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HUMAN IDENTIFICATION BASED ON FACE RECOGNITION SYSTEM

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Abstract: Due to, the great electronic development, which reinforced the need to define people's identities, different methods, and databases to identification people's identities have emerged. In this paper, we compare the results of two texture analysis methods: Local Binary Pattern (LBP) and Local Ternary Pattern (LTP). The comparison based on comparing the extracting facial texture features of 40 and 401 subjects taken from ORL and UFI databases respectively. As well, the comparison has taken in the account using three distance measurements such as; Manhattan Distance (MD), Euclidean Distance (ED), and Cosine Distance (CD). Where the maximum accuracy of the LBP method (99.23%) is obtained with a Manhattan and ORL database, while the LTP method attained (98.76%) using the same distance and database. While, the facial database of UFI shows low quality, which is satisfied 75.98% and 73.82% recognition rates using LBP and LTP respectively with Manhattan distance.

Keywords: *Face recognition, Local Binary Pattern, Local Ternary Pattern, Manhattan distance, Euclidean distance, Cosine distance.*

1. Introduction

The human face is the most important identity used universally in determining people's identities. Therefore, biometric traffic techniques have illustrated the rules of data and methods for identifying persons, especially in the last two decades. Which is considered as one of the most popular identify the system. As well as, one of the most vital fields that play an important role in the identification system. It is used to overcome the limitation of traditional identification systems such as: that depends on Personal Identification Number (PIN), user name, and password [1], [2]. The face is often used in various social activities to determine the identity of people; therefore, an effective descriptor has to be found to determine which is used to carry out this process. Consequently, face recognition algorithms reserved the attention of the researcher and turned out to become one of the most subjects in the field of biometrics and computer vision [3], [4]. So, many applications have been launched recently, which is an applicative operation in various domains such as human-machine interaction, biometric identifications, visual-surveillance operation, video conference, and image content retrieval. Based on a scientific point of view, the face considered as dynamic and non-rigid texture, therefore recognition operation is not easy to deal with because the trait is changed under different environments such as freezing, illumination, age, pose, and face make-up [5]. To distinguish faces features, three fundamental steps have been considered such as detection, extraction and classification are three fundamental steps of the face recognition system. Feature extraction provides potential guessing of face images to reduce the computational perplexity of the classifier. Therefore, a robust face recognition system required a powerful feature extractor and an impact classifier [6]. There are several manners for extracting the most beneficial features from (pre-processed) face

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images to execute face recognition. The most powerful feature extraction manners are (LBP) and (LTP) methods. These proportional modern methods were being presented in 1996 through Ojala et al.[7].

With LBP it is probable to explain the texture and figure of a digital image by separating an image into different blocks through which the features are being extracted [8]. While the LTP method is a noise-resistant version of LBP, both methods are utilized for encoding the power contrast between the middle pixel and its neighbors'. LBP is sensitive to the noise because even a small change in the grey level, while mask center pixel may result in different codes for the equivalent neighbor values.

In fact, the LTP method overcomes the problem of noise sensitivity in LBP by encoding the difference in pixels into a third state, named "-1" negative value. LTP uses a constant threshold value instead of thresholding the pixels into 0 and 1 as in LBP to threshold the pixels into three-level values [9].

Several kinds of research have been applied to LBP and LTP methods such as

K. Meena et al., [10] have been presented multimodal biometric authentication by combining face, iris, and finger features. Biometric features are extracted by Local Derivative Ternary Pattern (LDTP) in the contourlet domain and an extensive evaluation of LDTP is implemented using Support Vector Machine (SVM) and Nearest Neighbor Classifier (NNC). It is observed that the combination of face, fingerprint, and iris gives better performance in terms of accuracy, False Acceptance Rate (FAR), and False Rejection Rate (FRR) with minimum computation time.

Yazhini J et al., [11] presented a multimodal framework approach utilized for acknowledgment of individuals of numerous traits. LTP method has been applied for features extraction from the face, fingerprint, and iris images. These traits have been fused utilizing features level fusion. The machine-vectors acquired from LTP were profoundly discriminative and valuable for promoting acknowledgment.

Malhotra et al., [8], proposed an illumination invariant face recognition algorithm based on the combination of gradient-based illumination normalization and fusion of two illumination invariant descriptors. The ratio of gradient amplitude and original image intensity allows an invariant visual representation of the illumination. The feature sets obtained from LBP and LTP methods were consolidated into a single feature set by using feature normalization and feature selection. Where an artificial neural network was used in the classification stage.

Shan et al.,[12] investigated the LBP method for texture encoding in facial expression description. Two methods of feature extraction were proposed, in the first one, features were extracted from a fixed set of patches. In the second method, the features are extracted from most probable patches found by boosting.

Nishatbanu Nayakwadi et al., [13] have been presented a new method to recognize faces using the LTP method and signed a bit multiplication to extract the local features of the face. The image is divided into small, non-overlapping windows. These windows are processed to extract features. The testing features are compared with all training images using Euclidean distance.

Jianfeng Ren et al., [14] proposed a new method of LTP called Relaxed LTP. This method described the concept of uncertain state for encoding the small difference between pixels. They don't know about its sign and magnitude and are equally likely to represent it as both 0 and 1. The proposed Relaxed LTP is tested on the CMU-PIE database and Yale B database. The recognition rates of the proposed method were

98.40% for the CMU-PIE database and 98.71% for the Yale B database.

This paper is organized as follows: In section 2, we described the Recognition system. Section 3 is devoted to the Results and Analysis. Finally, the conclusions are drawn in section 4.

2. Methodology

The system consists of three main stages namely: image acquisition, feature extraction, and matching presented in Fig.1.

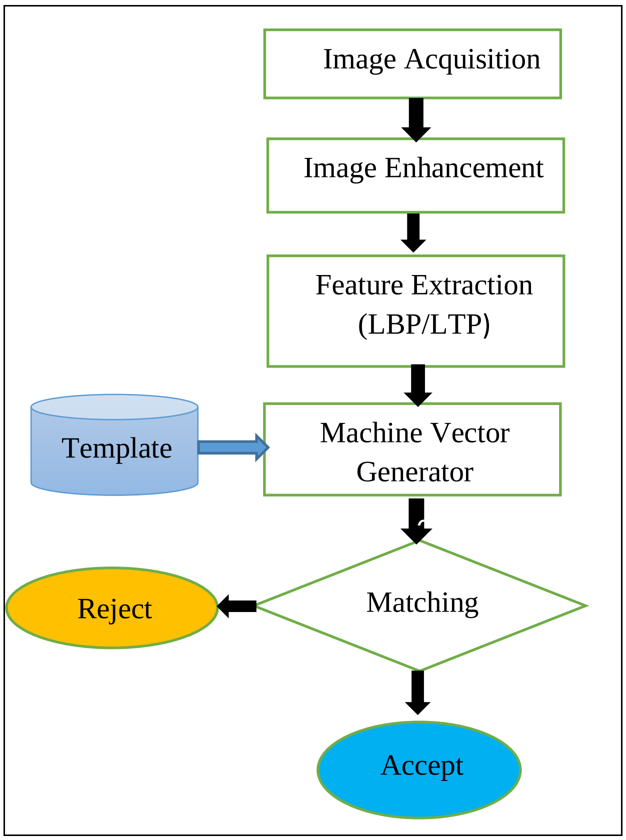

Figure1: The proposed face recognition system.

2.1 Feature Extraction

The working steps of texture description and feature extraction methods: LBP and LTP are explained as follows,

2.1.1 LBP Method

In this method, the face image is divided into four sub-images. In each one, a (3 × 3) mask is applied to calculate the binary patterns of each divided region [16]. These binary patterns are serialized to derive facial descriptors. Face descriptor is a facial feature that is known as facial image texture features [17]. This approach is primarily used for grey facial images and it is illustrated according to the following steps [18]:

Step1: Divide the examined image into cells.
Step2: For each pixel in a cell, compare the pixel to each of its neighbors'.
Step3: Follow the pixels along a circle, if the center pixel's value is greater than the neighbors'
value write "0", otherwise write "1"as in eq. (3). This gives a binary number (which is usually switched to decimal for betterment).
Step4: Compute the histogram, over the cell, of the frequency of each "number" occurring.
This histogram is a 256-dimension feature vector.

Mathematically the LBP calculated according to (1) [19], [20]:

$$LBP_{R,P} = \sum_{P=0}^{P-1} s(g_p - g_c).2^p \tag{1}$$

Where

g_p: neighbourhood pixels in each block

g_c: centre pixel value

P: sampling points (p = 0, 1…, 7 for a 3x3 cell, where P = 8)

R: radius (e.g. for 3x3 cell, it is 1). Coordinates of "gc" is (0,0) and of "gp" is (2)

$$gp\ (x, y) = (x + R\cos(2\pi\ p/P),\ y - R\sin(2\pi p/P)) \tag{2}$$

Where, the threshold function (3) [21]:

$$S(x) = \begin{cases} 1 & x >= 0 \\ 0 & x < 0 \end{cases} \tag{3}$$

LBP method is named uniform in case of the binary pattern consists of at most two transitions zero-to-one or one-to-zero. For instance, 00010000 (two transitions) is a uniform pattern, 01010100 (six transitions) not uniform. In the computation of the LBP histogram, the histogram has a split-off bin for each uniform pattern and for all non-uniform patterns they dedicated to a single bin. Uniform value can be found using (4) below [22]:

$$U(LBP_{P,R}) = |s(g_{p-1} - g_c) - s(g_0 - g_c)| + \sum_{p=1}^{p-1} |s(g_p - g_c) - s(g_{p-1} - g_c)| \qquad (4)$$

If U≤ 2 LBP is uniform else its non-uniform, where the uniform LBP has output values represent by (5) [22]:

$$\boldsymbol{o}utput\ values = p * (p - 1) + 3 \qquad (5)$$

where

p: sampling points (for a 3x3 cell P = 8, for 4×4 cell p=12 and so on).

The LPB operator has been extended to consider different neighborhood sizes. For example, the operator $LBP_{8,1}$ uses only 8 neighbors while $LBP_{16,2}$ considers 16 neighbors on a circle of radius 2. In general, the $LBP_{P,R}$ operator refers to a neighborhood size of P equally spaced pixels on a circle of radius R. Fig. 2 shows different values chose for P and R [23].

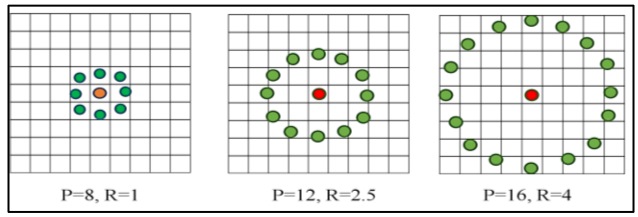

Figure 2. The circular (8,1), (16,2), and (8,2) neighborhoods.

An example of LBP method operating is shown in Fig.3.

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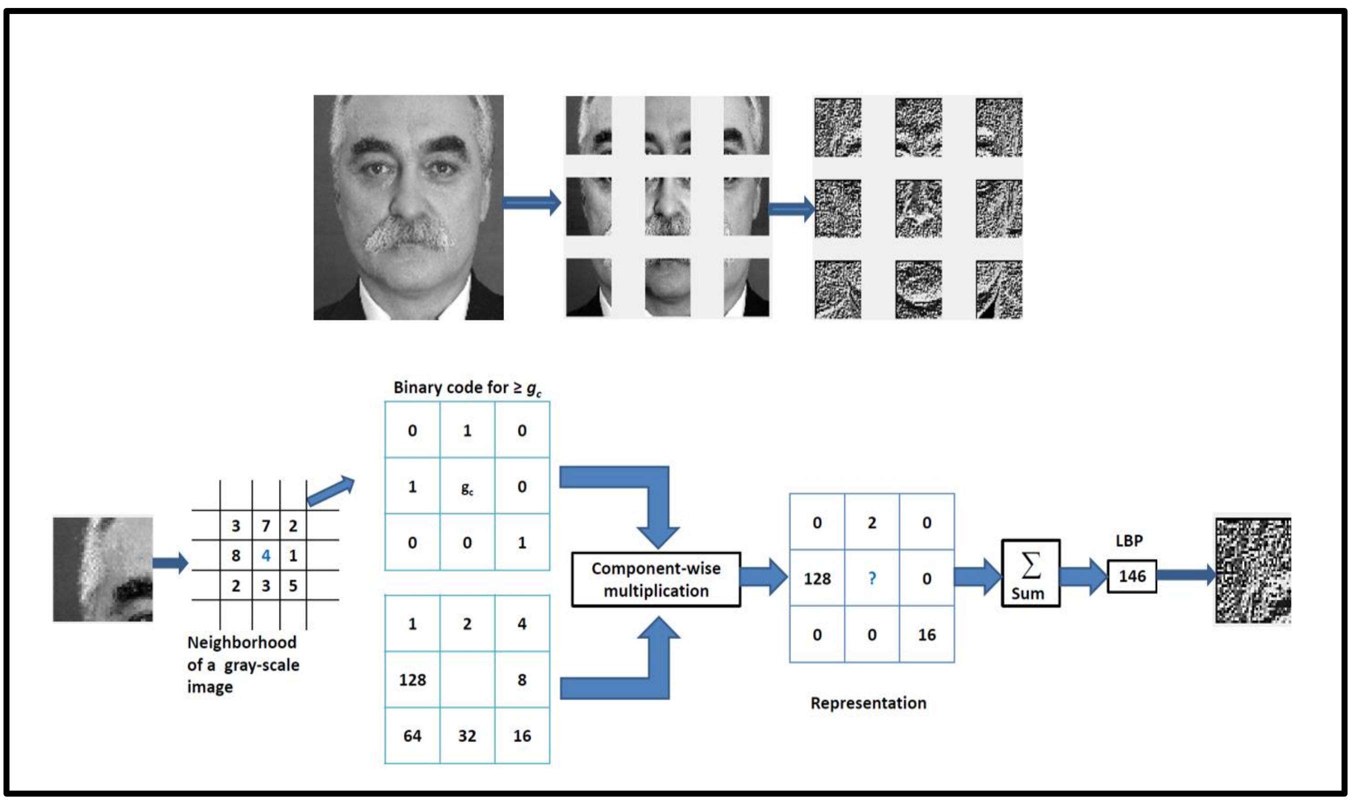

Figure 3. Computation of Local Binary Pattern.

2.1.2 LTP Method

It is partially solving the noise-sensitive problem by coding the small pixel difference in a separate state. The mask values are divided into a positive and negative LBP code. This may result in losing significant information. Moreover, the positive and negative histograms of LBP method are strongly correlated, where the grey levels are set to zero within a range of (±t), the values above (+t) are expected to be 1 and those below to (-t) are expected to be -1 [24]. The LTP code is obtained as shown in (6)

$$LTP_{P,R} = \sum_{n=0}^{P-1} s'(i_n - i_c)3^p \quad (6)$$

Where

i_n: represent neighbour pixels.

i_c: represent center pixel.

where the step function is s' (x, t) and a predefined threshold is t as in (7) [25].

$$s'(x,t) = \begin{cases} 1, & x > c + t \\ 0 & x > c - t \text{ and } x < c + t \\ -1, & x < c - t \end{cases} \quad (7)$$

Where

x: neighbor pixel

c: center pixel.

t: threshold value.

An example of LTP operating procedure shown in Fig.4.

3. Databases

Two types of facial databases are considered to construct this biometric system they are:

• Olivetti Research Laboratory (ORL): contains 400 images (10 different images of each of 40 different individuals). The images had been taken at different phases, lighting rate, facial expression, and poses. Each image is 92x112 pixels, with bit depth equals to 7 bits. 9 samples per person are used in the training set and 1 sample in the test set [15]. Fig.5 shows samples for ORL databases.

Figure 5: Samples of ORL dataset.

• Unconstrained Facial Images (UFI): these datasets represent an authentic photographs images; two different partitions are being found, the Large Images Dataset (LID) and Cropped Images Dataset (CID), this type is cropped faces that were automatically extracted from the photographs using the Viola-Jones algorithm. The facial image is approximately uniform, and have just a small portion of the background. This group contains images of 401 subjects with 7 samples for every subject in the training and one sample in the testing. The datasets images are cropped to the size of 128 x 128 pixels [15]. Fig.6 shows samples for UFI databases

Figure 6. Samples of UFI dataset.

4. Matching Operations

To implement matching operations three kinds of distance measurements have been applied. The distance between the testing vector and the stored training vectors are computed using three measuring points of distance methods as follows [26]:

1- Manhattan distance:

$$d(x,y) = \sum_{i=1}^{n} |(x_i - y_i)| \quad (8)$$

2- Euclidean distance:

$$d(x,y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \quad (9)$$

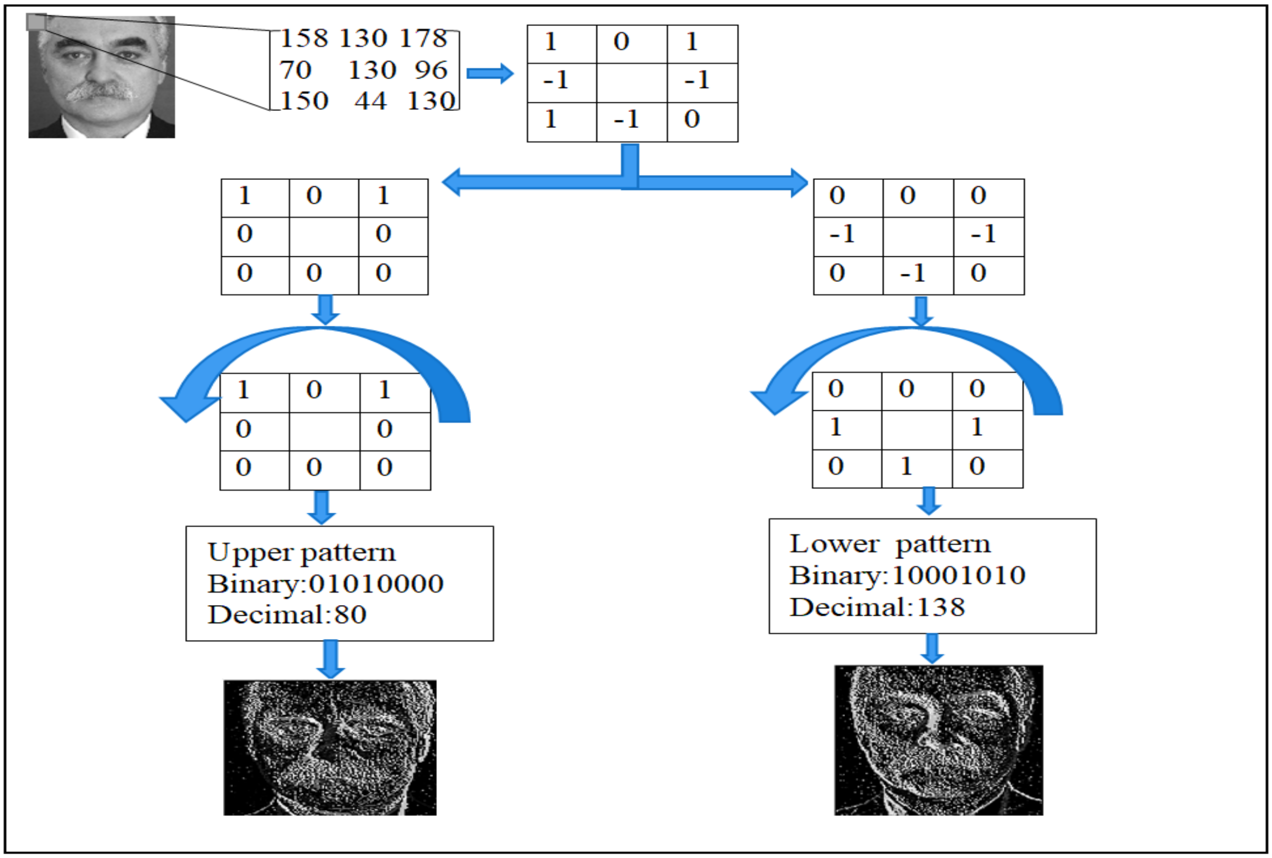

Figure 4. Computation of Local Ternary Pattern.

3- Cosine distance:

$$d(x,y) = 1 - \frac{\sum_{i=1}^{n}(x_i * y_i)}{\sqrt{\sum_{i=1}^{n} x_i^2 * \sum_{i=1}^{n} y_i^2}} \qquad (10)$$

Where
n: feature vector length in one template.
x_i: testing template.
y_i: face template that stored in database.

5. Results and Analysis

To evaluate the performance of the classification methods, three classifiers and two databases utilize two feature extraction methods. are illustrated below.

5.1 Performance calculation

In this stage, the facial images are evaluated using three important statistics: False Acceptance Rate (FAR), False Rejection Rate (FRR), and the resultant Accuracy (ACC) percent which are defined in equations FAR, FRR, and the resultant accuracy percent which are defined in (11), (12) and (13) [14], [27],[28], [29].

$$FAR = \frac{NO.of\, accepted\ imposter}{Total\ NO.of\ imposter\ assessed} * 100\% \qquad (11)$$

$$FRR = \frac{NO.of\, Rejection\ genuine}{Total\ NO.of\ genuine\ assessed} * 100\% \qquad (12)$$

$$ACC = \left(1 - \frac{FAR+FRR}{2}\right) * 100 \qquad (13)$$

The intersection point between FAR and FRR called Equal Error Rate (ERR) at this point the maximum ACC is obtained.

5.2 LBP Results

The recognition rates for 40 subjects from the ORL dataset show that the Manhattan classifier satisfied a better accuracy rate (99.23%) than

Euclidean and Cosine (98.76%, 98.53%) respectively. Fig. (7,8.9 and 10) show the performance of the three classifiers and their FAR and FRR rates.

The 401 subjects from the UFI dataset, show that the Manhattan classifier satisfied a better accuracy rate (75.98%) than Euclidean and Cosine (72.75%, 74.13%) respectively. Fig. (11,12,13 and 14) show the performance of the three classifiers with their FAR and FRR rates.

5.3 LTP Results

In this method, the recognition rates for 40 subjects from the ORL dataset show that the Manhattan classifier satisfied the maximum accuracy rate (98.76%) than Euclidean and Cosine (95.64%, 64.55%) respectively. Fig. (15,16,17 and 18) shows the performance of the three classifiers and associated FAR and FRR rates.

The 401 subjects from the UFI dataset using the LTP method show that the Manhattan classifier satisfied the maximum accuracy rate (73.82%) than Euclidean and Cosine (71.38%, 62.92%) respectively. Fig. (19,20,21 and 22) shows the performance of three classifiers and their associated FAR and FRR rates.

All accuracy rates are tabulated in Table 1.

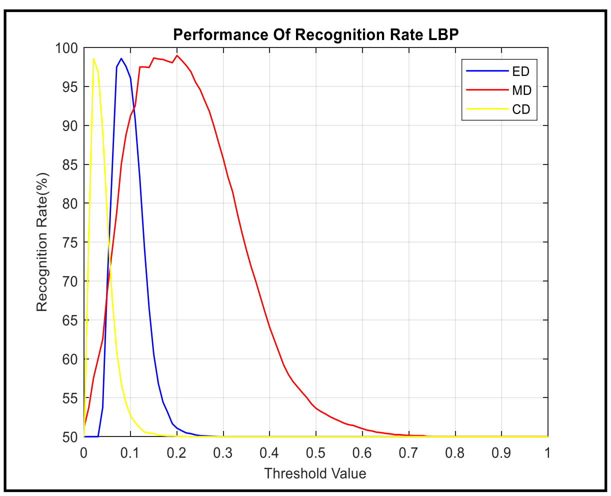

Figure7. Recognition rate curves of LBP with ORL database.

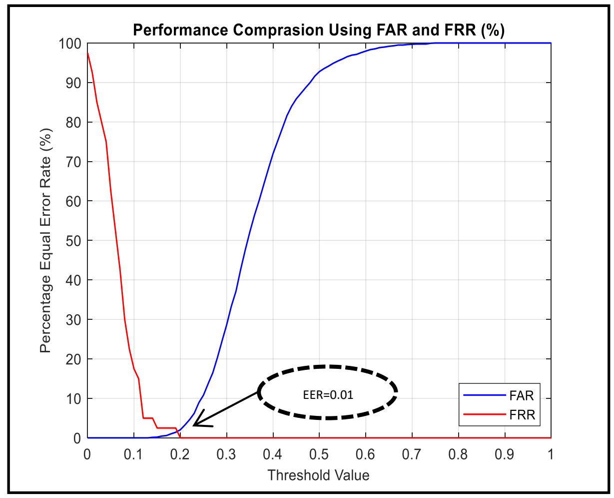

Figure8. ROC curve of LBP using Manhattan Distance with ORL database.

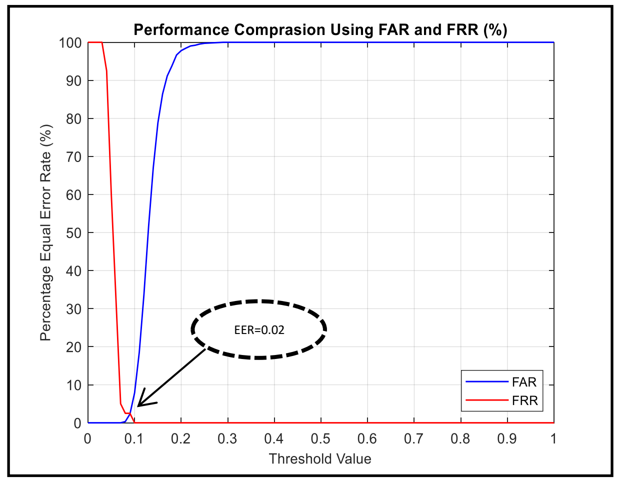

Figure 9. ROC curve of LBP using Euclidean Distance with ORL database.

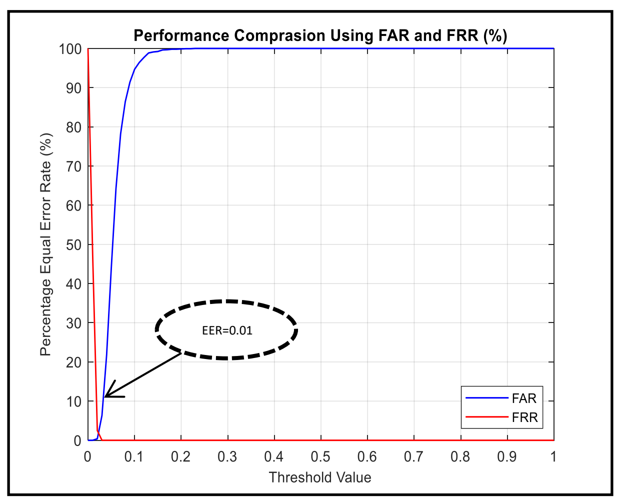

Figure 10. ROC curve of LBP using Cosine Distance with ORL database.

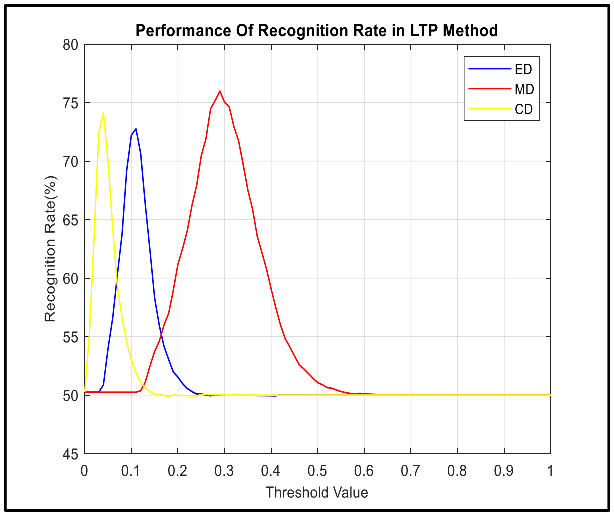

Figure11. Recognition rate curves of LBP with UFI database.

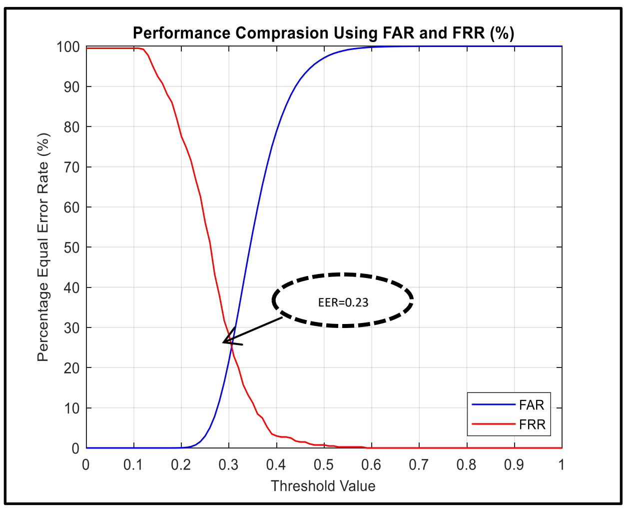

Figure12. ROC curve of LBP using Manhattan Distance with UFI database

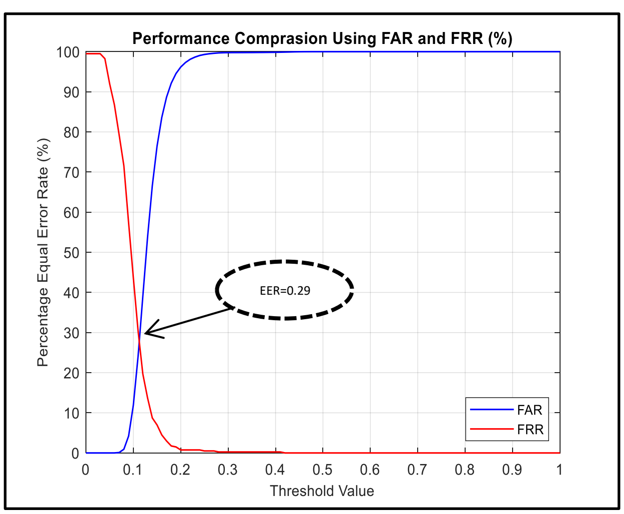

Figure 13. ROC curve of LBP using Euclidean Distance with UFI database.

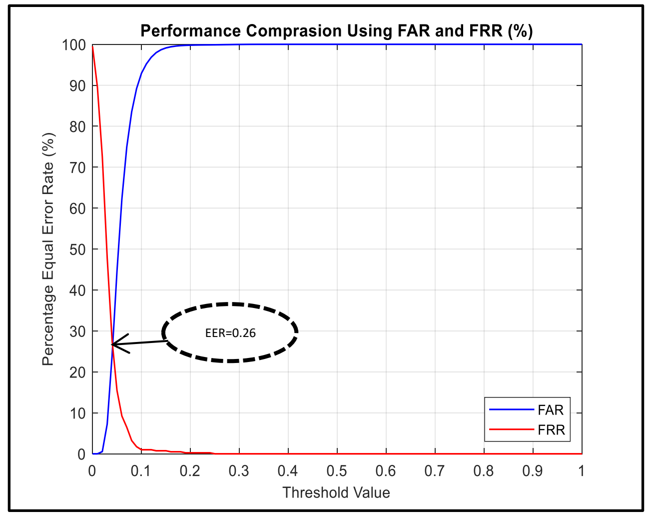

Figure 14. ROC curve of LBP using Cosine Distance with UFI database

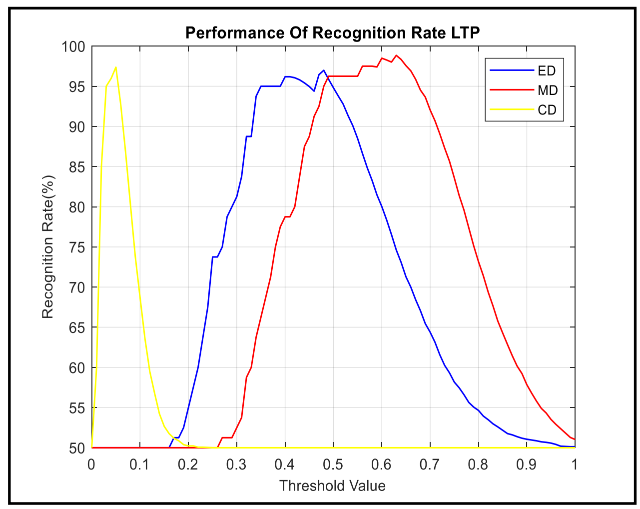

Figure15. Recognition rate curves of LTP with ORL database.

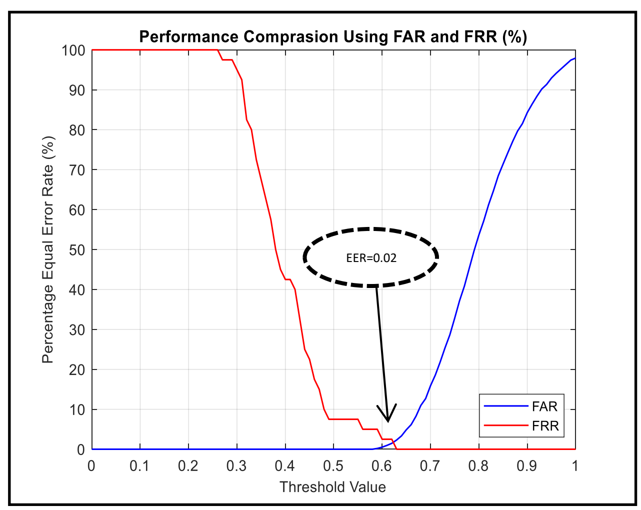

Figure16. ROC curve of LTP using Manhattan Distance with ORL database

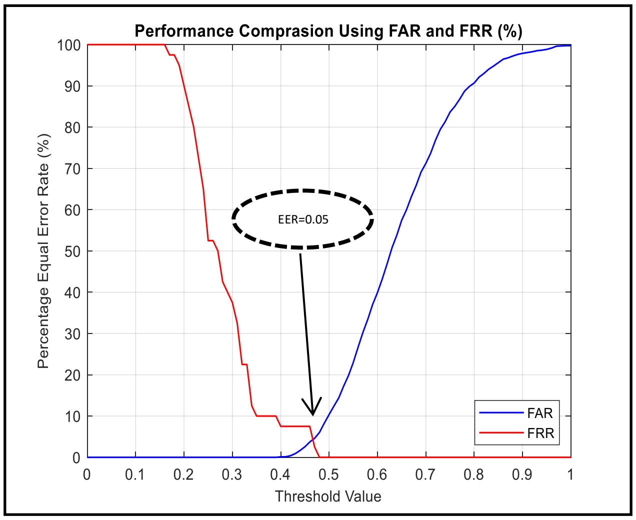

Figure 17. ROC curve of LTP using Euclidean Distance with ORL database

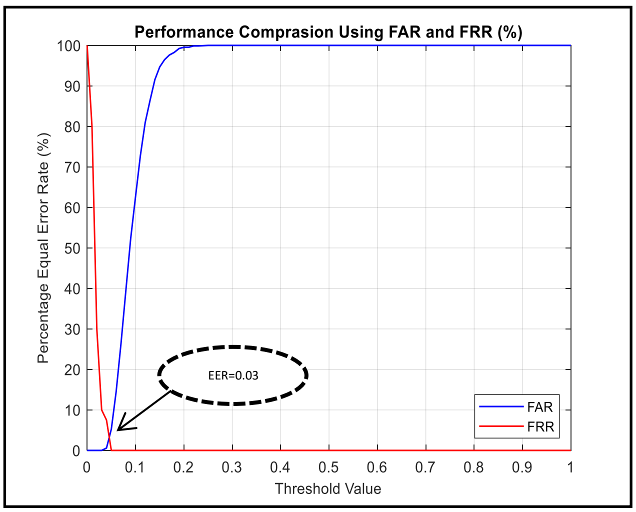

Figure 18. ROC curve of LTP using Cosine Distance with ORL database

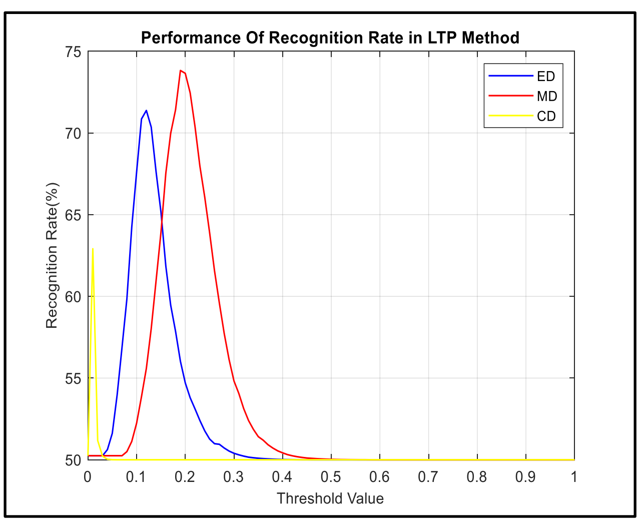

Figure 19. Recognition rate curves of LTP with UFI database.

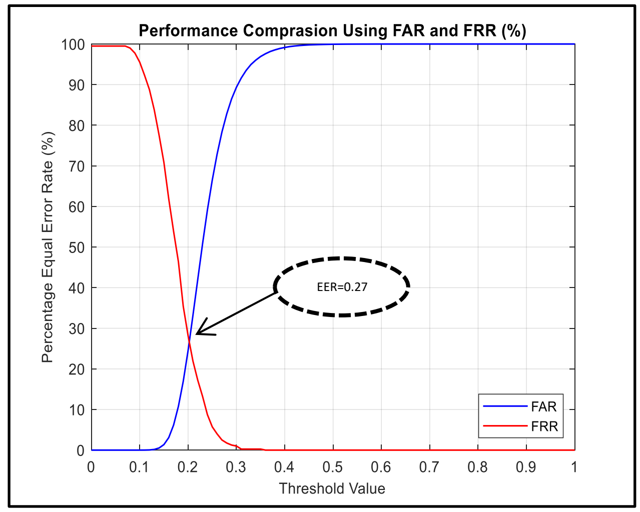

Figure 20. ROC curve of LTP using Manhattan Distance with UFI database

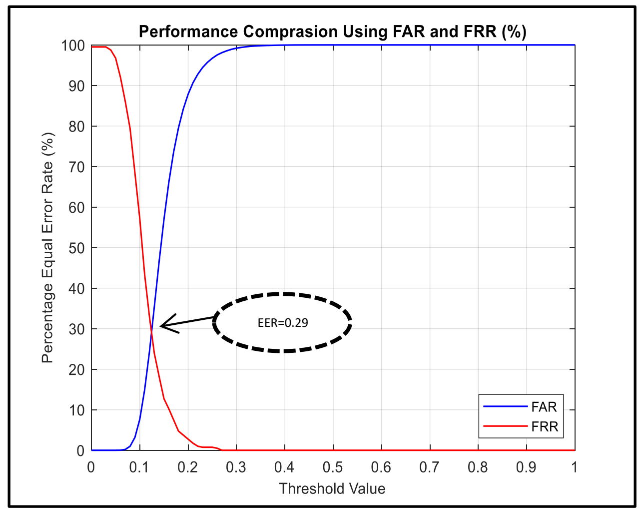

Figure 21. ROC curve of LTP using Euclidean Distance with UFI database

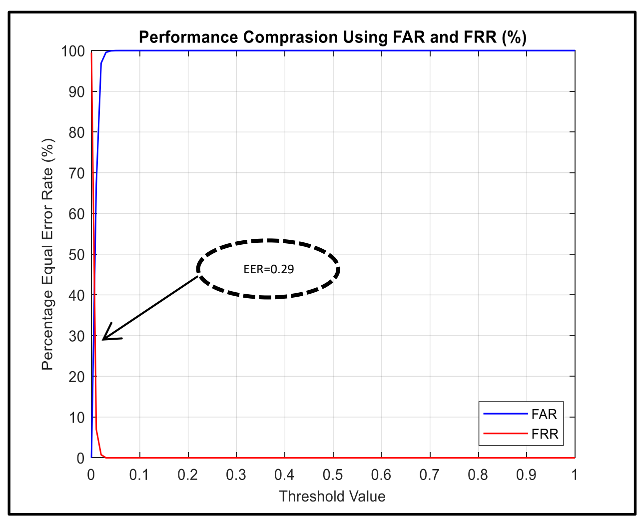

Figure 22. ROC curve of LTP using Cosine Distance with UFI database

Table 1. Performance Comparison between LBP and LTP in different datasets

Extraction Method	Database	Accuracy (%)			Matching Time (sec.)
		MD	ED	CD	
LBP	ORL (40 person)	99.23	98.58	98.55	1.858s
	UFI (401 person)	75.98	72.75	74.13	62.197s
LTP	ORL (40 person)	98.76	95.64	64.55	3.814s
	UFI (401 person)	73.82	71.38	62.92	120.254s

From Table 1 the LBP advanced the LTP with the ORL and UFI datasets measured by all measurements. This means that the recognition accuracy of the LBP satisfied the highest score than the LTP method even with the low-quality dataset like UFI. The experimental comparison results show that the LTP method is suitable for noisy images but not for difficult ones, in contrast to the LBP method that is working better than LTP with difficult images from the public domain viewfinder. Those outcomes are helpful for new biometric system developers in choosing their feature extraction method that satisfies better system performance.

5.4 The Comparison with Related Approaches

It is difficult to find other biometric systems that have the same data and the same feature extraction methods. So the comparison with other researches closest to this proposed system as follows.

- Nishatbanu Nayakwadi et al. have used LTP and have obtained the accuracy of 90% [13], have reported the recognition rate on the ORL database.

- Zuodong Yang et. al [30] in another work has reported the recognition rate with LBP as 79.40% and LTP 85.53% using the Yale database. In this approach, we can obtain face recognition rate of 99.23% with LBP and 98.76% with the LTP method. The face recognition of related works is compared with the proposed method in Chart 1

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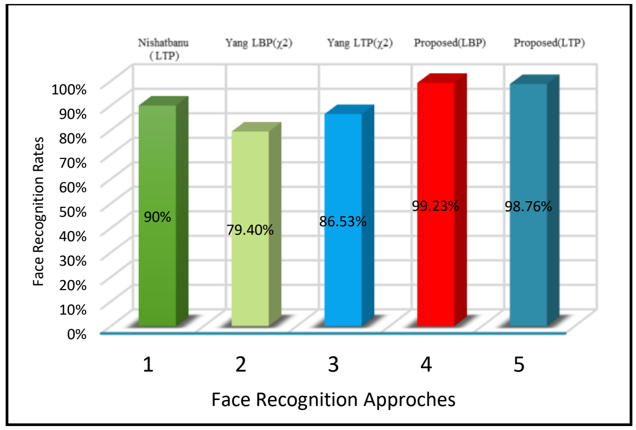

Chart1: Performance Comparison between this work with other researches.

6. Conclusions

The design of two unimodal biometric systems based on the two different feature extractors and two facial databases were demonstrated and implemented. The vital face information was extracted using two texture analysis and description methods: local binary pattern and local ternary pattern. In addition, three distance measures were considered for deep comparison and accurate evaluation of system performances. The recognition accuracy for LBP and LTP was very satisfied when the ORL database was employed with all classifiers and the maximum accuracy (99.23%) was achieved with LBP and MD measurement. The performance of the low-quality facial images existing in the UFI datasets was attained relatively low recognition rates. However, for 401 subjects, the LBP and LTP method achieved (75.98% and 73.82%) accuracy rates using the MD measurement only. As a conclusion, the LBP extraction method shows better performance results in comparing with the LTP method especially when the test done on unimodal.

Acknowledgements

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Conflict of interest

There are not conflicts to declare.

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