

# Multimodal Biometrics Recognition System using EBGM

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**Abstract** - Unimodal biometric system has several limitations like sensitivity to noise data, lack of performance, spoofing, etc. To overcome the limitations of unimodal biometric system, we propose multimodal biometric recognition system consisting combination of face and ear (physical traits). The face is the most promising rich biometric trait. The ear has an advantage since it is co-located with the face so that data can be collected with the same or similar sensor. In this project, we propose combination of face and ear biometric modalities, in which we employ a wavelet transform for feature extraction, which describes the ratio between dark and bright areas. Elastic Bunch Graph Matching is used for matching module. Inputs from Face and ear datasets from a biometric database were used to evaluate the performance of the system. The modalities are normalized using z-score method for better fusion results. Further, match score fusion approaches were used for matching the face and ear data.

**Index Terms** – Multimodal biometrics, Face, ear, Gait recognition, Wiener Filter, Haar Transformation, Elastic Bunch Graph Matching.

## I. INTRODUCTION

Biometrics (ancient Greek: bios = “life”, metric = “measure”) refers to biological sciences that has been studied and applied for several generations and is viewed as “biological statistics”. Biometrics recognition involves measuring of unique physiological human characteristics or Behavioral traits[13]. Biometric characteristics can be divided in two main classes:

- Physiological
- Behavioral

Physiological characteristics are shape of a body, fingerprints, structure of the face, DNA, hand/palm geometry, iris patterns, and odour/scent. Behavioural characteristics are keystroke, gait, and voice.

Biometric recognition can be done in two ways Unimodal and Multimodal Biometrics. In Unimodal biometric recognition, any one unique physical or behavioral trait is measured to authenticate the person. In Multimodal biometrics, two or more biometric modalities are imposed to authenticate and verify the individuals[1]. The multimodal biometric recognition is more resistant to noise compared to Unimodal biometric systems, as they have more than one modality data for matching[1]. These systems are less vulnerable to spoofing, as it is difficult to spoof more than one modality simultaneously.

Even the best Unimodal biometric traits till date are facing numerous problems. Those problems can be solved by installing multiple sensors that capture different biometric traits. Such system is known as multimodal biometric system. Multimodal biometric systems are more reliable due to the presence of different modals which meets the requirements imposed by various applications. The main reason of using these three biometric traits is that, this system requires no significant user co-operation and can work from a long distance[1]. The base objective of the proposed system is to develop a multimodal Biometric system using the combination of face and ear biometric modalities with reduced intra class similarity, noise resistance and less vulnerable to spoofing.

## II. OVERVIEW OF PROPOSED SYSTEM

In this proposed system, a novel multimodal biometric recognition system using two modalities including face and ear to provide security and authentication. Multimodal biometrics refers to the use of a combination of two or more biometric modalities in a verification/ identification system.

### FACE:

In terms of acceptability, the face is considered the most promising biometric trait. Face data can be collected easily and non-intrusively as it is rich in distinct features. Very high recognition rates have been obtained for faces. This application present different

technical challenges such as variant to pose, illumination, size, age, expressions, occlusion and structural components. Face images can be captured from video cameras, so it is used for surveillance purposes.

**EAR:**

Ear Recognition is also non-intrusive. The ear has some advantages over the face: (a) almost no aging and expression problems for adults; (b) ear has a uniform distribution of color; (c) ear's surface is smaller so as to allow less storage requirement and lower computational cost.

### III. DESIGN OVERVIEW

The Proposed System consists of six modules such as Image Acquisition, Preprocessing, Feature Extraction, Matching, Normalization, Fusion and Final Decision.

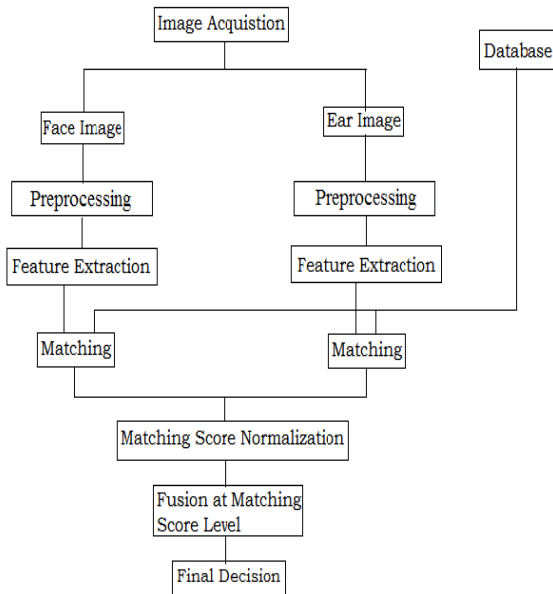


Fig. 1 Schematic diagram of the proposed multimodal biometric system

#### Phase I - Data Extraction

##### A. Image Acquisition module:

The first step for the use of a biometric recognition system is the acquisition of biometric data from biometric sensor hardware. An acquisition module can request an image from several different environments. The final result of enrollment process is an image or signal captured directly from individuals.

##### B. Preprocessing module:

The preprocessing images commonly involve removing low-frequency background noise,

normalizing the intensity of individual particles images, removing reflections, and masking portions of images. Image preprocessing is the technique of enhancing data images prior to computational processing. Image preprocessing techniques serve to enhance or in some way alter the qualities of blur, motion, noise and the quality of an image. In this module filtering and contrast enhancement is done. The aim of preprocessing module is to bring the image towards what it would have been if it had been recorded without degradation.

#### WIENER FILTER

The Wiener filter is a filter used to produce an estimate of a desired or target random process by linear time-invariant filtering an observed noisy process, assuming known stationary signal and noise spectra, and additive noise. The Wiener filter minimizes the mean square error between the estimated random process and the desired process.

Wiener filter assumed to have knowledge of the spectral properties of the original signal and the noise, and one seeks the linear time-invariant filter whose output would come as close to the original signal as possible. Wiener filters are characterized by the following:

1. Assumption: signal and (additive) noise are stationary linear stochastic processes with known spectral characteristics or known autocorrelation and cross-correlation
2. Requirement: The filter must be physically realizable / causal (this requirement can be dropped, resulting in a non-causal solution)
3. Performance criterion: minimum mean-square error (MMSE)

Wiener de-convolution can be useful when the point-spread function and noise level are known or can be estimated. The Wiener filter is:

$$G(u,v) = H^*(u, v) P_s(u, v) / |H(u, v)|^2 P_s(u, v) + P_n(u, v)$$

where

$H(u, v)$  = Degradation function

$H^*(u, v)$  = Complex conjugate of degradation function

$P_n(u, v)$  = Power Spectral Density of Noise

$P_s(u, v)$  = Power Spectral Density of un-degraded image

#### CONTRAST ENHANCEMENT

The Preprocessing techniques contain several image enhancement routines. Three functions are particularly suitable for contrast enhancement: *imadjust*,

*histeq*, and *adapthisteq*. This technique compares their use for enhancing gray scale and true color images.

*C. Feature Extraction module*

Transforming the input data into set of features is called feature extraction. The input data contain some redundant information so the features that are needed is extracted and those features are given to neural network for classification. In this work, for extracting the features Discrete Wavelet Transform is used.

**DISCRETE WAVELET TRANSFORM**

The discrete wavelet transform (DWT) is an implementation of the wavelet transform using a discrete set of the wavelet scales and translations obeying some defined rules. Discrete Wavelet Transform decomposes the input signal into a set of basic functions. These basis functions are called wavelets. These wavelets are obtained when the single prototype wavelet  $y(t)$  called mother wavelet undergoes the process of dilations and shifting.

$$\psi_{a,b}(t) = (1/\sqrt{a})\psi((t-b)/a)$$

Where  $a$  is the scaling parameter and  $b$  is the shifting parameter.

**HAAR WAVELET TRANSFORM**

The definition of Haar wavelet is

$$\psi(t) = \begin{cases} 1 & 0 \leq t < 1/2, \\ -1 & 1/2 \leq t < 1, \\ 0 & \text{otherwise.} \end{cases}$$

Haar wavelet operates on data by calculating the sums and differences of adjacent elements. The Haar wavelet operates first on adjacent horizontal elements and then on adjacent vertical elements. The Haar Transform is computed using  $\frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$

The Haar basis is obtained with a multi-resolution of piecewise constant function. The scaling function is a piecewise constant approximation defined as

$$\phi(t) = \begin{cases} 1, & 0 \leq t < 1 \\ 0, & \text{otherwise} \end{cases}$$

The wavelet transform of “ $f$ ” is defined as

$$\langle f(t) \Psi_{a,b}(t) \rangle = 2^{-j} \langle Df_{a,b}(t) \phi_{a,b}(t) \rangle$$

where  $D_p$  is the derivative of the function and  $\phi$  is the smoothing kernel. The wavelet coefficients obtained with the Haar wavelet  $\psi$  are, therefore, proportional to

the local averages of the derivative of the image at given resolution. This is particularly interesting property, which makes Haar representation useful for image representation. Haar wavelet has compact support and describes the ration between the dark and bright areas within the kernel so that it can capture the image features effectively. It is also relatively robust to lighting changes because they compute the gray level difference between the white and black rectangles.

*D. Matching module*

In this module, matching is performed by Elastic Bunch Graph Matching technique. All human faces share a similar topological structure. Faces are represented as graphs, with nodes positioned at fiducial points (such as the eyes, the tip of the nose, some contour points, etc.;). Face recognition is based on labeled graphs. A labeled graph is a set of nodes connected by edges; nodes are labeled with jets; edges are labeled with distances. Thus, the geometry of an object is encoded by the edges while the grey value distribution is patch-wise encoded by the nodes (jets). To identify a new face, the face graph is positioned on the face image using elastic bunch graph matching. The goal of Elastic graph matching is to find the fiducial points on a query image and thus to extract from the image a graph which maximizes the graph similarity function.

The EBGM technique can be done by following steps:

- Change of image in Black and White
- Minimization of image
- Face detection
- Landmark Localization(Manually or Automatically selected points
- Graph Creation
- Similarity measurement
- Identification

*Phase II - User Verification*

This work is currently in implementing the following modules and we have planned to perform a simulation based analysis at the end of this second phase. The modules implemented in this phase are as follows

*E. Normalization module*

Normalization addresses the problem of incomparable classifier output scores in different combination classification systems. Normalization includes mapping the scores obtained from each modality into a common domain. Good normalization method should be robust and efficient. In proposed system, normalization is done using z-score method.

$$x' = \frac{x - \mu}{\sigma}$$

Where  $x'$  is normalized scores,  $x$  is the scores,  $\mu$  is the mean of the data set,  $\sigma$  is the standard deviation

#### F. Fusion module

In proposed system in order to combine the scores reported by the three matchers fusion at the match score level is usually preferred, as it is relatively easy to access and combine the scores presented by the different modalities. Fusion at match score level uses two different techniques including weighted sum method and weighted product method.

By fusion at the matching score level, each system provides a matching score indicating the proximity of the feature vector with the template vector and these scores can be combined to recognize the claimed identity. Here, rather than combining the feature vector, we process them separately and individual matching score is found, then depending on the accuracy of each biometric channel we can fuse the matching level to find composite matching score which will be used for classification.

#### G. Decision module

In this module, for Verification Systems if the similarity score is greater than a fixed threshold the system decides that templates belong to the same person. In Identification System the database templates are compared query template and higher similarity score templates. The decision module uses the matching scores to either determine an identity or validate a claimed identity.

### IV. SIMULATION RESULTS

This Section presents the details of the simulation study carried on various databases using the proposed method. The databases include GAID database and CASIA database for gait, USTB ear database, AR database, UWA database for face and ear, ORL face database.

#### PREPROCESSING:

In the proposed multimodal biometric systems, image preprocessing is done to remove the blur, noise effect and to enhance the contrast of the image. This can be done by filtering and contrast enhancement.

#### FILTERING:

In this Filtering is done using wiener filter. The simulation results explain how the wiener filter removes the blur and noise from the image. The first image is acquired from the video so it may be blurred with noise and other effects. So using wiener filter the

blur is removed. Again same technique is used to remove the noise and quantized to get a perfect image for the feature extraction.

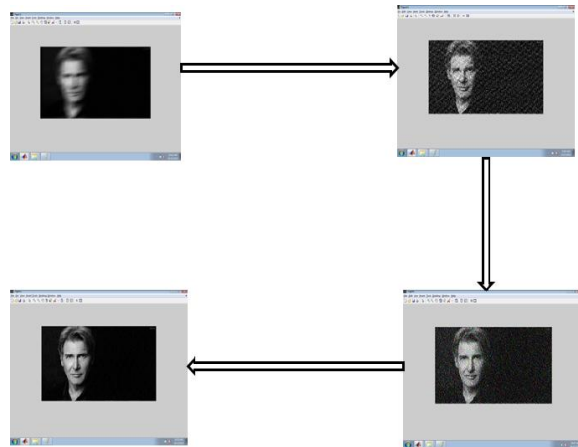


Fig. 2

#### CONTRAST ENHANCEMENT:

The Preprocessing technique contains several image enhancement routines. Three functions are particularly suitable for contrast enhancement: *imadjust*, *histeq*, and *adaphisteq*. This technique compares their use for enhancing *grayscale* and *truecolor* images.

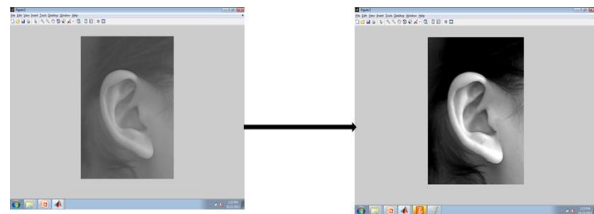


Fig. 3

#### FEATURE EXTRACTION:

Discrete Wavelet Transform decomposes the input signal into a set of basic functions. These basis functions are called wavelets. These wavelets are obtained when the single prototype wavelet  $y(t)$  called mother wavelet undergoes the process of dilations and shifting. The three level decomposition of face image using Haar wavelet is shown in the simulation. In this, the original image is convolved with the Haar wavelet filter up to three level decomposition to get down approximated image and detailed image.

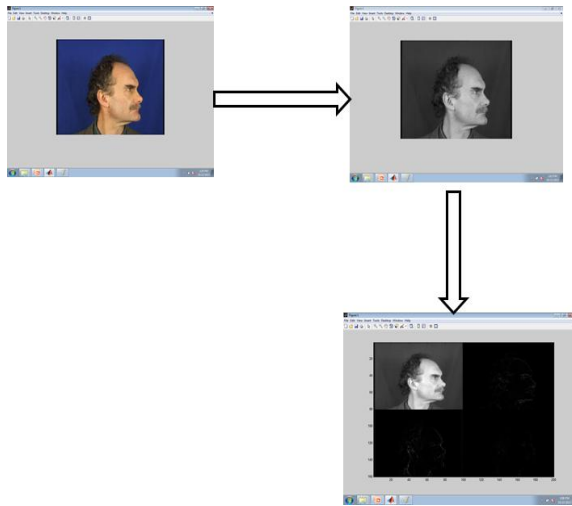


Fig. 4

*Elastic Bunch Graph Matching*

Implementing **Matching Module** is performed by Elastic Bunch Graph Matching technique. The EBGM technique can be done by following steps:

- Change of image in Black and White
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- Landmark Localization(Manually or Automatically selected points
- Graph Creation
- Similarity measurement
- Identification

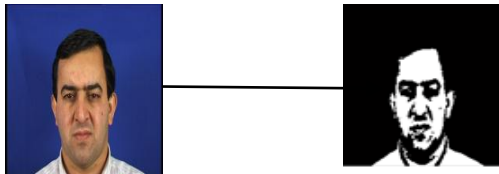


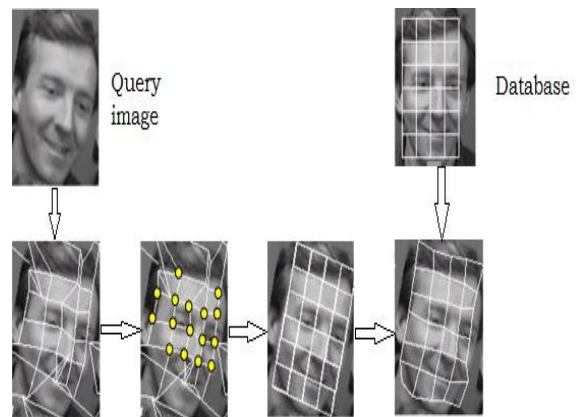
Fig. 5

This screen shot show the RGB image which is converted to Black and White image.



Fig. 6

This screen shot shows the detection of face which is marked in red color box.



g. 7

This screen shot shows the image which has to be matched with the database. First graph is formed on the detected face. The nodes are manually marked on the image. Graph is drawn from the nodes and similarity of the image is checked.

V. CONCLUSION

In this paper, a new multimodal biometric recognition system using three modalities including face, ear and gait has been studied. Feature extraction done using discrete wavelet transform and train data sets using artificial neural network. And fusion at matching score level is proposed. The effect of different fusion methods and different score normalization methods on the recognition performance of our multimodal biometric system are studied in this paper. We show that our approach also exhibits excellent recognition performance and outperforms unimodal systems on a variety of image databases including face, ear and gait images.

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