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Performance Evaluation of Gabor Wavelet Features for Face Representation and Recognition

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Abstract: *The choice of the object representation is crucial for an effective performance of cognitive tasks such as object recognition, fixation, etc. Face recognition is an example of advanced pattern recognition. The main aim is to investigate alternative methods to be used for face recognition, in particular the use of wavelets. The representation of images by Gabor wavelets is chosen for its biological relevance and technical properties. The Gabor wavelets are of similar shape as the receptive fields of simple cells in the primary visual cortex (V1). In the proposed work, use of Gabor wavelets for efficient face representation is demonstrated. Face recognition is influenced by several factors such as shape, reflectance, pose, occlusion and illumination which make it even more difficult. The present work introduces the Gabor wavelets for an efficient face recognition system simulating human perception of objects and faces. The system is tested for the standard database like YALE, JAFFE, ORL and FEI. Experimental results show the effectiveness of the proposed system. Thus Gabor wavelet approach provides a better representation and achieves lower error rates.*
Keywords: *Face recognition, Feature extraction, Gabor wavelet, Sensitivity, Specificity.*

I. Introduction

Face Recognition systems have the advantage of being non-intrusive. This opens up a new realm of interesting possibilities. Face recognition has become a popular area of research in computer vision and one of the most successful applications of image analysis and understanding. Because of the nature of the problem, not only researchers are interested in it, but neuroscientists and psychologists also. It is the general opinion that advances in computer vision research will provide useful insights to neuroscientists and psychologists into how human brain works, and vice versa.

The main aim is to investigate alternative methods to be used for face recognition, in particular the use of wavelets. Wavelets are mathematical functions that divide the data into different frequency components, and then study each component with a resolution matched to its scale. They have advantage over traditional Fourier methods in analyzing physical situations when the signal contains discontinuities and sharp spikes. Wavelets were developed independently in the fields of mathematics, quantum physics, electrical engineering and seismic geology. Interchanges between these fields during the last ten years have led to many new wavelets. Here Gabor wavelets are used to implement face recognition system. The representation of images by Gabor wavelets is chosen for its biological relevance and technical properties. The Gabor wavelets are of similar shape as the receptive fields of simple cells in the primary visual cortex (V1). They are localized in both space and frequency domains and have the shape of plane waves restricted by a Gaussian envelope function. Simple cells in the primary visual cortex have receptive fields (RF) which are restricted to small regions of space and highly structured. Earlier examinations by Hubel and Wiesel [1] lead to a description of these cells as edge detectors. More recent examinations showed that the response behavior of simple cells of cats corresponds to local measurements of frequencies. The use of Gabor wavelets for face recognition has several advantages such as invariance to some degree with respect to translation, rotation and dilation. Furthermore, it has the ability to generalize and to abstract from the training data and to assure that a maximum of object information is coded. Further advantages include – saves neighborhood relationship between pixels, robust against illumination when face is correctly normalized, robust against noise and fast recognition.

In seismology, the data used by geologists was non stationary and the Fourier Transform worked with stationary data. The wavelets were designed with such a non-stationary data in mind. The Heisenberg's uncertainty principle states that the position and velocity of an object cannot be measured exactly at the same time in theory [2][3]. In signal processing terms this means it is impossible to know simultaneously the exact frequency and exact time of occurrence of this frequency in a signal. In order to know its frequency the signal must be spread in time or vice-versa [2]. Before wavelets short-time Fourier Transform were introduced. It is also called Window Fourier Transform which provided only one resolution for each window size. But, wavelet transform provides Multi-Resolution, giving good frequency resolution at low frequencies and good time resolution at high frequencies [2][3][4]. The Gabor Wavelet Transform has some impressive mathematical and biological properties and has been used frequently in research on image processing [14]. This wavelet has Multi-Scale and Multi-Resolution properties, and is found advantageous over geometric based approach [5]. Gabor wavelet is a feature based approach, which can be either global or bag of features [6]. Global is obtained by concatenating pixels to form one global vector per image. In bag of feature approach N vectors are obtained for N local patches/regions, each feature vector may be obtained by holistic or local feature extraction. Gabor wavelet comes under bag of feature approach. The strong reason for bag of feature approach is the tendency of preserving the spatial arrangement of different facial parts is largely compromised [5]. Therefore, the use of Gabor wavelet appears to be quite perspective and has several advantages such as invariance to some degree with respect to homogeneous illumination changes, small changes in head poses and robustness against facial expressions, glasses and image noise in face recognition.

II. Design and Implementation

The entire work is divided into three sections:

- Image Acquisition and Pre-processing
- Feature extraction
- Identification/Verification

2.1 Image Acquisition and Pre-processing

The standard databases are used here. Since availability of database is in both color and grayscale images, the color images needed to be converted to grayscale image. The next section requires the features to be extracted from center of the face i.e. from the inner facial area. Therefore cropping of inner facial area is required. This can be done with help of 'impixel' function of the image processing toolbox in Matlab. The usage of impixel function requires 3 points to be selected on an image which is to be cropped. Thus a manual operator is needed every time the image is to be cropped. This is quite complex. Hence an automatic approach is required. The present work incorporates an automatic approach that uses edge detection technique. The edge detection provides a logic level image. Enhancement techniques such as histogram equalization and median filters are used.

2.2 Feature Extraction

Feature extraction involves several steps - dimensionality reduction, feature extraction and feature selection. These steps may overlap, and dimensionality reduction could be seen as a consequence of the feature extraction and selection algorithms. Both algorithms could also be defined as cases of dimensionality reduction. The representation of images by Gabor wavelet features is chosen for its biological relevance and technical properties. The Gabor wavelets are of similar shape as the receptive fields of simple cells in the primary visual cortex (V1). They are localized in both space and frequency domains and have the shape of plane waves restricted by a Gaussian envelope function.

Generation of Gabor wavelets:

$$\psi_{i,j,k}(x,y) = \frac{f_i^2}{2\pi} \exp\{-0.5 f_i^2 [(x - c_{xk})^2 + (y - c_{yk})^2]\} * \sin\{2\pi f_i [(x - c_{xk}) \cos\theta_j + (y - c_{yk}) \sin\theta_j] \qquad (1)$$

where f_i denotes the frequency, θ_j denotes orientation and C_{xk}, C_{yk} denote wavelet position. This generates 5x8 2D Gabor Wavelet basis functions, where frequency f_i varies from $1/4\sqrt{2}$ to 1/2, and orientation varies from -180 degree to +180 degree as shown in Fig. 1.

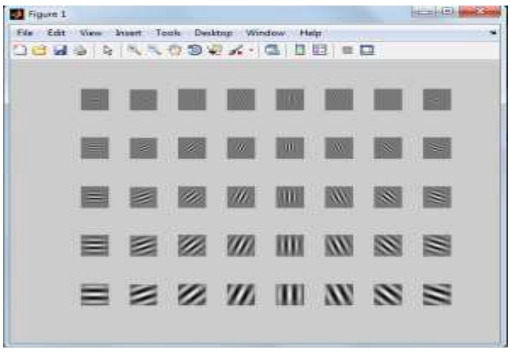


Fig. 1. 5x8 2D Gabor Wavelet basis functions

Two approaches are used for feature extraction:

- Correlation
- Convolution

2.2.1 Correlation

The cropped image is divided into four parts as shown in Fig. 2.

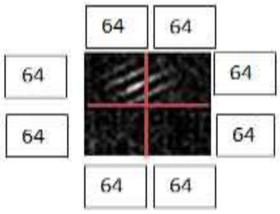


Fig. 2. Feature extraction using correlation

Each part is correlated with Gabor Wavelet basis function. Each correlation leads to a single value. Thus each wavelet provides 4 values and 40 wavelets lead to 160 values.

2.2.2 Convolution

Convolving an image with Gabor wavelet basis functions tuned to 5 scales and 8 orientations results in 40 magnitude and phase response maps of the same size as image. Therefore, considering only the magnitude response for the purpose of feature description, each pixel can be now represented by a 40 dimensional feature vector (by concatenating all the response values at each scale and orientation) that describe the response of Gabor filtering at that location.

Convolution of a given image with Gabor Wavelet leads to ghost-like image as shown in Fig. 3. Obtaining four values as illustrated in Fig. 4, from an image are the features. Thus 40 wavelets provide 160 values.

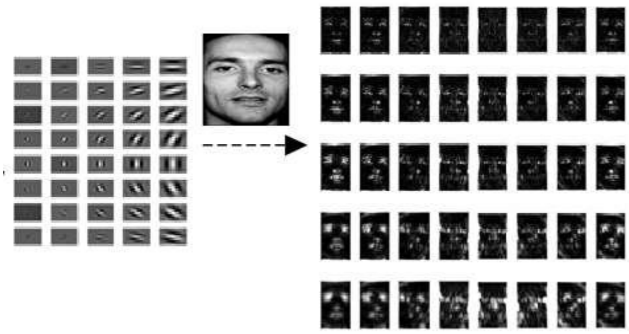


Fig. 3. Convolution of Gabor Wavelets with an image

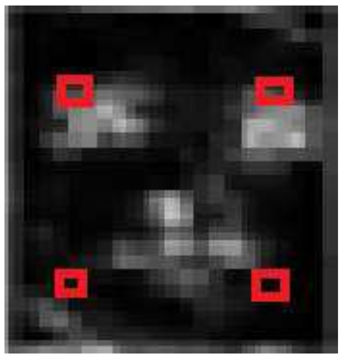


Fig. 4. Feature extraction using convolution

Thus in each method, 160 values are obtained as feature vector for one image. All images in the training set are used to form feature matrix.

2.2.3 Identification Section

Euclidean distance metric is used for identification. The features are obtained for a test image and Euclidean distance is computed for a test image and row vector of feature matrix. The minimum among Euclidean distances is found and the corresponding index is obtained to show the matched image. For the purpose of testing, a Graphical User Interface (GUI) is developed for the proposed system to provide the facility to interact and apply the test image from various databases.

III. Results and Discussion

3.1 JAFFE Database

In the standard JAFFE database, 10 individuals, each with 21 images (total of 210) are present. Here for experiment purpose, all the images in the database with variations in lighting conditions, facial expressions (normal, happy, sad, sleepy, angry, depression and surprised) are used. The database is divided into 130 images as test set and 80 images as train set.

Experiment 1: The purpose of this experiment is to extract Gabor features of image KA.NE1.26.tiff by applying 40 Gabor wavelets stored in 5 x 8 cell in gabor.mat file and compared row wise with the features in feature.mat file. Match is found with KA.HA4.32.tiff having minimum Euclidean distance. The results demonstrate correct recognition for images having some variation in face expression and lighting condition, as shown in Fig. 5(a) and 5(b).

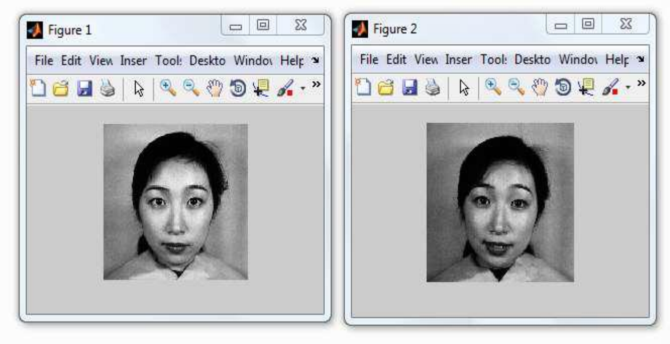


Fig. 5(a) Test image Fig. 5(b) Equivalent image

Experiment 2: The purpose of this experiment is to extract Gabor features of image KA.AN1.39.tiff by applying 40 Gabor wavelets stored in 5 x 8 cell in gabor.mat file and compared row wise with the features in feature.mat file. Mismatch is found with NM.SU1.101.tiff having minimum Euclidean distance. The results here indicate that the developed system does not recognize correctly for the input images having wide variation in face expression, as shown in Fig. 6(a) and 6(b).

Fig. 6(a) Test image Fig. 6(b) Mismatched image

The developed algorithm is tested using both convolution and correlation methods discussed in the section 2 for JAFFE Database and their performance is shown in Table 1.

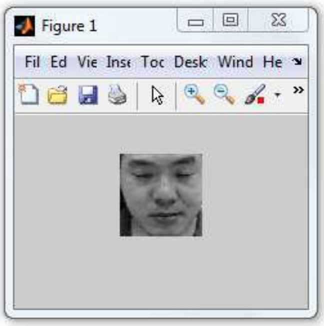
Table1. Performance comparison between Convolution and Correlation method for JAFFE Database

Method	Number of Test images	Number of images correctly recognized	Number of images mismatched	Face Recognition Rate (%)
Correlation	130	117	13	90.0
Convolution	130	125	05	96.15

It is observed that the convolution method provides better performance than that of correlation. Therefore, performance evaluation is carried out using convolution method for other databases such as YALE, ORL and FEI.

3.2 YALE Database

For experiment purpose, 10 individuals, each with 17 (total of 170) images having variations in lighting conditions, facial expressions (normal, happy, sad, sleepy and surprised) and with or without glasses are used. Among these, 100 images for training and 70 images for testing are used. One such experiment output is displayed in Fig. 7(a) and 7(b).



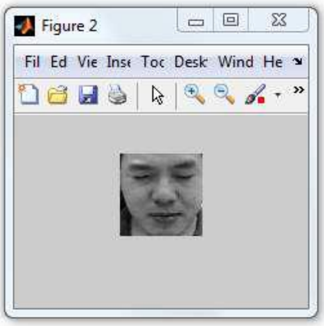
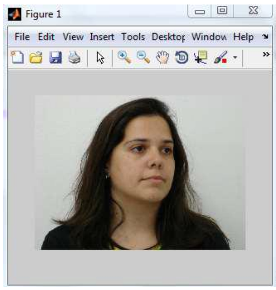
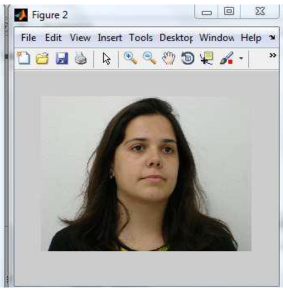


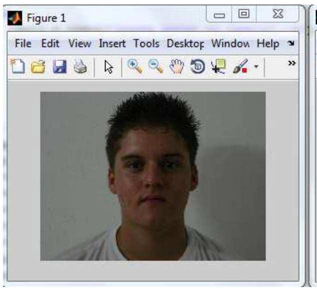
Fig. 7(a) Test image Fig. 7(b) Equivalent image

3.3 FEI Database

For experiment purpose, 17 individuals, each with 9 images (total of 153) having variations in lighting conditions, facial expressions and pose variation are taken. The database is divided into 85 images for training and 68 images for testing. Test results shown in Fig. 8 and Fig. 9 illustrate that the system does correct recognition for the input images having variations in pose and illumination.







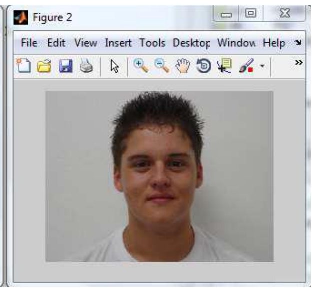


Fig. 8(a) Test image Fig. 8(b) Equivalent image Fig. 9(a) Test image Fig. 9(b) Equivalent image

The developed algorithm is tested with JAFFE, YALE, FEI and ORL database and their performance is shown in Table 2.

3.4 ORL Database

For experiment purpose, 12 individuals, each with 10 images (total of 120) with varying lighting, facial expressions (open/closed eyes, smiling/not smiling) and homogeneous background are taken. The database is divided into 72 images for training and 48 images for testing. Test result shown in Fig. 10 illustrate that the system does correct recognition for the input images.

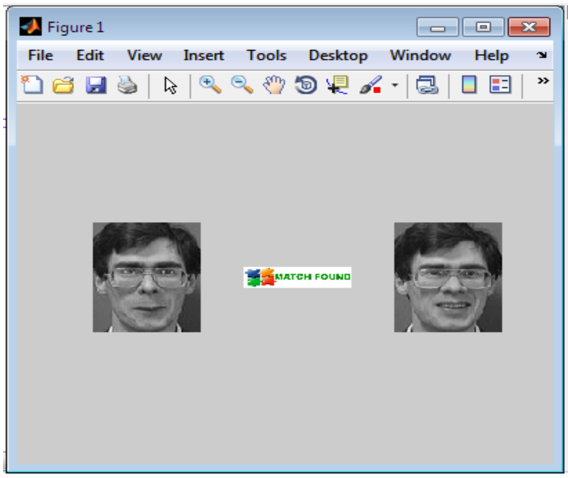


Fig. 10. Test image and Equivalent image

Table 2. Performance analysis for different Database using convolution method

Database	No. of Train images	No. of Test images	No. of images correctly recognized	No. of images mismatched	Face Recognition Rate (%)
JAFFE	100	50	48	02	96.00
YALE	100	70	68	02	97.14
FEI	85	68	66	02	97.05
ORL	72	48	47	01	97.91

For testing and evaluating the performance, a GUI is developed for the proposed system to input the test image from various databases. After the complete execution of the module, it reports the time of execution and displays the matched equivalent image from the corresponding training set.

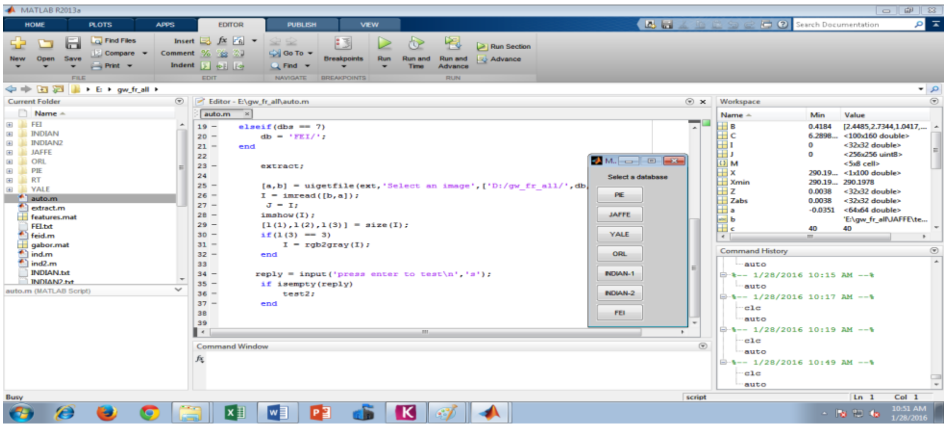


Fig. 11. GUI for Test image selection

Confusion matrix is used to compare the actual classification of data set. To evaluate the performance of face recognition system being developed, following classification measures are used.

i) Sensitivity = TP/(TP+FN)
ii) Specificity = TN/(FN+TN)
iii) Accuracy = (TP+TN)/(TP+FP+TN+FN)

where, TP = True Positive, i.e., correctly recognized/accepted
FP = False Positive, i.e., incorrectly Recognized/accepted
TN = True Negative, i.e., correctly rejected
FN = False Negative, i.e., incorrectly rejected

Sensitivity relates to the test's ability to correctly recognize the person who belongs to the correct class and specificity relates to the test's ability to reject the person who does not belong.

Table 3. Performance analysis displaying Confusion matrix, Sensitivity, Specificity and Accuracy for different database

Database	No. of Train images	No. of Test images	Confusion Matrix		Sensitivity (%)	Specificity (%)	Accuracy (%)
JAFFE	100 (10 x10) Subjects x Images	50 (10x5)	48	02	92.30	95.83	94.0
			04	46			
YALE	100 (10x10)	70 (10x7)	68	02	93.15	95.65	94.36
			04	66			
FEI	85 (17x5)	68 (17x4)	66	02	90.41	96.82	93.38
			07	61			
ORL	72 (12x6)	48 (12x4)	47	01	92.15	97.77	94.79
			04	44			

Table 3 shows the classification measures such as sensitivity, specificity and accuracy for standard databases JAFFE, YALE, FEI and ORL with specified number of train and test images. The experimental results demonstrate that the system has the ability to generalize, to abstract from the training data and to assure that a maximum of object information is coded with Gabor wavelet features, hence providing high recognition rate.

IV. Conclusion

For a given set of images, due to high dimensionality of images, the space spanned is very large. But in reality, all these images are closely related and actually span a lower dimensional space. The Gabor wavelet approach for feature extraction in the proposed work makes it easier to match any two images and thus face recognition. The Gabor wavelet approach appears to be the best for simultaneously handling variations in illumination, pose and expression. This is due to the fact that, the significant feature of wavelets is the property of time-frequency joint representation. The system is designed and tested for the standard database like YALE, JAFFE, ORL and FEI. Experimental results show the effectiveness of the proposed system. Thus Gabor wavelet approach provides a better representation and achieves lower error rates in face recognition.

References

[1] D. H. Hubel and T. N. Wiesel, "Receptive fields of single neurons in the cat's striate cortex", Journal of Physiology (1959) 148, pp.574-591.
[2] K P Soman, K L Ramachandran & N G Reshmi, "Insight into Wavelets from Theory to Practice", Third Edition, PHI Learning.
[3] Chun Lin, Liu, "A Tutorial of Wavelet Transform", Feb. 23, 2010.
[4] M Sifuzzaman, M R Islam and M Z Ali, "Applications of Wavelet Transform & its advantages compared to Fourier Transform", Journal of Physical Science, vol.13, 2009, pp.121-134.
[5] Michael Lyons, Shigeru Akamatsu, "Coding facial expressions with Gabor wavelets", Proceedings of Third IEEE International Conference on Automatic Face & Gesture Recognition, April 1998, Nara Japan, pp. 200-205.
[6] M. Saquib Sarfraz, Olaf Hellwich and Zahid Riaz (2010), Feature Extraction and Representation for Face Recognition, Milos Oravec (Ed.), ISBN:978-953-307-060-5.
[7] Daugman J., "Complete Discrete 2-D Gabor Transforms by Neural Networks for Image Analysis and Compression", IEEE Trans. of Acoustics, Speech, and Signal Processing, Vol. 36, No. 7, pp. 1169-1179, 1988.
[8] Matthew A. Turk and Alex P. Pentland, "Face recognition using eigenfaces", IEEE Computer Society Conference on Computer Vision and Pattern Recognition, pp. 586-591, 1991.
[9] Porat M. and Zeevi Y., "The Generalized Gabor Scheme of image representation in biological and machine vision", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 10, No. 4, pp. 452-468, 1988.
[10] Unser M., Aldroubi A. and Laine, A., IEEE Transactions on Medical Imaging: Special Issue on Wavelets in Medical Imaging, 2003.
[11] Morlet J., Arens G. Fourgeau E. and Giard D. "Wave propagation and sampling theory, Part1: Complex signal land scattering in multilayer media". Journal of Geophysics, 47: pp. 203-221, 1982.
[12] T. S. Lee, "Image representation using 2D Gabor wavelets," IEEE Trans. Pattern Analysis and Machine Intelligence, 18(10), 1996.
[13] J.G. Daughman, " Two dimensional Spectral analysis of cortical receptive field profile", Vision Research, vol.20, pp. 847-856, 1980
[14] http://disp.ee.ntu.edu.tw/~pujols/Gabor%20wavelet%20transform%20and%20its%20application.pdf.