

Have MULTIMODAL SECURITY SYSTEM BY USING FACE AND FINGERPRINT IMAGES

Puja N. Patil¹, Krishna Chauhan²

¹Student, Department of Electronics & Telecommunication, Sagar Institute of Research and Technology, Bhopal, Madhya Pradesh, India, ppatil805@gmail.com

²Professor, Department of Electronics & Telecommunication, Sagar Institute of Research and Technology, Bhopal, Madhya Pradesh, India, krishnachauh@gmail.com

ABSTRACT

Biometrics is the science and technology of measuring and analyzing biological data of human body, extracting a feature set from the acquired data, and comparing this set against to the template set in the database. Experimental studies show that Unimodal biometric systems had many disadvantages regarding performance and accuracy. Multimodal biometric systems perform better than Unimodal biometric systems and are popular even more complex also. In this paper we introduce face and thumb images recognition using Transform Domain and Spatial Domain Techniques. Also In this paper we use a pixel-level image fusion scheme using discrete wavelet transform (DWT). Wavelet coefficients at different decomposing levels are fused using absolute maximum fusion rule. And extract the feature of fused images by Principal Component Analysis (PCA) and texture feature extraction. Person will be categorized as known or unknown face after matching with the present database. The test and database fused features are compared using Euclidean Distance (ED).

Keywords: Preprocessing, Discrete wavelet transform (DWT), Fusion Rules Principal component analysis (PCA), Gray level co-occurrence matrix (GLCM)

1. INTRODUCTION

In the last few years multimodal recognition has become one of the most actively used for security system, credit card verification and criminal identification .in unimodal biometric system had many disadvantages regarding performance and accuracy .multimodal biometric system perform better than unimodal biometric system. In this paper we are used face and thumb image recognition.

With the aim to recognize face and thumb images. Several interesting approaches for human detection have been reported till date. Sirovich and Kirby had efficiently represented human faces using principal component analysis [1]. M.A. Turk and Alex P. Pentland[2] developed a near real time Eigen faces system for face recognition using Euclidean distance.

In all biometric recognition schemes, fingerprint is one of the most widely studied and used form of recognition [3], with its history dates back to 1800 century [4]. It is the cheapest, fastest, most convenient and highly reliable way to identify individual.

In this paper we are preprocessed both the images of face and thumb and each image is decomposed as four sub bands using DWT. These four sub bands are approximation sub band (LL), horizontal detail sub band (LH), vertical detail sub band (HL), and diagonal detail sub band (HH).and these sub bands of face and thumb are fused by maximum selection rule [5]by using IDWT combine all sub band into single image and then features of LL band are extracted by PCA and in HL and LH band extract the texture features the same process is repeated on database images finally the feature of test fused image is match with database image by different classifier like Euclidean distance.

2. EXISTING METHOD

2.1 Unimodal system

Three Classical Methods

There are many algorithms developed in face recognition domain over recent two decades. Three classical algorithms (according to National Institute of Standards and Technology), Principle Component Analysis (PCA), Linear Discriminant

Analysis (LDA), and Elastic Bunch Graph Matching (EBGM), are briefly reviewed as follows.

PCA is used for dimensionality reduction to find the eigen vectors which best account for the distribution of all face images in the database [6], [7]. These eigenvectors are commonly referred to as eigenfaces. Notice that the number of eigenfaces depends on a particular implementation and the number of images in database. All faces including the training images (in database) and the probe image are projected onto eigen faces to find a set of weights (feature vector) for each face. Each weight in a set actually describes the contribution of corresponding eigenface. Identification of a face image is to find the closest face (i.e., feature vector) in the database according to a distance measure. PCA algorithm typically requires frontal face images, and all images should have the same size and line up eyes and mouth of the subjects.

LDA [8] is to find an efficient way to represent the faces using the face class information. The Fisherface algorithm [9] is derived from the Fisher Linear Discriminant, which uses class specific information. By defining different classes with different statistics, the images in the training set are divided into the corresponding classes. Then, techniques similar to PCA algorithm are applied. The Fisherface algorithm results in a higher accuracy rate in recognizing faces when compared with Eigenface algorithm [9].

In EBGM algorithm [10], [11], faces are represented as graphs, with nodes positioned at fiducial points (such as eyes, nose, mouth), and edges labeled with 2-D distance vectors. Each node contains a set of 40 complex Gabor wavelet coefficients, including both phase and magnitude, known as a jet. Wavelet coefficients are extracted using a family of Gabor kernels with 5 different spatial frequencies and 8 orientations. A graph is labeled using a set of nodes connected by edges, where nodes are labeled with jets, and edges are labeled with distances. Thus, the geometry of a face is encoded by the edges, whereas, the gray value distribution is patch-wise encoded by the nodes (Jets). To identify a probe face (also called query face), the face graph is positioned on the face image using elastic bunch graph matching, which actually maximizes the graph similarity function (equivalent to face alignment) [10].

3. PROPOSED METHOD

Proposed method has mainly five modules viz., preprocessing, wavelet transform, fusion, feature extraction and classification. Preprocessing is done by median filter and histogram equalization. Fusion is carried out by absolute maximum selection rule. Features are extracted by principal component analysis and gray level co-occurrence matrix and classification is done by Euclidean distance.

Proposed method Block Diagram and its explanation are as follows:

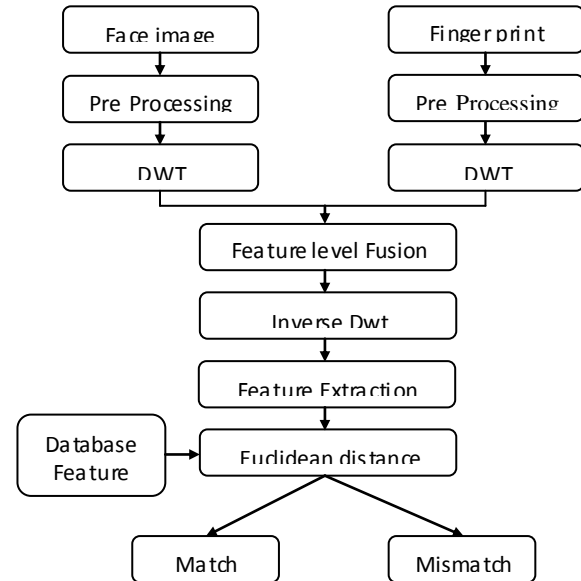


Fig-1: Building blocks of the multimodal face and thumb recognition

Block Diagram is explained below:

1. Input images are of face and fingerprint.
2. Each image is preprocessed by resizing, enhancement and filtering.
3. Each image is decomposed using DWT.
4. All high and low frequency components are fused by feature level fusion i.e. maximum selection method.
5. Again inverse DWT is applied on fused image
6. PCA features of low frequency component like mean value, difference between input and mean etc are extracted and texture feature are also extracted.
7. Same process is repeated on data base images and extracted feature are store in memory.
8. Now apply Euclidean distance for comparing test image feature and database image feature.
9. Check whether test image features are match with database features or not if matched then that person is authentic otherwise unauthentic.

4. DWT AND PCA

The Discrete Wavelet Transform (DWT) is a very popular and commonly used transform for image processing. The DWT decomposes an image into a set of basic functions called wavelets; decomposition is defined as the “resolution” of an image. The DWT then performs a multi-resolution analysis of

a signal with localization in both time and frequency domains. 2D-DWT is implemented as a set of filter banks, comprising of a cascaded scheme of high-pass and low-pass filters. The final result obtained is a decomposition of the input image into four non-overlapping multi-resolution sub-bands: LL, LH, HL and HH. The sub-band LL represents the coarse-scale DWT coefficients while the sub-bands LH, HL and HH represent the fine-scale of DWT coefficients. In this work HH is explored for face recognition.

Principal component analysis (PCA) for face recognition is based on the information theory approach. It extracted the relevant information in a face image and encoded as efficiently as possible. It identifies the subspace of the image space spanned by the training face image data and decorrelates the pixel values. The classical 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, decorrelation and dimensionality reduction to facilitate decision making. In mathematical terms, the principal components of the distribution of faces or the eigenvectors of the covariance matrix of the set of face images, is sought by treating an image as a vector in a very high dimensional face space [12][13][14].

5. TEXTURE FEATURE EXTRACTION

Texture feature extraction is based on GLCM. GLCM creates a matrix with the directions and distances between pixels, and then extracts meaningful statistics from the matrix as texture features.

Commonly used features of texture in GLCM are shown as follows:

GLCM expresses the texture feature according the Correlation of the couple pixels gray-level at different Positions. It quantitatively describes the texture feature. In this paper, four features is selected, include energy, contrast, correlation and homogeneity.

Energy is given by

$$E = \sum_x \sum_y p(x,y)^2 \quad (1)$$

It is a gray-scale image texture measure of homogeneity changing, reflecting the distribution of image gray-scale uniformity of weight and texture.

Contrast is given by

$$I = \sum_x \sum_y (x - y)^2 p(x,y) \quad (2)$$

Contrast is the main diagonal near the moment of Inertia, which measure the value of the matrix is distributed and images of local changes in number, reflecting the image clarity and texture of shadow depth. Contrast is large means texture is deeper.

Correlation is given by

$$C = \sum_{i,j} \frac{(i - \mu_i)(j - \mu_j)p(i,j)}{\sigma_i \sigma_j} \quad (3)$$

A statistical measure of how correlated pixel is to its neighbor over the whole image. Range = [-1 1]. Correlation is 1 or -1 for the perfectly positively or negatively correlated image. Correlation is Nan for a constant image.

Homogeneity is given by

$$H = \sum_{i,j} \frac{p(i,j)}{1 + |i - j|} \quad (4)$$

Closeness of distribution of elements in GLCM to the GLCM diagonal.

Range = [0 1]. Homogeneity is one for a diagonal GLCM.

6. FUSION RULES USED

In the proposed method of image fusion, we have fused the wavelet coefficients by the absolute maximum selection fusion rule. Suppose $I_1(x,y)$ and $I_2(x,y)$ are the two images to be fused and their wavelet coefficients are $W_1(m,n)$ and $W_2(m,n)$ respectively, then Absolute Maximum Selection Fusion Rule is used to combine wavelet coefficients as below:

$$W(m,n): \begin{cases} W_1(m,n) & \text{if } |w_1(m,n)| \geq |w_2(m,n)| \\ W_2(m,n) & \text{if } |w_2(m,n)| \geq |w_1(m,n)| \end{cases} \quad (5)$$

7. EUCLIDEAN DISTANCE (E.D.)

The Euclidean distance is the nearest mean classifier which is commonly used for decision rule is denoted as

$$d_E(x, w_k) = \sqrt{(x - w_k)^T + (x - w_k)} \quad (6)$$

Where the claimed client is accepted if $d_E(x, w_k)$ is below the threshold and rejected otherwise.

8. RESULT AND DISCUSSION



Fig-2: Output of proposed method (Authorized)

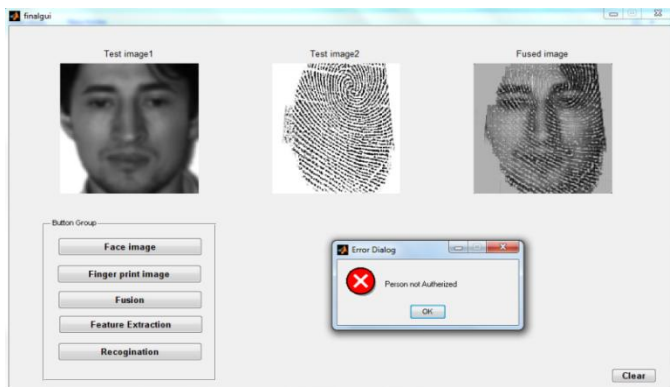


Fig-3: Output of proposed method (Not Authorized)

Above Fig-2 and 3 shows the output of our proposed method. The classification of our system is done by Euclidean distance, if Euclidean distance is zero means test image is authorized else he/she is unauthorized.

9. CONCLUSION AND FUTURE SCOPE

There are different type of recognition systems are available like as Unimodal, multimodal we design a multimodal security system by fusing face and finger print. And we taken face and fingerprint as a test image and apply wavelet transform for both images and fused low and high frequency sub bands by using absolute maximum selection rule after fusion extract the PCA features in LL sub band of fused image and extract the texture feature in LH and HL sub band of fused image same

process is repeated for data base images and compare those features by using Euclidean distance and classified.

REFERENCES

- [1]. Kirby and Sirovich, 1990. Application of Karhunen-Loeve procedure for the Characterization of human faces. IEEE Trans. pattern analysis and machine intelligence, 12:103-108.
- [2]. Turk, M.A. and A.L. Pentland, 1991. Face recognition using Eigen faces. Proc. IEEE computer society Conf Computer Vision and pattern recognition, pp: 586-591.a
- [3]. D. Maltoni, D. Maio, A. K. Jain, and S. Prabhakar, "Handbook of Fingerprint Recognitio,," 2nd Edition, Springer-Verlag, 2009.
- [4]. A.K Jain and S. Pankanti, "Biometrics Systems: Anatomy of Performance,," IEICE Trans. Fundamentals, Vol.E00-Q, NO.1 2001.
- [5]. Om Prakash, Richa Srivastava, Ashish Khare" BIORTHOGONAL WAVELET transform based image fusion using absolute maximum fusion rule" proceedings of 2013 iee conference on information and communication technologies (ict 2013)
- [6]. Moon H, Phillips P J, 2001, "Computational and performance aspects of PCA-based face-recognition algorithms," Perception 30(3), 303 -321, 2001.
- [7]. W. Zhao, R. Chellappa, A Krishnaswamy, "Discriminant Analysis of Principal Components for Face Recognition," Proc. of the 3rd IEEE International Conference on Face and Gesture Recognition, FG98, 14-16, pp. 336-341, April 1998, Nara, Japan.
- [8]. Lu, K.N. Plataniotis, AN. Venetsanopoulos, "Face Recognition Using LDA-Based Algorithms," IEEE Trans. on Neural Networks, Vol. 14, No. I, pp. 195-200,2003.
- [9]. L. Wiskott, J.M. Fellous, N. KrUger, C. von der Malsburg, "Face Recognition by Elastic Bunch Graph Matching," IEEE Trans. Pattern Anal. Mach. Intell. 19 (7),775-779,1997.
- [10]. L. Wiskott, J.-M. Fellous, N. KrUger, and C. von der Malsburg, "Face Recognition by Elastic Bunch Graph Matching," in L. C. Jain, U. Halici,1. Hayashi, S. B. Lee and T. Tsutsui (eds.), Intelligent Biometric

Techniques in Fingerprint and Face Recognition," pp. x355-396, CRC Press, USA, 1999.

- [11]. W. Zhao, R. Chellappa, A. Rosenfeld, P.J. Phillips, "Face Recognition: A Literature Survey," ACM Computing Surveys, 35(4), pp. 399-458, 2003.
- [12]. P. J. B. Hancock, V. Bruce and A. M. Burton, "Testing Principal Component Representations for Faces", Proc. of 4th Neural Computation and Psychology Workshop, 1997.
- [13]. Jonathon Shlens, "A Tutorial on Principal Component Analysis", Systems Neurobiology Laboratory, Ver.2, 2005
- [14]. Zhuji, Y.L.Y., 1994. Face recognition with Eigen faces. Proc.IEEE Intl. Conf. IndustrialTechnol. Pp: 434-438. 2008