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Multi-Instance Face Recognition System Using Pca And Ann

Adhi Kusnadi[1*] , Wella[1,2] , Rangga Winantyo[1] , Ivranza Zuhdi Pane[1] , Muhammad Iqbal Fasa[1,2]

[1]Faculty of Engineering and Information, Universitas Multimedia Nusantara, Tangerang 15227, Indonesia.

[2]Islamic Economics and Business Department, Raden Intan State Islamic University, Bandar Lampung 35131, Indonesia.

Abstract: Multi-instance Biometrics is a biometric system configuration in which biometric information is taken in different conditions, coming from the same biometric type. This study uses biometric from two-dimensional image of face that is taken from two sides of the face itself and compares the effect of Principal Component Analysis (PCA) on face recognition where the system is run by NN Backpropagation artificial neural network. This study finds that the recognition performance and learning speed of network systems are better when PCA is used and have an accuracy of up to 97%.

Keywords: Multi-instance biometric, face recognition system

Introduction

Biometrics can be described as a technology that uses the biological characteristics of a person to identify their identity. Biometric identifiers are divided into two types: physiological and behavioral. Physiological characters are related to the shape or pattern structure of the body, such as fingerprints, faces, DNA, palms, blood vessels in the hands, iris, retina, while behavioral characteristics relate to a person's behavior patterns such as typing, walking, and voice [1].

The unibiometric system itself is a system that performs recognition from one biometric source, and this system itself still has many problems such as noisy data caused by sensors that are not adequately maintained, non-universality - which can cause the system not to recognize biometric, non-individuality - occurs when there are identical biometrics from different people such as twins or children and parents, non-invariant representation - caused by inappropriate interactions between the user and the sensor (changing angles when acquiring the biometric, different facial expressions, etc.) and very easy to spoof [2] [3].

To overcome the weakness of unibiometric, multibiometric is designed to recognize the identity of an individual from multiple biometric source because the fusion of information from different source can give a more accurate result [4]. The advantages of using multibiometric are the increasing level of recognition accuracy, does not limit the user to just one type of biometrics, reduces the possibility of spoofing because it is challenging to produce a large number of fake biometrics at the same time, and reduces noisy data because it uses data from various kinds of origin [5].

In some cases, the use of biometric can be used together with traditional user validation schema like password or passcode and moreover, the use of multiple sensors to acquire one type of biometric can allow the use of system in different environments. The before mentioned examples showed the importance of the use of method for the effective fusion of biometric that can consolidate information from various source [5].

Research on fusion features has been done before, such as research [6] which found a method for building a dictionary that could be used in supervised dictionary learning and had good accuracy in face recognition. Apart from that, there was also research [7] which used the multi-feature fusion method for thermal facial recognition and resulted in better facial recognition compared to using only one feature and was more resistant to noise, occlusion, expressions, and low-resolution images.

In the biometric system itself, there is five categories that is distinguished by the source of the biometric itself, which are [5]:

- Multi-sensor system: the system uses multiple sensors to acquire a biometric from an individual.
- Multi-algorithm system: the system uses more than one algorithm to increase the performance of the system.
- Multi-sample system: the system uses multiple sample that is acquired from the same biometric that is obtained from a sensor.
- Multi-instance system: the system uses biometric information that is extracted from multiple instances of a body part.
- Multimodal system: the system uses a combination of result that is acquired from a biometric trait for identification purpose.

Research on multi-instance biometrics has also been carried out before such as research [8] who used Discrete Cosine Transform (DCT) to extract features from the right and left palms, research [9] used a variety of facial images taken from video to perform multiple face recognition simultaneously, research [10] used several facial expressions captured in three dimensions to improve the quality of facial recognition in three dimensions.

Although there have been many studies on fusion features and multi-instance biometrics, there are also drawbacks such as the need for more devices to acquire data when more than one type of biometric is used, requiring more computations due to data extraction from different source, and allows for data redundancy because more features are used [6]. For that reason, this study is designed to resolve the weakness that is caused by fusion feature and multi-instance biometric as well as finding recognition method that is easy, quick, and accurate.

In this study, the general recognition system framework begins with taking facial images from two sides. Then the data from the two images are combined, while in the study [11], the data was reconstructed into a 3-dimensional model using epipolar geometry before being recognized. The system is compared to research [11] in order to find the best system. After the merging, the data will be applied two different methods: without the use of Principal Component Analysis (PCA) and by using PCA. NN Backpropagation is then used for facial recognition.

From the previously mentioned method, PCA is one of the methods used because PCA can re-express data in lower vector dimensions and reduce data redundancy without eliminating too much original data [12]. The use of PCA is significant because of the existing step of combining facial image data taken from two sides, where the merged image results in a larger dimension size, but smaller data size is needed to be used at a later stage by reducing the dimensions of the data.

The data is then used as input in the backpropagation neural network algorithm for recognition. In comparison, one of the existing neural network algorithms, namely the Restricted Boltzmann Machine (RBM), which is part of deep learning, has not been chosen since the algorithm uses more layer [13]. Beside the use of more layer, there is also advantages and also bigger disadvantage in term of bigger computation compared to backpropagation. Due to the high number of layers used, the processor needs to compute more.

This study was conducted to compare facial recognition accuracy and training speed between methods that did not use PCA and used PCA, which was then applied to the artificial neural network system. From the experimental results, it was found that the method using PCA had better performance rather than the method that did not use PCA, both in terms of recognition accuracy and training speed.

This research report divided into several parts, namely part 2 explaining the theories that are discussed and used in this study, part 3 describes the method used, part 4 describes the experimental results, and part 5 will conclude the results of this experiment.

2 Literature Study

2.1. Multi-Instance

Multi-instance refers to the system that acquired multiple instances of a biometric trait, for example the use of left and right irises for recognition, the use of two or more fingerprints from an individual, and the use of the multiple images of a person’s face [14]. Multi-instance systems may use the same feature extraction and matching methods for all instances of the biometric trait. The system itself can be cost-effective if a single sensor is used to acquire the multiple instances sequentially and it can also be expensive when multi-unit data need to be obtained simultaneously [4].

2.2. Principle Component Analysis (PCA)

Principal Component Analysis (PCA) is a statistic method under the broad title of factor analysis and has been used in a lot area of pattern recognition and signal processing. The purpose of using PCA is to extracting important information from data and expressing this information as the new set of orthogonal variables that is called as principal components [15].

One of the various ways to determine the number of components that can be used is the Scree Test technique, where the number of principal components is determined when the curve becomes flat by looking at the main component axis [14].

2.3. Backpropagation

Backpropagation is a supervised learning algorithm that uses a Multi-Layer Perceptron to change the weights associated with neurons in the hidden layer. In neural networks, when feedforward is completed, backward propagation is required using the previous output error to change the value of the previous weight [15].

The use of backpropagation on an artificial neural network can train the existing network to recognize the patterns used during data training and provide the correct response to input patterns that are similar to the patterns used during training [16].

3 Method

The image's face is taken from the right and the left side of the face at 45-degree angle. Then, these two images are combined to be converted into a two-dimensional array. Then, the two-dimensional array is transformed into a one-dimensional array through flattening. The data that has been obtained is then divided into training data and testing data with a predetermined proportion.

Data is then reduced using PCA using the Scree Test technique to find the most optimal number of components. On the resulting graph, the point where the curve of the Scree Test changes drastically indicates the number of components being held [17].

The next stage is to train the acquired data which are both reduced and non-reduced training data. On the research, Scikit-Learn library MLP and the Rectified Linear Unit (Re LU) activation function are used to build the network. In the used artificial neural network, there are three layers, namely: input layer, hidden layer, and output layer.

Hidden layer plays an important role because it can strongly influence the training step of a model – whether it can produce a good working model or not. There is no exact number to determine the number of hidden nodes used in an artificial neural network, so an estimator or approximate value is needed for the number of hidden nodes needed in the content case after several tests.

4 Implementation

4.1. Testing Scenarios

The following scenarios are used:

- The data sharing ratio is 60% for training data and 40% for testing data.
- Scree Test experiment with component parameter multiples of 10 and cumulative explained above 10 is obtained in number 20. Figure 1 is the result of the Scree Test performed.

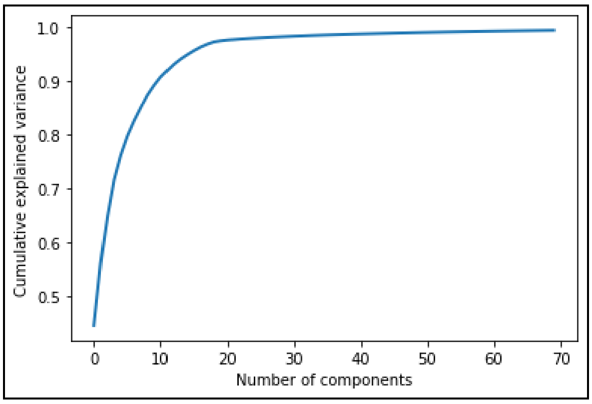

Fig.1 Scree Test Result

- For the artificial neural network, input of 20,000 nodes are used for the method without PCA implementation and 20 nodes for the method with PCA implementation.
- The number of hidden nodes tested in this study were 50, 100, and 120.
- The learning rate parameters used have been tested through hyperparameter tuning, namely at values of 0.001, 0.0008, and 0.0005.
- The number of output layer nodes use the number of labels used, which is 10.

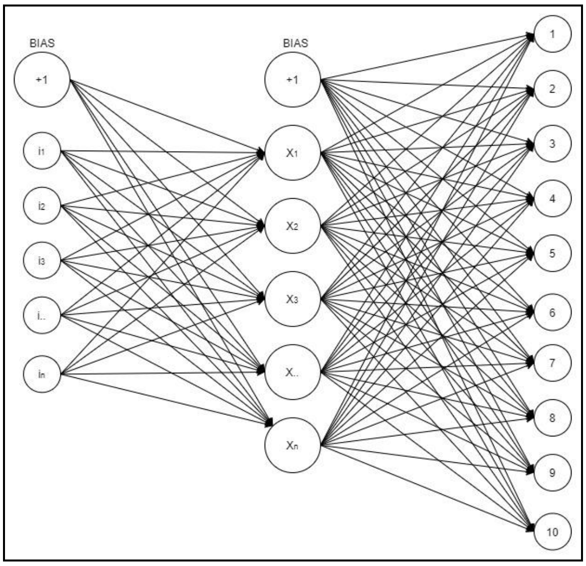

Fig.2 Artificial Requirements Network Architecture

4.2. Test Result

Table 1 compares the training results, while Figure 3 shows the speed comparison of the training scenario without data reduction with PCA.

Tab. 1 Results of A PCA-Free Training Scenario Trial

Learning rate	**Hidden node**	**Epoch**	**Accuracy**	**Speed**
0.001	50	16	12%	0.60
	100	16	12%	1.05
	120	15	12%	1.23
0.0008	50	16	12%	0.89
	100	16	12%	1.48
	120	15	12%	1.64
0.0005	50	16	12%	0.83
	100	16	12%	1.53
	120	15	12%	1.67

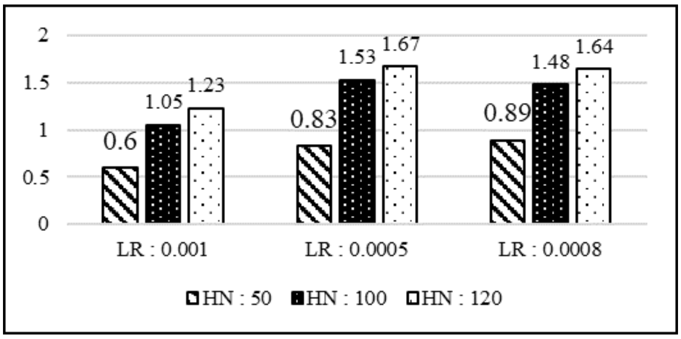

Fig.3 Comparison of Speed from the Results of the Scenario Trial Without PCA

From the test results in Table 1, it can be seen that the training results have not reached the optimal point because the characteristic of the Re LU activity function is that there is no progress in pattern recognition before reaching a certain point, so the given result still has a low level of accuracy. This also affects on the number of used epochs that is low, due to the nature of Re LU that has not been able to reach a certain point, makes changes in results not visible, and stops forcibly on unsatisfactory results. In terms of data training speed, the obtained speed is the fastest at 0.60 seconds with learning rate parameter of 0.001 and hidden node of 50, while the slowest speed is at the learning rate parameter of 0.0005 and hidden node 120.

Tab. 2 Results of a Training Scenario Trial with PCA

Learning rate	**Hidden node**	**Epoch**	**Accuracy**	**Speed**
0.001	50	89	75%	0.04
	100	38	45%	0.02
	120	24	97%	0.01
0.0008	50	21	75%	0.02
	100	19	85%	0.02
	120	33	87%	0.04
0.0005	50	13	62%	0.01
	100	15	97%	0.02
	120	14	87%	0.02

Table 2 displays a comparison of the trial results of a training scenario using PCA. In Table 2, the result shows that there is a rise to the highest accuracy of 97% at learning rate of 0.001 with 120 hidden nodes and learning rate of 0.0005 and 100 hidden nodes. There has been an increase in training speed with the average speed obtained at 0.02 seconds, with the slowest speed at 0.04 seconds at learning rate parameter of 0.001 with 50 hidden nodes, and learning rate of 0.0008 with 120 hidden nodes. At the fastest speed of 0.01 seconds, it is obtained through learning rate parameter of 0.001 with 120 hidden nodes, and learning rate of 0.0005 with 50 hidden nodes. Compared with research [11], the best result obtained from this study is obtained through the combination of 10 hidden nodes and learning rate of 0.01. From this combination, an accuracy rate of 95% is obtained with a training speed of 369.44 seconds. Comparison of accuracy and speed graphically can be seen in Figure 4 and Figure 5 respectively.

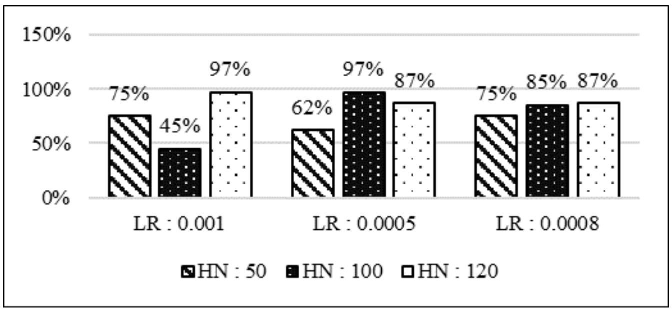

Fig. 4 Comparison of Accuracy with PCA Training Scenarios

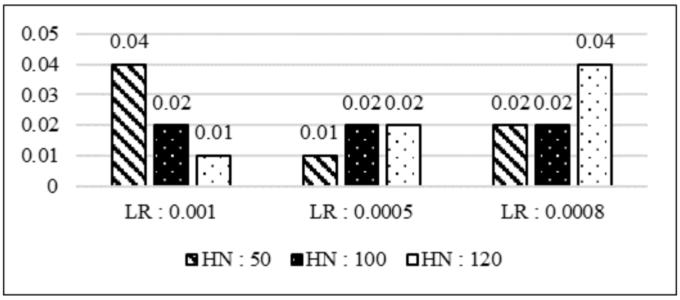

Fig. 5 Comparison of Speed and Training Scenarios with PCA

4.3. Discussion

With the results of the trials that have been carried out, it can be seen that the use of PCA provides an increase in the recognition accuracy and speed in the carried-out data training. In the test without using PCA, the obtained result showed that the accuracy did not increase and stays at a constant value of 12% in all variations of the experiment. Whereas in testing using PCA, the best accuracy result was 97%, with the lowest accuracy resulted at 45%. The best result was obtained in 2 test variations, namely when using learning rate of 0.001 with 120 hidden nodes, and when using learning rate of 0.0005 with 100 hidden nodes.

With the use of PCA, there was an increase in data training speed compared to not using PCA. When PCA was not used, the speed ranged from 0.60 seconds to 1.67 seconds. By using PCA, the speed was increased to be in the range from 0.01 seconds to 0.04 seconds. From the speed increase, it is shown that the dimensional reduction in image size makes the number of input nodes formed less, which indicates that it can drastically affect the training speed.

5 Conclusion

From this research, it can be said that the use of PCA in artificial neural network to perform multi-instance facial recognition can drastically affect the level of accuracy and speed of training compared to without the use of PCA. However, in this study, the subject was still limited to two-dimensional facial images and had relatively less amount of data. Similar research with three-dimensional facial objects can be conducted to prove that the use of PCA can also improve facial recognition performance by using artificial neural networks.

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