Modified distance measures for PCA-based face recognition

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ABSTRACT

In this paper, we compare 5 weighted distance measures between feature vectors with respect to the recognition performance of the principal component analysis(PCA)-based face recognition method, and propose modified weighted distance. The proposed method was modification of z, the weighted vector. The simulation was performed using the ORL face database, showed the best result for some weighted distances such as weighted manhattan, weighted angle-based, weighted modified manhattan, and weighted modified SSE. We also showed that using some various values of z(weighted values) we can achieve better recognition results that using the existing weighted value.

***Keywords**: Face recognition, PCA, Distance measures.*

1. INTRODUCTION

Principal Component Analysis(PCA) is a statistical method for the dimensionality of high dimensional data, where the data is represented as a vector. PCA is popular because it is easy to implement, is a natural dimensionality reduction method.

In 1991, Turk[1] developed a face recognition system using PCA. In this method, faces are represented by a linear combination of weighted eigenvector, named eigenface. Comparison is performed by calculating the distance between these vectors. In general, comparison of face images is performed by calculating the Euclidean distance between these features vectors. In 2000, Yambor[2] analyzed the role of eigenvector selection and eigenspace distance measures on PCA-based face recognition systems. In 2003, Moon [3] introduced the computational analysis of PCA-based face recognition algorithms. He experiment with different implementations of each module, and evaluate the different implementations using the September 1996 FERET evaluation protocol.

Recently, Perlibakas[4] compared recognition performance of 14 distance measures including Euclidean, angle-based, Mahalanobis and their modifications. Also, Song[5] analyzed the recognition performance of PCA/LDA by distance measures. Although there exist many other distance measures, we were able to find only few attempts to create, compare and use other distance measures in order to achieve better recognition results.

In this paper we compare recognition performance of 5 weighted distance measures such as weighted manhattan, weighted SSE(Some Square Error), weighted angle-based, weighted modified manhattan, and weighted modified SSE. Also, we propose the modified weight value(that is z) for weighted distance. The experiments showed that the proposed distance measures were among the best distance measures with respect to first one recognition rate in ORL face database.

The remainder of this paper is organized as follows. In Section 2, we explain PCA-based face recognition, and in section 3, the distance measures are described. Simulation results are presented in Section 4. Finally, conclusions are offered in Section 5.

2. PCA-BASED FACE RECOGNITION

PCA is popular for facial feature extraction and used to find a low dimensional representation of data. Let us consider a set of N sample images $\{x_1, x_2, \cdots, x_n\}$ taking values in an n-dimensional image space, and assume that each image belongs to one of C classes $\{X_1, X_2, \cdots, X_C\}$. Let us also consider a linear transformation mapping the original n-dimensional image space into an m-dimensional feature space, where $m < n$. The new feature vectors $y_i \in R^m$ are defined by the following linear transformation:

$$y_i = W_{PCA}^t (x_i - \mu), \qquad i = 1,2,\cdots,N \qquad (1)$$

where W_{PCA} is a $n \times m$ matrix. If the total scatter matrix S_T is defined as

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$$S_T = \sum_{i=1}^{N}(x_i - \mu)(x_i - \mu)^t \qquad (2)$$

where N is the number of sample images, and $\mu \in R^n$ is the mean image of all samples, then after applying the linear transformation, W^t_{PCA}, the scatter of the transformed feature vectors $\{y_1, y_2, \cdots, y_N\}$ is $W^t S_T W$. In PCA, the projection W_{PCA} is chosen to maximize the determinant of the total scatter matrix of the projected samples, i.e.,

$$\begin{aligned} W_{PCA} &= \arg\max_W \left|W^t S_T W\right| \\ &= [w_1, w_2, \cdots, w_m] \end{aligned} \qquad (3)$$

where $[w_1, w_2, \cdots, w_m]$ is the set of n-dimensional eigenvectors of S_T corresponding to the m largest eigenvalues. Distance between $[w_1, w_2, \cdots, w_m]$ is usually measured using the Euclidean distance, some researchers measures the distance between the feature vectors in the eigenspace using the angle-based measure, but other distance measures also could be used as Appendix A.

3. DISTANCE MEASURES

Let X, Y be eigenfeature vectors of length n. Then we can calculate the following distances between these feature vectors. The conventional method is that z_i is $\sqrt{1/\lambda_i}$. The proposed method is that eq. of z_i changes to $\sqrt[3]{1/\lambda_i}$. Generally, it is known that the weighted distance measures improve the recognition performance[5]. The general distance is introduced Appendix A, and the performance is Appendix B.

- Weighted Manhattan distance

$$d(X,Y) = \sum_{i=1}^{n} z_i |x_i - y_i|, \quad z_i = \sqrt{1/\lambda_i} \qquad (4)$$

- Weighted SSE distance

$$d(X,Y) = \sum_{i=1}^{n} z_i (x_i - y_i)^2, \quad z_i = \sqrt{1/\lambda_i} \qquad (5)$$

- Weighted angle-based distance

$$d(X,Y) = -\frac{\sum_{i=1}^{n} z_i x_i y_i}{\sqrt{\sum_{i=1}^{n} x_i^2 \sum_{i=1}^{n} y_i^2}}, \quad z_i = \sqrt{1/\lambda_i} \qquad (6)$$

- Weighted modified Manhattan distance

$$d(X,Y) = \frac{\sum_{i=1}^{n} z_i |x_i - y_i|}{\sum_{i=1}^{n} |x_i| \sum_{i=1}^{n} |y_i|}, \quad z_i = \sqrt{1/\lambda_i} \qquad (7)$$

- Weighted modified SSE-based distance

$$d(X,Y) = \frac{\sum_{i=1}^{n} z_i |x_i - y_i|}{\sum_{i=1}^{n} |x_i| \sum_{i=1}^{n} |y_i|}, \quad z_i = \sqrt{1/\lambda_i} \qquad (8)$$

Fig. 1 shows the value of eigenvalues according to dimensions in PCA. As the graph, the higher dimension the smaller value. That is, the weighted distance measure means that the values of high order dimensions make weaken. We are known that first order dimension is related to illumination. Therefore, using z_i means that it improves the performance reduced by illumination

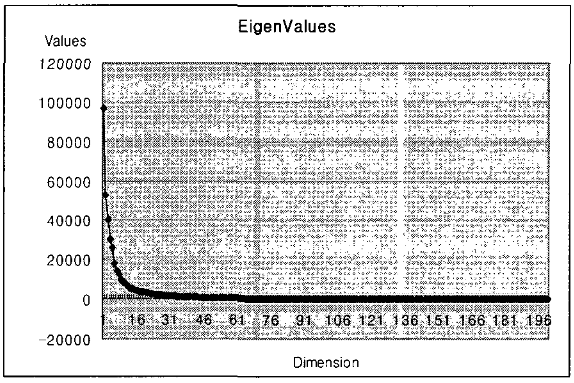

Fig. 1. The value of eigenvalues according to dimensions

4. SIMULATION RESULTS

The proposed method is tested on the ORL face image database[6]. The ORL database consists of 40 distinct persons. There are 10 images per person. The images are taken at different times and contains various facial expressions (open/closed eyes, smiling/not smiling) and facial details (glasses or no glasses). The size of image is 92×112 pixels with 256 gray levels. For the face recognition experiments, five images are randomly chosen for training from each person and the other five images are used for testing. Thus the total number of training images and testing images are both 200.

Tab. 1 shows the best recognition rate according to distance measures in PCA method. We simulated using the weighted values both $\sqrt{1/\lambda_i}$ and $\sqrt[3]{1/\lambda_i}$.

The existing method has the best performance 94 % with the weighted SSE, and the proposed method has also the best result 94.5%. But other weighted distance measures almost improved with respect to the best recognition rate. Also, the dimension of PCA that has the best recognition rate is higher the proposed method than existing method. But, if it is compare to the dimension that has same best recognition rate, the proposed method is improved for dimension reduction. For example, the weighted manhattan had same best recognition rate both 44 dimension for existing method and 30 dimension for the proposed method.

Table 1. The simulation result according to distance measures

Distance measures	The best recognition rate (%)		PCA (Dimension)	
	$z=\sqrt{1/\lambda}$	$z=\sqrt[3]{1/\lambda}$	$z=\sqrt{1/\lambda}$	$z=\sqrt[3]{1/\lambda}$
Weighted manhattan	92.5	93.5	44	44(30)
Weighted SSE	94	94.5	53	63(62)
Weighted angle-based	93.5	93.5	86	60(60)
Weighted modified manhattan	88	89.5	20	49(19)
Weighted modified SSE	89	90.5	28	41(26)

5. CONCLUSION

We proposed the modified weight value(that is z) for weighted distance. This method improved the performance of the existing weighted distance measures. In general, weighted distance measures used the square function, but it is the large weight values against distance. Therefore the original distance values are left the mean because of the large weight value. The proposed method overcomes the problem using cube root. We were able to improve performance of the various weighted distance measures for PCA-based face recognition.

Appendix A: The general distance measures

- Mnikowski (L_p metrics)

$$d(X,Y)=\left(\sum_{i=1}^{n}|x_i-y_i|^p\right)^{1/p}, \text{ here } p>0;$$

- Manhattan distance (L_1 metrics)

$$d(X,Y)=\sum_{i=1}^{n}|x_i-y_i| \;;$$

- Euclidean distance (L_2 metrics)

$$d(X,Y)=\sqrt{\sum_{i=1}^{n}(x_i-y_i)^2} \;;$$

- Some Square Error (SSE)

$$d(X,Y)=\sum_{i=1}^{n}(x_i-y_i)^2 \;;$$

- Mean Square Error (MSE)

$$d(X,Y)=\frac{1}{n}\sum_{i=1}^{n}(x_i-y_i)^2 \;;$$

- Angle-based distance

$$d(X,Y)=-\frac{\sum_{i=1}^{n}x_iy_i}{\sqrt{\sum_{i=1}^{n}x_i^2\sum_{i=1}^{n}y_i^2}} \;;$$

- Modified Manhattan distance

$$d(X,Y)=\frac{\sum_{i=1}^{n}|x_i-y_i|}{\sum_{i=1}^{n}|x_i|\sum_{i=1}^{n}|y_i|} \;;$$

- Modified SSE

$$d(X,Y)=\frac{\sum_{i=1}^{n}(x_i-y_i)^2}{\sum_{i=1}^{n}x_i^2\sum_{i=1}^{n}y_i^2} \;;$$

Appendix B:

Table. 2. The simulation result by general distance measures

Distance measures	The best recognition rate (%)	PCA (Dimension)
Minikowski	91.5	51
Manhattan	94	81
Euclidean	91.5	51
SSE	91.5	51
MSE	91.5	51
Angle-based	91.5	51
Modified manhattan	92.5	62
Modified SSE	89	43

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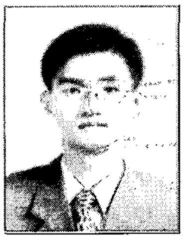

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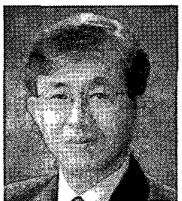

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