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INFLUENCE OF EIGENVECTOR ON SELECTED FACIAL BIOMETRIC IDENTIFICATION STRATEGIES

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ABSTRACT

Face identification strategies are becoming more popular among biometric-based strategies as it measures an individual's natural data to authenticate and identify individuals by analyzing their physical characteristics. For face identification system to be efficient and robust to serve it purpose of security, there is need to use the best strategy out of the many strategies that have been proposed in literatures for face identification. Amidst the most popularly used face identification strategies, Principal Component Analysis PCA, Binary Principal Component Analysis BPCA, and Principal Component Analysis – Artificial Neural Network PCA-ANN were selected for performance evaluation. The research was experimented by varying the eigenvector of the training images for each strategy to compare the performance using Recognition Rate RR and Total Recognition Time TR as performance metrics. Results showed that PCA – ANN strategy gave the best recognition rate of 94% with a trade-off in recognition time. Also, the recognition rates of PCA and B-PCA increased with decreasing number of eigenvectors but PCA-ANN recognition rate was negligible. Hence PCA-ANN outperforms the other face identification strategies.

KEYWORDS: Biometric, Identification, Principal Component Analysis, Artificial Neural Network, Recognition Rate, Total Recognition Time.

1. INTRODUCTION

In the last decades the concern for different biometric identification systems among individuals has developed. Government agencies and private organizations are interested in technology of biometric identification as it increases the level of protection of secret and the security of confidential information. Biometric is a science identifying the person's biological data by using both distinctive physical description and technology. Biometric measures and analyzes human body description such as voice, facial patterns, fingerprints, eye irises, and hand measurements, by taking advantage of information technology (Anot and Singh, 2016).

Face identification system is one of the biometric systems that automatically verify a person's identity using facial features and expressions. Face Recognition System has many applications in the modern world such as logging in to a computer using facial verification as a password, gaming, people tagging, security and so on (Gao, 2015) The current Face Recognition Systems and applications in the market have deficiencies that range from reliability problems, reduced recognition accuracies in certain environment, complicated feature extraction, high setup costs and performance issues. However the demand for a robust face biometric system applicable across various industrial uses, organizations and the general public is increasing dramatically (Thakur and Rai, 2016). Human face as a key to security, biometric face identification technology has received significant attention due to its ability to serve crime deterrent purpose because face images that have been recorded and archived can later help identify a person thereby dropping rate of criminal activities in the society (Agarwal *et al,* 2018).

For face identification system to be efficient and robust to serve it purpose of security, there is need to use the best strategy out of the many strategies that have been proposed in literatures for face identification. Little research work has been done to evaluate which of these strategies is the most efficient. Hence, there is need to conduct a performance evaluation on selected face identification strategies.

1.1 Face Identification Process

Face identification system passes through four stages during its operation as shown in Figure 1. These stages include capturing face image, pre-processing face image, extracting face features, and matching face features (Saud, 2016). Face Detection is the prior step and the entry point of the face identification process. This step is where digital captured face image under consideration is presented to the face identification system. Pre-processing stage is to normalize and filter face image after detection. It determines the location and size of the captured image face. Some pre-processing steps that can be applied include; face image size.

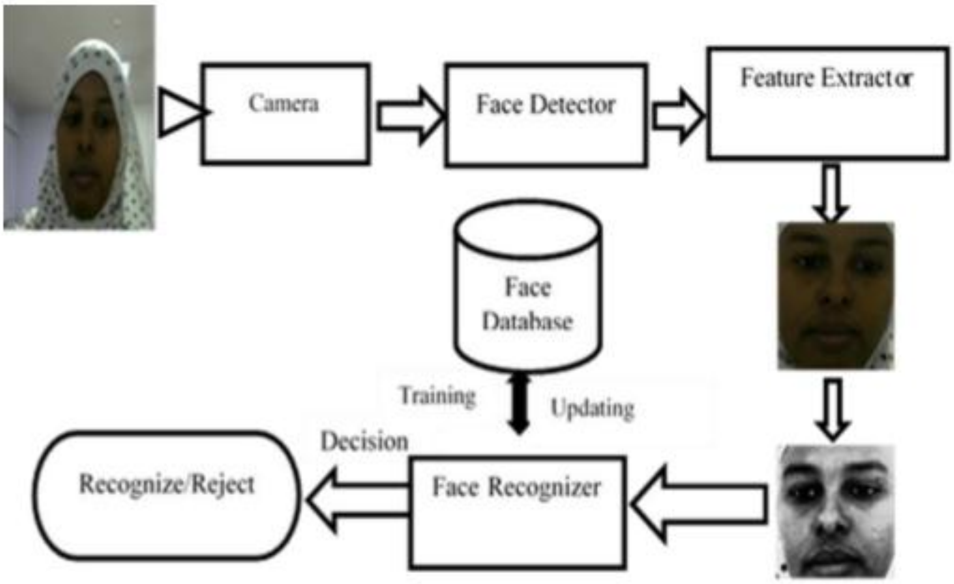

Figure 1: A framework for Facial Biometric Identification System (source: Saud, 2016).

Normalization, histogram equalisation, filtering the media and background removal. Feature extraction stage extracts a compressed set of personal discriminating geometrical and biometrical features of the face image. That is, key for classification and matching process. Feature matching stage is a stage that is concern with using geometric feature or vector to identify facial inages already enrolled in the database.

Furthermore, face identification techniques can be separated into two groups based on the face representation used: 1. Appearance-based: which uses holistic texture features and is applied to either whole-face or specific regions in a face image. 2. Feature-based: which uses geometric facial features (mouth, eyes, brows, cheeks etc.) and geometric relationships between them. Among many approaches to the problem of face recognition, appearance-based subspace analysis is one of the oldest and still gives the most promising results. Subspace analysis is done by projecting an image into a lower dimensional space (subspace) and after that recognition is performed by measuring the distances between known images and the image to be recognized. The most challenging part of such a system is finding an adequate subspace. When using appearance-based methods, an image of size n x m pixels is usually represented by a vector in an n x m dimensional space.

1.2 Face Biometric Identification Approaches

Many field of application of face identification systems hindered the development of a unified face identification algorithm which also gives rise to varieties of approaches. The approaches includes; template or geometric approach, holistic approach, appearance or model based approach and statistical or neural network approach (Louban, 2009).

1.2.1 Template or Geometric approach

The template based methods compare the input image with a set of templates. The set of templates can be constructed using statistical tools like Support Vector Machines (SVM), Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA). While geometry feature-based methods analyze local facial features and their geometric relationships.

1.2.2 Holistic Approach

This approach involves processing facial features independently without taking the relationship between the feature and the whole face into consideration. Example is Hidden Markov Model (HMM).

1.2.3 Appearance or Model based approach

Appearance-based methods represent a face in terms of several raw intensity images. Then statistical techniques are usually used to derive a feature space from the image distribution and compared to the training set. On the other hand, the model-based approach tries to model a human face. The new sample is fitted to the model, and the parameters of the fitted model used to recognize the image.

1.2.4 Statistical or Neural network approach

In statistical approach patterns are represented as features. The recognition function is a discriminant function while in neural network approach pattern representation may vary because of the presence of a network function in some point.

2.1 Selected Facial Biometric Identification Strategies

Among other face identification strategies Principal Component Analysis PCA, Binary Principal Component Analysis (BPCA), and Principal Component Analysis – Artificial

Neural Network (PCA-ANN) remains the three most commonly used. Hence this work selected them to test their performance to variation in eigenvectors.

2.2 The Principal Component Analysis (PCA)

PCA is one of the most commonly used strategy in prediction, feature extraction, image identification, etc. Because PCA is a strategy which work in the linear domain, applications having linear models are suitable, such as signal processing, image processing, system and control theory and communications. The purpose of PCA is to reduce the large dimensionality of the data space (observed variables) to the smaller intrinsic dimensionality of feature space (independent variables), which is needed to describe the data economically (Jain and Singh, 2011). The basis vectors constructed by PCA have the same dimension as the input face images. The representation of a face image is obtained by projecting it to the coordinate system defined by the principal components. The projection of face images into the principal component subspace achieves information compression, de-correlation and dimensionality reduction to facilitate decision making (Turk and Petland, 1991).The main idea of using PCA for face recognition is to express the large 1-D vector of pixels constructed from 2-D facial image into the compact principal components of the feature space. This can be called eigenspace projection. Eigenspace is obtained by identifying the eigenvectors of the covariance matrix gotten from a set of facial images (vectors).

2.3 Binary Principal Component Analysis (BPCA)

Binary PCA (B-PCA) is the combination of PCA and Haar-like binary box functions into a non-orthogonal subspace representation that can be computed very efficiently and at the same time capture the structure information of the data. A desirable property of these box functions is that their inner product operation with an image can be computed very efficiently (Tang and Tao, 2007). Haar-like features are digital image features used in object recognition. A Haar-like feature considers adjacent rectangular regions at a specific location in a detection window, sums up the pixel intensities in each region and gives the difference between these sums. This difference is then employed to categorize subsections of an image. These features are not relating to objects such as eyes and ears, but rather to classes such as relatively light areas next to relatively dark areas, dark areas surrounded by lighter areas, and lengths of lighter color bounded on two sides by dark areas (Wilson and Fernandez, 2006). One obvious property of binary box bases is that they are not necessarily orthogonal to each other and span as Non-Orthogonal Binary Subspace (NBS) (Tang and Tao, 2007). PCA is an orthogonal subspace and has been proved to have good performance in image representation and recognition. Its capability to capture image structure information, orthogonal base vectors are complement to NBS. This makes it natural to combine NBS and PCA to the proposed binary PCA representation. The problem of searching for the best subspace representation in a set of predefined non-orthogonal base vector dictionary is known to be NP-hard. Two popular greedy solutions to this problem are the Matching Pursuit (MP) approach and the Optimized Orthogonal Matching Pursuit (OOMP) method (Tang and Tao, 2007).

2.4 PCA- Artificial Neural Network (PCA-ANN)

In Principal Component Analysis - Artificial Neural Network strategy, PCA is used during the feature extraction stage since it is found to be the simple and popular strategy used for feature extraction. Meanwhile, the ANN based on feed-forward neural networks is used during classification stage because it is one of the machine learning algorithms which is widely used for classification and can perform both linear and non-linear operations (Agarwal *et al*, 2010). An ANN is an adaptive nonlinear system that learns to perform a function from data. Adaptive means that the system parameters are changed during operation, normally called the training phase. After the training phase the ANN parameters are fixed and the system is deployed to solve the problem at hand. The ANN is built with a systematic step-by-step process to optimize a performance criterion or to follow some implicit internal constraint, which is referred to as the learning rule (Bevilacqua *et al*, 2006). A wide range of models of ANN has been developed for varieties of purposes. They differ in structure implementation and principle of operation but share common features. ANNs are computing systems made up of a number of simple highly interconnected signal or information processing units (Artificial neurons) with the following features (Omidiora *et al*, 2008). A successful face identification strategy depends heavily on the particular choice of the features used by the pattern classifier. MLP and many other neural networks learn using an algorithm called back-propagation. Back propagation learning algorithm consists of forward pass and backward pass. Training a network by back-propagation involves three stages: the feed-forward of the input training pattern, the back-propagation of the associated error, and adjustment of the weights. With back-propagation, the input data is repeatedly presented to the neural network. With each presentation the output of the neural network is compared to the desired output and an error is computed. This error is then fed back (back-propagated) to the neural network and used to adjust the weights such that the error decreases with each iteration and the neural model gets closer and closer to producing the desired output. This process is known as "training". The MLP refer to the network consisting of a set of sensory units (source nodes) that constitute the input layer, one or more hidden layers of computation nodes, and an output layer of computation nodes. The input signal propagates through the network in a forward direction, from left to right and on a layer-by-layer basis (Nazeer and Khalid, 2009).

3.1 Research Methodology

The following stages were involved in the development of the face recognition system: face acquisition, face pre-processing, feature extraction, training and testing or identification stage. At the face acquisition stage, the training images were acquired by the system and converted into values suitable for processing by the computer. The face pre-processing stage reduces every face image size in order to enhance the data. At this stage captured images of 140 x140 pixels were cropped to 50 x 50 pixels in order to extract major features like eyes, nose, eyelid and lips. The coloured image acquired were converted into gray scale which was two dimensional, so as to make the image suitable for processing. Images were also down sampled and converted from 2D to 1D. Feature Extraction stage extracts eigenfaces using PCA algorithm. The training stage involves the use of the training images and the identification stage compares test images with those of the training images to identify the class the testing image belong. Experiments were performed on the created database using PCA, BPCA and PCA – ANN separately. The effect of the size of eigenvectors used for training was investigated by using 75, 150 and 300 eigenvectors. Figure 2 shows some samples of face images used. The strategies were evaluated using Recognition Rate RR and Total Recognition Time TR. The recognition Rate (RR) was computed using the formula below, measured in percentage

$$RR = \frac{CC}{TTI} \times 100\% \qquad (1)$$

Where CC is correct classification and TTI is the total number of images tested.

Figure 2: Samples of Face Images Used.

3.2 Face Identification Using PCA

Eigenvectors were calculated using PCA algorithm and experiment was performed by varying the number of eigenvectors used to calculate the feature vectors of the images. Facial images in the training stage were projected onto the eigenvectors to obtain a set of weight (feature vectors). The face was recognized by finding the different between the projected training and testing images using Euclidean distance as the similarity measuring technique**.** The PCA algorithm is as follows:

Begin

M = Total number of images in database

S = the summation of images

Γ = an image vector

ψ = the mean image

Set S = 0

For n = 1 to M

$S = S + \Gamma_n$

End

$\psi = \frac{S}{M}$

Compute images from the mean

Φ is centered images

For I = 1 to M

$\Phi_i = \Gamma_i - \psi$

End

Compute the covariance, C

S = 0;

For n = 1 to M

$S = S + \left(\Phi_n . \Phi_n^T\right)$

End

$C = \frac{S}{M}$

Compute eigenfaces

Project eigenvectors onto the Eigenspace

K = number of selected eigenfaces

U = number of eigenvectors

For k = 1 to K

$\omega_k = u_k^T \left(\Gamma - \psi\right)$

$\Omega = [\Omega \quad \omega_k]$

End

Return the projected images Ω

END.

3.3 Face Identification Using B-PCA

The images were acquired per class from face library. Each image was converted to binary data (1 and 0). The image matrix data was then converted into a vector and added to the set. Using training samples, PCA guided NBS method was implemented to compute the B-PCA base vectors and the BPCA base vectors were stored. Each image was projected to BPCA base vectors and the coefficients were used as features. The images were identified by finding the difference between the projected training and training images using Euclidian distance as the similarity measuring strategy. The algorithm for the B-PCA is as follows:

Begin Set N = numbers of BPCA base vectors to compute

For k $\longleftarrow$ 1 to N

Pre-BPCA $\longleftarrow$ PCA(X)

(BPCAs[k], NB[k]) $\longleftarrow$ OOMP (Pre-BPCA, thresh)

X $\longleftarrow$ X - RECONSTRUCTION (X, BPCAs)

Next k

Return (BPCAs, NBSs)

End

OOMP

Begin

Get training data X and precision threshold ζ, through base vectors, Φ_Λ

Compute the Projection process

$$P_{\Phi_\Lambda}(X) = \Phi_\Lambda(\Phi_\Lambda^T \Phi_\Lambda)^{-1} \Phi_\Lambda^T X$$

Compute the reconstruction residual

$$Error(j) = X - P_{\Phi_A}(X)$$

Compute the component of Φ_i that is orthogonal to each available base vector

Fori =1 to k

$$\gamma_i = \Phi_i - P_{\Phi_{\Lambda k}}(\Phi_i)$$

Compute new approximation

$$\text{Error (j+1)} = \frac{\text{Dot product of } \gamma_i \text{ and error}}{}$$

Select vectors with minimum error

Next i

Return $P_{\Phi_\Lambda}(X)$ and error (j+1)

End

Reconstruction

Begin

Get training data and BPCA base vectors Ψ

Return $\Psi\left(\Psi^T\Psi\right)^{-1}\Psi^T X$

End.

3.4 Face Identification Using PCA-ANN

A neural network for PCA based classification was prepared. The feature vectors from PCA were loaded and then used to train ANN objects. The numbers of artificial neural network object created were 100 which are equal to number of individuals in the database. One ANN object was used for each person in the face library and their feature vectors are used as inputs to train the networks. The initial parameters of the Neural Network used in the experiment are as provided below:

1. Type: Feed forward back propagation network
2. Number of layers: 3 (input, two hidden layer, output layer)
3. Number of neurons in input layer: Projected images from PCA
4. Number of neurons in hidden layer: 20
5. Number of neurons in output layer: 1
6. Transfer function of the ith layer: Tansig
7. Training algorithm: Levenberg_Marquardt (Trainlm)
8. Number of epochs used in training: 100
9. Back propagation weight/bias learning function: learngdm
10. Performance function: Mean-Squared Error (mse)
11. Performance goal: $\leq 10^{-4}$

During the training of the ANN, the target of all the images that belong to a class are set to 0, that is, the feature vector that belong to the same person are used as minimized examples for the person's network (such that, the network gives 0's output) and maximized example for other networks (such that, the network gives 1's output). Training of network was done by back propagation which was a training process where the input data was repeatedly presented to the neural network.

4.1 RESULT AND DISCUSSION

All the algorithms were implemented using matrix laboratory (Matlab). The toolboxes used include image processing toolbox and neural network toolbox. The code implementing the face identification system was tested on an Intel Pentium M system with 1.73GHz processor, 1GB RAM and windows XP operating system.

The result showed that PCA, BPCA and PCA-ANN had recognition rates of 91%, 86% and 94% when 75 eigenvectors were selected. When 150 eigenvectors were selected, the recognition rates of the systems were 75%, 70% and 93%. Selecting 300 eigenvectors, the recognition rates were 56%, 55% and 93%. The systems also had recognition time of 5.2 sec, 5.5 sec and 140.5 sec when 75 eigenvectors were selected. Selecting 150 eigenvectors, the recognition time of the systems were 5.5 sec, 5.6 sec and 143.5 sec. The systems had recognition time of 5.1 sec, 5.4 sec and 140.3 sec when 300 eigenvectors were selected. These results are represented in Figure 3, 4 and 5.

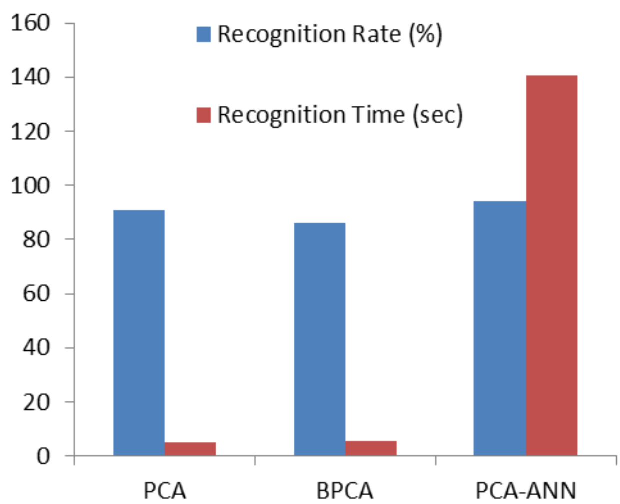

Figure 3: Recognition Rate and Recognition Time using 75 Eigenvectors.

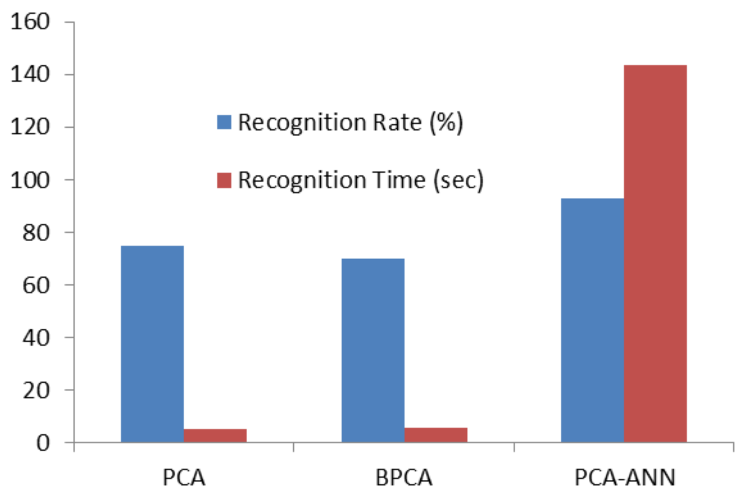

Figure 4: Recognition Rate and Recognition Time using 150 Eigenvectors.

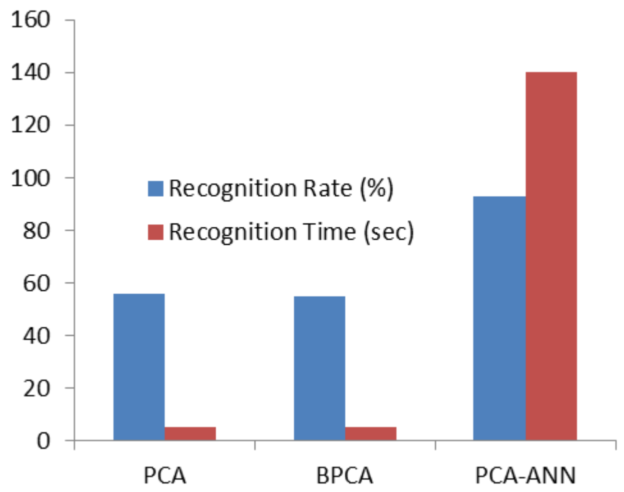

Figure 5: Recognition Rate and Recognition Time using 300 Eigenvectors.

PCA – ANN had the highest recognition rate and virtually constant recognition time when eigenvectors were varied. This is attributed to the inherent non linearity nature of the ANN to learn sharply the reduced image dimension and correctly classify observed image signal. And also the robustness of the hybrid algorithm and its insensitivity to eigenvector‘s variation. The recognition rates of PCA and BPCA increased with decreasing size of eigenvectors, this was because there were more relevant components in the reduced eigenvectors that well represented the image signals. Some of the noise of the face had been cut-off‖ with the eigenvector reduction. The change in recognition rate was negligible in PCA-ANN because of the stable nature or robustness of the neural network that took part in the hybridization process. Also, PCA-ANN had highest accuracy to justify the non-linearity of the different shapes attained by the faces with different expressions which is virtually and highly captured by the neural network. It was observed from the results that, varying eigenvectors had significant effects on the system performance. All the parameters considered were actually affected, as the selected eigenvectors reduced, the recognition rates increased.

5.1 CONCLUSION

The performance evaluation of the three PCA-based face biometric strategies showed that PCA – ANN technique gave the best recognition rate with a trade-off in recognition time for 50x50 pixels with different size of eigenvectors considered. Also, the recognition rates of PCA and BPCA increased with decreasing number of eigenvectors but PCA-ANN recognition rate was negligible.

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