An Investigation of the Use of Eigenvalues in Human Face Modeling for Recognition Tasks

Abstract:

The face image modeling by eigenvalues is not a new track in the literature. However, a much complete study is required to achieve a comprehensive investigation of the topic. In this research paper, an experimental methodology is conducted for studying the different alternatives of utilizing the eigenvalues for human face recognition. For a better universal investigation, three popular databases are tested; Orl_faces, extended Yale face_A, and extended Yale face_B datasets. The main objective of the study is to find the best choice of using eigenvalues in face recognition. The technique of the moving average filter is combined with that of eigenvalues to enhance the results. Probabilistic neural network is used for classification. The study proved the possibility of using eigenvalues in conjunction with a suitable filter to get acceptable results for all types of image limitations. The concluded ideas elicited from the study spot the light on the usefulness of utilization of eigenvalues in the face recognition tasks.

Keyword: Face recognition, Eigenvalue, Smoothing, Moving average filter, Probabilistic neural network.

1. Introduction

Security has top priority in our contemporary daily life. Starting from international and governmental institutions till individual persons, they looking always for new technologies to guarantee their own privacy. Very important issues in security include authentication and authorized access control. Different methods are in use today such as ID cards with photo, credit cards, and employment of users name and passwords, which can be stolen or hacked. Methods that are more efficient include biometric based techniques such as fingerprints, ears, iris, and face identification. In the last few decades, face recognition has attracted many scientists in different disciplines like signal processing, neural networks, security, and pattern recognition, for doing intensive research in this area due to its wide range of applications. Different types of research methods have been introduced in the literature.

Face recognition techniques can be separated into three approaches [1], namely, constituent-based methods, face-based methods [2, 3], or hybrid methods which are a combination of the former two approaches. A constituent-based method depends on the correlation between face boundary and the facial features of the person such as mouth, nose, and eyes [4-6]. A face-based technique treats the face as a whole [7-9]. The third approach combines the features of the first two techniques. Face recognition still meets big challenges especially when there are differences between the tested image and trained images such as illumination, face position, facial expression … etc [10, 11].

Many techniques and algorithms for face recognition tasks were proposed. The Eigenface method, proposed by Sirovich and Kirby, is also called principal component analysis (PCA) [12, 13], where a set of eigenvectors are calculated for a face image and represented in a linear combination [14]. The non-linearity of the neural network has been very attractive for face recognition. Therefore, it has been widely used as a face recognition technique[15-17]. Image gradient orientation (IGO),is also used in facial recognition systems to detect the edges by the change in the direction of the intensity or color of an image, instead of using pixel intensities, which result in an associated illumination problem [18-20]. The wavelet transform-based technique was intensively used for image feature extraction [21], in combination with other algorithms to create a reliable method for face identification. The wavelet transform was used in combination with fast Fourier transform and discrete cosine transform [22]. For face recognition, wavelet decomposition with (PCA) [23], and Neural Networks [24] were presented. Wavelet transform as a tool also has been used for different tasks of recognition [25-27].

In this paper, eigenvalues (EV) is used to extract the features out of the face image, and then will be used in combination with the method of Moving average filter (MAF) to study its impact on the results. Probabilistic neural networks (PNN) is used for classification.

2. Method

In this study, we present a face recognition method based on a combination of then eigenvalues features and probabilistic neural networks for face image classification. The presented method is an updated approach of the popular eigen theory to be used for face recognition algorithm with better specifications. The motivation behind using this method that it allows the number of features generated to be small. Therefore, the feature vector to be added to the classifier is relatively a low dimensional vector a desirable property that leads to low sophistication. This idea will guarantee that the method will require a less elapsed time. So, the main contribution of this paper is to find out an method of very low feature extraction dimensionality with a less elapsed time. The following steps summarize the used system in three steps (see Fig. 1)

1. Preprocessing: the image format is a portable grey map format (PGM) that is converted into a text matrix by “imread” function in MATLAB. The image in a text format is given to further processing of feature extraction, and the result as a feature vector is given to the classifier to be trained or tested.

2. Eigenvalues: in this stage, the image is converted into a text matrix and given to the eigenvalue function after decomposing the matrix into small square matrices to calculate a column vector containing the eigenvalues of each square matrix.

3. Moving average filter: the output data of the Eigenvalues column vector are given to a moving average filter to be prepared for the next step of classification by the PNN. The motivation behind that is to smooth the data by cutting the edges for enhancing the recognition rates. The moving average filter depends on the defined window type. This will guarantee how the data is averaged over the window. The used windows could have a specific influence on the results. For instance, Gaussian, Blackman, or multiple-pass moving average.

4. Classification: the last stage of our system is the classification, where the final decision is taken. The classification method used in this system is the PNN. The feature vector of the image is given to the PNN where it is used for training:

   NET=PNN(B,T,S)

   Where, NET is the output of the PNN function, B is the input matrix of training data, T is the target of class sequential number T= [1 2 3 …N], where N is the total number of classes, S is the spread and generally it is one. After training, testing process is done to get the final recognition rate.

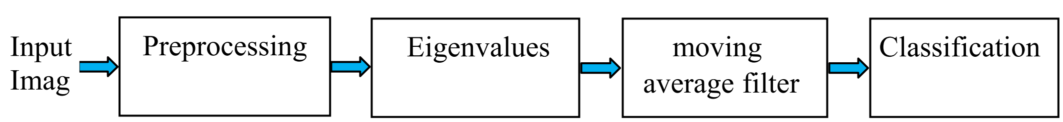

Figure 1: Block diagram of the proposed system.

3. Results and Discussion

To study the proposed method, several experiments were conducted over three public datasets. The used datasets are ORL_face database, extended Yale face_A database, and extended Yale face_B database.

The ORL_face database was created at Olivetti Research Laboratory in the UK, between years 1992 to 1994. Forty subjects were involved in the database recording 10 images of each, where ten images for each subject were taken [28].

Yale faces_A database contains 165 PGM of 15 persons, 11 images for each taken under different conditions and limitations, such as lighting variations, center-light, left-light, and right-light. Spectacle variations include a spectacle with and without glasses. Facial expressions include those sleepy, sad, happy, normal, wink and surprised [29].

In extended Yale face_B database some limitations were added to the process by using slightly varying lighting, glasses/no glasses, and facial expression. The size of each image is 92x112, 8-bit grey levels, and it offers 16,128 images of 38 human subjects (9 poses and 64 illumination conditions, thus the total of 576 images each of 640×480 pixels of each human subject). The data format of this database is the same as the Yale face_B database [30]. In our experiments, we only used selected images of (0-35) illumination for each person. So, 28 images were used for each person. The total persons were 38. The reason for that is the need to reduce the processing time of the whole recognition system.

In the first experiment, the recognition rate for the Orl_faces database of 40 persons was investigated for the three training/testing systems; (3/7), (5/5)),and (7/3). The results were taken as an average of 100 loops of a random same training set (see Fig. 2), and this is used for all the following investigations. Three methods were tested to determine the most useful approach for the Orl_faces database; the eigenvalue method (EV), the method of moving average filter (MAF), and the proposed method of eigenvalue with moving average filter (EVMAF). The feature extraction elapsed time is calculated for more elaboration on the investigation results. The results tabulated in Table 1 show that the proposed EVMAF method for all training/testing systems is superior with 85.064%, 91.965%, and 95.608%, respectively. The elapsed time of preprocessing and feature extraction are 6.57 second, 6.58 second, and 6.57 second, respectively (see tab. 1). The elapsed time of the proposed method roughly speaking remains without a big deviation even after using the additional method of MAF in the proposed method. We can notice that the MAF shows the best elapsed time. Therefore, the proposed method shows better recognition rate with longer time than MAF.

Table 1: The recognition rate (RR) results for Orl_faces for different training/testing systems (Tr/Tst).

Tr/Tst	Method	RR [%]	Feature extraction elapsed time [sec.]
3/7	EV	80.83	6.44
	MAF	84.17	0.98
	EVMAF	85.06	6.57
5/5	EV	89.21	6.48
	MAF	91.45	0.83
	EVMAF	91.96	6.58
7/3	EV	93.26	6.34
	MAF	94.91	0.82
	EVMAF	95.60	6.57

In the second experiment, the recognition rate for the Yale face_A database of 15 persons is investigated for three training/testing systems; (4/7), (6/5), and (8/3). The three aforementioned methods were tested to determine the most useful approach for the Yale face_A. The feature extraction elapsed time is calculated for more elaboration on the investigation results. The results tabulated in Table 2 show that the three methods are roughly speaking equal for all training/testing systems with slight improvement by MAF for each training/testing system by 0.88%, 0.37%, and 1.15%, respectively. The elapsed time of feature extraction is better for the MAF method. The improvement by the MAF method is justified as follows: the limitations and conditions in the Yale face_A distort the features extracted from the image. Therefore, the EVMAF cannot improve the results. This is because of the fact that the use of eigenvalues in EVMAF cannot improve the performance of the feature extraction method. Thus, the MAF might helps extracting better results for such image limitations and conditions. The elapsed time for the MAF method is the smallest. The elapsed time of the proposed method practically remains without a big deviation.

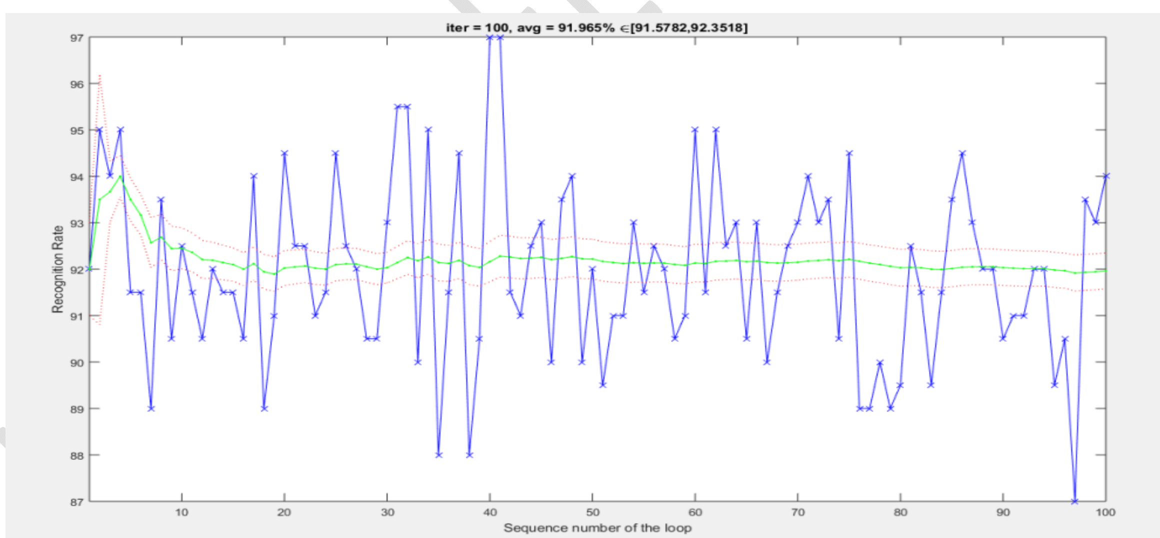

Figure 2: The results illustration of 100 loops of the recognition rates taken by EVMAF for (5/5) training/testing system. The considered result in the investigation is achieved as an average of 100 loops of a random same training set.

Table 2: Theresults for Yale faces_A database

Tr/Tst	Method	RR [%]	Feature extraction elapsed time [sec.]
4/7	EV	79.02	17.807534
	MAF	80.48	1.412763
	EVMAF	79.61	18.310944
6/5	EV	81.48	17.916054
	MAF	81.89	1.437695
	EVMAF	81.52	18.401565
8/3	EV	82.68	18.502050
	MAF	83.31	1.432061
	EVMAF	81.95	18.294562

In the third experiment, the recognition rate for Yale face_B database of 38 persons was investigated for (9/19), (14/14), and (20/8) training/testing systems. The same three methods were tested to determine the most useful approach for this database. The difference between this database and the previous two databases is due to the illumination degree and the angle of capturing the image. The feature extraction elapsed time is calculated for more elaboration on the investigation results. The results are tabulated in Table 3. The best method was EV. The reason behind that is the details and conditions of the Yale face_B. The best results are for EV of the three training/testing systems 72.79%, 80.27%, 85.14%, respectively. The elapsed time for the MAF is the smallest. The elapsed time of the proposed method practically remains without a big deviation.

Table 3: The calculated recognition rates for YalefaceB

Tr/Tst	Method	RR [%]	Feature extraction elapsed time [sec.]
9/19	EV	72.78	6.548917
	MAF	58,72	3.183886
	EVMAF	67.68	6.863231
14/14	EV	80.26	6.516120
	MAF	67.91	3.120679
	EVMAF	76.17	6.850079
20/8	EV	85.13	6.613369
	MAF	74.59	3.185259
	EVMAF	81.69	6.813643

In order to improve the results of the proposed method, additional five filters were tested instead of MAF. **The filters are**:

a) local regression using weighted linear least squares & a 1st degree polynomial model (LLS-1st),

b) Local regression using weighted linear least squares and a 2nd degree polynomial model (LLS-2nd),

c) Savitzky-Golay filter (SGF),

d) A robust version of LLS-1st that assigns lower weight to outliers in the regression. The method assigns zero weight to data outside six mean absolute deviations (RLLS-1st).

e) A robust version of LLS-2nd that assigns lower weight to outliers in the regression. The method assigns zero weight to data outside six mean absolute deviations (RLLS-2nd) [31].

The results are tabulated in Table 4. The training ratio is 50% for the three databases. The most significant results are the results for the Yale faces_B database, where the recognition rate is improved significantly by EVLLS-2nd filter. As shown in the results in Table 3 the EV method was better than the EVMAF method, but by using the EVLLS-2nd filter instead of MAV the EVMAV method was improved and become better.

Table 4: The results of different filters used in conjunction with EV for recognition of the three databases.

50%	**Orl_faces**	**Yale faces_A**	**Yale faces_B**
EVMAF	91.96	81.52	76.17
EVLLS-1st	90.93	81.90	77.55
EVLLS-2nd	89.20	81.42	80.40
EVSGF	90,86	81.30	78.42
EVRLLS-1st	90.92	81.68	71.16
EVRLLS-2nd	80.69	81.08	73.08

To be more confident of the results of EVLLS-2nd for Yale face_B, 30%, 50%, and 70% are also investigated (see Table 5). The results indicate that EVLLS-2nd has improved the recognition rate for about 5% for the three (Tr/Tst) systems.

Table 5: The recognition rates of Yale faces_B with EVLLS-2st for 30%, 50%, and 70%.

Yale faces_B	30%	50%	70%
EVMAF	67.68	76.17	81.69
EVLLS-2st	72.82	80.40	85.38

4. Conclusion:

This paper has investigated the use of eigenvalues as a feature vector for the face recognition. A moving average filter to cut the edges was used to smooth the eigenvalues taken from the raw data. The purpose of the study is to explore and investigate the possibility of modeling the image of the human face by eigenvalues. The experiments conducted have had a lot of valuable results and elaborations. Different filters were tested to enhance the results. At the end of this study, many conclusions can be drawn in the following points. First, the eigenvalues with moving average filter as a proposed method was superior for Orl_faces database on all training/testing systems, in comparison with eigenvalues method and moving average method. The elapsed time for moving average filter was distinctly smaller than the other two methods. For the Yale face_A database, the performance of the proposed method was almost same as that of the moving average filter. For the Yale face_B database, the eigenvalues method was superior for each of the three training/testing systems. The results were enhanced after using different filters instead of a direct moving average filter to make the proposed method the superior again.

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