H-030

Eigenphase of Local Normalized Image

Jesus Olivares-Mercado[*†] *Kazuhiro Hotta*[†] *Haruhisa Takahashi*[†] *Hector Perez-Meana*[*]

Abstract

This paper proposes a robust faces recognition method based on the Phase Spectrum Features of the local normalized image. The Principal Components Analysis (PCA) and the Support Vector Machine (SVM) are used in the classification stage. We evaluate how the proposed method is robust to illumination, occlusion and expressions using "AR Face Database", which includes the face images of 109 subjects (60 males and 49 females) under illumination changes, expression changes and partial occlusion. The proposed method provides results with a correct recognition rate more than 95.5%.

1 Introduction

The development of security systems based on biometric features has been a topic of active research during the last three decades. The terrorist attacks happened during the last decade have demonstrated that it is indispensable to have reliable security systems in offices, banks, airports, etc.; increasing in such way the necessity to develop more reliable methods to people recognition. The biometrics systems consist of a group of automated methods for recognition or verification of people identity using physical characteristics of the person under analysis [1]. In particular the face recognition has been a topic of active research because the face is the most direct way to recognize the people. In addition, the data acquisition of this method consists in taking a picture, doing it one of the biometric methods with larger acceptance among the users. Various kinds of face recognition methods have been proposed [2, 3]. In recently years, faces are recognized with high accuracy recognition. However, partial occlusion, illumination variations and expression decrease the accuracy drastically.

The recognition is a very complex activity of the human brain. For example, we can recognize hundred of faces learned throughout our life and to identify familiar faces at the first sight, even after several years of separation. However it is not a simple task for a computer. For instance, recently proposed face recognition systems, achieve a recognition rate of about 90% when the face in the image is not rotated or the rotation is relatively low [4]. Although this recognition rate is good enough for several practical applications, it may be not large enough for applications where the security should be extreme; such that we cannot tolerate a high erroneous recognition rate. In particular illumination, occlusion, facial expressions are big obstacles in the practical environment. This paper proposes a face recognition algorithm that is able of achieving an erroneous recognition rate below 5% with this characteristics.

In recent years, the robust face recognition method using phase spectrum has been proposed [5]. However, they extracted phase information from global image. Global features are influenced easily by illumination, occlusion and expression [12, 13]. Therefore, we use the device for emphasizing the local features of a face image before extracting phase spectrum. Concretely, the norm of local region is normalized in advance. This process is effective for face recognition. When the part of a face is occluded by something such as sunglasses or scarf, global similarity between images is much influenced. In local normalized image, the similarities of some local regions are influenced by occlusion but the similarities of almost local regions are not influenced. Therefore, the local normalized image is robust to partial variations. After normalizing the norm of local region, we extract the phase information in the frequency domain representation. This method is very useful because the phase spectrum of an image retains the most of the intelligibility of this. Furthermore, we can increase the recognition accuracy using the PCA to obtain the main characteristics of the training faces. The features obtained by PCA are fed into one-vs-all SVM.

The proposed method is evaluated using "AR Face Database" [10]. This includes the face images with partial occlusion, illumination variations and expression. The phase spectrum of local normalizes image outperforms conventional eigenphase method [5]. In particular the robustness to partial occlusion is also improved. This shows the effectiveness of the proposed approach.

[*]ESIME Culhuacan, National Polytechnic Institute of Mexico, Santa Ana No. 1000, San Francisco Culhuacan, 04430 Mexico City.
[†]The University of Electro-Communications, 1-5-1 Chofugaoka, Chofu, Tokyo 182-8585, Japan.

2 Proposed System

This section provides a detailed description of the proposed face verification algorithm. Figure 1 shows the block diagram of proposed algorithm.

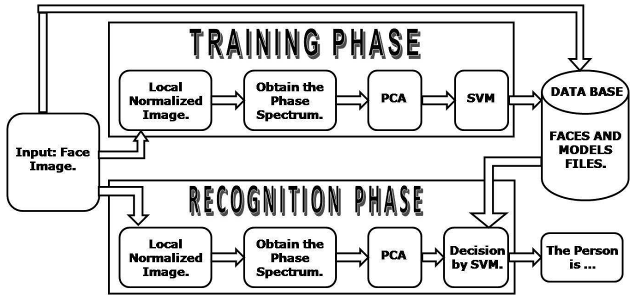

Figure 1: Proposed face recognition algorithm.

Firstly we normalize the norm of the local region of the image. The phase spectrum is extracted from the local normalized image, after that, the Principal Components Analysis (PCA) [6, 14] is applied to the phase spectrum to obtain a dominant feature of the faces. Next, the features in principal components space are fed into classifier based on Support Vector Machine (SVM) [7, 11]. In the final step of training, one-vs-all SVM is used to classify multi-classes. In the final step of test, PCA features of phase spectrum of a test image are fed into all SVMs and the test image is classified to the class given maximum likelihood.

2.1 Feature Extraction Stage.

The proposed algorithm uses the Phase Spectrum of Local Normalized Image. To obtain local normalized image, the norm of local regions of $M \times M$ pixels where $M = 3, M = 6$ and $M = all$ are normalized to 1. Figure 2 shows this process. By normalizing the norm of local regions, it becomes robust to partial variation such as illumination changes or occlusion. We note local region as $I(x)$ where x is the center position of local region, the local norm is normalized as:

$$I(x)' = \frac{I(x)}{\|I(x)\|} \tag{1}$$

where $\|I(x)\|$ is the norm of the local region. All the training images must be normalized before training. In the test, we need to apply the same process before extracting the phase spectrum. In this paper we consider the local normalized image to improve the accurate classification and robustness to partial variations. After normalizing the norm of local region, we extract the phase spectrum. This can be computed through of a Fourier Transform which are given by:

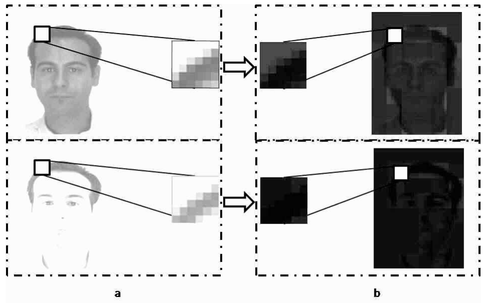

Figure 2: a) Original image. b) Image after apply the normalization.

$$F(u) = |F(u) \exp^{j\phi(u)}| \tag{2}$$

where

$$|F(u)| = [R^2(u) + I^2(u)]^{\frac{1}{2}} \tag{3}$$

is the magnitude, and

$$\phi(u) = \arctan\left[\frac{I(u)}{R(u)}\right] \tag{4}$$

is the phase. Oppenheim et. al [8, 9] have shown that phase information of an image retains the most of the intelligibility of an image. This is also demonstrated by Oppenheim's experiment, please refer [8, 9].

2.2 Classification stage.

To perform the face classification task, a PCA is used to obtain the main characteristics of the faces training, Figure 3 shows the process:

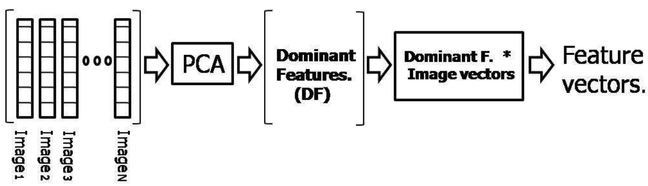

Figure 3: Scheme of feature extraction by PCA.

Image 1, Image 2...Image N in Figure 3 are the phase spectrum of the training faces. In training phase, basis vectors are obtained by PCA. In the testing phase, the basis vectors obtained in training phase are used to extract the features for SVM.

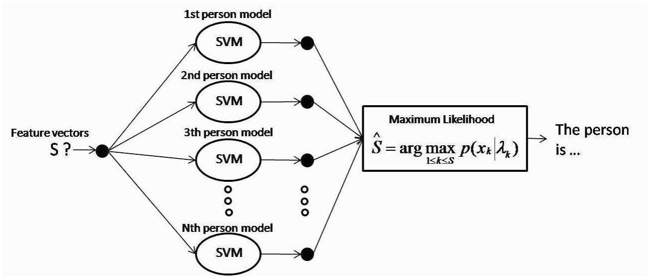

Figure 4: Classification phase by SVM.

After extracting the features by PCA, SVM is used to classify a test face image. Figure 4 shows classification phase. S is the feature vector of the person to recognize. S is applied to all one-vs-all SVMs. The class given the Maximum Likelihood is used as the person's identity, the equation to obtain the Maximum Likelihood is as follows:

$$\hat{S} = \arg\max_{1\le k\le S} P(\lambda_k|x) \tag{5}$$

where $\hat{S}$ is the winner and thus reveals the person's identity to whom this picture was assigned, x is the column vector of the image to analyze and λ_k is the SVM model of the person k.

3 Evaluation Results

The evaluation of proposed system was carried out by computer simulations using "AR Face Database"which includes the face images of 109 subjects (60 males and 49 females) under illumination changes, expression changes and partial occlusion. The images size is 288×384 pixels. In this paper, we resize the image of a 48×36 pixels for processing. Each subject has 39 images, in the followings experiments, 6 images per subject are used in training and the remaining 33 images per subject are used in test.

First the algorithm estimates the normalized image and extract the phase spectrum. Once the normalized image and phase spectrum have been estimated, the image is converted in a column vector and so on with all the training images to implement the process to obtain the features vectors as shown in Fig. 3.

Next, the feature vectors of training images are applied to a SVM to obtain the model of the each class, these models are used in the classification stage, where the input of each one is the feature vector of the face to classify and the output is a probability, and the class to which it belongs is obtained by selecting maximum likelihood as shown in Fig. 4.

In this work we take 3 different variants in the window size to make the local normalized image, and comparing these with the method that only uses the phase spectrum of standard image. We try $M = 3, M = 6$ and $M = all$. $M = all$ means that the window is equal to the size of the image. The local norm is normalized with non-overlap manner. We take another option which is "Normal"as shown in Table 1, "Normal"means that the image will be processed without being normalized. Namely, this is nearly same as eigenphase approach [5].

Table 1: Accuracy on face recognition

	M=3	M=6	M=All	Normal
Training images 1	95.8	94.6	93.2	93.2
Training images 2	79.5	78.3	75	75

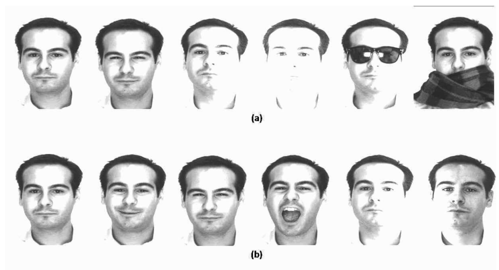

Figure 5: a) Training images 1. b) Training images 2.

The table 1 shows the results with 2 sets of images of training, in the first set of images (training images 1) takes 6 images in which illumination variations, expressions, sunglasses and scarf are included. The Figure 5(a) shows the example of training images 1. The recognition accuracy of $M = 3$ achieves 95.8%, our method outperforms the eigenphase method. The improved rate is 2.6%.

The second set of images (training images 2) takes 6 images which only illumination variations and expressions are included. Therefore the accuracy to the second set shows the robustness to partial occlusion. Figure 5(b) shows the example of the second training set. Table 1 and figure 7 shows accuracy to training image 2. The recognition accuracy of $M = 3$ achieves 79.5%. The improved rate is 4.5%. The difference from eigenphase method becomes larger than that in the training images 1. This shows that the local normalizes image has the robustness to partial variations. Simulation results show that proposed algorithm performs fairly well in comparison with other previously proposed methods [4, 5], even with faces that present different variations, the proposed method achieves high accuracy.

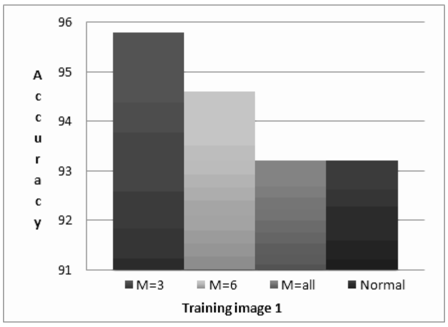

Figure 6: Accuracy using the Training images 1.

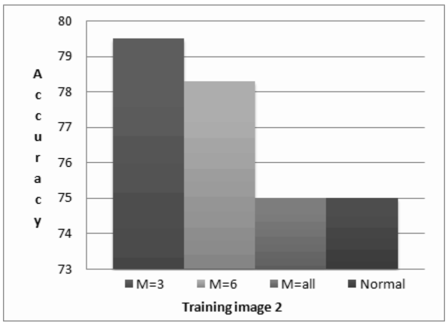

Figure 7: Accuracy using the Training images 2.

4 Conclusions

This paper proposed a face recognition algorithm based on the *Phase Spectrum Features of the local normalized image.* PCA is used for dominant feature extraction and the SVM is used to perform the recognition task. Evaluation results shows that the proposed system achieves a accuracy between 93.2% in the worst case and 95.8% at best when we use the training image 1. We obtain a accuracy between 75% in the worst case and 79.5% at best when we use the training image 2 in which face images with partial occlusion are not included.

Hence, we can see that the proposed system improved about 2% to 4% by taking the normalization of local part of an image. Although the database includes the variations face images of 109 subjects with as illumination changes, facial expressions and partial occlusion of the face, high accuracy is obtained. This is the main contribution in this work.

Acknowledgments.

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