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EAR RECOGNITION USING LOCAL BINARY PATTERN

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ABSTRACT

In this paper an efficient complete Ear Recognition System (ERS) has been proposed based on the Local Binary Pattern (LBP) approach that can investigate maximum recognition rate; hence it can be used for surveillance applications. The feature extraction is based on calculating the LBP feature for the ear image and dividing the resultant LBP image into several overlap regions, and then extracts the histogram from each region. These histograms are considered as a similarity measure in the classification phase. To evaluate the proposed approach, the Indian Institute of Technology (IIT) Delhi processed ear image dataset has been considered, which contains 125 individual, each with at least three images acquired in the age group between 14 and 58 years.

Practical experiments are employed on the proposed ERS to find the best image division regions at best LBP parameters (radius and neighbors) that lead to maximum recognition rate. Detailed experiments show that the proposed system achieved 93.75 % rank-one recognition rate. Furthermore, an experimental study is achieved to examine the less Equal Error Rate (EER). Some identities from the database are considered as imposters. In a verification scenario, the system achieved an Equal Error Rate (EER) of 14.94 %. The Receiver Operating Characteristics (ROC) curve showed that the Genuine Acceptance Rate (GAR) is about 84%.

KEYWORDS: Biometric, Ear Recognition, Local Binary Pattern, Feature Extraction, Histogram.

1. INTRODUCTION

Biometric techniques are security procedures that provide a reliable security system that is much more effective than traditional systems, such as keys, passwords and identity cards that can be easily stolen, faked or forgotten and cannot prevent the attacks against data modification and authentication. Researchers have done general biometric studies on faces, fingerprints, palm prints, gaits and irises. On the other hand, ear biometrics, have received scant attention. The “Biometrics” field related with the usage of individual biological features to verify or recognize a person. Therefore, Biometric is the measurable characteristic of an individual used for recognizing a person. What a person has is called Physiological characteristics and depend on the structural information of human body. Whereas, what a person does, is called behavioral characteristics, and are dependent on the behavior of an individual (Prakash and Gupta, 2015). Biometrics can be either passive or active. The passive biometrics can be fruitful done without lively sharing of a person as in Ear or Facial recognition. The active biometrics cannot be prepared without personal assistance, as in fingerprint, retina scanning, signature recognition (Purkait, 2007).

An ear-based recognition system is considered better than many other famous biometric systems because ear images have sure advantages over the more established biometrics; as Bertillon pointed out in (Bertillon, 1890); they have an ironic and almost fixed shape that changes slight with age, making it suitable for long-term identification. Unlike face, the ear does not drop from deviances as happen with facial impression and the other issues such as mood, cosmetics, eye glasses, health and clothing, and is inflexibly fixed in the middle of the side of the head so that the prompt circumstantial is more expectable.

The proposed ear recognition model suggested by Arbab-Zavar and Nixon (2011) was a part-wise description of the ear follow-on by a stochastic clustering on a set of scale invariant features of the training set. The exterior curves of ear were further tested with log-Gabor filter. Ear recognition was made by fusing the model-based and outer ear metrics, they reported 89.4% as rank-1 recognition rate on XM2VTS face profile

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dataset from 63 subjects. In the work introduced by (Abaza and Harrison, 2013), the similarity generated by LBP operator is computed by Chi-square distance technique. Various testes were directed to tune the parameters of the LBP operator and region divisions. The rank-one recognition rate reached 93.75 % on IIT Delhi processed ear image database with 493 images from 125 subject, one image in gallery set has at least two images in probe set.

In medical field, particularly in circumstance of accidents and death, where the victim's face cannot be known, the the ear recognition is supportive to identify the victim. It is possible to take a picture of the ear easily and from a distance without permission or knowledge of the concerned person. Consequently, the biometric ear is an effective method in many applications that require monitoring and safety security (Boodoo-Jahangeer and Baichoo, 2013).

Mahatma et al. (2014) proposed a new method for human recognition using ear biometrics which is based on Statistical approach, Vector based proposal and Neural based proposal, they reported above 90% Recognition Rate using University of Notre Dame database, a set of 10 people, 10 images for each.

The Medical records show that the disparity of the ear verses time is remarkably noticeable during the age from 4 months to 8 years old and start to deviate at 70 years old. In the duration 4 months-to-8 year, the ear development is roughly linear, from 8-70 years old the grows is mostly constant, and after 70 years the growth increases again. The stretch rate due to gravity is not linear, but it mainly affects the lobe of the ear due to its stability and predictable changes (Kumar and Srinivasan, 2014). Biometric strength lies in the biological aspect of the ear that does not change much with the age of humans.

The Anatomy of external ear is shown in figure 1, the outer border (helix) and ridges (anti-helix) parallel to the helix, the lobe, the concha (hollow part of ear) and the tragus (the small prominence of cartilage over the meatus). The crus of the helix is the beginning of helix.

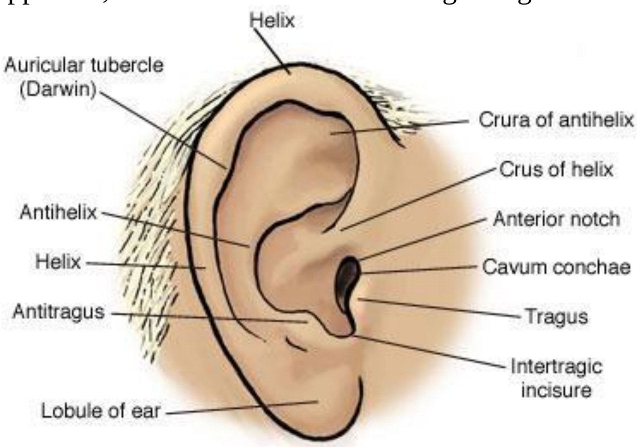

Fig. 1: Anatomy of external ear (D'Alessandro, 2012)

In this paper, an efficient Ear Recognition System (ERS) based on the Local Binary Pattern (LBP) is proposed. The feature extraction is based on calculating the LBP feature for each ear image, and dividing the resultant LBP image into several overlap regions or blocks producing the histogram from each region. The aim of this work is an investigation to find the best recognition rate. The remainder of the paper is organized as follows: in addition to the current section; section 2 presented the proposed system. The results are explored in section 3. In section 4 the comparison with other research is presented. The conclusion is specified in section 5.

2. PROPOSED SYSTEM

The process of ear recognition can be split into four main phases. These are database, feature extraction, classification and decision. The basic procedure is outlined in figure 2:

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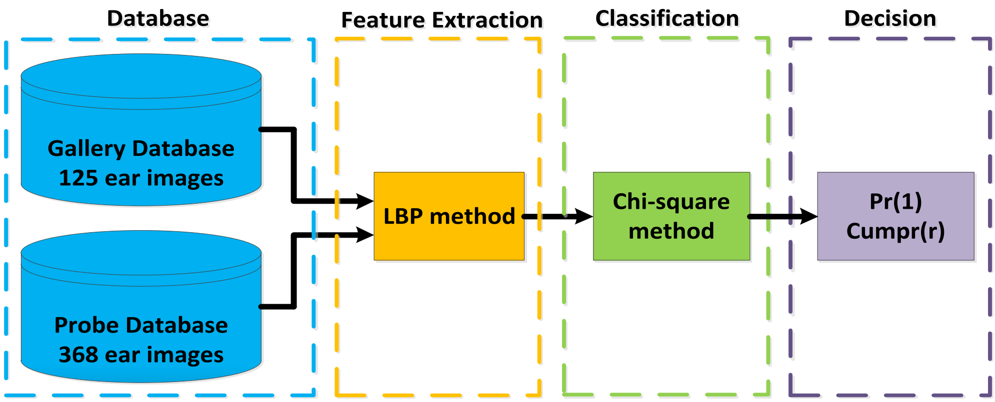

Fig.(2):- The Proposed Ear Recognition System

2.1 Database

In this paper, the processed ear image database from the Indian Institute of Technology (IIT) Delhi is used. This large dataset is made available in reference (Kumar, 2007). The IIT Delhi ear image database was acquired from 125 different subjects. Each subject has one image in the gallery set which contains images with known identities and at least two images in the probe set which holds images with unknown identities. Since various subjects have assorted number of images in the database, therefore the numbers of possible images in the gallery set and in the probe set are 125 and 368 ear images respectively. Figure 3 show the sample processed of ten ear images from the database.

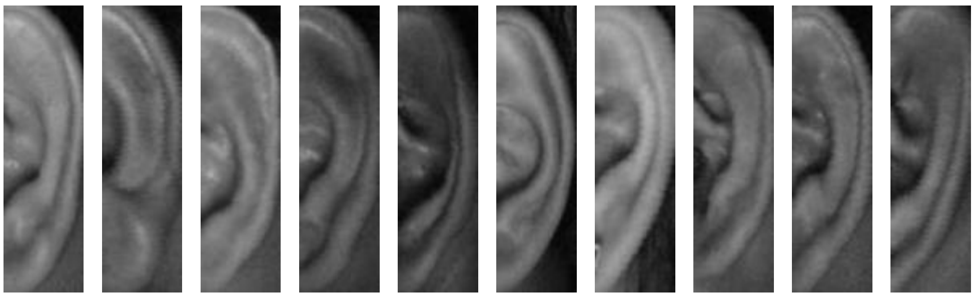

Fig.(3): -Sample Ear Images

2.2 Feature Extraction

The communal visual features comprise color, texture and shape. The texture feature methods are classified into two categories: spatial texture feature extraction and spectral texture feature extraction. One of the spatial feature extraction methods is the Local Binary Pattern (LBP). The LBP method is becomes a popular approach in various applications. The original LBP was presented by Ojala et al. (1996) and it is extended by researches from the University of Oulu in Finland (Ahonen et al, 2004).

The novel form of the LBP operator works with eight neighbors of surrounding pixels (3 × 3 mask window). The pixels in this mask are thresholded by its focus pixel value pw_c. If a neighbor pixel pw_i with i ϵ {0, . . . , 7} has a higher gray value than the center pixel (or the same gray value), then a one is assigned to that pixel, otherwise it gets a zero, figure 4 illustrates the basic LBP operator. The value or label of the center pixel is (Ojala et al., 1996).

$$LBP = \sum_{i=0}^{i=7} LB(pw_i - pw_c) \,.\, 2^i \qquad (1)$$

Where, $LB(pw_i - pw_c) = \begin{cases} 1, & pw_i \geq pw_c \\ 0, & pw_i < pw_c \end{cases}$

For instance, combinations of 2^8 = 256 different labels can be picked up in association to the comparative gray values of the center and the eight pixels in the neighborhood. The LBP number derived is 123, as shown in figure 5.

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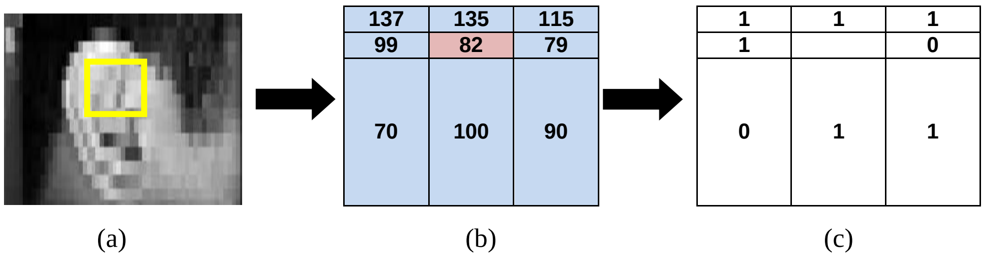
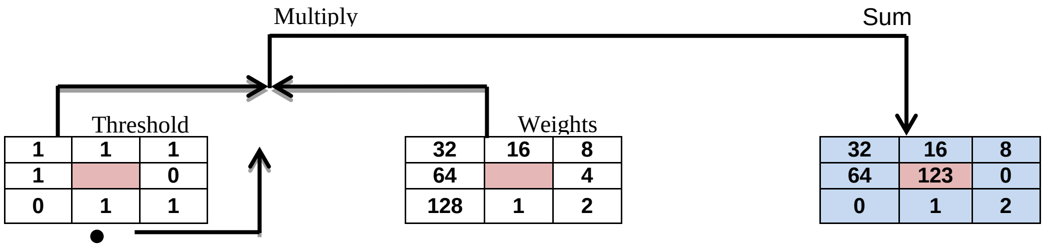


Fig. (4):- Basic of LBP operator: (a) Sample image (64×64), (b) Gray value, (c) Corresponding binary pattern



$$(1*2^0) + (1*2^1) + (0*2^2) + (1*2^3) + (1*2^4) + (1*2^5) + (1*2^6) + (0*2^7)$$
$$1 + 2 + 0 + 8 + 16 + 32 + 64 + 0 = 123$$

Fig. (5):- LBP decimal number calculation

The LBP operator can be extended to make use of neighborhoods at different sampling points P and radius R (see figure 6). This process enables an extra prospect to treat textures at diverse scales. Suppose that the coordinates of the center pixel are (xc, yc) then the coordinates of the P neighbors (xp, yp) on the circumference of a circle with radius R can be calculated with the sinus and cosines (Julsing, 2007):

$$x_p = x_c + R\cos\left(\frac{2\pi p}{P}\right) \tag{2}$$

$$y_p = y_c + R\sin\left(\frac{2\pi p}{P}\right) \tag{3}$$

In this case, a circle is made with radius R from the center pixel (xc,yc). P, sampling points on the edge of this circle are computed according to equations (2) and (3) with attendant coordinate (xp, yp). Each sample on the circumference of a circle with radius R is compared with the value of the center pixel. Using circular neighborhoods and bilinear interpolation of the pixel values, any radius and number of samples in the neighborhood can be handled.

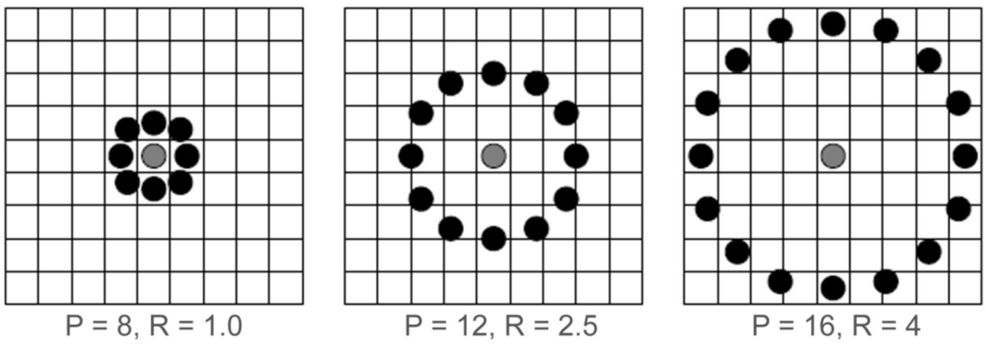


Fig. (6): -Circularly neighbor-sets for three different values of P and R

An important type of the special local binary pattern is the uniform patterns or fundamental patterns (Ojala et al., 1996). A LBP is called uniform, if it contains at most two bitwise transitions from 0 to 1 or opposite. If P is the total number of sampling points on the edge of the circle, then according to (Ahonen et al., 2004) possible combinations for patterns with one or two bitwise transitions are calculated by $P\ (P{-}1)$ produces 57 labels and 2 labels with zero

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transition for neighborhoods of 8 sampling points. Thus, the number of different output labels for mapping the patterns of P bits is P (P − 1) + 2. Each of these patterns has its own bin in the LBP histogram; the rest of the patterns with more than 2 transitions will be accumulated into a single bin. In our experiments, the non-uniform patterns are accumulated into bin1, and then, the rest of uniform patterns are accumulated into the other bins. For examples, bin2 for zero transition with the pattern 00000000, bin59 for zero transition with the pattern 11111111 and the remainder bins, i.e. from bin3 to bin 58 for the patterns with one or two transition. This type of LBP histogram is denoted by $LBP^{u2}_{(P,R)}$, containing less than 2^P bins.

The feature extraction is based on calculating the LBP feature for each ear image in gallery and probe set, and dividing the resultant LBP image into several overlap regions or blocks producing the histogram from each region. These histograms represent the feature vector and considered as a similarity measure in the classification phase.
In figure 7 an example of ear image in which the LBP code calculated for every pixel and divided the resultant LBP image into 14 overlap regions, with for every region a histogram, which forms the feature vector.

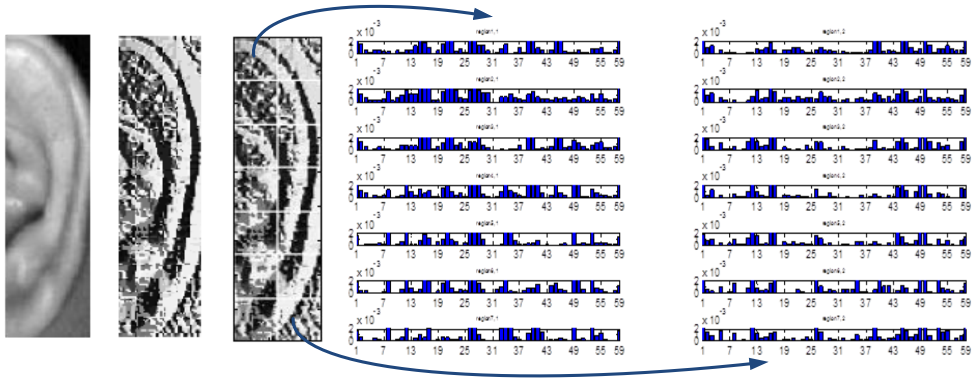


Fig. (7): -LBP ear image divided into ky×kx=7×2 overlap regions r(I,J),where I=1:ky and J=1:kx, along with every corresponding region histogram

2.3 Classification

A gallery or sample (S) and a probe or model (M) are compared via corresponding histogram feature vectors. The distance between vectors is measured. The Chi-square is utilized in the measurement that performs slightly better than other measurement methods (Ahonen et al., 2004). The Chi-square presented in equation (4) is applied to compute regional dissimilarity measures between spatially LBP histograms for different region blocks r(I, J) of the corresponding sample and model regional as:

$$\chi^2(\mathrm{I},\mathrm{J}) = \sum_{m=1}^{P(P-1)+3} \frac{(S_m(\mathrm{I},\mathrm{J})-M_m(\mathrm{I},\mathrm{J}))^2}{S_m(\mathrm{I},\mathrm{J})+M_m(\mathrm{I},\mathrm{J})} \quad (4)$$

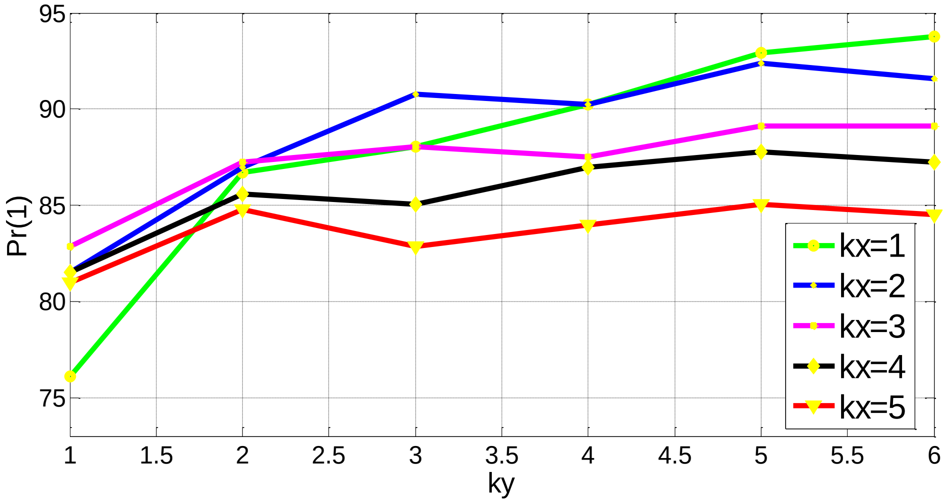
Where $S_m(\mathrm{I},\mathrm{J})$ and $M_m(\mathrm{I},\mathrm{J})$ are the sample and model histograms from region (I,J) of bin *m*.
The overall dissimilarity measures between sample and model histograms are calculated by summing the regional Chi-square measures (Ahonen et al., 2004):

$$\chi^2(S,M) = \sum_{I=1}^{k_y}\sum_{J=1}^{k_x}\chi^2(\mathrm{I},\mathrm{J}) \quad (5)$$

Where *ky* and *kx* are the number of division along the height and width of LBP image respectively.

3. EXPERIMENT RESULTS

An experimental investigation are implemented to assess the performance of the proposed LBP based ear recognition system using the IIT Delhi processed ear images database. In the implementation process, the LBP parameters R, P, along with the number of divide regions $k_y \times k_x$ are varied. Then the highest rank-one recognition rate Pr(1) is computed as a function of R, k_y and k_x while maintain the value at P=8 .
Figure 8 and Figure 9 show that the recognition rate and the execution time are the most important factors. The experiment resulted in a best rank-one recognition rate Pr(1) of 93.75 % at less time under LBP configuration P=8 and R=5 $LBP^{u2}_{8,5}$ at region division of ky = 6 and kx = 1.



Fig, (8): -Performance of Pr(1) results at R=5

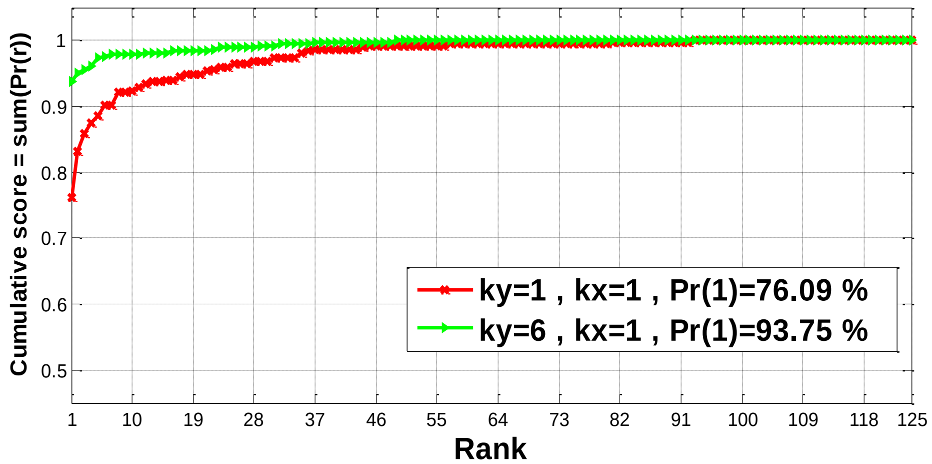


Fig.(9): -Cumulative rank score Cumpr(r) curve at R = 5

In a verification condition, our system achieves an Equal Error Rate (EER) of 14.94 % at 0.45 threshold value. The EER is the rate at which both FAR (False Acceptance Rate) and FRR (False Rejection Rate) errors are equal. Therefore, as shown in figure 10 the intersection of FRR and FAR curves occurred at specific value of threshold TH = 0.45. At threshold value TH = 0.45, the ERR = FRR (0.45) = FAR (0.45) = 14.94. On the other hand, the ROC curve (Introna and Nissenbaum, 2009) shown in figure 11 represent the GAR verse FAR. As shown in figure 11 the intersection point between GAR and the straight line connecting the upper left corner (coordinates 0, 100) to the lower right corner (coordinates 100, 0) occurred at horizontal point where FAR = ERR = 14.94. At this point the projected vertical value of GAR (14.94) ≈ 84 %

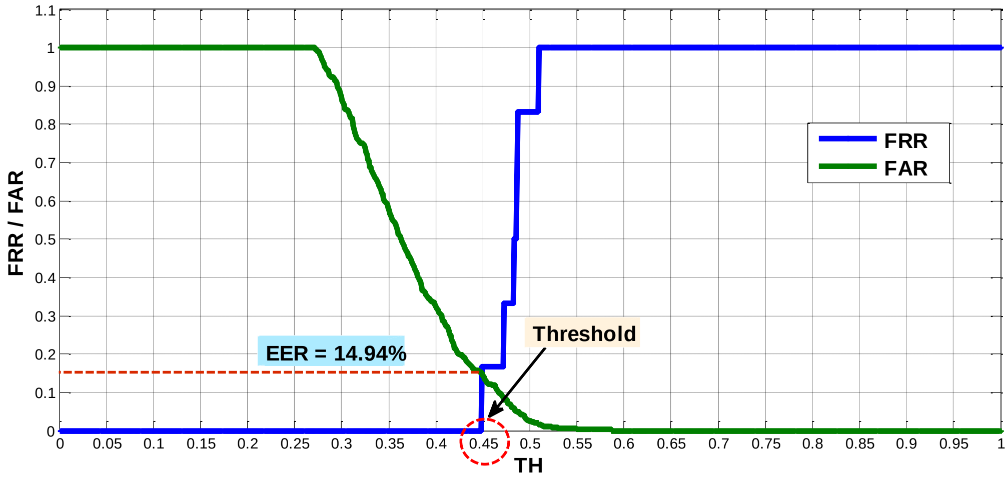


Fig. (10):- Threshold versus FAR and FRR curves

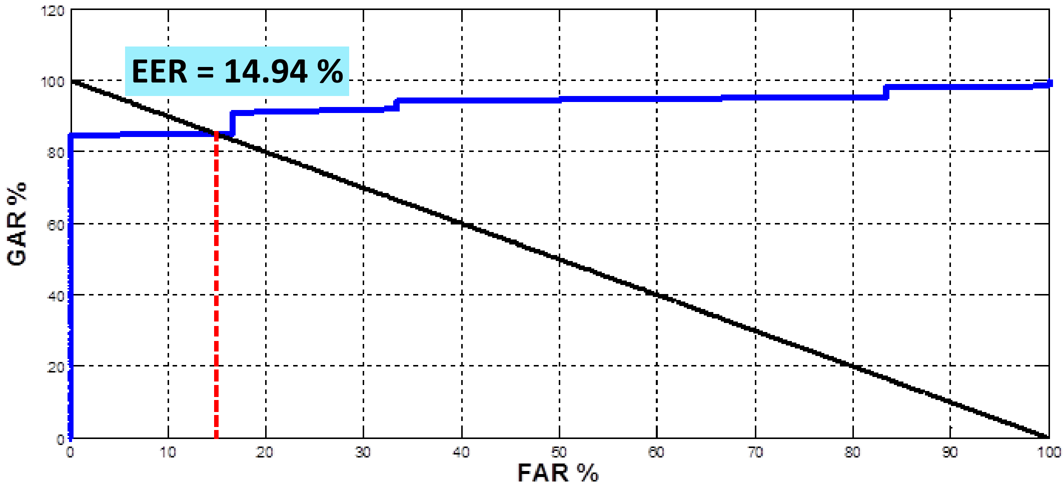


Fig.(11): -The ROC curve

4. COMPARISON OF PERFORMANCE

The results of the proposed Ear Recognition System (ERS) in this paper and those of other work in ear recognition fields are exposed in Table 1. The work introduce by Arbab-Zavar and Nixon (2011) the Ear recognition was made by fusing the model-based and outer ear metrics, they reported 89.4% as rank-1 recognition. In the work by Boodoo-Jahangeer and Baichoo, 2013, the experiments were done on the IIT Delhi ear image database and results show that LBP yields a recognition rate of 93 % while PCA gives only 85 %. While, the paper presented by Mahatma et al. (2014) proposed a new method for human recognition using ear biometrics, which is based on Statistical approach, Vector, based proposal and Neural based proposal, they reported above 90% recognition rate using University of Notre Dame database. In this work, the LBP image is divided into the sub-regions and the best rank-one recognition rate Pr(1) is computed as a function of LBP image division into uniform $k_y \times k_x$ regions at different values of R while maintain the value at P=8 .

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Table (1)::- Performance Comparisons of ERS

Ref.	Approach	Database	Performance
Arbab-Zavar and Nixon (2011)	part-wise model based and Log-Gabor Filters	XM2VTS face profile Dataset: 63 subjects, 252 images	Rank-1: 89.4% (30% occlusion from above)
Boodoo-Jahangeer and Baichoo (2013)	LBP and PCA	IIT Delhi database, 125 subjects, 493 raw ear image	Rank-1: 93% by LBP and 85% by PCA
Mahatma et al. (2014)	Vector based proposal and Neural based proposal	University of Notre Dame database, 10 subjects, 10 images	Rank-1: 90%
This Work	LBP	IIT Delhi database, 125 subjects, 493 processed ear image	Rank-1: 93.75%

5. CONCLUSIONS

In this paper, an ear recognition system based on the LBP is proposed. The feature extraction is based on calculating the LBP feature for each ear image in gallery and probe set, and dividing the resultant LBP image into several overlap regions or blocks producing the histogram from each region. These histograms represent the feature vector and considered as a similarity measure in the classification phase. The overall difference measures between sample and model histograms are calculated by summing the regional Chi-square measures. An investigate is achieved to find the greatest rank-one recognition rate Pr(1) as a function of LBP image division into uniform $k_y \times k_x$ regions at different values of R.

In an Identification scenario our system realizes most recognition rate Pr(1) = 93.75 % at less execution time of 5.22 Minutes. These results are taken under the closed set of processed IIT Delhi ear image database utilizing the $LBP_{8,5}^{u2}$ operator at region division of ky = 6 and kx = 1.

In a verification phase, our system achieves an Equal Error Rate (EER) of 14.94 %. The EER is the rate at which both FAR and FRR errors are equal. The Receiver Operating Characteristics (ROC) curve shows that the Genuine Acceptance Rate (GAR) is about 84%.

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