Improved accuracy of recognizing of low-quality face images using two directional matrix in 2D-PCA algorithms and euclidean distance

R D K Kuncoro* and E Sugiharti
Computer Science Department, Faculty of Mathematics and Natural Sciences, Universitas Negeri Semarang, Indonesia

*Corresponding author: rizkidanang123@students.unnes.ac.id

Abstract. Face recognition is a technique that can be used to distinguish the characteristic facial patterns of a person. A very influencing factor in the facial recognition process is image quality, so it can affect the level of accuracy. Improving the accuracy of low-quality facial recognition can be done by processing the image for its feature extraction using Two Directional Matrix on 2D-PCA. From the extraction process, the Eigenfaces value is then generated to be classified. Image classification is done by using Euclidean Distance. Furthermore, the accuracy results between image recognition with or without Two Directional Matrix will be compared. The data used were the AT&T face of database and database of Essex. Of the 18 tests carried out on the Two Directional Matrix method, it was proven to improve facial recognition accuracy by as many as 12 trials. In 5 other experiments the accuracy decreased and 1 experiment was unable to increase or decrease facial recognition accuracy. The highest accuracy result in the experiment using AT&T was 98.25%, while in Essex it was 97.27%. Suggestions for further research by conducting experiments with more diverse dataset ratios in order to get better low-quality image accuracy results.

1. Introduction
Face recognition is a technique that can be used to distinguish the characteristics of a person's face pattern. Face recognition is a pattern recognition specifically for faces that compares input images with data in a database [1]. The face is one of the easiest physiological measures and is often used to distinguish individual identities from one another, because the face is a part of the human body that cannot be duplicated [2]. Face recognition technology is now very sophisticated and is applied in almost all the latest systems that manage images and photos, for example social media sites like Facebook and Google Plus that are able to recognize human faces and even predict the name of the owner of the human face [3]. Detection of face recognition technology is also more accurate than detection of signatures despite poor image quality [4].

Face classification system is an application that allows a machine to recognize a person's face according to a face image that has been trained and stored in the machine's database [5]. One of the most challenging issues in the fields of image analysis, computer vision and pattern recognition is face recognition [6]. Therefore there are several facial recognition methods that have been widely developed in research including Eigenfaces, neural networks, fisherfaces, elastic bune graph matching, template matching, and image segmentation selection methods are divided into two categories: fixed
segmentation selection and variable segmentation selection [7]. At present, there are many methods of facial recognition [8], which is largely divided based on geometric characteristics, based on Eigenfaces, local features, elastic models and neural networks. The PCA (Principal Component Analysis) method proposed by Turk and Pentland is a face recognition method based on Eigenfaces [9], because this method is simple and widely used. In 2004, who proposed 2D-PCA (Two-Dimensional Principal Component Analysis) to extract features, this method is that the sample is considered as a matrix for feature extraction with a two-dimensional matrix, apparently the resulting accuracy is higher than traditional PCA [10].

2D-PCA algorithm is an increase in PCA using the two-dimensional projection method directly. Feature extraction is based on a two-dimensional matrix rather than a one-dimensional vector. Covariance matrices calculated by 2D-PCA are relatively easy and convenient compared to PCA, and computational costs are greatly reduced, time consumption is reduced, and extracted features are more efficient [11]. By calculation, 2D-PCA has better computational time performance compared to PCA because the covariance matrix in 2D-PCA is directly obtained from the face image matrix [12].

The 2D-PCA method has two important advantages over the PCA method. First, it's easier to evaluate the covariance matrix accurately. Second, we don't need much time to determine the right eigenvector [13]. The main idea behind 2D-PCA is that it is based on 2D matrices that are in conflict with the standard PCA, which is based on 1D vectors. Although 2D-PCA obtains higher recognition accuracy than PCA, the important unresolved problem of 2D-PCA is that it requires more coefficients for image representation than PCA and the main problem in face recognition is how to deal with variations in pose, differences in attributes, and lighting [14]. Then it produces a low-quality face image so that it becomes an obstacle to increasing accuracy in face recognition.

There are several studies conducted using face images in different lighting scenarios, the results of the study show a decrease in the value of recognition accuracy of 30% to 60% [15]. 2D-PCA basically works in the direction of the row of images, taking into account the direction of rows and columns, developed 2D-PCA two-way using Two Directional Matrix, for face representation and recognition that is more accurate and efficient than 2D-PCA algorithm even though it uses a quality face image low.

The final stage in face recognition is the classification process. After important facial features are generated in the extraction process, these features will be used for the classification process. Based on research conducted by Saputra, shows that the use of Euclidean Distance as a classifier can provide a fairly high degree of accuracy. For facial images included in the training, 91% correct identification can be obtained [16].

Based on the description of the problem above which shows that the 2D-PCA method has better accuracy than the PCA method, but the use of 2D-PCA still needs to be improved by considering the direction of the rows and columns so that Two Directional Matrix is developed in the 2D-PCA method.

2. Methods

In general, the stages of this research include image decomposition with multi-level reverse biorthogonal wavelets, feature extraction with two types of PCA, 1D-PCA & 2D-PCA, and classification with Euclidean Distance. In this study, carried out by applying the Two Directional Matrix on 2D-PCA and Euclidean Distance. The following stages of data analysis in this study: (1) Take datasets from AT&T The Database of Face and University of Essex Dataset, (2) Divide the data into two parts, namely training data and testing data. This division is carried out repeatedly with a percentage of training data of 10% testing data 90% to training data 90% and testing data 10%. (3) Stage of facial image feature extraction using 2D-PCA. The result of this feature extraction is the eigenface value for each image, (4) Classification stage. The classification stage is carried out by matching the eigenface data training with the testing data using the Euclidean Distance algorithm, (5) The final results of this study will be obtained in the form of an accuracy value in each image classification. With this research step, it can be seen the comparison of accuracy in the classification of low-quality face image recognition with 2D-PCA and Euclidean Distance algorithms with Two-directional Matrix 2D-PCA and Euclidean Distance algorithms.
The 2D-PCA method only works in the direction of the row or column of the image. At this point, the 2D-PCA Two Directional Matrix algorithm is proposed to conduct PCA on the row and column of image pixels simultaneously. This stage of the method starts with building a small pixel image with each surrounding pixel image. The covariance matrix of an image can be defined as \( G \) which is a fixed matrix with the following formula:

\[
\bar{X} = \frac{1}{M} \sum_{i} x_i
\]  

(1)

From the 2D-PCA equation, a formula is defined to be \( G_1 \) as in the following equation.

\[
G_1 = \frac{1}{M} \sum_{j=1}^{M} \sum_{i=1}^{n} (X_{jk} - \bar{X}_k)^2 (X_{jk} - \bar{X}_k)
\]  

(2)

Then it can be concluded that the covariance matrix of image \( G_1 \) in Equation 2 can be obtained from the directional vector of the image line. Likewise, the original 2D-PCA functions in the direction bar of the image. Following the same path, \( G_2 \) in Equation 3 as a vector column directional product vector can be used to obtain. So the previous definition in row direction can be changed for column vectors \( k \) of \( X_i \) and \( \bar{X} \) as follows:

\[
G_2 = \frac{1}{M} \sum_{j=1}^{M} \sum_{i=1}^{n} (X_{jk} - \bar{X}_k) (X_{jk} - \bar{X}_k)^T
\]  

(3)

The projection matrix \( V_1 \) is produced from the orthogonal eigenvector of \( G_1 \) corresponding to all eigenvalues while the projection matrix \( V_2 \) consists of the orthogonal eigenvector \( G_2 \) corresponding to all eigenvalues. For each training and test image, set the image projection can be defined as:

\[
Y_i = V_2^T X_1 V_1
\]  

(4)

\( X_1 \) shows the pixel matrix image \( i \). In the feature extraction phase, the Two Directional Matrix in 2D-PCA is applied to all images separately by using a two-way matrix projection of a set of pixel images that can be obtained by Equation 4.

The next process after the image is extracted using Two Directional Matrix in 2D-PCA is the process of image classification with Euclidean Distance. The first step is the entry of the image that has been calculated the eigenface value then the value is compared with the training data, then the calculation of the distance between the eigenface testing and eigenface training uses the Euclidean Distance formula as in Equation 5. After obtaining the Euclidean Distance value in each image then the value is searched the smallest, for example the smallest value \( D \) then \( D \) compared to \( \theta \), \( \theta \) is the threshold value, if \( D \) is smaller than the threshold then the image is recognized and in accordance with the image in the dataset.

Euclidean Distance is the metric most commonly used to calculate the similarity of two vectors. Euclidean Distance formula as in Equation 5, which is the root of the square of two vector differences.

\[
d_{ij} \sqrt{\sum_{k=1}^{n} (x_{ik} - x_{jk})^2}
\]  

(5)

Information:
\( d_{ij} = \) level of difference
\( n = \) number of vectors
\( x_{ik} = \) input image vector
\( x_{jk} = \) comparison vector image or output

Euclidean Distance is chosen because this method is suitable for calculating the distance between pixel points of two different images. Euclidean Distance is calculated between this weight vector and
the image formed by the training image. This distance is a measure of the similarity between the image being tested and the face image in the dataset.

Classification of facial recognition with the Two Directional Matrix in the 2D-PCA algorithm and Euclidean Distance begins by changing the matrix of the face image into a two-dimensional two-way matrix using the 2D-PCA Two Directional Matrix. Then do the classification process with Euclidean Distance as shown in Figure 1.

![Figure 1. Face Recognition Process](image)

3. Result And Discussion

3.1. Result

The system is implemented with the Python programming language version 3.6.4. The libraries used are OpenCV, Numpy, Os and Scipy. GUI (Graphic User Interface) based programs are built using the Tkinter and Pandas libraries to display program results. All features are provided by the Python library via the PIP package in Python 3.6.4. PIP is a Package Management System that is used to download and manage Python packages. There are thousands of packages that can be found at PyPI.

The initial page is designed to display the thesis title page. When the face recognition program starts, the landing page or landing page is first seen. The appearance on the start page and the home display on this face recognition system can be seen in Figure 2.

![Figure 2. Main Page (Left), and Method Page (Right)](image)

The total tests carried out were 36 tests (18 attempts using the AT&T Face Dataset and Dataset of Essex by 2D-PCA feature extraction and 18 trials using the AT&T Face Dataset and Dataset of Essex by extracting the 2D-PCA Two Directional Matrix feature). The output of the test carried out is the result of the accuracy of the face recognition displayed in the form of image data being tested, correct testing, wrong testing and percentage of testing. The results of each test are then displayed in a graph consisting of graphs of the accuracy results with the 2D-PCA method, the Matrix Two Directional method and a graph of the overall results of the two methods.

The results of the accuracy of facial recognition by the 2D-PCA method and 2D-PCA Two Directional Matrix method on the AT&T dataset and the Essex dataset as a whole, ranging from testing with training data 10% to 90% can be seen in Table 1.
Table 1. 2D-PCA and 2D-PCA Two Directional Matrix Experiment Results

| Training Data % | 2D-PCA Experiment Results | 2D-PCA Two Directional Matrix Results |
|-----------------|---------------------------|----------------------------------------|
|                 | AT&T                      | Essex                                  | AT&T                    | Essex        |
| 10              | 69.30                     | 82.11                                  | 71.35                   | 82.11        |
| 20              | 81.58                     | 87.78                                  | 81.25                   | 85.56        |
| 30              | 87.22                     | 87.06                                  | 89.10                   | 84.71        |
| 40              | 86.84                     | 95.00                                  | 92.11                   | 94.38        |
| 50              | 90.00                     | 96.00                                  | 94.74                   | 94.00        |
| 60              | 88.16                     | 93.57                                  | 95.39                   | 95.00        |
| 70              | 92.11                     | 90.77                                  | 98.25                   | 96.15        |
| 80              | 93.42                     | 90.83                                  | 97.37                   | 96.67        |
| 90              | 92.11                     | 90.91                                  | 97.37                   | 97.27        |

The results of the overall level of facial recognition accuracy, consisting of 2D-PCA method with AT&T dataset and the Essex dataset, then with the 2D-PCA Two Directional Matrix method on the AT&T dataset and the Essex dataset. From testing with training data of 10% to 90% can be seen in Table 4.7. The overall graphic display displayed into the face recognition system using the Python programming language can be seen in Figure 3.

Figure 3. Overall Testing Results

3.2. Discussion

From the 18 tests conducted on the Two Directional Matrix method, it was proven to improve facial recognition accuracy by 12 experiments. In the other 5 trials the Two Directional Matrix experienced a decrease in accuracy and as much as 1 trial was unable to increase or decrease the accuracy of facial recognition.

The advantage of face recognition with the Two Directional Matrix method in 2D-PCA and Euclidean Distance is that it shows more accurate results than the 2D-PCA and Euclidean Distance method. The drawbacks of facial recognition with the Two Directional Matrix method in 2D-PCA and
Euclidean Distance are that they cannot show an increase in regular accuracy results in low quality images, increasing accuracy only if the training dataset is above 50%.

The cause of the increase in facial recognition accuracy with the Two Directional Matrix method in 2D-PCA and Euclidean Distance because image extraction is done in a two-dimensional two-way matrix and then produce a better image Eigenface value, so that the value is smaller than the threshold then the image is more easily recognized.

The cause of the decrease in accuracy of facial recognition with the Two Directional Matrix method in 2D-PCA and Euclidean Distance in the Essex dataset because the image dataset is of low quality, so that it requires a training dataset that is high enough to be able to improve accuracy, such as the accuracy of using the training dataset 60% up to 90% have improved facial recognition accuracy with the Two Directional Matrix method in 2D-PCA and Euclidean Distance methods.

4. Conclusion
The results of the experiment using AT&T show that the Two Directional Matrix method is able to improve facial accuracy results quite well, almost all tests on the AT&T dataset have increased, the accuracy results only decreased in the 20% training dataset test. Testing on the Essex dataset shows that the Two Directional Matrix method is able to increase the facial accuracy results from 2D-PCA, the accuracy is the same and does not increase the 10% training data, the accuracy decreases by 2.24% on the 20% training data, the accuracy decreases by 2, 35% on training data 30%, accuracy decreased 0.62% on training data 40%, accuracy decreased by 2% on training data 50% to 90% accuracy increased, the greater the training data the greater the level of accuracy. In contrast to the AT&T dataset, testing on the Essex dataset has decreased accuracy, especially on 20-50% training data, while training data of 60-90% has increased accuracy. Of the 18 tests carried out on the Two Directional Matrix method, it was proven to improve facial recognition accuracy by as many as 12 trials. In the other 5 trials, Two Directional Matrix experienced a decrease in accuracy and 1 experiment was unable to increase or decrease facial recognition accuracy.

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