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A Multimodal Biometric Recognition System using Principal Component Analysis and Feedforward Neural Network for Mobile Applications

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Abstract

Nowadays biometric systems are used to authenticate a process in many mobile applications. This brings the importance of multimodal biometric system, which provides more authenticity. The biometric features are complex multidimensional visual model and developing a computational model for a biometric recognition system is difficult. In this paper we present a technique for multimodal biometric recognition system using principal component analysis, wavelet decomposition and feed forward neural network. When neural network is used for recognition the time required for learning a pattern is high. This learning time can be reduced if the data is pre-processed and clustered. The learning rate of neural network has substantially reduced because of pre-processing and feature extraction.

Keywords

Multimodal biometrics, principal component analysis, neural network, feature extraction.

I. Introduction

Biometrics refers to measurement of human characteristics. Biometric recognition involves measuring unique physiological and behavioural traits of human being. Physiological character includes face, finger print, palm print, signature, DNA, ear, iris pattern, finger vein etc. Behavioural character involve gait, voice etc. Nowadays identification and authentication of each individual is becoming important. More traditional means access controls like tokens, password etc. are being replaced by biometrics.

(i) Types of Biometrics

Each biometrics characteristics have unique advantages and disadvantages. The usage of biometrics for authentication depends upon the application requirements [2]. Face recognition analyses the facial characteristics of each individual for which a digital camera is used to get the facial image of an individual for authentication. It is one of the easy ways to conduct authentication. Fingerprint obtains the pattern found in fingertip. It is found to be one of the most reliable biometrics. The pattern found in the fingertips is basically ridges and bifurcations. Iris authentication has greater advantage, the fact that the iris pattern is unique for each and every individual and even it varies for identical twins and does not change over time.

GAIT is a behavioural characteristic which is used to authenticate the people by the way they walk [3]. But this characteristic is not used for high security scenarios since it is not distinctive across individuals and moreover a video sequence analyser is required which is very costly. Voice is combination of physical and behavioural characteristic of voice signal pattern. The physical characteristic is related to the appendages that form the sound and the behavioural characteristic is related to the emotional and physical state of the speaker.

(ii) Biometric Systems

There are two types of biometric system used for authentication purpose. (1) Unimodal biometric system and (2) Multimodal biometric system.

Biometric system which uses single biometric traits of an individual for identification and verification is called unimodal biometric system and on the other hand a system which uses more than one is called multimodal biometric system.

(iii) Limitations of Unimodal Biometric System

There are numerous errors in using unimodal biometric system while enrolling a large population. Facial biometric may not work for identical twins as the camera might be able to distinguish between two individuals resulting in inaccurate matching [4]. Unimodal biometrics can be easily spoofed. For example, finger print recognition can be easily spoofed using silicon or rubber finger print.

II. Multimodal Biometric System

Multimodal biometric system uses multiple traits that results in high accuracy and secure biometric identification system [4]. By using combination of different modalities the recognition rate is improved. There are some types of multimodal biometric systems that can be applied, allowing the user verification.

Multi-algorithmic biometric system uses single sensor to capture single samples that can be processed with two or more different algorithms. Multi-instance biometric system captures two or more different instances of a same biometric characteristics using a single sensor. For example, capturing images of multiple fingers using a system is considered to be multiple instances. Multi-sensorial biometric system uses two or more distinctly different sensors to capture the same biometric traits. Processing of images can be done using one algorithm or combinations of different algorithms.

(i) Stages in Biometric System

Pre-processing stage involves processing of biometric data which is acquired from sensor. [2] The biometric data is pre-processed to improve its quality. The pre-processing stage is always used for getting the region of interest in order to extract the features. Several algorithms are used for pre-processing and obtaining the region of interest.

Feature Extraction is one of the important stages in biometric system. It involves simplification of certain amount of resource which describes large set of data. Feature extraction is mainly used to minimize the original database by getting some features that can be used to classify and get patterns that are present in input

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image. Different algorithms are used for extracting features from different biometric traits. Some of the methods are Fast Fourier Transforms, Discrete Wavelet Transforms, Gabor Filters, Discrete Cosine Transform, Hough Transform etc.
Training and Recognition are done with the help of Artificial Neural Network. Artificial neural network are nonlinear signal processing devices that are built by interconnecting the elementary processing devices called neurons. ANN was inspired from biological nervous systems like brain processing system. This system consists of interconnected networks called neuron which works together to solve a specific problem.

III. Proposed System

The below fig.3.1 is the proposed block diagram for multimodal biometric recognition. Face and iris are treated as input.

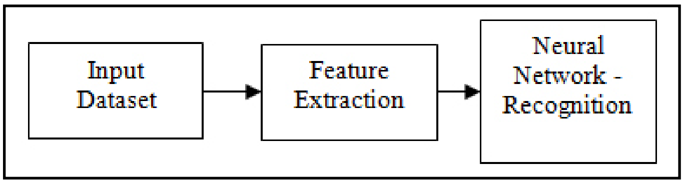

Fig 3.1: Block Diagram

The input database is taken from the open source. Face database are taken from AT&T Laboratories Cambridge database of faces and iris database is taken from CUHK Iris image dataset. This dataset is first pre-processed. PCA is used for extracting feature from face images. The Eigen vectors and Eigen values of an image is obtained by finding covariance matrix. By this way the image is compressed and features are extracted. The features from iris image are extracted using discrete wavelet transforms. Wavelet transforms decomposes image using low pass filter and high pass filter. The image after passing from each filter will provide coefficients. Approximate coefficients are obtained from low pass filters and definite coefficients are obtained from high pass filters. These coefficients are the compressed image of the given data. The feature extracted images are then trained and recognized by using Artificial Neural Networking. We use a supervised feed forward network for recognition.

1. Feature Extraction

(i) Iris Feature Extraction

The iris is a muscle in eye that regulates the pupil size to control the supply of light ray that enters the eye. The human iris is thin and annular region in eye located around pupil and covered by cornea, as shown in fig.3.2. which will provide unique and independent information about an individual [2].

Fig 3.2 : Iris Image

Iris patterns are too unique that not only differs between identical twins but also differs between left and right eye. Based on the information, iris recognition system is very effective because of their speed and accuracy which popularizes this biometric system.
Wavelet transform [5] using matlab software is applied to pre-process and extract the features from iris. A wavelet app is also present in the matlab software for extracting the features.

(ii) Face Feature Extraction

Principal component analysis [7] is a useful technique that has found application in many fields such as video, audio classification, face recognition, image compression etc., it is a simple method of extracting relevant information from dimensional datasets. With minimal effort, PCA provides a road map for reducing the complex data set to a lower dimensional dataset.
Using this methodology, we have taken only the 32 principal components from our data set for processing.

2.Recognition

Backpropagation (BP) algorithm is most widely used for face recognition [8]. Since the BP algorithm used for training often gets trapped by the local minima problem due to large dimension data. Reducing its dimension solves the problem. Hence the method of dimensionality reduction using PCA and Wavelet transform is deployed here.

IV. Algorithm

1. Principal Component Analysis

PCA is used to reduce the dimensionality of a given data. AT&T database is used for our experiments. There are 40 individuals in the database. The images are in Portable Gray Map Graphic format. Out of 40 individuals 20 are considered as training data and 20 as testing data. Five patterns for each individual are taken so a total of 100 images as used as training data. The following steps are followed for dimensionality reduction.

01. The whole database is read and stored in an array. Let the database of 'n' patterns be $Z=\{Z_1,\ldots,Z_n\}$ Where n=number of patterns

02. The training data is read and the images are reshaped in such a way that a training data matrix comprises of all 100 images.

03. The images are converted to double format

04. The mean for the training set is calculated.

$$\psi = \frac{1}{m}\sum_{i=1}^{n} Z_i \quad (1)$$

05. Difference between training data and mean is calculated

$$\phi_i = Z_i\text{-}\psi \quad (2)$$

06. The covariance is calculated for ϕ_i

$$C = \phi_i{}^*\phi_i^T \quad (3)$$

07. The Eigen vectors and Eigen values are calculated for the covariance matrix.

$$E=\{E_1, E2_{\ldots} Et\} \quad (4)$$

08. The Eigen vectors are sorted in descending order

09. The highest order Eigen vectors are taken
10. Faces from higher dimensional image space are projected to 32 dimensional feature vectors.

$$X=E_T Z \tag{5}$$

2. Wavelet Transform

DWT is a multi-resolution analysis and decomposes images into wavelet coefficients and scaling functions [6]. In DWT, a time-scale representation of the digital signal is obtained using digital filtering techniques. A 2D wavelet can be seen as 1D wavelet which transforms along the rows and then 1D wavelet transforms along the column. The row of arrays which are processed first will undergo one level of decomposition. The arrays will be divided into two vertical halves with one storing the approximate coefficient and other storing the detailed coefficients. Wavelet transform is applied to iris dataset and obtained wavelet coefficients are used for recognition using neural network.

3. Neural Network

The feature extracted face and iris datasets are given as input data to a BPN neural network. They are trained using Marquardt-Levenberg algorithm in matlab.

V. Experimental Results

1. Principal Component Analysis

The dimension of the input data is 10304*1. This is reduced to 32 features using PCA. The data is projected with it principal components. Finally, the projected image was reconstructed. The original input data and reconstructed data is show below.

The iris dataset is pre-processed using 2D Wavelet transform. The output coefficients are further processed using a neural network.

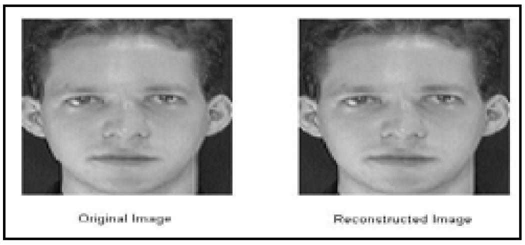

Fig.5.1: The Original and The Reconstructed Data

2. 2-D Wavelet Transform

The iris dataset is pre-processed using 2D Wavelet transform. The output coefficients are further processed using a neural network.

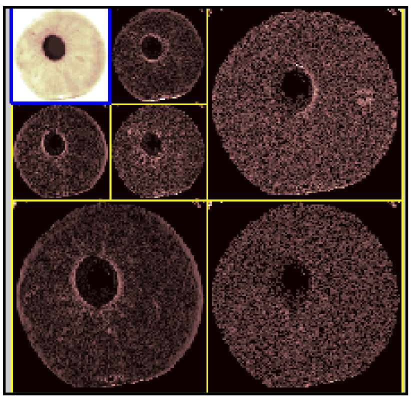

Fig.5.2 : Wavelet Transform of Iris

3. Neural Networks

The backpropagation network is trained with the given data set without feature extraction. A performance graph is plotted against mean square error and number of epochs. It clearly reveals that the learning time required by the network is more than 4 minutes. The graph below shows that number of epochs required for training is more than 70 epochs.

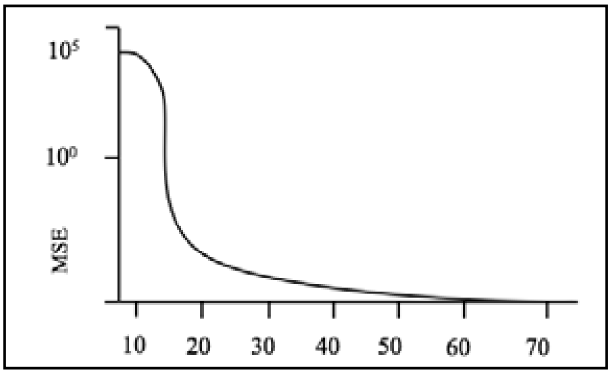

Fig. 5.3 : Learning Rate of BPN Trained with the Original Data

The same data which is pre-processed and feature extracted is given for training. Again the mean square error and the number of epochs are plotted. It is clear that the number of epochs required for this projected data is comparatively less.

When tested with other patterns which doesn't belong to the trained class the patterns were rejected. The training algorithm used for this simulation is Levenberg Marquardt algorithm.

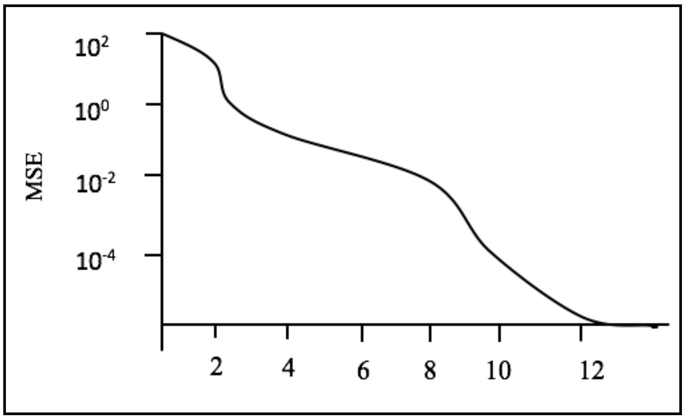

Fig. 5.4 : Learning Rate of BPN Trained with transformed Dataset

The trained data is simulated against various input pattern for recognition. This process has been done separately for Iris and Face dataset and results are plotted below. The results indicate closeness between the trained data and input for a match and it has produced scattered output for mismatch. This process is repeated for various trials to evaluate the performance of the proposed algorithm.

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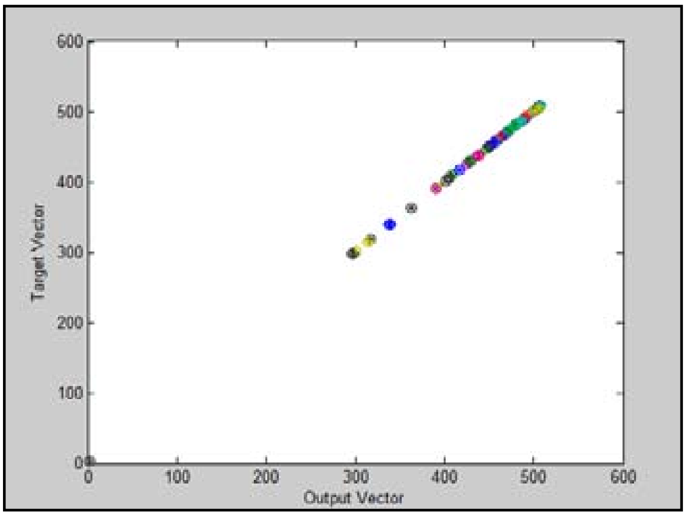

Fig 5.5 : Trial number 1 – Iris dataset

The figures 5.3 and 5.4 are the simulated results of ANN applied to iris features. Out of the trials executed most of the results showed that the data were matching. Very few showed a data mismatch. The time taken for the iterations was ranging between 00:23:32 minutes and 00:14:47 minutes. The number of iterations for each trial was 1000.

The figures 5.5 and 5.6 are the simulation results of ANN applied to face features. Out of numerous trials executed most of the results showed that the data were matching. The time taken for the iterations was ranging between 00:00:01 minutes and 00:00:03 minutes. The number of iterations for each trial was 500.

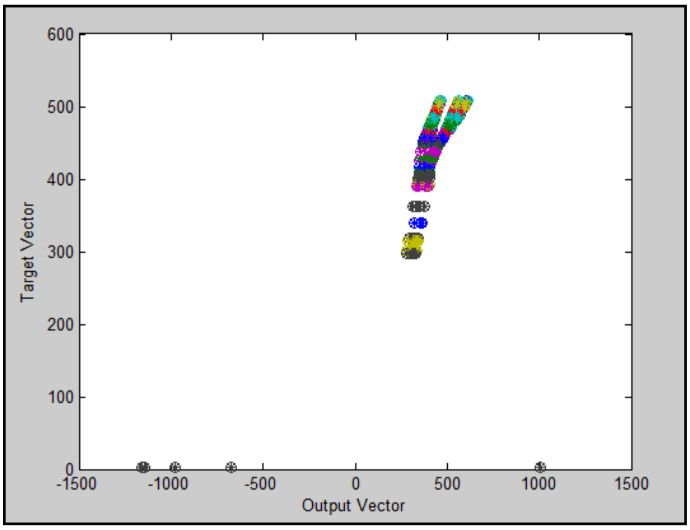

Fig 5.6 : Trial number 1 – Iris dataset

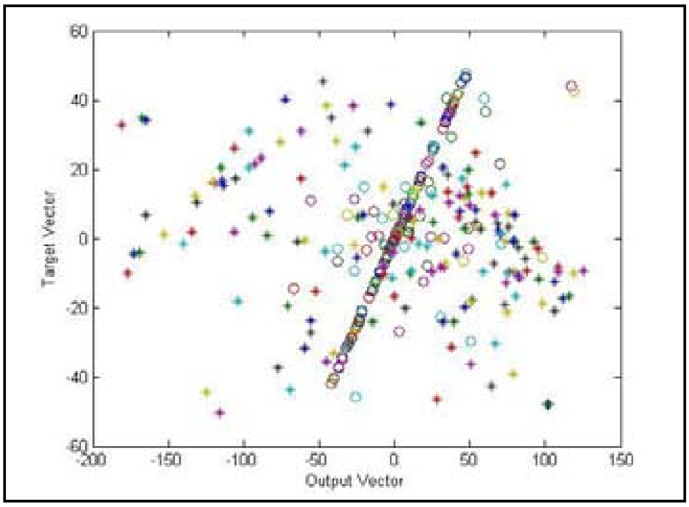

Fig 5.7 : Trial number 1 – Face dataset

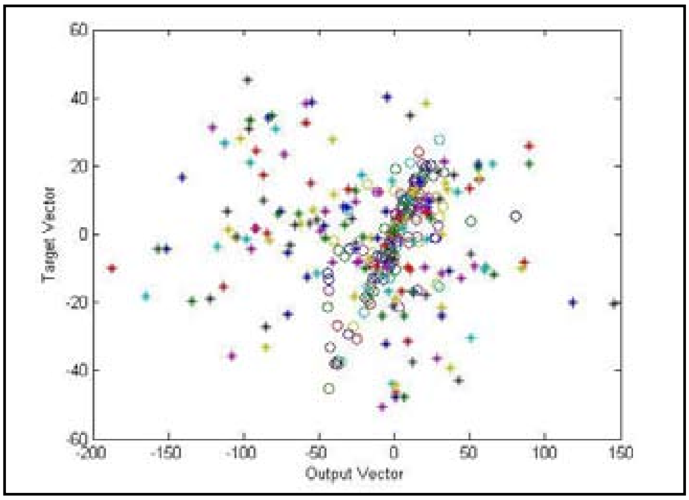

Fig 5.8 Trial number 2 – Face dataset

VI. Conclusion

From the results obtained it is inferred that as the dimension of the data is reduced i.e. if only the principal components and wavelet coefficients of the original data sets are considered for recognition the processing time for recognition is reduced. The pre-processed and feature extracted data which is used for training the backpropagation network took less time and less number of epochs when compared with the actual data whose dimensions are not reduced. Thus pre-processing and feature extracted minimizes the training time of the neural network. As the computational requirements in mobile computing systems are limited, more emphasize in this paper is given to reduction of learning time of the neural network. All the algorithms are written and simulated in MATLAB.

References

[1] *Dr.Devaraj.D and Lathika.B.A (2014),"Artificial Neural Network Based Multimodal Biometrics Recognition System", International Conference on Control, Instrumentation, Communication and Computational Technologies (ICCICCT).*

[2] *Muhtahir O.Oloyede and Gerhard P.Hancke (2016)," Unimodal and Multimodal Biometric Sensing Systems: A Review", IEEE Access, volume 4.*

[3] *Jinyan Chen,"Gait Correlation Analysis Based Human Identification",Scientific Journal,2014.*

[4] www.bayometric.com/unimodal-vs-multimodal/
[5] Graps A (2002),"An Introduction to wavelets", IEEE Computational Science and Engineering (Volume 2, Issue 2, Summer 1995).
[6] Dipalee Gupta and Siddhartha Choubey (2015),"Discrete wavelet transforms for image processing", International Journal of Emerging Technology and Advanced Engineering (Volume 4, Issue 3).
[7] B. K. Gunturk, A. U. Batur, and Y. Altunbasak, "Eigenface-domain super-resolution for face recognition," IEEE Trans. Image Process., vol. 12, no. 5, pp. 597–606, May 2003.
[8] D. Valentin, H. Abdi, A. J. O'Toole, and G. W. Cottrell, "Connectionist models of face processing: A survey," Pattern Recognit., vol. 27, no. 9, pp. 1209–1230, 1994.
[9] Rafael C. Gonzalez, Richard E. Woods, Steven L. Eddins,"Digital Image Processing Using MATLAB", second Edition
[10] Anil K. Jain, Robert P.W. Duin, and Jianchang Mao. Statistical Pattern Recognition: A Review. IEEE Transactions on Pattern Analysis and Machine Intelligence, 22(1):4 - 37, January 2000.
[11] Sunita Kumari, Pankaj K. Sa, and Banshidhar Majhi. Gender classification by principal component analysis and support vector machine. In ACM International Conference on Communication, Computing & Security, ICCCS 2011, pages 339 - 342, Rourkela, India, 2011.
[12] Rafael Gonzalez and Richard Woods. Digital Image Processing. Addison Wesley, 1992.
[13] Turk.M.A and Pentland.A.P Eigen faces for Recognition. Journal of Cognitive Neuroscience, 3(1):71 - 86, 1991.
[14] Turk.M.A and Pentland.A.P Face recognition using eigen faces. In IEEE Computer Society Conference on Computer Vision and Pattern Recognition, CVPR 91, pages 586 -591, 1991. 23
[15] Martin T. Hagan, Howard B. Demuth, Mark Hudson Beale, Orlando De Jesus,Neural Network Design, 2nd Edition".
[16] Sivanandam.S.N, Sumathi.S, Deepa.S.N, "Introduction to Neural Networks using MATLAB 6.0."
[17] www.mathworks.com
[18] J. Lu, K. N. Plataniotis, and A. N. Venetsanopoulos, "Face recognition using kernel direct discriminant analysis algorithms," IEEE Trans. Neural Netw., vol. 14, no. 1, pp. 117–126, Jan. 2003.
[19] B. K. Gunturk, A. U. Batur, and Y. Altunbasak, "Eigenface-domain super-resolution for face recognition," IEEE Trans. Image Process., vol. 12, no. 5, pp. 597–606, May 2003.
[20] B. L. Zhang, H. Zhang, and S. S. Ge, "Face recognition by applying wavelet subband representation and kernel associative memory," IEEE Trans. Neural Netw., vol. 15, no. 1, pp. 166–177, Jan. 2004.
[21] Q. Liu, X. Tang, H. Lu, and S. Ma, "Face recognition using kernel scatter-difference-based discriminant analysis," IEEE Trans. Neural Netw., vol. 17, no. 4, pp. 1081–1085, Jul. 2006.
[22] W. Zheng, X. Zhou, C. Zou, and L. Zhao, "Facial expression recognition using kernel canonical correlation analysis (KCCA)," IEEE Trans. Neural Netw., vol. 17, no. 1, pp. 233–238, Jan. 2006.
[23] X. Tan, S. Chen, Z. H. Zhou, and F. Zhang, "Recognizing partially occluded, expression variant faces from single training image per person with SOM and soft k-NN ensemble," IEEE Trans. Neural Netw., vol. 16, no. 4, pp. 875–886, Jul. 2005.
[24] T.Yahagi and H. Takano, "Face recognition using neural networks with multiple combinations of categories," J. Inst. Electron. Inf. Commun. Eng., vol.J77-D-II, no. 11, pp. 2151–2159, 1994, (in Japanese).
[25] S. Lawrence, C. L. Giles, A. C. Tsoi, and A. D. Back, "Face recognition: A convolutional neural-network approach," IEEE Trans. Neural Netw., vol. 8, no. 1, pp. 98–113, Jan. 1997.
[26] S. H. Lin, S. Y. Kung, and L. J. Lin, "Face recognition/detection by probabilistic decision-based neural network," IEEE Trans. Neural Netw., vol. 8, no. 1, pp. 114–132, Jan. 1997.
[27] H. H. Song and S. W. Lee, "A self-organizing neural tree for large-set pattern classification," IEEE Trans. Neural Netw., vol. 9, no. 3, pp. 369–380, May 1998.
[28] C. M. Bishop, Neural Networks for Pattern Recognition. London, U.K.: Oxford Univ. Press, 1995.
[29] www.face-rec.org
[30] Stan Z. Li Anil K. Jain, A handbook of face recognition