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Face Recognition Technique using Gabor Wavelets and Singular Value Decomposition (SVD)

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Abstract—**Gabor wavelets (also known as Gabor filters) and Singular Value Decomposition (SVD) have been exploited extensively in the area of face recognition. In this paper, a face recognition system is developed combining features extracted using both Gabor wavelets and SVD. For Gabor wavelets, the extracted feature vectors are selected from only 12 out of 40 Gabor wavelets. The outputs from the 12 filters are selected because it provides relatively more prominent features than the other. This offers the advantage of reducing computational time. As for SVD, only the first five singular values are selected and its associated right singular vectors are used as the feature vectors. The five singular vectors are the one that carry the maximal energy of the image. The combination of Gabor wavelets and SVD offers the advantage of increasing the reliability of the face recognition system. In the face verification stage, the similarity level between facial images is determined by computing the distance between the resulting facial feature vectors obtained from Gabor wavelets and SVD, respectively. The experimental result tested using JAFFE database indicates an average correct acceptance rate of 75.2% and correct rejection rate of 100%. The results show that the combined methods provide a reliable face recognition system.**

***Keywords*-Gabor wavelets, Singular Value Decomposition, Face Recognition**

I. INTRODUCTION

Face recognition is one of the well-known biometric identification. Even though there are many published work on face recognition techniques, this field continues to be an active research area. The face recognition is considered as non-intrusive and user-friendly technique as it does not require the user to go through tedious scanning process unlike other biometric recognition technique such as iris, retina and fingerprints.

Generally, face recognition can be categorized into two major approach which are feature-based approach and template-based approach. In feature-based approach, facial features such as eyes, nose, mouth, eyebrows and chin which are unique features of the face are used to represent the individual face. As for template-based approach, the entire face is used to represent individual face. In most application, face recognition based on template-based approach outperforms feature based approach because it collects more facial information by using the entire face [1].

Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA) and Linear Binary Pattern (LBP) are among popular feature extraction techniques. In PCA, faces are represented in terms of an optimal coordinate system where the coordinate system is constructed based on the feature vectors called eigenvectors [2]. LDA applies the same principle as the PCA except it preserves the class discriminatory information by maximizing the between-class variance and minimizing within-class variance [3]. As for LBP, the face images are first divided equally into small regions and LBP texture features are extracted from these small regions. These extracted features will be concatenated into a single feature histogram [4].

This paper is organized in the following sequence. In Section II the Gabor wavelets and its facial feature extraction is described. Next, the singular value decomposition and SVD-based feature extraction is introduced in section III. Section IV describes the combination of Gabor wavelets and SVD for feature extraction. Experimental results and discussion is presented on section V and conclusion is drawn on section VI.

II. FEATURE EXTRACTION USING GABOR WAVELETS

Biological relevance and computational properties of Gabor wavelets are the driven factors for its widespread use in automatic face recognition system. For biological property, 2-D Gabor wavelets can be used to represent simple cells in the visual cortex of mammalian brains. For computational properties, Gabor wavelets exhibit appealing properties such as orientation selectivity and spatial locality [5]. Gabor wavelets is a complex exponential modulated by a Gaussian function in the spatial domain [6]. The 2-D Gabor function in the spatial domain can be defined as (1):

$$\varphi_{u,v}(x,y) = \frac{{f_u}^2}{\pi\gamma n} e^{-\left(\frac{f^2}{\gamma^2}x'^2+\frac{f^2}{n^2}y'^2\right)} e^{-j2\pi f_u x'}, \tag{1}$$

where the parameters of the $\varphi_{u,v}(x,y)$ are defined as follows: $x' = x\cos\theta_v + y\sin\theta_v$, $y' = -x\sin\theta_v + y\cos\theta_v$. Here, n and θ_v refer to the size of the Gaussian envelope and the orientation of the Gabor wavelets while γ define the ratio between center frequency with its central frequency, f_u is defined as

$$f_u = \frac{0.25}{\sqrt{2}^u}, \tag{2}$$

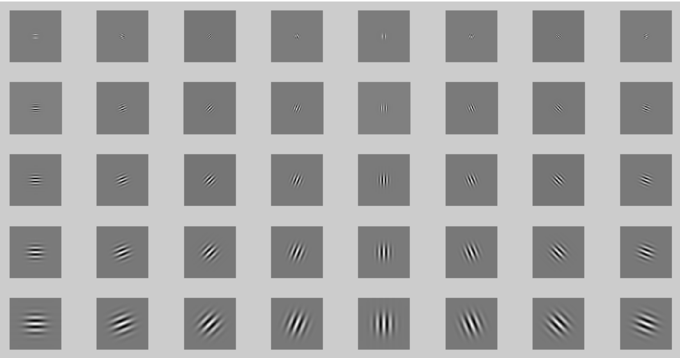
where u defines as the scale of the Gabor wavelets. Gabor wavelets with 5 scales ($u = 0,\dots,4$) and 8 orientations (v =0,…,7) are commonly used in face recognition application

[7]. The real parts and the magnitude responses of Gabor wavelets with 5 scales and 8 orientations are shown in Fig.1 (a) and (b).

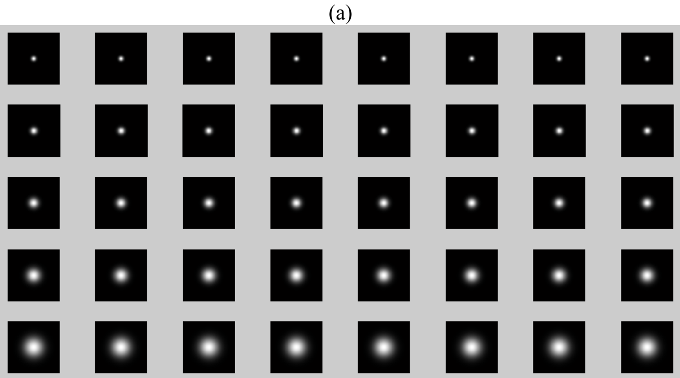
Gabor facial feature is extracted from an image through convolution between facial image and Gabor wavelets as defined in (3) where $I(x, y)$ represent grey-scale face image, $\varphi_{u,v}(x, y)$ represent the Gabor wavelets and convolution is denoted by $*$ operator

$$G_{u,v}(x, y) = I(x, y) * \varphi_{u,v}(x, y). \tag{3}$$

The real parts and magnitude responses of the convolution outputs for a sample image shown in Fig.2 with Gabor wavelets with 5 scales and 8 orientations are shown in Fig.3.(a) and (b), respectively. From Fig.3 (a) and (b), it is clear that at certain orientation, the Gabor wavelets are shown to be relatively more discriminating and significant compared to the rest of the Gabor wavelets [8].



(a)



(b)

Fig.1 (a) Real Parts (b) Magnitude Responses of Gabor wavelets with 5 scales and 8 orientations

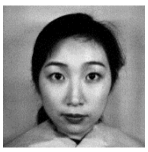
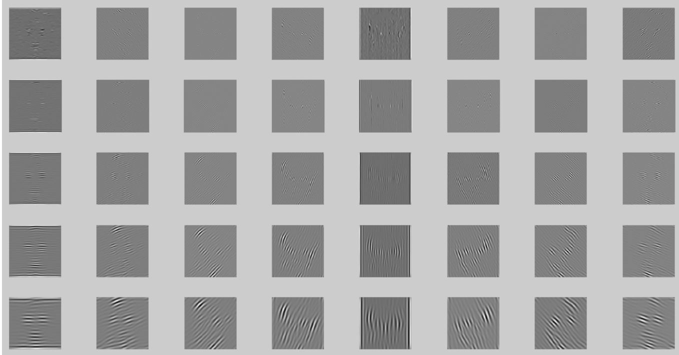
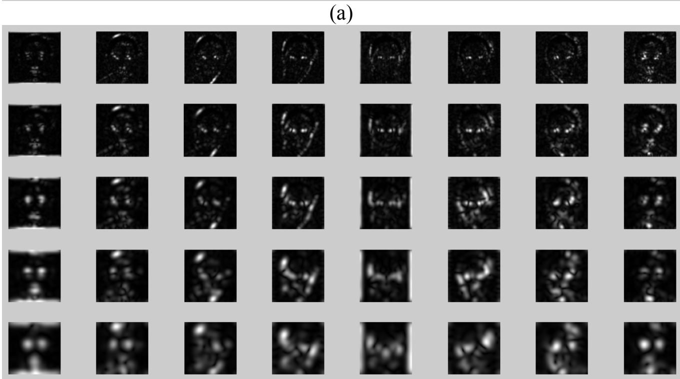


Fig.2 Sample JAFFE Image



(a)



(b)

Fig.3 (a) Real parts and (b) Magnitude Responses of the convolution output for sample image in Fig.2

III. Feature Extraction Using SVD

Suppose a matrix A with dimension of M x N ($A \in R^{MxN}$). The SVD of matrix A will factorize the matrix to the following form (4):

$$A = U * S * V \tag{4}$$

where U and V are orthogonal matrices with dimension of M x M and N x N, respectively whereas S is a diagonal matrix with dimension of M x N. The orthogonal matrices U and V are respectively the left and right singular vectors of A whereas the diagonal of S consists of singular values of the matrix arranged in descending order. Columns of U and V are the orthonormal eigenvectors of matrix AA^T and A^TA, respectively while the singular values of the matrix A are equivalent to the squared root of eigenvalue of matrix A^TA or AA^T. These singular values represent the variance of the linearly independent component along the dimension [9].

SVD-based face recognition method is an algebraic feature extraction approach in which its facial features are extracted and stored in the singular vectors of U and V and singular values of S. its singular value is shown to be invariant against translation and rotation [10]. The image reconstruction from lesser singular values and its associated singular vectors of SVD is able to diminish noises and varying illuminating condition in the face image and therefore improve the recognition rate [11]. Besides, image reconstruction using smaller set of singular values and singular vectors preserve the essential information of an image with smaller memory space

[12]. The singular values are shown to have insufficient information for face recognition whereas the orthogonal matrices U and V contain the most important features about the faces [13]. This validates the use of singular vectors as the feature vectors in this application.

IV. COMBINATION OF GABOR WAVELETS AND SINGULAR VALUE DECOMPOSITION FOR FEATURE EXTRACTION

The usage of 40 Gabor wavelets for feature extraction is too time-consuming and computational expensive. For this reason, only 12 out of 40 Gabor wavelets which exhibit better ability in extracting discriminating facial feature are selected for feature extraction. The selection of most prominent Gabor wavelets is described in experimental results and discussion section.

As for SVD, only first five right singular vectors are selected to represent the discriminating facial feature for face recognition because its carry the maximal energy of the face image. The selection of first five singular vectors is justified in the experimental result and discussion.

In this project, the facial features of facial image are extracted by applying 12 prominent Gabor wavelets and first five right singular vectors. The extracted facial feature vectors for both Gabor wavelets and SVD are used in computing distance between test image and training image by performing cosine of principal angles. The distance between test image and training image is known as similarity score and expressed in percentage form. The similarity scores for Gabor wavelets and SVD which exceed certain preset similarity threshold are recognized as valid user and approved by the system.

V. EXPERIMENTAL RESULTS AND DISCUSSION

A. Selection of Prominent Scales and Orientations of Gabor Wavelets

Grayscale facial images of one person with five different expressions are randomly selected from the JAFFE (Japanese Female Facial Expression) database. The entire facial images are preprocessed to remove the background as shown in Fig.4. All the facial images are then convolved with 40 Gabor wavelets with 5 scales and 8 orientations resulting in 200 Gabor outputs. The similarity scores between Gabor outputs with same scale and orientation are computed for 5 different facial images. After the similar scores are obtained, the average similarity scores for the same scale and orientation of Gabor outputs are computed and plotted as in Fig. 5. The Gabor wavelets with average similarity score higher than 89% are selected and labelled as in Fig.5. There are a total of 12 Gabor wavelets with its average similarity scores higher than 89%. Therefore, these 12 prominent Gabor wavelets are used for feature extraction for the rest of the experiment.

Besides that, it is reasonable to set similarity threshold to be 88% since the average similarity scores of 12 selected Gabor wavelets is 89%. Furthermore, with only 12 Gabor wavelets in extracting feature, execution time for constructing Gabor wavelets and convolution between single facial image and Gabor wavelets is much shorter as compared to using all 40 Gabor wavelets. Table 1 shows the execution time for 12 and 40 Gabor wavelets. Note that the execution time of 12 Gabor wavelets is approximately 4 seconds while the execution time of 40 Gabor wavelets is around 12 seconds.

Fig.4 Facial image of the same person with 5 different facial expressions

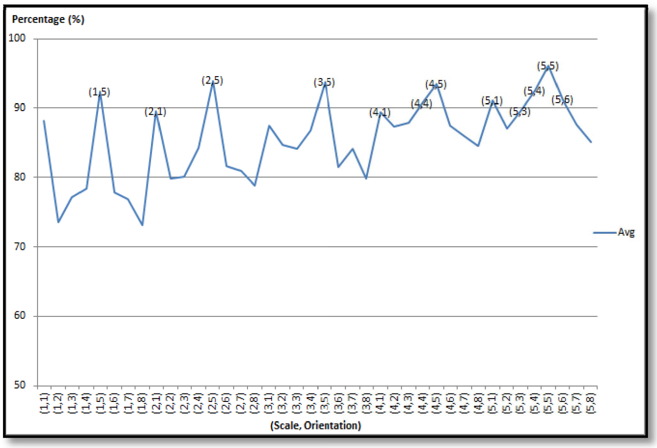


Fig.5 Average similarity score for 40 Gabor wavelet with 5 facial images (as in Fig.4)

Table 1.

Number of Gabor wavelets	40	12
Execution Time (in seconds)	12	4

B. Selection of Principal Singular Vectors based on Singular Values

A sample image from JAFFE database is shown in Fig. 6 where we applied an SVD in order to obtain the singular values and singular vectors. The singular values are plotted in Fig. 7. Figure 7 shows that only the first few singular values of the facial images have outstanding magnitude and then the magnitude of the rest of the singular values decrease abruptly and start to approach 0. This shows that only the first few singular values and its corresponding singular vectors carry the maximal energy. In other words, they contain the most discriminating features of the facial image. In this project, the first five right singular vectors are used to represent the facial features. The similarity scores are obtained by computing the distance between these singular vectors between facial images.

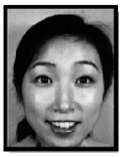


Fig.6 Sample facial image from JAFFE database

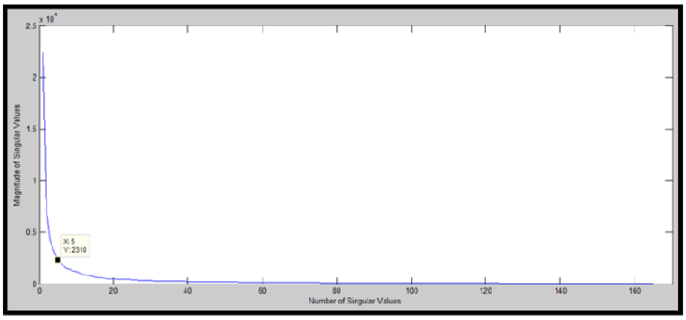


Fig.7 Plot of singular values for sample image in Fig.6

C. Performance of Gabor-SVD based face recognition system on JAFFE database

The face recognition is conducted by using the 12 prominent Gabor wavelets and principal singular vectors of SVD. The similarity thresholds for Gabor wavelets and SVD for this project are set to be 88% and 85% respectively. Two facial images are used as training images to improve the robustness of the system. The similarity scores of the test image have to reach or exceed the similarity threshold for both Gabor wavelets and SVD in order to be accepted as legitimate user.

The performance of Gabor-SVD based face recognition system is tested on JAFFE database to obtain correct acceptance rate and correct rejection rate. There are a total of ten different individuals with different facial expressions in the database. Correct acceptance rate of the system is tested by randomly selecting two facial images of one person as training images as shown in Fig.8 and then use the facial images of the same person with different facial expression as its test images as shown in Fig.9. Table 2 shows similarity score for the test images Fig.9. Note that all the similarity scores of the test images have achieved similarity threshold of 88% for Gabor wavelets and 85% for SVD. The same procedure is applied to the rest of the JAFFE database to obtain overall correct acceptance rate. Similarly, correct rejection rate of the system is tested by selecting the facial images of person which are different from the training images as test images. An example can be showed with test images of Fig.10 with training images of Fig.8. Table 3 shows similarity scores for test image of Fig.10. It can be seen that almost all of the similarity scores are below the similarity threshold. The same procedure is applied to the rest of the JAFFE database to obtain overall correct rejection rate.

Fig.8 Training images T1 and T2

Fig. 9 Test Images F1, F2, F3, F4 and F5

Table 2 Similarity scores (in percentage) for the test images of Fig.9 with training images of Fig.8

TEST IMAGES	TRAINING IMAGES			
	T1		T2	
	GABOR	SVD	GABOR	SVD
F1	92	93	93	91
F2	92	92	92	90
F3	90	89	98	88
F4	95	96	96	95
F5	88	91	89	90

Fig. 10 Test Images E1, E2, E3, E4 and E5

Table 3. Similarity scores (in percentage) for the test images of Fig.10 with training images of Fig.8

TEST IMAGES	TRAINING IMAGES			
	T1		T2	
	GABOR	SVD	GABOR	SVD
E1	75	66	75	65
E2	87	83	88	83
E3	85	68	86	64
E4	81	81	83	78
E5	78	58	79	58

VI. CONCLUSION

The Gabor-SVD based face recognition system is investigated and validated. This hybrid technique used less number of Gabor wavelet to extract the facial feature, which is only 12 out of 40 filters which reduces computational complexity. For feature extraction using SVD, it only uses the first five singular vectors that carry the maximal energy of the face matrix. The Gabor-SVD based face recognition system is proved to be a reliable system with average correct acceptance rate of 75.2% and average correct rejection rate of 100% tested on JAFFE database. The use of SVD in addition to the Gabor wavelets has improved the reliability of the face recognition system. This face recognition system has proved its robustness by recognizing the individual with various facial expressions. In addition, with only 12 Gabor wavelets used for feature extraction, the execution time is 3 times faster than the conventional Gabor wavelets face recognition technique. However, further experiments need to be conducted in order to investigate the sensitivity of the system with change of illumination. In addition, this work can be further verified with other facial database such as ORL, FERET and YALE databases.

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