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by Indah Siradjuddin

Three-Directional of the 1D-Diagonal Fisherface Modeling based Feature Extraction

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***Abstract*— Three directional of the 1D diagonal fisherface for feature extraction is proposed in this research for the face recognition system. Three directional of the diagonal matrix is built in the proposed method, i.e. the input face image is transformed into a diagonal matrix. Therefore, another form of the input image is created for the feature extraction using the diagonal matrix of the input image. The diagonal matrix is then transformed into 1D matrix for each training set. The feature extraction used this matrix to create the projection and weight matrix using Fisher Face. Two until ten features are extracted using the proposed method. There are four distance methods are used in the experiments, i.e. Euclidian, Manhattan, Canberra, and Chebychev. The experiments of the proposed system are conducted on three databases, i.e. ORL, University of Bern, and YALE-A databases. The recognition accuracy of the proposed model for face recognition achieved up to 92% accuracy.**

Keywords—Three Directional Matrix; Principal Component Analysis; Fisherface; Euclidian, Manhattan, Canberra, Chebychev.

I. Introduction

Currently, face recognition is still an interesting field for the researchers, since it can be used in many fields and many kinds of application. The most popular application of the face recognition is the security system. In the security system, only the recognized face is allowed to enter the restricted system. Many approaches are developed by the researches to achieve the higher accuracy of the face recognition system.

To build the face recognition system, there are two main stages are required, i.e. feature extraction and classification. There are four basic approaches to the feature extraction technique [1], i.e. Geometry based, Template based, Appearance, and Color based approach. In the appearance based, we will have a small number of features; therefore, it will reduce the computation time in the classification phase of the recognition system. Principal Component analysis is one of the methods for feature extraction in the appearance approach. This method project the input space into a lower dimension of the feature space [2]. However, this method is sensitive to small changes in the input face image.

Fisherface as feature extraction is used in this research since it showed lower error rates compare with PCA [3]. The disadvantage of the PCA method is that the scatter being maximized is due not only to between class scatter (useful for the classification) but also within class scatter, and this would be unwanted information for the classification process. In the fisherface method, there is a computation of the within and between class scatter matrix. These matrices are used to maximize the distance between the class, and minimize the distance between the sample in the same class [3]. Hence, in this research we use fisherface as the feature extraction phase. Our proposed model introduce the new form of the input matrix, i.e., three directional of the input matrix. This three directional input matrix is used to obtain the projection and weight matrices using fisherface method.

II. Three Directional 1D Fisherface

Three main stages are required in our proposed model as seen in Figure 1. First, create three directional input image matrices. The input image is transformed into diagonal matrix three times. This transformation is depicted in Figure 2. The transformed input image matrix is used as an input matrix of the Fisherface feature extraction.

The first phase of fisherface feature extraction is training phase. The training phase yields a projection and a weight matrix. The projection matrix is used to extract the features of the input matrix in the testing phase. Meanwhile, weight matrix is an extracted feature of the training matrices, and therefore we can compute the distance between the features from input matrix and the weight matrix to classify the input image.

In the fisherface feature extraction, a set of eigenvectors are calculated first using Principal Component Analysis (PCA, see diagram of the proposed model in Figure 1) [2] [3] [4], i.e.

1. Transform each data in the training set (three directional matrix) into column vectors. Therefore each column of the matrix represents each data of the training set. Suppose there are M data in the training set, and let face space is $\Gamma_1, \Gamma_2, \Gamma_3, \ldots, \Gamma_M$, and then compute the average of each column in the face space (Ψ).
2. Create the average face vectors by computing the difference between the face space vector and the average vector as seen in (1)

$$\phi_i = \Gamma_i - \Psi \,. \quad (1)$$

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3. Compute the covariance matrix using the average face vectors as seen in (2)

$$A = \phi^T \phi . \quad (2)$$

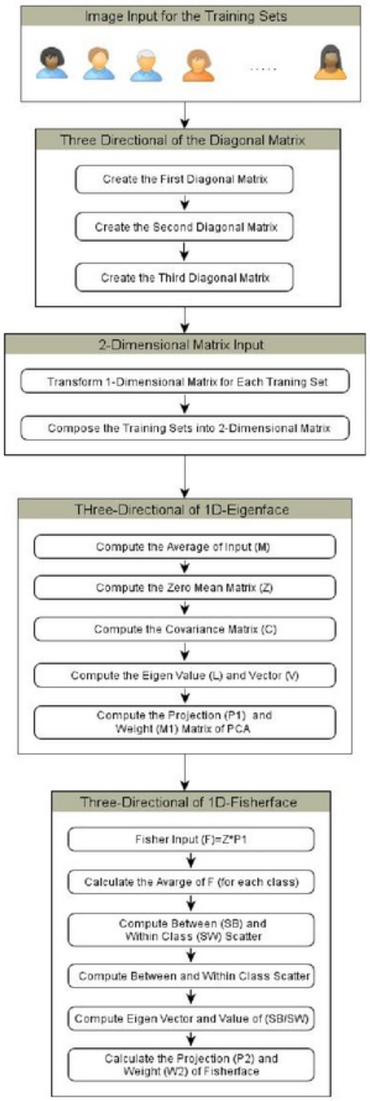

Fig. 1. Three Directional of 1D Fisherface Feature Extraction

Fig. 2. Three Directional matrix of input image

4. Compute the eigen value λ and eigen vector v
5. Sort the eigen vector based on the eigen value, and compute the projection matrix using (3) and (4).

$$V' = \phi . v \quad (3)$$

$$W_{PCA} = \frac{V'}{\|V'\|} \quad (4)$$

In the fisherface feature extraction method, we compute between-class and within-class scatter matrix. These scatter matrices are computed to make the distance between classes are at maximum. Meanwhile, the distance between training data in the same class are at minimum [3].

The stages in the Fisherface feature extraction are:

1. Compute within class scatter matrix (Sw) and between class scatter matrix (SB), and project the two matrices using PCA projection matrix as seen in (5) and (6)

$$Sww = W_{PCA}^T Sw W_{PCA} \quad (5)$$

$$S_{BB} = W_{PCA}^T S_B W_{PCA} \quad (6)$$

2. Compute the Eigenvalue and Eigenvector, and sort the eigenvector based on the eigenvalue.
3. Calculate the projection matrix of Fisherface, and transform the input matrix into weight matrix based on the projection matrix.

To recognize the input image, the calculation of the distance between extracted features of the input image and extracted features in the training dataset is required. Four distance methods are compared in the recognition phase of the proposed model, i.e. Euclidian, Manhattan, Canberra, and Chebychev distances [5] [6] [7].

Euclidian distance measures the two points (x and y) using straight line as seen in (7)

$$dist = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \quad (7)$$

where n is the number of features.

Manhattan distance measures two points (x and y) in a grid, based on its strictly vertical or horizontal path of two points. The distance is the sum of vertical or horizontal components, as seen in (8)

$$dist = \sum_{i=1}^{n} |x_i - y_i| \quad (8)$$

where n is the number of features.

Canberra distance measures two points (x and y) based on its fraction of differences of two points as seen in (9) with n is the number of features.

$$dist = \sum_{i=1}^{n} \frac{|x_i - y_i|}{|x_i + y_i|} \quad (9)$$

Chebychev distance measures two points (x and y) with n features by finding the maximum value of the distance between the features of the two points, as seen (10)

$$dist = \max_i(|x_i - y_i|) \quad (10)$$

Where x_i and y_i are an i^{th} feature of the x and y points.

III. Results and Discussions

Three databases were employed to evaluate the proposed approach, i.e. the ORL, University of Bern (UOB), and YALE-A databases. There are 40 people in the ORL database, and 10 pose in each person. In the UOB database, there are 30 people, and 10 pose in each person. Meanwhile, 15 people and ten pose in each person in the YALE-A database. The example of the face images in all databases can be seen in Figure 3. For the experiment, we selected randomly four images as the training sets and the rest of images were utilized as the testing sets. The similarity measurements were conducted by using two until ten features only. There are four kinds of similarity measurements, i.e. Euclidean, Manhattan, Canberra, and Chebyshef distance.

Fig. 3. Example of dataset from ORL, UOB, and YALE-A database

The first experiment is conducted on ORL database. The recognition accuracy of the first experiment is depicted in Figure 4. For all similarity distances, more number of features makes the recognition accuracy increased. The lowest recognition accuracy is achieved when the number of features is two, i.e. 41.25% (Euclidian distance), 41.25% (Manhattan distance), 40.83% (Canberra distance), and 40% (Chebychev distance). The highest accuracy is achieved for the number of features is ten, i.e. 92.08% (Euclidian distance), 91.67 (Manhattan distance), 75.42% (Canberra distance), and 87.5% (Chebychev distance). A Number of features are important for the recognition rate, therefore in the experiment, the highest accuracy is achieved when the most number of features are extracted in this experiment. However, there is some certain threshold for the number of features. If the number of extracted features is more than the certain threshold, then the recognition rate is decreasing.

We can see also that Canberra and Chebyshev distance yield lower accuracy compare to Euclidian or Manhattan distance since both distance measurement (Canberra and Chebychev) are very sensitive. The Canberra distance is sensitive to a small change especially when the booth computed points are nearest to zero, meanwhile the Chebychev also sensitive to outlying measurements.

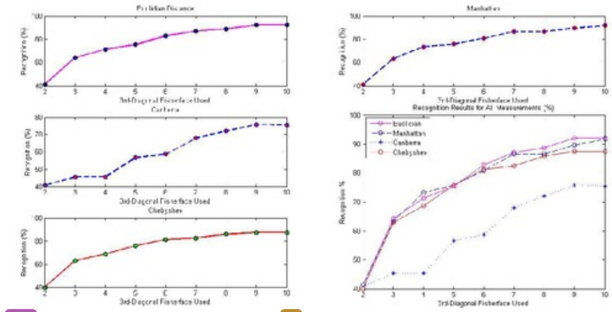

Fig. 4. Face Recognition accuracy of the ORL database

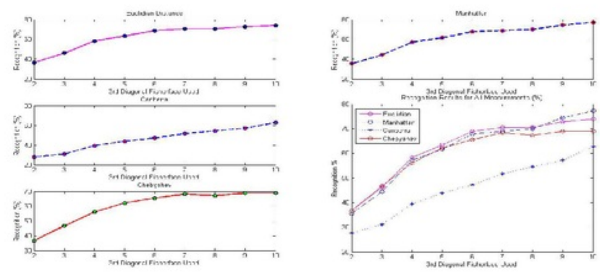

Fig. 5. Face Recognition accuracy of the UOB database

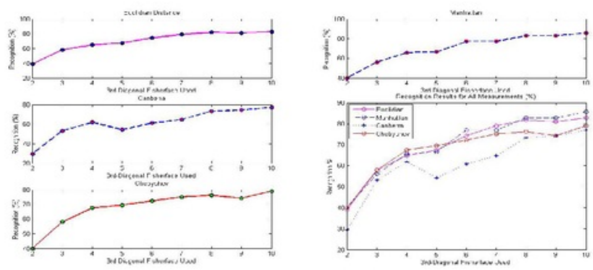

Fig. 6. Face Recognition accuracy of the YALE-A database

In the second experiment, the lowest accuracy is achieved when the number of the feature is two, i.e. 36.67% (Euclidian distance), 35.56% (Manhattan distance), 27.78% (Canberra distance), and 36.67% (Chebychev distance). The highest accuracy is achieved when the number of the feature is ten, i.e. 73.89% (Euclidian distance), 72.22% (Manhattan distance), 62.78% (Canberra distance), and 68.89 % (Chebychev distance). A similar result is obtained by the third experiment, i.e. the lowest accuracy is achieved when the number of the feature is two, and the highest accuracy is achieved when the number of feature is ten.

Canberra and Chebychev in the second and third experiment also yield lower accuracy rate compare with

Euclidian and Manhattan distance since the two distance measurement method is very sensitive to a small change of the data.

IV. Conclusion

This research proposed a new model of feature extraction for the face recognition, i.e. Three Directional of 1D Fisherface. In our proposed model, we create a diagonal matrix of the input image three times. This diagonal matrix is used as the input in the 1D Fisherface. Four distance measurement are used in the experiment, they are, Euclidian, Manhattan, Canberra, and Chebychev distance. The result of the experiment of the three databases (ORL, UOB, and YALE-A) yields Euclidian and Manhattan distance is best distance measurement method compare with Canberra and Chevychev distance since Canberra and chebychev are sensitive to the certain condition of the data. The result of the experiments also shows that the more number of extracted features makes the recognition accuracy increasing.

Acknowledgment

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