using NMF representations has been known to be robust especially to partial occlusion. In this experiment, the performances of the original NMF [14] and modified local NMF (LNMF) [15] on the same face DB were evaluated for comparison. In addition to these, the performance of our algorithm has been compared to the LEM method (LEM) [6], and the method by Martinez (AMM) [7]. Similar to our method, both algorithms use a single frontal face image for the training of each individual. To guarantee the automatic face recognition and lessen the effect of the parameters, we fixed all parameters of our algorithm with the values obtained in Section 5.2.

The AR face DB was used for the performance evaluation of the algorithms under varying conditions. The Face-ARG with 70 nodes was constructed from each face. The neutral frontal views of 135 people were used for the gallery and other face images in Figs. 4b, 4c, and 4d were used for the test on expression changes, illumination variations, and occlusion by sunglasses and scarf, respectively. The recognition results are presented in Table 1. It is noted that since it may be meaningless to use NMF, LNMF, and AMM without any preprocessing for illumination compensation when there are large illumination variations the corresponding columns read N/A (Not Applicable). In most cases, the proposed algorithm produced superior performance compared to other face recognition approaches. Especially, for the case of the extreme

TABLE 1
The Recognition Rate on the AR Face Database

	Smile	Angry	Scream	Glasses	Scarf	Left-Light	Right-Light	Both-Light
1-NN	96.3%	88.9%	57.0%	48.1%	3.0%	22.2%	17.8%	3.7%
PCA	94.1%	79.3%	44.4%	32.9%	2.2%	7.4%	7.4%	2.2%
NMF	68.1%	50.4%	18.5%	3.7%	0.7%	N/A[a]	N/A	N/A
LNMF	94.8%	76.3%	44.4%	18.5%	9.6%	N/A	N/A	N/A
LEM[b]	78.6%	92.9%	31.3%	74.8%	47.4%	92.9%	91.1%	74.1%
AMM[c]	96.0%	96.0%	56.0%	80.0%	82.0%	N/A	N/A	N/A
Face − ARG	**97.8%**	**96.3%**	**66.7%**	**80.7%**	**85.2%**	**98.5%**	**96.3%**	**91.1%**

[a] *N/A: Not Applicable.* [b] *Results in [6] with 112 people in the AR face DB.* [c] *Results in [7] with 50 people in the AR face DB.*

expression such as screaming, where most features still exist but severely distorted, the proposed algorithm produced much better results than other approaches. We have observed that the performance of our algorithm on the faces with scarf was better than with glasses. This is because our Face-ARG model utilizes the features near the eyes heavily in constructing the graph nodes, so occlusions in those regions may cause substantial degradation in the recognition performance. Under varying illumination conditions, similarly the proposed algorithm outperformed the conventional appearance-based recognition techniques. Note that the performance of the LEM method is better than the appearance-based methods too since LEM also uses the line features that are relatively insensitive to illumination changes. However, when the lighting condition becomes severe such as when both lights are lit on, local specularity, or shading might cause substantial amount of distortions or loss of facial features. In this case, the recognition rate of LEM dropped significantly by about 18 percent. However, the proposed algorithm showed only 5.1 percent to 7.4 percent decreases in the overall recognition rate. From these results, we can conclude that the proposed algorithm is quite robust to the local changes, partial occlusions, and imprecise low-level processing.

5.4 Computational Complexity

Since the proposed algorithm uses a single face image of a person for the gallery, the training and updating time is negligible. Most of processing time of the algorithm goes to the partial graph matching. As is common to most graph matching techniques, the computational complexity of the proposed ARG matching algorithm is relatively high, so that currently it takes about 4 seconds for two Face-ARGs with 70 nodes on a Pentium 2.7GHz CPU. It is one of our future goals to implement the algorithm faster.

6 Conclusion

In this paper, we proposed a novel face recognition algorithm using the partial ARG matching. A face is described by a line feature based Face-ARG model. Since the proposed Face-ARG encodes the whole geometric structure information as well as local features of a face, it is in accordance with cognitive psychological finding, "*face features are perceived in a holistic (or configurational) manner with some kind of interactions between features by human beings*." In order to identify individuals, the correspondence graph of the reference Face-ARG and the test Face-ARG is constructed first by using the partial ARG matching technique. Then, the matching score is obtained by evaluating the similarity between the corresponding subgraphs of the two Face-ARGs.

Since the proposed algorithm can detect and exclude unreliable and inconsistent features by the partial ARG matching, the recognition of face is very robust. Moreover, unlike most algorithms, our algorithm requires a single training face image for a person, so that it can be applied in more general situations where many training samples are not available. The performance results for the AR face DB showed that even in the extreme cases such as screaming and occlusion by sunglasses or scarf, the proposed algorithm produced more robust and superior performance over other methods.

Since the proposed algorithm is based on the 2D RTS invariant binary relations between features, it has shortcomings under severe pose variations. Thus, the extension of our approach to the pose variation problem will be our future research topic. It will be also our future work to address the computational complexity.

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References

[1] W. Zhao, R. Chellappa, J. Phillips, and A. Rosenfeld, "Face Recognition: A Literature Survey," *ACM Computing Surveys*, vol. 35, no. 4, Dec. 2003.

[2] M. Turk and A. Pentland, "Eigenfaces for Recognition," *J. Cognitive Neuroscience*, vol. 3, pp. 71-86, 1991.

[3] P.N. Belhumeur, J.P. Hepanha, and D.J. Kriegman, "Eigen Faces versus Fisherfaces: Recognition Using Class Specific Linear Projection," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 19, no. 7, pp. 711-720, July 1997.

[4] P.N. Belhumeur and D.J. Kriegman, "What Is the Set of Images of an Object under All Possible Illumination Conditions?" *Int'l J. Computer Vision*, vol. 28, no. 3, pp. 245-260, July 1998.

[5] A.S. Georghiades, P.N. Belhumeur, and D.J. Kriegman, "From Few to Many: Illumination Cone Models for Face Recognition under Variable Lighting and Pose," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 23, no. 6, pp. 643-660, June 2001.

[6] Y. Gao and M.K.H. Leung, "Face Recognition Using Line Edge Map," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 24, no. 6, pp. 764-779, June 2002.

[7] A.M. Martinez, "Recognizing Imprecisely Localized, Partially Occluded, and Expression Variant Faces from a Single Sample per Class," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 24, no. 6, pp. 748-763, June 2002.

[8] S. Romdhani, V. Blanz, and T. Vetter, "Face Identification by Fitting a 3D Morphable Model Using Linear Shape and Texture Error Functions," *Proc. Seventh European Conf. Computer Vision*, May 2002.

[9] R. Gross, I. Matthews, and S. Baker, "Appearance Based Face Recognition and Light Fields," Technical Report CMU-RI-TR-02-20, Robotics Inst., Carnegie Mellon Univ., Aug. 2002.

[10] A.M. Martinez and R. Benavente, "The AR Face Database," CVC Technical Report no. 24, June 1998.

[11] A. Leonardis and H. Bischof, "Robust Recognition Using Eigenimages," *Computer Vision and Image Understanding*, vol. 78, pp. 99-118, 2000.

[12] M. Black and A. Jepson, "Eigentracking: Robust Matching and Tracking of Articulated Objects Using a View-Based Representation," *Int'l J. Computer Vision*, vol. 26, no. 1, pp. 63-84, 1998.

[13] B.W. Hwang and S.W. Lee, "Reconstruction of Partially Damaged Face Images Based on a Morphable Model," *IEEE Trans. Pattern Analysis and Machine Intelligence,* vol. 25, no. 3, pp. 365-372, Mar. 2003.

[14] D.D. Lee and H.S. Seung, "Learning the Parts of Objects by Non-Negative Matrix Factorization," *Nature,* vol. 401, pp. 788-791, 1999.

[15] S.Z. Li, X.W. Hou, H.J. Zhang, and Q.S. Cheng, "Learning Spatially Localized, Part-Based Representation," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, pp. 207-212, 2001.

[16] B.G. Park, K.M. Lee, S.U. Lee, and J.H. Lee, "Recognition of Partially Occluded Objects Using Probabilistic ARG-Based Matching," *Computer Vision and Image Understanding,* vol. 90, no. 3, pp. 217-241, June 2003.

[17] W. Zhao, R. Chellappa, and P. Phillips, "Subspace Linear Discriminant Analysis for Face Recognition," Technical Report CAR-TR-914, Center for Automation Research, Univ. of Maryland, College Park, 1999.

[18] A. Shashua and T. Riklin-Raviv, "The Quotient Image: Class Based Re-Rendering and Recognition with Varying Illuminations," *IEEE Trans. Pattern Analysis and Machine Intelligence,* vol. 23, no. 2, Feb. 2001.

[19] T.W. Lee, *Independent Component Analysis: Theory and Applications.* Boston: Kluwer Academic Publishers, 1998.

[20] V. Bruce, E. Hanna, N. Dench, P. Healey, and M. Burton, "The Importance of "Mass" in Line Drawings of Faces," *Applied Cognitive Psychology*, vol. 6, pp. 619-628, 1992.

[21] B.S. Tjan, W.L. Braje, G.E. Legge, and D.J. Kersten, "Human Efficiency for Recognizing 3-D Objects in Luminance Noise," *Vision Research*, vol. 35, no. 21, pp. 3053-3069, 1995.

[22] V. Bruce, *Recognising Faces.* Lawrence Erlbaum Assoc., 1988.

[23] I. Roth and V. Bruce, *Perception and Representation.* Open Univ. Press, 1995.

[24] A.M. Martinez, "Recognizing Expression Variant Faces from a Single Sample Image per Class," *Proc. IEEE Conf. Computer Vision and Pattern Recognition,* 2003.

[25] A.M. Martinez, "Matching Expression Variant Faces," *Vision Research,* vol. 43, no. 9, pp. 1047-1060, 2003.

[26] R. Nevatia and K.R. Babu, "Line Extraction and Description," *Computer Graphics and Image Processing,* vol. 13, no. 1, pp. 250-269, July 1980.

[27] Y. Yacoob and L. Davis, "Smiling Faces Are Better for Face Recognition," *Proc. Int'l Conf. Face Recognition and Gesture Analysis,* pp. 59-64, 2002.