Texture descriptors for better face recognition performance

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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 40,401 and 10 subjects taken from ORL, UFI and Self-Created 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 as standard 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. Hereby, the LBP based biometric system performs excellence recognition accuracy even with difficult face images that contain different expressions, different poses, and varied illumination like the UFI dataset.

1. Introduction
The human face is the most important trait 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 [1], [2]. Also, selection a suitable descriptor that is working properly with variety conditions is an essential operation [3], [4]. So, many applications have been launched recently, which is applicative operation in various domains such as: human-machine interaction, visual-surveillance operation, and image content retrieval, are 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 of 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 face recognition system. Feature extraction provides a 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]. The LBP and LTP are the most powerful feature extraction manners were being presented in 1996 by Ojala et al.[7], and our work aims to provide a clear vision for biometric system developers in choosing the suitable texture descriptor approach that satisfy maximum recognition rates with presence of different database quality. Therefore, two face recognition systems based LBP and LTP are designed and compared using three different database qualities. The recognition accuracies for the two systems have been carefully compared by three distance measurements. The nine performance outcomes of each biometric system will provide a clear vision for developers and readers to which feature descriptor method should be chosen, that is still working effectively with normal and low quality facial datasets.
2. Related work

In this section some recent researches that have been reviewed.

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 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.

K. Meena et al., [9] have been presented multimodal biometric authentication by combining face, iris, and finger features. Biometric features are extracted by Local Derivative Ternary Pattern (LDTP) in contourlet domain and an extensive evaluation of LDTP is implemented using Support Vector Machine (SVM) and Nearest Neighbourhood 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., [10] presented a multimodal framework approach utilized for acknowledgment of individual of numerous traits. LTP method has been applied for features extraction from face, fingerprint, and iris images. These traits have been fused utilizing features level fusion. The machine-vectors acquired from LTP was profoundly discriminative and valuable for promote acknowledgment.

Shan et al.,[11] 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 fixed set of patches. In the second method, the features are extracted from most probable patches found by boosting.

Nishatbanu Nayakwadi et al., [12] have been presented a new method to recognize faces using LTP method and signed bit multiplication to extract the local features of the face. The image is divided into small, non-overlapping windows and the Euclidean distance was applied for as a classifier.

Jianfeng Ren et al., [13] proposed new method of LTP called Relaxed LTP. This method described the concept of uncertain state for encoding the small difference between pixel. 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 CMU-PIE database and 98.71% for Yale B database.

3. Research Method

The system consists of three main stages namely: pre-processing image, feature extraction, and matching or classification as explained in Figure1.

Figure 1. The proposed face recognition system.
3.1 Face databases

Three types of facial databases are considered in this work for accurate evaluation and precise
decision about the best feature descriptor method that still effective for different dataset
qualities.

- Olivetti Research Laboratory (ORL): contains 400 images (10 different images of each of 40
different individual). 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. Nine
samples per person are used in the training set and one sample in the test set [14]. Figure 2
shows samples for ORL dataset.

![Figure 2. Samples of ORL dataset [14].](image)

- Unconstrained Facial Images (UFI): this dataset represents an authentic photographs images;
two different partitions are being found, the Large Images Dataset (LID) and Cropped Images
Dataset (CID). 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 size of 128 x 128
pixels [15]. Figure 3 shows samples for UFI databases.

![Figure 3. Samples of UFI dataset [14].](image)

- Self-Created dataset: This type of dataset is created for 10 persons by web Camera (Logitech).
Each person has 10 images, 9 for training and 1 for testing. These images are taken under different
conditions like: flash mode, normal light and different facial expressions as shown in Figure 4. The
assessed distance between the person and the camera is (50 cm).

![Figure 4. Samples of Self-Created face dataset.](image)

3.2 Pre-processing

A low pass filter like median (3×3) filter is applied to enhance the facial images and improving the
feature detection and extraction resultant in the successor stages.

3.3 Feature Extraction

The procedure of the two feature description methods is explained in the following sections.

- LBP Method

First, the face image is divided into four sub-images, each one is scanned by a (3 × 3) mask to
determine the binary patterns of the scanned region [15]. These binary patterns are serialized to
derive facial descriptors [16].
Mathematically, the LBP is calculated according to Equation (1) [17], [18], [19]:

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

(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 “$g_c$” is (0,0) and of “$g_p$” is explained in Equation (2) [19]:

$$g_p(x,y) = (x + R \cos(2\pi p/P), y- R \sin(2\pi p/P))$$

(2)

Where, the threshold function explained in Equation (3) [20]:

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

(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. 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 Equation (4) [21].

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

(4)

If $U \leq 2$, LBP is uniform, else it is non-uniform. The uniform LBP has output values as defined by Equation (5) [22]:

$$output \ values = p \ast (p-1) + 3$$

(5)

where
- p: sampling points (for a 3x3 cell P = 8, for 4x4 cell p=12 and so on).

The LBP operator has been extended to consider different neighbourhood sizes. For example, the operator $LBP_{8,1}$ uses only 8 neighbours while $LBP_{16,2}$ considers 16 neighbours on a circle of radius 2. In general, the $LBP_{P,R}$ operator refers to a neighbourhood size of P equally spaced pixels on a circle of radius R. Figure 5 shows different representation of (P,R) values [22], also Figure 6 is an example of LBP operation.

![Figure 5](image-url)
Figure 6. Computation of Local Binary Pattern.

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 a 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 (-t) are expected to be -1 [23]. The LTP code is obtained as shown in Equation (6) and Equation (7):

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

(6)

Where

- \( i_n \): represent neighbour pixels.
- \( i_c \): represent centre pixel.

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

(7)

where the step function is \( s'(x, t) \) and a predefined threshold is \( t \), \( x \) is a neighbour pixel, \( c \) is a centre pixel [24]. An example of LTP operating procedure shown in Figure 7.

Figure 7. Computation of Local Ternary Pattern.
3.4 Matching Operations

Three distance measures are applied for calculating the distance between the testing vector and the training machine vectors (template) as follows [25]:

1- Manhattan distance:

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

2- Euclidean distance:

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

3- Cosine distance:

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

Where:

- \( n \): is a feature vector length in one template.
- \( x_i \): is a testing template.
- \( y_i \): is a face template.

3.5 Performance calculation

In this stage, the facial images are evaluated using FAR, FRR, and the resultant percent accuracy which are defined in Equations (11), (12) and (13) [26],[27], [28].

\[ FAR = \frac{\text{No. of accepted imposter}}{\text{Total No. of imposter assessed}} \times 100\% \]  
(11)

\[ FRR = \frac{\text{No. of Rejection genuine}}{\text{Total No. of genuine assessed}} \times 100\% \]  
(12)

\[ ACC = \left( 1 - \frac{\text{FAR} + \text{FRR}}{2} \right) \times 100 \]  
(13)

4. Result and Analysis

The performance of the two feature extraction methods has been comprehensively compared depending on the two factors, the quality of the facial dataset and the type of classifier. The Self-Created dataset has the most qualified facial images, while the UFI contains the most difficult images in their expressions and poses.

4.1 LBP Results

From Figure 8, the recognition rates for 40 subjects of ORL dataset shows that Manhattan classifier satisfied better accuracy rate (99.28%) than Euclidean and Cosine classification (98.56%, 98.53%) respectively. The classification of 401 subjects of UFI dataset is explained in Figure 9, it shows that the Manhattan classifier satisfied better accuracy rate (75.98%) than Euclidean and Cosine classification (72.75%, 74.14%) respectively. Finally, the recognition rates for 10 subjects of Self-Created dataset show that all classifiers satisfied maximum accuracy (100%), which reflects the effecting of image quality on the recognition accuracy when the LBP method is employed.

4.2 LTP Results

In this method, and as explained in Figure 11, the recognition rates for 40 subjects of ORL dataset show that Manhattan classifier satisfied highest accuracy rate (97.76%) than Euclidean and Cosine classification (95.64%, 64.55%) respectively. Also, Figure 12 shows that Manhattan classifier satisfied highest recognition rate (73.82%) than Euclidean and Cosine classification (71.38%, 62.92%) respectively for identifying 401 subjects of UFI dataset. The recognition rates for 10
subjects of Self-Created dataset show the equalities in the accuracy (100%) for all classifiers as explained in Figure 13.

Clearly, the experimental results show that, the LBP has achieved better performance than LTP in identifying subjects in low quality environment like the UFI and ORL databases. Therefore, these results represent an evidence that the LTP is dedicated for noisy image only and the LBP is still effective and working well for variety image quality. Table 1 and Table 2 summarize the maximum recognition rates with their associated FAR and FRR values. It is noticed that, the maximum accuracy value is satisfied at the intersection of the two curves (FAR = FRR), which is called ERR; for example, in Table 1, the highest LBP accuracy is 99.28% at EER= 0.72, and from Table 2, the highest LTP accuracy is 97.76% at EER= 2.24.

Figure 8. LBP Performance using ORL dataset.

Figure 9. LBP Performance using UFI dataset.

Figure 10. LTP Performance using Self-Created dataset.

Figure 11. LTP Performance using ORL dataset.

Figure 12. LTP Performance using UFI dataset.

Figure 13. LTP Performance using Self-Created dataset.
### Table 1. LBP Performance Comparison for different datasets.

| Datatype               | Distance measures | FAR% | FRR% | ACC%  |
|------------------------|-------------------|------|------|-------|
| ORL (40 Subject)       | Manhattan         | 0.72 | 0.72 | 99.28%|
|                        | Euclidean         | 2.05 | 0.05 | 98.56%|
|                        | Cosine            | 0.448| 2.5  | 98.53%|
| UFI (401 Subject)      | Manhattan         | 16.36| 31.67| 75.98%|
|                        | Euclidean         | 24.07| 30.42| 72.75%|
|                        | Cosine            | 24.04| 27.68| 74.14%|
| Self-Created (10 Subject) | Manhattan       | 0.002| 0    | 100%  |
|                        | Euclidean         | 0.003| 0    | 100%  |
|                        | Cosine            | 0.001| 0    | 100%  |

### Table 2. LTP Performance Comparison for different datasets

| Datatype               | Distance measures | FAR% | FRR% | ACC%  |
|------------------------|-------------------|------|------|-------|
| ORL (40 Subject)       | Manhattan         | 2.24 | 2.24 | 97.76%|
|                        | Euclidean         | 8.71 | 2.5  | 95.64%|
|                        | Cosine            | 70.89| 0    | 64.55%|
| UFI (401 Subject)      | Manhattan         | 16.94| 35.41| 73.82%|
|                        | Euclidean         | 24.32| 32.91| 71.38%|
|                        | Cosine            | 67.18| 6.98 | 62.92%|
| Self-Created (10 Subject) | Manhattan       | 0.005| 0    | 100%  |
|                        | Euclidean         | 0.067| 0    | 100%  |
|                        | Cosine            | 0.005| 0    | 100%  |
5. Conclusion
The process of image acquisition from uncontrolled environment and/or equipment is definitely affected by external factors such as illuminations and internal factors like cameras. These factors in addition to the image difficulties (different poses and expressions) are all existed in the UFI dataset as it automatically extracted its facial images from the authentic photographs, and therefore, it represents a big and critical challenge to the biometric system robustness. This paper verified the performance of LBP and LTP on three datasets and three distance measures. Both methods achieved maximum recognition accuracy with the high-quality (Self-Created) dataset, while the LBP advanced the LTP with the ORL and UFI datasets measured by all classifiers. This means that the recognition accuracy of the LBP satisfied highest score than 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 satisfy better system performance.

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https://uomustansiriyah.edu.iq/

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