Comparative Analysis of Eigenface and Learning Vector Quantization (LVQ) to Face Recognition

R Chandra\(^{1,}\)*, S An-Nissa\(^{1}\) and E M Zamzami\(^{2}\)

\(^{1}\)Master Programme in Informatics, Universitas Sumatera Utara, Medan, Indonesia
\(^{2}\)Faculty of Computer Science and Information Technology, Universitas Sumatera Utara, Medan, Indonesia

*Email: rudychandra0@gmail.com

Abstract. Face recognition is a topic most often discussed in this era because it can be applied and developed for several needs that can be useful in daily life. Face recognition always use learning method like eigenface and learning vector quantization (LVQ). The learning process is using the face of a digital image taken from a camera in five angles for one person that will apply for dataset learning (training and learning data set), and the live image is taken from the camera for testing (testing data image). The first step image will be detected with a haar cascade and captured by a camera. It will use to processing images to get the best image and prepare to be input into the network. From the experiments with 10 testings with various parameter values, the experiment results obtained the LVQ is more accurate than eigenface to identifying faces with average accuracy 66.29% and eigenface is 56.67% with comparison 9.62%, but eigenface is faster in running time with average time 4.39 seconds and 7.38 seconds for LVQ with comparison 2.98 seconds.

1. Introduction
Developing a computational model of face recognition is quite difficult because faces are complex, multidimensional, and meaningful visual stimuli. Researcher and interest activities in face recognition have increased significantly over the past few years. Face recognition identification systems developed based on differences in biometrics-based facial features that have high accuracy [1]. Finally, human face recognition technology has gradually evolved into one of the universal biometric solutions because it is considered more accurate if we compared it to other biometric identification options [2]. Face recognition applications can be seen in daily life, such as attendance systems at schools and companies, security systems for banking authentication, security systems for access control, and etc. In the process of face, recognition requires a method that is able to imitate the behavior and learn how to recognize a certain pattern that has its own characteristics [3, 4, 14]. These problems can be solved by using the Artificial Neural Network (ANN) technique.

Artificial Neural Network (ANN) is a non-linear statistical data modeling tool. ANN can be used to model complex relationships between inputs and outputs to find patterns in data. Artificial neural network in its attempt to imitate human intelligence. ANN has many algorithms to recognize some faces, such as Learning Vector Quantization (LVQ), Self-Organizing Maps (SOM), Kohonen, Eigenface, etc.

Eigenface is primarily a dimension reduction method, and a system can represent many subjects with a relatively small set of data. As a face-recognition system, it is also fairly invariant to large reductions in image sizing; however, it begins to fail considerably when the variation between the seen images and
probe image is large [5, 6]. The weights of each gallery image only convey information describing that image, not that subject. An image of one subject under frontal lighting may have very different weights to those of the same subject under strong left lighting. This limits the application of such a system. Experiments in the original Eigenface paper presented the following results: an average of 96% with light variation, 85% with orientation variation, and 64% with size variation [7].

Learning vector quantization (LVQ) is a method for training supervised competitive layers. The competitive layer will learn automatically to classify the given input vector. If several input vectors have very close distances, the input vectors will be grouped in the same class. [8] The system can accurately detect more than one face in a relatively fast time. To record the attendance of all students, it only takes 40 seconds time for a total of 50 students. This system had succeeded in recording students' entry and exit time according to the time when their face was photographed. From the results of our experiments, we can also conclude that performance improvements in estimated time attendance are very significant if we compared to the traditional attendance systems.

This paper is presented as follows; the first section will discuss the background, the application of face recognition, name of the method to recognize. The second section will discuss theory and method about face recognition algorithm that is eigenface and learning vector quantization. The third section will discuss steps that will be done in this research, which can be seen as a flowchart. The fourth section will do some experiments and testing to get the result from the analysis of this algorithm. In the final section, we will conclude all the discussions that have already been done.

2. Review of Literature

2.1. Image

Digital images are tiles arranged in the form of coordinate matrices. Each tile formed is called a pixel and has coordinates (x, y). X-axis (horizontal): column (column), y-axis (vertical): line (line, line). Digital Images must have an image type and file size, so it can be processed by a computer [9].

2.2. Haar cascade

Haar cascade is using the intensity values of a pixel, uses the change in contrast values between adjacent rectangular groups of pixels [10]. The contrast variances between the pixel groups are used to determine relative light and dark areas. Two or three adjacent groups with a relative contrast variance form a Haar-like feature [11]. Haar features can easily be scaled by increasing or decreasing the size of the pixel group being examined. This allows features to be used to detect objects of various sizes [12].

2.3. Neural network Eigenface

To recognize the faces, gallery images those seen by the system are saved as collections of weights describing the contribution each eigenface has to that image. When a new face is presented to the system for classification, its own weights are found by projecting the image onto the collection of eigenfaces. This provides a set of weights describing the probe face. These weights are then classified against all weights in the gallery set to find the closest match. A nearest-neighbor method is a simple approach for finding the Euclidean distance between two vectors, where the minimum can be classified as the closest subject [13].

Algorithm:

- Given input image vector \( U \in \mathbb{R}^n \), the mean image vector from the database \( M \), calculate the weight of the kth eigenface as:

\[
 w_k = V_k^T (U - M) 
\]  

Then form a weight vector

\[
 W = [w_1, w_2, ..., w_k, ..., w_n]
\]
• Compare W with weight vectors $W_m$ of images in the database. Find the Euclidean distance.

\[ d = ||W - W_m|| \] (3)

• If $d < \varepsilon_1$, then the entry in the database is a candidate for recognition.
• If $\varepsilon_1 < d < \varepsilon_2$, then $U$ may be an unknown face and can be added to the database.
• If $d > \varepsilon_2$, $U$ is not a face image.

2.4. Neural network Learning Vector Quantization (LVQ)
LVQ is a neural network with a single layer feeder (Single Layer Feedforward) architecture type, which consists of an input unit and output unit. A competitive layer will automatically learn to classify input vectors. The classes obtained as a result of this competitive layer depend only on the distance between the input vectors. If two input vectors are close together, then the competitive layer will place the two input vectors into the same class [9].

Algorithm:
• Set: Initial Weight (W), Maximum Epoch (MaxEpoch), and Learning rate ($\alpha$).
• Input:
  a. Input: $x(m,n)$; $m$ is the amount of input, $n$ is the amount of data.
  b. Target: $T(1,n)$
• Set First Condition:
  a. Epoch=0
• Do if: (epoch < MaxEpoch)
  a. Epoch = epoch + 1
  b. Do for $i=1$ until $n$
     - Fixed J such that $||X - W_j||$ minimum (call as $C_j$ (distance Euclidian))
     - Repair $W_j$ with the conditions:
       i. If $T = C_j$ so: $W_j(new) = W_j(old) + \alpha (X - W_j(old))$ (4)
       ii. If $T \neq C_j$ so: $W_j(new) = W_j(old) - \alpha (X - W_j(old))$ (5)
  c. Subtract the value $\alpha$

3. Research Methods

3.1. Flowchart
In analyzing Eigenface and Learning Vector Quantization (LVQ) algorithm to face recognition, the researchers prepare the steps that will be done in this research which can be seen as flowchart Figure 1.
4. Results and Discussion

Based on the training and simulation results can be obtained a comparison of speed and accuracy between the Eigenface and Learning Vector Quantization (LVQ) algorithm. Face suitability testing has been done on a number of students of computer science and information technology, where each student's face is photographed 5 times in different angles and saved in the dataset. Furthermore, the results of this photo will be compared to the original face. The student will bring his face to the camera to take a picture, and the system will compare the face to the stored dataset image. If the face is suitable, it will be detected and show the result as the student’s name [8]. Testing is done by using 5 different angle digital images where each image will be training by a network. The network parameters used are a maximum error, learning rate, and epoch number, as can be seen in table 1 [9].

Table 1. Network parameters testing algorithm.

| Network Parameters | Value          |
|--------------------|----------------|
| Epoch              | 100, 500, 1000 |
| Learning Rate      | 0.1, 0.5, 1    |
| Minimum Error      | 0.1, 0.01, 0.001 |

The test results are done by using parameters in table 1 with the number of tests 10 faces each face is tested 10 times for all parameters can be seen as in table 2.

Table 2. Face recognition testing results.

| No | E  | LR | ME | Eigenface | LVQ |
|----|----|----|----|-----------|-----|
|    | E  | LR | ME | R | NR | RT | R | NR | RT |
|---|----|----|----|---|----|----|---|----|----|
| 1 | 100 | 0.1 | 0.1 | 3 | 7 | 3.36 | 5 | 5 | 6.37 |
| 2 | 100 | 0.1 | 0.01 | 2 | 8 | 3.38 | 4 | 6 | 6.44 |
| 3 | 100 | 0.1 | 0.001 | 4 | 6 | 3.41 | 5 | 5 | 6.41 |
| 4 | 100 | 0.5 | 0.1 | 4 | 6 | 3.48 | 6 | 4 | 6.49 |
| 5 | 100 | 0.5 | 0.01 | 5 | 5 | 3.56 | 5 | 5 | 6.52 |
| 6 | 100 | 0.5 | 0.001 | 4 | 6 | 3.59 | 7 | 3 | 6.58 |
| 7 | 100 | 1   | 0.1 | 6 | 4 | 3.58 | 6 | 4 | 6.57 |
| 8 | 100 | 1   | 0.01 | 6 | 4 | 4.02 | 5 | 5 | 6.58 |
| 9 | 100 | 1   | 0.001 | 3 | 7 | 4.08 | 5 | 5 | 6.59 |
| E  | LR  | ME  | R  | NR  | RT  |
|----|-----|-----|----|-----|-----|
| 10 | 500 | 0.1 | 5  | 5   | 4.31 | 6   | 4   | 7.13 |
| 11 | 500 | 0.01| 6  | 4   | 4.36 | 7   | 3   | 7.00 |
| 12 | 500 | 0.0001| 5  | 5   | 4.29 | 8   | 2   | 7.11 |
| 13 | 500 | 0.01| 6  | 4   | 4.34 | 6   | 4   | 7.15 |
| 14 | 500 | 0.01| 7  | 3   | 4.33 | 5   | 5   | 7.19 |
| 15 | 500 | 0.0001| 6  | 4   | 4.36 | 7   | 3   | 7.23 |
| 16 | 500 | 1   | 0.1| 5   | 4.50 | 6   | 4   | 7.26 |
| 17 | 500 | 1   | 0.01| 3  | 7   | 4.59 | 6   | 4   | 7.31 |
| 18 | 500 | 1   | 0.0001| 6  | 4   | 4.55 | 7   | 3   | 7.30 |
| 19 | 1000| 0.1 | 1  | 7   | 5.05 | 5   | 8   | 2   | 8.08 |
| 20 | 1000| 0.01| 6  | 4   | 5.06 | 9   | 1   | 8.14 |
| 21 | 1000| 0.0001| 7  | 3   | 5.09 | 7   | 3   | 8.24 |
| 22 | 1000| 0.5 | 0.1| 8   | 2   | 5.10 | 8   | 2   | 8.29 |
| 23 | 1000| 0.01| 7  | 3   | 5.19 | 7   | 3   | 8.34 |
| 24 | 1000| 0.0001| 8  | 2   | 5.18 | 7   | 3   | 8.45 |
| 25 | 1000| 1   | 0.1| 7   | 3   | 5.30 | 9   | 1   | 8.52 |
| 26 | 1000| 1   | 0.01| 8  | 2   | 5.32 | 8   | 2   | 9.02 |
| 27 | 1000| 1   | 0.0001| 9  | 1   | 5.36 | 10  | 0   | 9.07 |

Explanation:

E = Epoch  LR = Learning Rate  ME = Minimum Error
R = Recognized  NR = Not Recognized  RT = Running Time

In this experiment, the researchers use a computer with specification Processor Intel(R) Core(TM) i3-3110M CPU @ 2.40GHz 2.40 GHz, 6.00 GB memory (RAM), system type 64-bit operating system, x64-based processor, operating system windows 10 pro, hard disk drive 500 GB. The data set used 5 angles for 1 person each image has resolution 100 x 100 pixel.

The experiment needs images as a data set used for learning (training and learning data set). The researchers prepare the image of data set in this research which can be seen as image Figure 2:

![Figure 2. Image of dataset.](image-url)
Table 3. The result of the testing and recognizing experiment.

| Process               | Eigenface | LVQ  | Comparisons |
|-----------------------|-----------|------|-------------|
| Running Time Average  | 4.39 s    | 7.38 s | 2.98 s      |
| Average Accuracy      | 56.67%    | 66.29% | 9.62%       |

From table 3 we can see the LVQ is more accurate than eigenface to identifying faces with average accuracy 66.29% and eigenface is 56.67%, but eigenface is faster than LVQ with an average running time of 4.39 seconds and 7.38 seconds for LVQ.

5. Conclusions

From the results of experimental comparison between eigenface and Learning Vector Quantization, it can be made conclusion as follows: The recognition match rate depends on the combination of parameter values used in the learning process, the best combination of Learning Vector Quantization and eigenface is same and obtained the maximum is 1000 epoch, the learning rate is 1, and the minimum error is 0.001. From the experiments with 10 testings with various parameter values, the experiment results obtained the LVQ is more accurate than eigenface to identifying faces with average accuracy 66.29% and eigenface is 56.67% with comparison 9.62%, but eigenface is faster in terms of proven time with average time 4.39 seconds and 7.38 seconds for LVQ with comparison 2.98 seconds.

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