Face Recognition System Using Eigenface Method based on Facial Component Region

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Abstract

Development of face recognition methods afford capable method to recognizing face with expression, pose, noise variation and changes caused by illumination effects. In kind among others is eigenface method based on the Karhunen-Loeve expansion in pattern recognition, in other words the principal component analysis (PCA). Eigenface method reduce the N-dimension of face images to feature space M-dimension. Vector whole face images and facial component region saved on database. there are 6 component region that is forehead, eyes, nose, mouth, left side and right side. Face division is conducted when image saved on database and face recognition process. Each region is used to input eigenface process to get its feature space. Testing by considering characteristic of each facial component region gives better contribution than reference to characteristic whole face only. Even eigenface method gives succesfull recognition rate with adds effect as noise speckle, motion and illumination.

***Keywords** : Face recognition, eigenface*

1. Introduction

Face recognition is a pattern recognition especially for facial case. It can be describe as classify face known or not. Approach to object recognition and computer graphics are based on image without using 3-dimension model. Appearance based approach is the most used for face recognition, face image learned through training process using training data set. Generally, this method using statistic analysis technique and learning machine to find appropriate characteristic of face or non-face. In kind this method is eigenface, eigenface algorithm using principal component analysis (PCA) for reduce dimension to find vectors have best value to distribute face image in input face space. This vector define subspace named face space, training set projected into face space to find set of weight that describe contribution of each vector in face space.

Identification of testing image needs projection face image into face space to determine appropriate set of weight. Euclidean distance is used to compare weight of face space with weight of input image. More minimum distance determine more high resembling value. Until this time, Face recognition technology has not yet mature thus need to more developed. Recognition of face images is acquired in a setting with illumination changing, or pose variation of the subject, still remains a largely unsolved problem. Future research will direct to design method of face recognition have difference of pose, expression variation and illumination variation.

2. Eigenface Method

Eigenface applies the Karhunen Loeve expansion to extract feature within draft increasing efficiency. It can be decreasing feature dimension and handle possibility high discrimination. Karhunen Loeve is formed by eigenvector of covariance matrix from face vector. In face space high dimension, there is some initial eigenvalue which have high value. In other hand, energy most partly are located on subspace based on some initial eigenvector. Because of that, high compression can reached by permit eigenvector with high eigenvalue to representative face vector because eigenvector that connected to some initial eigenvalue looks like as face image. Eigenface presentation is known inside statistic literature as analysis main component. This method will efficient : for $M < N$, Karhunen Loeve representation have minimum mean square failure between possible probability using orthonormal M.

Vector base orthonormal is used to form feature space, image space can describe as a vector. Image by width *w* and height *h* will forms vector that have component by size w*h. This vector arranged by accumulating row image that arranged contiguous with others.

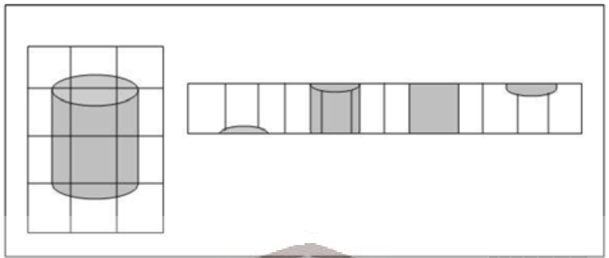

Figure 1. Formation Image Vector from 2 Dimensional Image [4]

Algorithm Eigenface Method

- Input pixel data image into matrix
  Suppose there is m training set with each image have dimension n pixel. Matrix represents images have dimension n x m.

$$u = \begin{bmatrix} u_{1,1} & \cdots & u_{1,m} \\ \vdots & \ddots & \vdots \\ u_{n,1} & \cdots & u_{n,m} \end{bmatrix} \qquad (1)$$

- Mean Vector
  Sum of vector training image divide by sum image in training set.

$$\bar{u} = \frac{1}{m}\sum_{k=1}^{m} u_{1,k} \qquad (2)$$

  From above, obtained mean vector matrix have dimension n x 1.

$$u = \begin{bmatrix} u_{1,1} \\ \vdots \\ u_{n,1} \end{bmatrix} \qquad (3)$$

- Covariance Matrix
  Subtraction image vector by mean vector will be input to obtaine covariance matrix.

$$C = \sum_{k=1}^{K}(x_k - u)(x_k - u)^T \qquad (4)$$

$$C = \Phi\Phi^T \qquad (5)$$

- Eigenvector and Eigenvalue

$$CV = \lambda V \qquad (6)$$

  The covariance matriks has a dmensionality N^2 *x* N^2, so one would have N^2 eigenfaces and eigenvalues. Computationally, this is not very efficient as most of those eigenfaces are not useful [2]. Thus eq. (6) is replaced become

$$\Phi^T\Phi V = \lambda V \qquad (7)$$

  Premultiplying both sides by A ,

$$\Phi\Phi^T\Phi V = \lambda\Phi V \qquad (8)$$

  from which we see that ΦV are the eigenvectors of $C = \Phi\Phi^T$.

Following these analysis, we construct the M x M matrix $L = \Phi^T \Phi$, where $L_{n,m} = \Phi_m{}^T \Phi_n$, and find the M eigenvectors, v , of L. These vectors determine linear combinations of the M training set face images to form the eigenfaces u_l .

$$u_l = \sum_{k=1}^{M} v_{lk} \Phi_k \tag{9}$$

With this analysis, the calculations are greatly reduced, from the order of the number of pixels in the images (N^2) to the order of the number of images in the training set (M) [3].

- Set of Weight
  The weights describing each face are found by projecting the face image onto each eigenpicture. A new face image U is transformed into its eigenface components by a simple operation [3],

$$\omega_k = (V_k)^T (U_i - \bar{u}) \tag{10}$$

- Euclidean Distance
  Euclidean distance is measure of similarity between two image. Output class is determined by smallest distance between weight of training set and weight of testing image.

$$\varepsilon_{C,k}^2 = \| \varphi_p - \varphi_k \|^2 \tag{11}$$

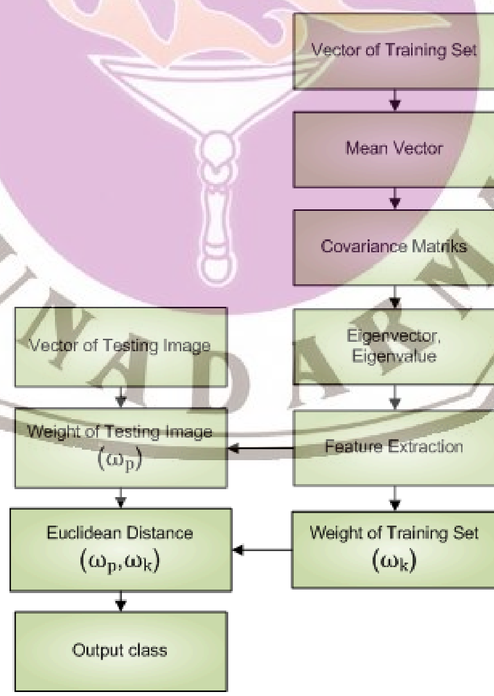

Figure 2. Process Face Recognition base with Eigenface Method

3. Face Division

The face Image is divided into 6 facial region that is forehead, eye, nose, mouth, left side and right side regions. The Figure 3 is face division illustration. First, face image is divided vertically into two region that is top face, this region must have forehead and eye region. Bottom face region must have nose and mouth region. Top of face is divided again into two region where possibility forehead existed on top and eye existed on bottom. Bottom face is divided into two region where 1/3 part is possibility nose existed and 2/3 part possibility mouth existed. Right and left face to be obtained by divide face image horizontally into two part. This step is conducted to face have difference of pose.

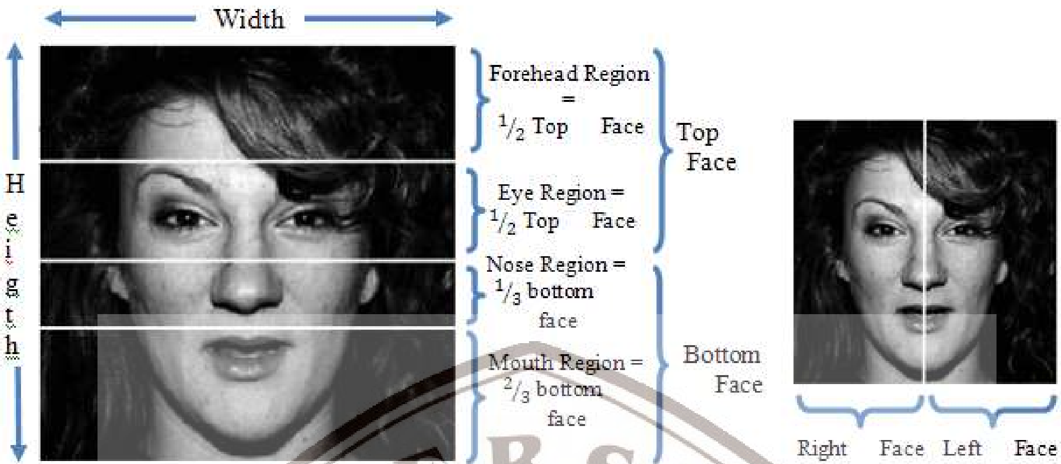

Figure 3. Face Division

4. Experimental Result

This experiment is conducted by using face database from The Psychology Image Collection at Stirling (PICtS) and The Japanese Female Facial Expression (JAFFE). 60 face images of 10 individuals (5 male, 5 female) of various pose (frontal, 45^0 and 90^0 of left side) and expression (neutral and happy) is used from The Psychology Image Collection at Stirling and 60 The Japanese Female Facial Expression (JAFFE) consist of 60 face image of 10 individuals of various expression (neutral, happy, sad, fear, surprise, mad). Each image is cropped to a width and height of 256 and 256 pixels respectively.

Figure 4. Face Database: a). The Psychology Image Collection at Stirling, b). The Japanese Female Facial Expression (JAFFE)

Training set amount gives influence towards recognition rate. On table 1 show that much more training set amount then recognition rate is better. The 5 images for each individual in the training set on face database PICtS gives optimal recognition rate (no.testing 5) while on face database JAFFE with 3 images for each individual gives optimal rate (no.testing 8).

Table 1. Testing Result based on Amount of Training Set

Database	NT*	Amount		Region (%)						Face (%)	Output (%)
		TS*	TI*	Left	Right	Nose	Mouth	Eye	Forehead		
PICtS	1	1	5	42	40	42	26	48	40	40	**44**
	2	2	4	50	65	55	42.5	52.5	55	62.5	**70**
	3	3	3	86.7	90	86.7	80	86.7	80	90	**93.3**
	4	4	2	80	90	85	75	85	70	95	**95**
	5	5	1	90	100	80	70	100	90	100	**100**
JAFFE	6	1	5	78	80	78	78	84	52	84	**88**
	7	2	4	87.5	82.5	87.5	92.5	90	72.5	87.5	**97.5**
	8	3	3	96.7	90	86.7	80	93.3	83.3	96.7	**100**
	9	4	2	100	95	95	100	100	85	100	**100**
	10	5	1	100	100	100	100	100	90	100	**100**

* TS : *Training Set* per individual; * TI : *Testing Image* per individual; * NT : No Testing

Experiment is conducted by adding image variation as give effect noise speckle, motion, illuminate changing and its combination. This conducted to know recognition rate when testing image had been manipulated. Figure 5 show testing image had been manipulated.

Figure 5. Image Variation. noise speckle with value a) 5, b) 15, c) 30, d) 40. Motion with value e) 10, f) 40, g) 70, h) 100. illumination i) -40, j) -20, k) 20, l) 40, m) noise speckle with value 5 and motion with value 40, n) figure m with illumination -20, o) figure m with illumination 20, p) original image.

Experiment with manipulated images is conducted using face database PICtS with 3 images of the training set, 3 images of the testing set and JAFFE with 2 images of the training set, 4 images of the testing set. From figure 5 could be seen that images by noise speckle and motion, it is hard enough to recognized but table 2 show that eigenface method gives good result for this variation. Noise speckle is gave to PICtS with value is 5, gives result achieving 80% and JAFFE achieving 82.5%. Effect motion on face database PICtS contributes 93.3% for value is 40 while on JAFFE achieving 95%. Illuminate low changing also contributes good enough recognition rate but with high changing influence toward recognition rate.

Table 2. Testing Result by Adding Variation

Database	NT	Variation		Region (%)						Face (%)	Output (%)
		Effect	V*	Left	Right	Nose	Mouth	Eye	Forehead		
PICtS	11	Noise Speckle	5	63.3	76.7	50	76.7	50	73.3	76.7	**80**
	12		15	56.7	76.7	40	63.3	43.3	70	70	**76.7**
	13		30	53.3	70	33.3	40	36.7	60	63.3	**73.3**
	14		40	56.7	66.7	33.3	40	33.3	60	60	**70**
	15	Motion	10	86.7	90	83.3	76.7	83.3	80	90	**93.3**
	16		40	80	83.3	76.7	60	70	76.7	83.3	**93.3**
	17		70	66.7	70	50	40	53.3	50	76.7	**80**
	18		100	46.7	66.7	36.7	36.7	36.7	50	66.7	**73.3**
	19	Ilumination	20	73.3	80	70	56. 7	76. 7	70	86.7	**90**
	20		-20	73.3	73.3	63. 3	53. 3	73. 3	53.3	80	**83.3**
	21		40	56.7	53. 3	60	40	56. 7	53.3	63. 3	**70**
	22		-40	40	46. 7	26. 7	23. 3	36. 7	23.3	43. 3	**46.7**
JAFFE	23	Noise Speckle	5	65	72.5	55	72.5	70	40	80	**82.5**
	24		15	50	62.5	50	52.5	57.5	40	72.5	**75**
	25		30	50	57.5	52.5	40	52.5	40	70	**75**
	26		40	47.5	60	45	42.5	42.5	40	65	**75**
	27	Motion	10	82.5	82.5	90	90	90	72.5	90	**97.5**
	28		40	82.5	80	85	82.5	75	67.5	85	**95**
	29		70	70	77.5	80	57.5	67.5	45	85	**90**
	30		100	62.5	57.5	75	45	37.5	37.5	67.5	**75**
	31	Ilumination	20	80	77.5	80	75	87.5	55	85	**90**
	32		-20	82.5	70	60	82.5	77.5	50	87.5	**87.5**
	33		40	52.5	37.5	40	47.5	47.5	27.5	50	**50**
	34		-40	55	22.5	37.5	55	30	32.5	62.5	**55**

*V : *Value*

Furthermore, experiment is conducted by adding various combination between noise speckle (value : 5) and motion (value : 40). This various combination images also obtain illumination changing achieve 20 and -20. Table 3 show recognition rate for this variation images.

Table 3. Testing Result by Adding Various Combination

Database	NP	Variasi	Region (%)						Face (%)	Output (%)
			Left	Right	Nose	Mouth	Eye	Forehead		
PICtS	35	S+M	56.7	66.7	40	50	36.7	63.3	56.7	**70**
	36	S+M+I^{+}	60	56.7	33.3	33.3	33.3	56.7	56.7	**60**
	37	S+M+I^{-}	33.3	46.7	26.7	40	33.3	46.7	43.3	**50**
JAFFE	38	S+M	47.5	55	30	55	45	40	57.5	**72.5**
	39	S+M+I^{+}	37.5	37.5	10	22.5	20	35	42.5	**40**
	40	S+M+I^{-}	52.5	30	35	60	17.5	20	50	**60**

*S+M : Speckle dan Motion; *S+M+I+ : Speckle, motion dan iluminasi +20;*S+M+I- : Speckle, motion dan iluminasi -20

5. Future Works

High illumination changing influences recognition rate especially for face recognition using eigenfac method. Illuminate normalization should be conducted to repair it or united by other method as fisherface. Eigenface method produces high total scatter matrix, it means produces within-class scatter matrix and between-class scatter matrix is maximum. For maximum recognition rate, within-class scatter matrix should be minimum. This can be a weakness of eigenface method especially for variations of illumination images because produces classification based on lighting conditions. Fisherface simplify classification by maximal ratio between within-class and between-class scatter matrix. Other works that can be conducted are unite eigenface method with other methods as artificial intelligence, neural networks, support vectors machine (SVM), etc.

6. Conclusion

This research shows that amount of training image variation is high enough then application of eigenface method will give good result. Face component region such as input image gives characteristic for recognition process so it can be consideration authentication yield. From experiment result are obtained that by consider characteristic facial component region can be increasing recognition rate than only consider the whole face. The 40 experiment is conducted, 32 experiment has better recognition rate than the previous research [4] and 2 experiment are contrary.

7. References

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