FRONTAL FACIAL SYMMETRY DETECTION USING EIGENVALUE METHOD

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Facial symmetry is correspondence of face components on the both sides of face, left and right of a dividing line or about a center or an axis. Most of the research use face component like eyes, nose and ears component to identify facial symmetry. In this paper we suggest to add mouth as another face component to increase accuracy in facial symmetry detection. The results of facial symmetry detection are used for authentication process, analysis in medical, psychology and anthropology scope. By using MATLAB 7.1 we develop a program that can analyze face, asymmetry or not with utilizing eigenvalue. The contribution of this analysis is to know whether eigenvalue is suitable or not in analyzing facial symmetry.

Keywords: eigenvalue, face components, facial symmetry

As one of the most successful applications of image analysis and understanding, face recognition has recently received significant attention, especially during the past few years. Undoubtedly if face recognition attract researchers from many disciplines such as image processing, pattern recognition, neural networks, computer vision, computer graphics, and psychology. One of Face Recognition topic is Facial Symmetry Detection.

Symmetry means exact correspondence of form and constituent configuration on opposite sides of a dividing line or plane or about a center or an axis. In mathematic, symmetry defines as an attribute of a shape or relation; exact reflection of form on opposite sides of a dividing line or plane. Facial symmetry is correspondence of face components on the both sides of face, left and right of a dividing line or about a center or an axis. Many paper and article from previous works claim that facial symmetry detection is a difficult task, for example in Y.Liu's paper that used eyes and nose to detect facial symmetry [1] and Maria Chan's that measure the position of face component to center line to detect facial symmetry [2].

The main point of facial symmetry is the same position and distance of face components both in left side and right side. But there is a problem in measuring position and distance of face components. Eigenface method is the answer for this problem.

Eigenface are a set of eigenvectors used in the computer vision problem of human face recognition. Basically, eigenfaces are a set of "standardized face ingredients", derived from statistical analysis of many pictures of faces. Any human face can be considered to be a combination of these standard faces. The higher the value, the closer the face is to that eigenface. Remarkably, it does not take many eigenfaces summed together to give a fair likeness of most faces. Also, because a person's face is no longer recorded by a digital photograph, but instead as just a list of eigenface values (one value for each eigenface in the database used), much less space is taken for each person's face. Eigenface consist of two, eigenvalue and eigenvector.

Eigenvalues are a special set of scalars associated with a linear system of equations (i.e., a matrix equation) that are sometimes also known as characteristic roots, characteristic values (Hoffman and Kunze 1971), proper values, or latent roots (Marcus and Minc 1988, p. 144)

The determination of the eigenvalues and eigenvectors of a system is extremely important in physics and engineering, where it is equivalent to matrix diagonalization and arises in such common applications as stability analysis, the physics of rotating bodies, and small oscillations of vibrating systems, to name only a few. Each eigenvalue is paired with a corresponding so-called eigenvector (or, in general, a corresponding right eigenvector and a corresponding left eigenvector; there is no analogous distinction between left and right for eigenvalues).

Measurement of facial symmetry have many advantages. In Psychology and anthropology, symmetry face are more useful then asymmetry face. Psychologists and anthropologists have considered facial asymmetry as a critical factor that can be used to evaluate attractiveness and expressions [3], even though most of it was done qualitatively using human observers. The approach that we want to do in this paper is to know whether eigenvalue is suitable or not in analyzing facial symmetry.

APPROACH

The general concept of the process is to measure distance between each face component and calculate the eigenvalue of each distance [4]. The eigenvalue of left side will be compare with right side.

Liu in his paper, proposed that to do facial symmetry detection, there are three point of face components used. Left eye, Right eye and nose which compose a triangle. By using only three face components, detection of facial symmetry will not be maximum. Example, if the detecting face have an abnormal mouth position, it will be a problem. In figure 1, if only used three components the face will be detected as symmetry face. Whereas, the mouth position is not symmetry.

To reduce this misidentification, we proposed to add mouth as another face component to increase accuracy in facial symmetry detection. Distances between each face component are distance from points existed in the face component square [4]. There are center point of right eye square, left eye square, mouth and nose.

From measurement above, we got eight distances which

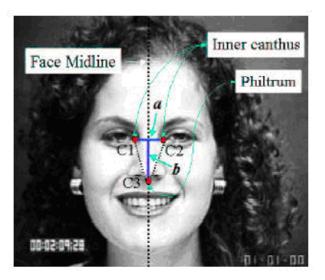


Figure 1: Analyze facial symmetry by using three components

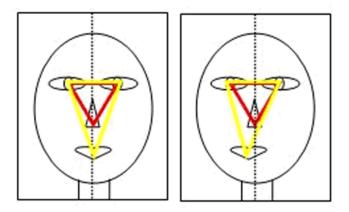


Figure 2: Face components that will be used in this analysis

will be an input for facial symmetry detection. There are: a) J1: Distance between right eye and left eye; b) J2: Distance between right eye and mouth; c) J3: Distance between left eye and mouth; d) J4: Distance between right eye and nose; e) J5: Distance between left eye and nose; f) J6: Distance between nose and mouth; g) J7: height of nose; h) J8: Wide of nose In this facial symmetry detection, there must be a deviation in measurement of face component. To handle it, Eigenvalue used to reduce deviation. Face are absolutely symmetry if eigenvalue of J2 equal with J3 and J4 equal with J5. Otherwise, Face are partly symmetry if eigenvalue of J2 equal with J3 or J4 equal with J5.

EXPERIMENTAL RESULT

This experiment is conducted by using face database from Student Image database from Gunadarma University. All of the images are in frontal position. The image will be grouped which consist of 8 images of each, to make block matrix of eigenvalue. By checking eigenvalue, we can analyze facial symmetry. We divided the experiment into two based on the combination of input data.

Facial Symmetry Detection with Randomize Data

In this experiment, we use 150 image data which consist of 8 face component distance of each. All of image data will be rendomized and grouped into 50 blocks of matrix with 8 image each group. So, From 50 blocks of matrix will be occured some repeating in use of image data.

From analysis of eigenvalue and eigenvector table, there are some images that have same value of j2-j3, j4-j5, or both of it. There are 101 images classified as partial symmetry image, 48 images classified as absolute symmetry and 104 images classified as not symmetry.

In this experiment, the repeated images are grouped into different matrix block combination. So, it can influence the calculation result. There are 4 images that classified in absolute symmetry class only, image 35, 58, 96 and 137. It is 2,6% from image database. It shows that success rate of this method is still small.

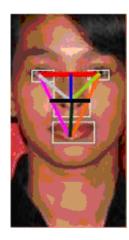


Figure 3: Eight distance that will be used in this analysis

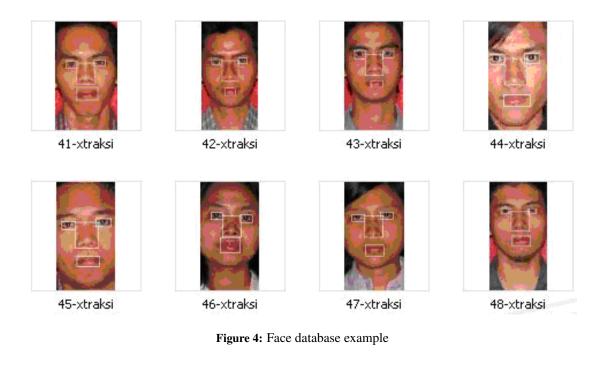


Table 1: First experiment matrix example									
49	61	60	38	38	26	29	31		
48	57	58	35	33	28	24	28		
47	59	56	37	31	28	24	30		
53	61	60	38	35	29	25	32		
44	53	54	36	34	21	27	28		
51	53	53	38	35	21	25	31		
47	57	55	34	30	29	21	29		
50	61	56	37	34	28	25	32		
53	56	59	35	36	27	24	33		
56	64	65	45	42	25	33	28		
55	62	68	41	43	27	31	34		
52	66	66	40	39	31	30	33		
48	61	63	35	36	31	26	30		
53	61	62	38	41	26	29	32		
49	64	66	37	39	31	29	31		
43	54	54	35	32	24	25	25		

Table 2: Second experiment matrix example									
44	56	53	35	31	25	25	26		
49	62	64	35	38	31	27	31		
50	61	56	37	34	28	25	32		
50	54	57	38	34	24	25	32		
45	55	53	35	31	25	24	28		
47	55	55	34	31	27	22	30		
54	60	60	38	37	28	25	33		
50	64	61	40	35	29	28	32		
46	60	56	38	34	25	28	29		
49	57	57	37	35	25	26	30		
49	61	61	37	36	29	26	30		
47	52	51	35	31	23	23	30		
51	54	56	36	34	25	23	31		
45	55	55	35	32	26	24	25		
51	59	57	39	38	23	29	31		
43	48	47	33	32	18	24	26		

No		J1	J2	J3	J4	J5	J6	J7	J8
	1	315.5505	0	0	0	0	0	0	0
	2	0	-1.35126	0	0	0	0	0	0
	3	0	0	-1.35126	0	0	0	0	0
- -	4	0	0	0	- <mark>1.92515</mark>	0	0	0	0
	5	0	0	0	0	-1.92515	0	0	0
	6	0	0	0	0	0	0.113059	0	0
	7	0	0	0	0	0	0	-0.37172	0
	8	0	0	0	0	0	0	0	-0.73902
	_								
No	71	J1	J2	J3	J4	J5	JG	J7	J8
No 1	-12	J1 -0.3724	J2 -0.2608	J3 -0.2608	J4 0.06793	J5 0.06793	J6 0.14688	J7 0.11214	
1						0 227)		- 17 Par 1	J8
1	-	-0.3724	-0.2608	-0.2608	0.06793	0.06793	0.14688	0.11214	J8 0.09634
1 2		-0.3724 -0.3491	-0.2608 0.03753	-0.2608 0.03753	0.06793 -0.189	0.06793 -0.189	0.14688 0.53908	0.11214 -0.4272	J8 0.09634 0.15668
1 2 3		-0.3724 -0.3491 -0.3504	-0.2608 0.03753 0.10299	-0.2608 0.03753 0.10299	0.06793 -0.189 -0.0073	0.06793 -0.189 -0.0073	0.14688 0.53908 0.10234	0.11214 -0.4272 -0.1227	J8 0.09634 0.15668 0.4172
1 2 3 4		-0.3724 -0.3491 -0.3504 -0.374	-0.2608 0.03753 0.10299 0.18519	-0.2608 0.03753 0.10299 0.18519	0.06793 -0.189 -0.0073 -0.0975	0.06793 -0.189 -0.0073 -0.0975	0.14688 0.53908 0.10234 -0.0769	0.11214 -0.4272 -0.1227 -0.0677	J8 0.09634 0.15668 0.4172 -0.4485
1 2 3 4 5		-0.3724 -0.3491 -0.3504 -0.374 -0.3333	-0.2608 0.03753 0.10299 0.18519 -0.5449	-0.2608 0.03753 0.10299 0.18519 -0.5449	0.06793 -0.189 -0.0073 -0.0975 0.47343	0.06793 -0.189 -0.0073 -0.0975 0.47343	0.14688 0.53908 0.10234 -0.0769 -0.1291	0.11214 -0.4272 -0.1227 -0.0677 -0.2015	J8 0.09634 0.15668 0.4172 -0.4485 -0.3466

Figure 5: Eigenvector and eigenvalue from first experiment

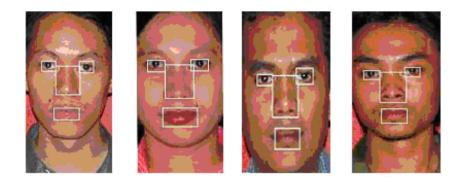


Figure 6: Symmetry face result from first experiment

No	J1	J2	J3	J4	J5	JG	J7	J8
1	317.9931	0	0	0	0	0	0	0
2	0	-5.05377	0	0	0	0	0	0
3	0	0	-5.05377	0	0	0	0	0
4	0	0	0	5.569156	0	0	0	0
5	0	0	0	0	1.383824	0	0	0
6	0	0	0	0	0	-0.45909	0	0
7	0	0	0	0	0	0	0.310277	0
8	0	0	0	0	0	0	0	0.310277
No	- 11	J2 -	J3 —	J4	J5	J6	J7	J8
1	-0.32817	0.394889	0.394889	0.056318	0.406783	0.089921	-0.15291	-0.15291
2	-0.37465	0.169065	0.169065	-0.54977	0.318078	-0.36507	-0.37897	-0.37897
3	-0.35921	-0.22327	-0.22327	-0.10684	0.047628	-0.30569	-0.21548	-0.21548
4	-0.34898	-0.27057	-0.27057	0.78613	-0.59651	-0.01799	0.492909	0.492909
4 5	-0.34898 -0.32922	-0.27057 0.115604	-0.27057 0.115604	0.78613	-0.59651 -0.1165	-0.01799 -0.00946	0.492909	0.492909
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5	-0.32922	0.115604	0.115604	0.142541	-0.1165	-0.00946	0.229442	0.229442

Figure 7: Eigenvector and eigenvalue from second experiment

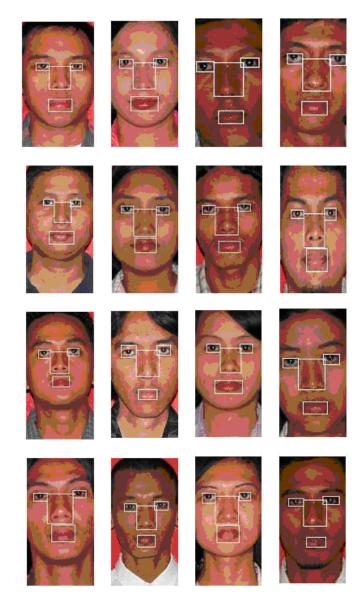


Figure 8: Symmetry face result from second experiment



Figure 9: Symmetry face result from first and second experiments

Facial Symmetry Detection with Fix Data

In this experiment, we use 152 image data which consist of 8 face component distance of each. All of image data will be grouped into 19 blocks of matrix with 8 image each group. Different with calculation by using randomize data, this experiment will not occurs repeating in use of image data.

From analysis of eigenvalue and eigenvector table, there are some images that have same value of j2-j3, j4-j5, or both of it. There are 56 images classified as partial symmetry image, 24 images classified as not symmetry, and 16 images classified as absolute symmetry. Images that classified as absolute symmetry are image 57, 58, 59, 60, 61, 62, 63, 64, 113, 114, 115, 116, 117, 118, 119 and 120. It shows that 10,5 % from 152 image database. Although still small, it is better from the previous analysis by using randomize image.

From 16 absolute symmetry images result in experiment with fix data and 4 absolute symmetry images result in experiment with randomize data, only 1 image (image 58) that existed in both of data. It shows that accuracy rate for facial symmetry detection is still low.

CONCLUSION

This research shows that analysis with fix data better than randomize data. The success rate in fix data is 10.5 %, it is 7.9% higher than success rate in randomize data that only 2.6 %. From 16 absolute symmetry images in fix data and 4 images in randomize data, only 1 image that existed in both of data. It shows that accuracy rate for facial symmetry detection is still low. It means the eigenvalue method is still not powerful enough to be used for facial symmetry detection.

In future, we plan to add another algorithm or method that will be combined with eigenvalue method to increase the accuracy in facial symmetry detection. Beside that, calculation percentage of facial symmetry is also needed and increase image database to avoid the used of redundant image.

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