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A Multimodal Biometric Identification Approach using Machine Learning

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Abstract –**Unimodal biometric systems have been in existence for some years, but are rather adapted to an average level of security. In fact, the higher the level of security, the more one will tend towards the use of multimodal systems, more efficient and safer.**
This paper develops an approach of multimodal biometric identification system from the fusion of Discrete Wavelet Transform (DWT) features of face and fingerprint images along with Gabor wavelet and wavelet moment features of Iris image and performing the results with Random Forest Classifier. Performance evaluation is done using confusion matrix plot with sensitivity, specificity and accuracy.

Keywords – **DWT, Gabor Wavelet, Wavelet Moment, Random Forest Classifier.**

I. INTRODUCTION

Some authors [1] mention that the Chinese, already in the 2nd century, used the fingerprint for the purpose of signing documents. The characteristics of these impressions attracted the attention of many people who were interested in the use of these for the identification of people. Sir Francis Galton [1] at the end of the twentieth century laid the first edifice that later made possible the elaboration of a universal system of identification of criminals that was used by the police of the entire world. Moreover Sir Francis Galton was not the first to notice the grooves and hollows existing inside our hands and under our feet, nor even to find useful applications for them [2].
The anatomist Marcello Malpighi (1628-1694) studied them with a new instrument called a microscope. After him the Czech physiologist Jan Evangelista Purkinge (1787-1869) worked to categorize fingerprints according to certain characteristics. A practical application of fingerprinting was carried out by Sir William Herschel (1738-1822), a British official in Bengal, who used the fingerprinting of contractual documents that bind traders to administration. Dr. Henry Faulds (1843-1930), a surgeon in Tokyo, gave a strong impulse to the development of a Classification by taking fingerprints [3].
Dactyloscopy (fingerprint identification) and bertillonnage were techniques quickly adopted by police forces around the world. An Argentine policeman was the first to identify a criminal by his fingerprints in 1892. Subsequently, fingerprinting became an anthropometric technique and the bertillonnage gradually faded.
Out of all technologies related to biometrics, identification from fingerprints remains the most common. More than a centenary after its development by Galton, this technique, improved several times since, is rather well. Large police forces have access to huge databases that hold fingerprint images of millions of people.
Nowadays, the increasing computing power of computers can be used to recognize individuals, thanks to devices coupled with complex computer programs. Since the attacks of 26 November 2008, governments have begun to give increasingly important budgets for security. In some countries, cameras are installed throughout public places: in airports, banks, stadiums, etc. The enormous amount of information provided by these capture devices certainly requires tremendous efforts to treat it and be able to take advantage of it [4]. This requires more than ever the use of powerful computers to be able to process and analyze this information quickly and draw the necessary conclusions [5]. However, if the computer excels in certain types of tasks, some others are very far from being obvious. Indeed to compensate for this, significant efforts are being made in the field of biometric research. Biometric applications are numerous and provide a higher level

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of security in terms of logical access (computers, bank accounts, sensitive data, etc.) or physical access (secure buildings, airports, laboratories, etc.). In several applications (access control, banking transactions) it is more than necessary to characterize a user by a signature in order to differentiate it from others in a precise manner [6]; this signature is the codification that identifies a person without repetition or fluctuation. Most biometric characters, such as fingerprints or genetic, meet these criteria. The voice, predisposed to vary by its nature, dislikes these rules. Despite these apparent difficulties, voice remains a biometric index interesting to exploit because practical and available via the telephone network, unlike its competitors [7].

Biometrics is the automatic identification of the person based on their physiological or behavioral characteristics, such as fingerprints, face, voice, etc [8]. However, the unimodal biometric system suffers from certain limitations, such as non-universality and susceptibility to forgery. To remedy these problems, information from different biometric sources is combined, and such systems are called multimodal biometric systems [9].

Biometrics attempts through mathematical tools often very advanced, to distinguish between individuals, forcing us to work in a context of great diversity. This diversity is also reflected in the considerable number of algorithms that have been proposed in the recognition.

Multimodal biometric system overcomes the limitations of unimodal biometric system such as intra-class variations, noisy-sensor data, spoofing attacks and non-universality, by using multiple individual modalities. Feature-level fusion is more powerful and efficient than other levels of fusion as the feature set comprises more data of the input biometric characteristic. Even though multimodality in biometrics, improves the accuracy of the system, but it uses a huge memory storage and expends more execution time because, gathers data from different resources. In this paper, fusion of DWT, Gabor wavelet and wavelet moment is proposed and performing the results with Random Forest Classifier.

II. Proposed Methodology

A. System Model

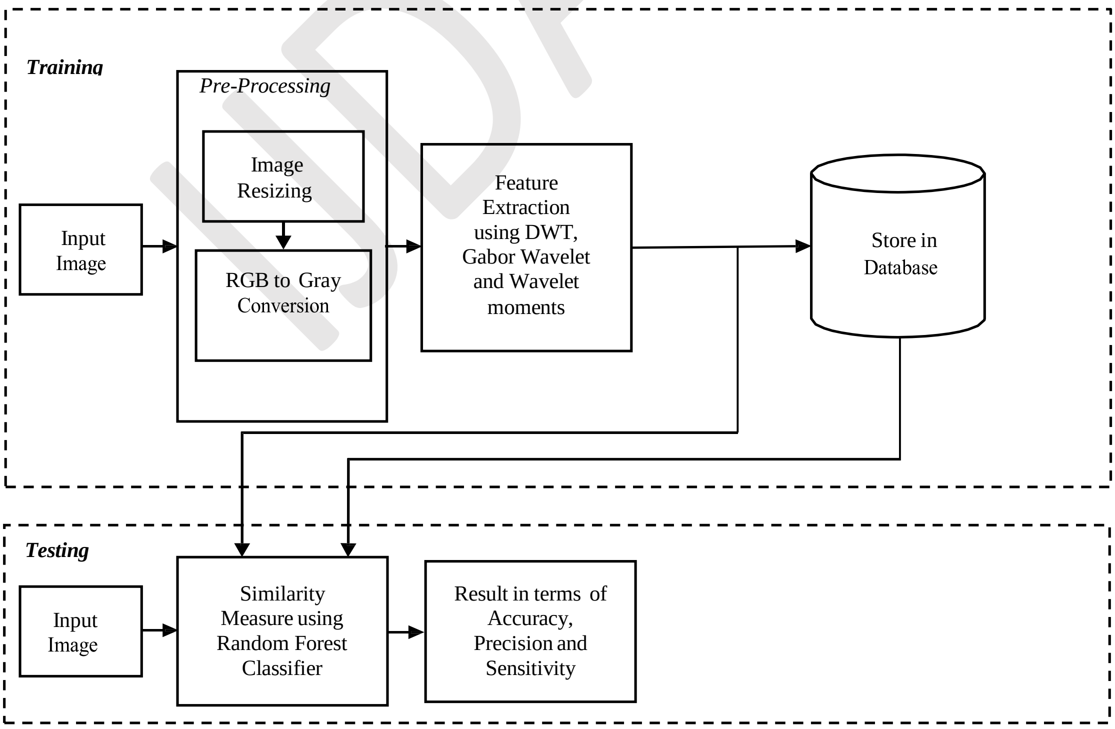

Figure 2: Proposed block diagram

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The multimodal method executes different algorithm according to different input patterns. The automated system is executed and different id will be generated according to training and testing input. As per the Figure 2, it is clear that there are two phases of this research; training phase and testing phase.

B. Description of Methodology

1) Training Phase

In the first step of training phase we take input images one by one. Then the image is fed into Pre-processing block. Preprocessing is done with the help to two sub processes namely; Resize the image and RGB to Gray conversion. Since most of digital filters work on 2-dimensional data rather than multi-dimensional data, so RGB to Gray conversion is used. Now the preprocessed image data is fed to feature extraction block. This block uses DWT, Gabor wavelet and wavelet moments approaches for feature extraction. These extracted features are stored in the database. This all is done in the training process.

2) Testing Phase

In the testing phase an input image is processed similar to training phase. Pre- processing and post-processing are done same as training phase. And the features extracted from the post processing is matched using Random forest classifier with other features present in the database. And the recognition is completed using the parameters namely; Accuracy, Precision and Sensitivity.

The detailed methodology is described below.

C. Pre-Processing Block

The phases involved in preprocessing are shown in the flow diagram in Figure 2. The points of interest are as per the following:

- The input image is resized to 250×250 pixels.
- After resizing, the RGB image is transformed to a gray scale image using rgb2gray function.

D. Feature Extraction

There are three features have been considered for proposed multimodal biometric recognition. DWT is used for the feature extraction of face and fingerprint images while the Gabor wavelet and wavelet moments are used for the feature extraction of iris image.

1) Discrete Wavelet Transform

The wavelet transform is established on the basis of a signal decomposition by wavelets whose expansion and translation parameters are continuous variables.

In addition, while dealing out with the digital signals, a discretization of the parameters a and b is necessary. Consequently, the integral of wavelet transform expressing the conservation of energy is also discretized, which raises the question of the conditions under which the approximation of this integral will be applicable.

It is necessary to give a rule on the discretization of the steps of dilation and translation of the wavelets.

As long as this rule is followed, the preservation of all signal information can be ensured, allowing a numerically applicable expression of the inverse transform as a discrete wavelet series.

We can choose to sample the signal using the wavelet "like a microscope": since the size of the wavelet varies according to the dilation, the conservation of the same time sampling step is redundant and useless.

At low frequencies, many wavelets would be used to represent little information, so the theoretical transform is redundant. Likewise, since the frequency band covered by the wavelet is wider at high frequencies, less wavelets will be needed to represent this band.

Morlet proposed to create bases of functions built on the following model:

$$\psi_{j,k}(t) = a_0^{-\frac{j}{2}}\psi\left(a_0^{-j}t - kb_0\right) \qquad (1)$$

With, $a_0 > 1$ and $b_0 > 0$ fixed and $j, k \in Z$

This discretization assigns values to the scale a on a logarithmic scale with proportional translation parameters:

$$a = a_0^j \text{ and } b = kb_0a_0^j \qquad (2)$$

A range of commonly used scales is the dyadic range, $a_0 = 2$ and $b_0 = 1$. We thus obtain families consisting of functions of the form:

$$\psi_{j,k}(t) = 2^{-\frac{j}{2}}\psi(2^{-j}t - k) \qquad (3)$$

However, one very often finds in the literature, a dyadic WT where only the scale parameter is sampled according to a dyadic sequence $[2^j]\ j \in Z$, and the parameter b remains a continuous variable. Such a transform, for a signal $x(t)$, can be written as:

$$DWT(2^j, b) = \frac{1}{\sqrt{2^j}}\int_{-\infty}^{+\infty} x(t)\psi^*\left(\frac{t-b}{2^j}\right)dt \qquad (4)$$

2) Gabor Wavelet

Gabor's Eye, developed by Dennis Gabor, is extensively used as a treatment of images because the Gabor wavelets salient properties: the localization frequency and selectivity in orientation. Frequency representations and orientation of Gabor are according to biometric recognition system [10]. The article [10] (the first is in Nature) indicate that representation by Gabor Wavelet of iris images irrespective of variations in illumination. The

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Gaussian envelope for iris recognition is represented as follows:

$$\psi_{u,v}(z) = \frac{\|K_{u,v}\|^2}{\sigma^2} e^{\frac{\|k_{u,v}\|^2\|z\|^2}{2\sigma^2}} \left[e^{ik_{u,v}z} - e^{-\frac{\sigma^2}{2}}\right] \quad (5)$$

Where $z = (x; y)$ is the coordinate point $(x; y)$. Where u and v are orientation and frequency respectively for kernels of Gabor. $\|.\|$ is the standard operator and σ is standard deviation of the Gaussian envelope.

The Gabor wavelet is the representation of convolution product of frequency and orientation claimed from equation (5). The convolution of image I and of a kernel of Gabor $\psi_{u,v}(z)$is defined by:

$$G_{u,v}(z) = I(z) * \psi_{u,v}(z) \quad (6)$$

The interest of using Gabor Wavelet to extract iris features is capturing face information in orientations and resolutions. In addition, they are invariant of illumination, distortions and variations in scale. Therefore, if only the amplitude response is considered, “Jet” and it has been widely used in the oldest systems, such as the DLA and the EGBM. Note that these are methods based on the characteristic points which must be detected very precisely. Several metrics have been tested for characteristics based on Gabor and the one that is most often used is the cosine distance.

3) Wavelet Moments

The wavelet transform is used to decompose low frequency images so as to differentiate high frequency components, in view of its capacity to catch particular transformed information of extracted image.

The arrangement of the data into multi resolution frequency permits to confine the frequency segments acquainted by intrinsic values due with expression or extraneous components (i.e light) into several sub bands. These techniques cut away these different sub bands, and spotlight on the sub bands which contain the most applicable data.

A 4-level DWT decomposition is used on image set. Therefore 4 subgroups are resulted in the form of detailed and approximation coefficients. The approximation coefficient is reconciliation (A), which is input image itself but with reduced size. Whereas the detailed coefficients are horizontal (h), vertical (v) and diagonal (d). The application of single level DWT on an image M, results in sub-groups given as [11]:

$$M = M_a^1 + \{M_h^1 + M_v^1 + M_d^1\} \quad (7)$$

To further reduce the dimension of input data, DWT can be applied N times to get N-level decomposition. Therefore at the end of four level DWT, image can be represented as:

$$M = M_a^4 + \sum_{i=1}^{4}\{\{M_h^i + M_v^i + M_d^i\}\} \quad (8)$$

At the end of 2-level DWT, input image with $m \times n$ is approximated to $\frac{m}{2} \times \frac{n}{2}$

DWT employees Fourier transform to convert time domain image into frequency domain. The mathematical expression of DWT is given by:

$$DWT_{x(n)} = \begin{cases} dd_{j,k} = \sum img(n)hh^*{}_s(n-2^s r) \\ ap_{j,k} = \sum img(n)ll^*{}_s(n-2^s r) \end{cases} \quad (9)$$

Where, $dd_{j,k}$ represents detailed coefficients and $ap_{j,k}$ are the approximate coefficients of DWT transform. Functions $hh(n)$ and $ll(n)$ are high and low pass filter respectively. Parameters s and r are wavelet scale and translation factors respectively.

It is assumed that we are interested in images or regions that have homogenous texture, therefore the mean and standard deviation are expressed as:

Mean

For a random variable vector A made up of N scalar observations, the mean is defined as:

$$\mu_{mn} = \frac{1}{N}\sum_{i,j=1}^{N} ap_{ij} \quad (10)$$

Where ap_{ij} approximate coefficient, N scalar observations,μ_{mn} is the mean value of wavelet values.

$$\sigma_{mn} = \sqrt{\frac{\sum_{i=1}^{m}\sum_{j=1}^{n}(|I_{mn}(i,j)| - \mu_{mn})^2}{N-1}} \quad (11)$$

Where $I_{mn}(i,j)$ represents the observed values of the sample items are, μ_{mn} is the mean value of these observations, and N is the number of observations in the sample. σ_{mn} is the standard deviation of wavelet values.

A feature vector f_g(wavelet moments) is created using $\mu_{mn}$and σ_{mn} as the feature components:

$$f_g = (\mu_{00}, \sigma_{00}, \mu_{01}, \sigma_{01} \dots \dots . \mu_{45}, \sigma_{45}) \quad (12)$$

E. Classification by Random Forest Classifier

The above extracted feature values can be combined to get optimal dataset for training of the classifier.

A random forest is a classifier containing of one group of structured tree predictors $[T(x,\ominus_k), k = 1, \dots .]$ where the $[\ominus_k]$ are random vectors of identical distributions and where every tree provides a unit poll for the furthermost common class of each entry x.

The main advantage of this structure is that it avoids the danger of over-learning for any method of prediction based on induction. BREIMAN [12] shows that when the number of trees involved in the prediction forest increases, the generalization error rate converges to a limit value, of which an upper bound can be estimated on the basis of the characteristics intrinsic features of the forest.

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The classification trees in RF is built by selecting features from random samples to obtain a class label. The organizational system of the RF classifier is depicted in Figure 3. The RF classifier is formed by a number of base learners and each base learner acts as an independent binary tree which adapts recursive partitioning.

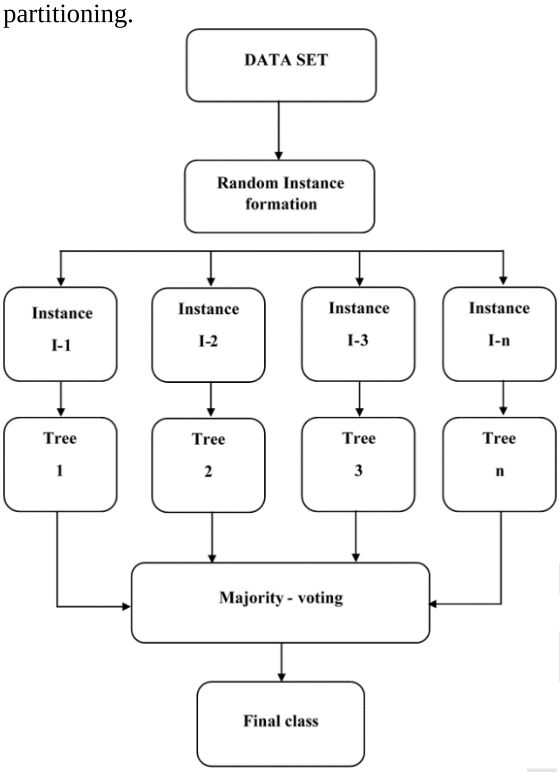

Figure 3: Random forest classifier structural network [12]

The best feature is selected by Gini index, which is used to build the binary tree. It has the following advantages:

- RF is one of the most accurate classifier in present scenario.
- Overfitting is reduced due overgrowing the trees hence it is ease to handle.
- It accepts a large number of input variables without any deletion of the variables.
- The number of base learners is the only setting parameter to give the highest accuracy.

If the marginal function of a random forest $T(X,\ominus)$

$$mr(X,Y) = P_{\ominus}(T(X,\ominus) = Y) - \max_{j \neq T} P_{\ominus}(T(X,\ominus) = j) \quad (13)$$

Which represents the confidence level of the ranking established by the trees of this forest on the population (X, Y), measured by the difference of probability between the prediction of the correct class Y and the best class erroneous j ≠ Y, one can define the prediction value of a game of trees $\{T\ (x,\ominus)\}$ by the mathematical expectation of this function

$$s = E_{x,y}[mr(X,Y)] \quad (14)$$

The dependency between trees in a forest ρ (⊖,⊖') is measured by the correlation between their gross marginal functions, and it is evaluated for fixed and distinct parameter values ⊖,⊖'. By means of these definitions, an upper limit to the error in generalization (TEG) of any random forest is given by the relation.

$$TEG \leq \bar{\rho}(1 - s^2)/s^2 \quad (15)$$

III. Simulation And Results

The performance of proposed algorithms has been studied by means of MATLAB simulation.

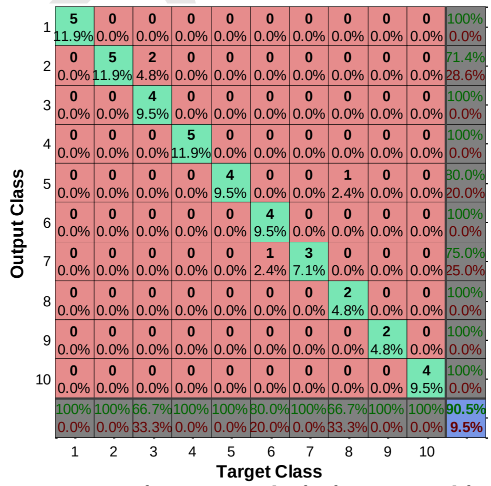

Figure 4: Confusion matrix plot for fingerprint and face recognition (40% training and 60% testing)

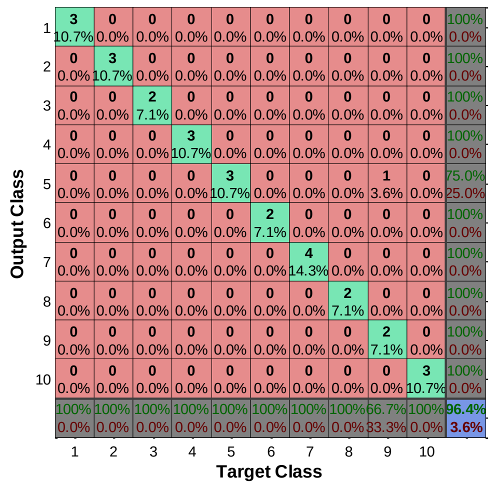

Figure 5: Confusion matrix plot for fingerprint and face recognition (60% training and 40% testing)

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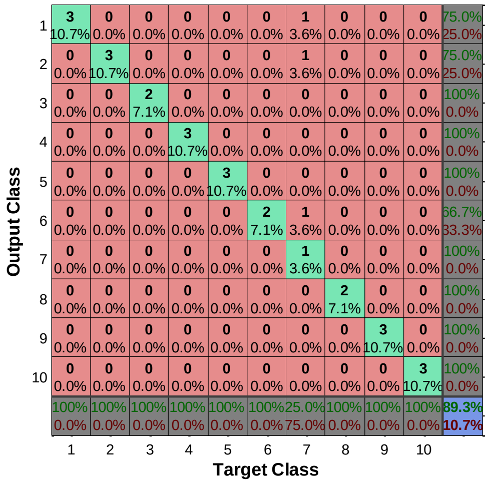

Figure 6: Confusion matrix plot for fingerprint and iris recognition (40% training and 60% testing)

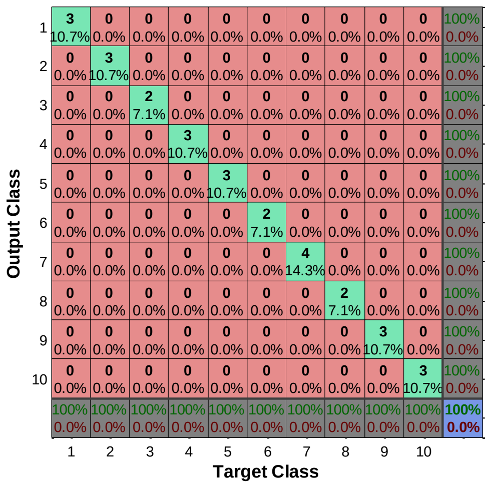

Figure 7: Confusion matrix plot for fingerprint and iris recognition (60% training and 40% testing)

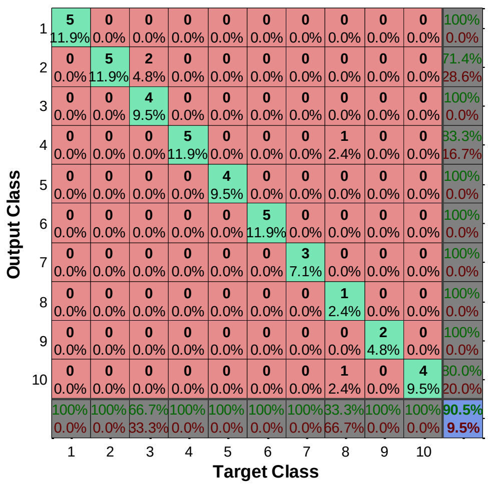

Figure 8: Confusion matrix plot for face and iris recognition (40% training and 60% testing)

IV. Conclusion

Biometric recognition is in constant technological evolution, it is widely used in many official and commercial fields for identification applications. The main purpose of recognition method is to compare user data with the reference data which will be obtained via an external sensor in order to prove the identity of the person subjected to the tests and possibly to authorize it or not to access a secured item. In this paper, multimodal identification system is implemented by combining information from three biometric sources namely fingerprint, face and iris. The raw data is initially pre-processed using image resizing and RGB to Gray conversion. Further the feature extraction is done by DWT, Gabor wavelet and wavelet moment. These extracted features are classified using the random forest classifier. The highest accuracy of this approach is 100% using 60-40 split case.

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