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Enhanced Local Ternary Pattern method for Face Recognition

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Abstract. Biometrics is a term used to determine an individual's identification based on physiological or behavioral traits. Such physiological or behavioral characteristics differ from person to person. For this reason, it is more secure and popular to authenticate the person using biological characteristics than other conventional authentication methods. The Local Binary Pattern (LBP) face recognition system is widely used but is noise sensitive. For the purpose of improving the performance, a descriptor of a local texture called Local Ternary Pattern (LTP) is introduced, which is more discriminating in uniform regions and less noise sensitive. The proposed method called Enhanced LTP (ELTP), uses pre-processing technique. Here, the input image is pre-processed using Gamma Correction and Histogram Equalization. The LTP is applied on pre-processed image to get the finalized feature vectors. Experimentation is conducted on the standard datasets ORL, UMIST and VTU (VISA) face datasets. It is proved that ELTP shows better accuracy than other face recognition methods.

Keywords: Biometrics, Authentication, Local binary pattern, Local ternary pattern, Discrete cosine transform.

1 Introduction

The primary applications of biometric technology are identification and access control. Signature, keystroke and voice are some of the biometrics of behaviour that use dynamic measurements based on individual actions. Fingerprint, iris, retina, hand geometry and face are some of the physiological biometric, that makes use of human body measurements. The standard authentication system, such as passwords and PIN numbers, is hard to remember and can be easily stolen. But the biometric properties are closely connected to an individual and cannot be forgotten, shared, stolen or hacked easily. When a biometric trait image is received by an access point, it is compared to a database that has previously been saved, and if the images match, the user is granted access. The work outlined in the entire paper is structured in the following way: Section 2 contains related works, section 3 contains proposed work, section 4 addresses results and discussions, section 5 contains conclusion and future work.

2 Related work

All Numerous areas and applications such as texture detection, segmentation and image synthesis or pattern recognition uses texture processing. In the area of facial recognition [18], the LBP [1, 5], a widely used technique for extracting texture information, has proven excellent robustness and efficiency. The changes in facial expressions, conditions of lighting, posture and occlusions degrade the efficiency of recognition. The solution for these problems can be provided by using HOG and LBP feature descriptors to incorporate thermal infrared images into the face recognition system [2]. Experiments in face recognition were performed using different face recognition algorithms like Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Linear Binary Pattern Histograms (LBPH) and Independent Component Analysis (ICA) [4, 6, 23]. The LBP features were used in the application such as texture classification but the later research also expanded the use of this on facial images [22]. The LBP process is mathematically illustratable as follows

$$LBP_{S,P}=\sum_{y=0}^{S-1} 2^y h(i_y - i_c) \quad (1)$$

$$\text{Where, } h(i_y - i_c)=\begin{cases}1 & i_y - i_c \geq 0\\ 0 & i_y - i_c < 0\end{cases} \quad (2)$$

Where i_c is pixel value of the centre, and i_y is the value of neighbour pixel in radius P and the number of neighbours is S. When neighbours are not precisely in the centre of the pixel, bilinear interpolation decides the neighbour. This stage is called Phase of Encoding. Based on the following equation, histogram is created after encoding phase

$$H(m)=\sum_{i=0}^{I}\sum_{j=0}^{J} f(\, LBP_{S,P}(i,j),m) \text{ , } m\epsilon[0,M] \quad (3)$$

$$f(x,y)=\begin{cases}1 & x = y\\ 0 & otherwise\end{cases} \quad (4)$$

Where, M is the maximal LBP pattern value.

Any number of sampling points from any circle with different radii is used to scale up the texture LBP operator. LBP's disadvantage is its sensitivity to noise. The dominant local

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binary pattern (DLBP) is a simple and computationally efficient approach that represents the dominant pattern in the texture image and also preserves the LBP method's invariant histogram equalization and rotation invariant properties [21]. The threshold dependent LBP approach can enhance noise robustness [17]. In order to boost the efficiency of the variants, the median robust extended descriptor LBP (MRELBP) can also be used. The attraction of this method is its properties such as invariance of rotation, strong discriminative and computational efficiency [9]. Discrete Cosine Transformation (DCT) transforms the image from spatial domain into frequency domain by extracting the proper face recognition feature [19]. In terms of the cosine function sum oscillating across various frequencies, a finite data point series can be represented by DCT [16]. A portion of the coefficients is selected after application of DCT to create feature vectors. Most traditional coefficient selection method is in zigzag form. The upper most coefficients represent the lowest frequency containing relevant information, and the lower most coefficients represent the higher frequency containing the noise-induced information. 2D DCT for MxN image is defined as:

$$F(u,v) = \alpha(u)\alpha(v)\sum_{i=0}^{m-1}\sum_{j=0}^{n-1} f(i,j)\cos\left[\frac{u(2i+1)\pi}{2m}\right]\cos\left[\frac{v(2j+1)\pi}{2n}\right] \quad (5)$$

Where,
$$\alpha(u) = \sqrt{\frac{1}{m}} \text{ if } u=0, \qquad = \sqrt{\frac{2}{m}} \text{ if } u=1, 2, 3\ldots m-1 \quad (6)$$

$$\alpha(v) = \sqrt{\frac{1}{n}} \text{ if } v=0, \qquad = \sqrt{\frac{2}{n}} \text{ if } v=1, 2\ldots n-1 \quad (7)$$

Even DCT coefficients can be used as the feature vectors in face image recognition [14]. DCT extracts dominant frequency information that is used as facial descriptors. Using zone DCT, local features can be extracted, and shape information can be extracted using Hu-Movements [10]. The appearance of the face image can differ considerably by changing the conditions of illumination thereby degrading the efficiency of face recognition. Thus, as a pre-processing stage face image is converted to a logarithm domain and DCT coefficients are then extracted from the face image to increase the recognition rate [15]. To achieve the optimum enhancement of contrast, it is possible to use the contrast-limiting adaptive histogram equalization (CLAHE). The image histogram based on the entire image intensity distribution can be modified using Histogram Equalization (HE). By scaling down some of the DCT low frequency coefficients, differences in the illumination of the face image are also reduced. Then, for further processing, the features can be extracted from this normalized image [13].

3 Proposed method

The benefit of using LBP is its simple implementing process, invariant to the lighting effects and easy computing. Differences of neighbouring pixel and central pixel intensities are used when calculating the pattern using above method. Since the central pixel here is used as a threshold, this method is very noise sensitive [7]. In some situations, a slight difference in the gray level intensities due to noise can drastically change the LBP code.

3.1 Local Ternary Pattern

LBP is extended to compute three-value code known as Local Ternary Pattern [8, 11, 12, 20]. That calculates ternary pattern code from {-1, 0, 1}, by tracking pixels which are almost equal to the pixel given. The LTP is an operator of texture, and is more robust to noise. This method initially defines a threshold t, then for each pixel value greater than t, it assigns value 1 if the value of pixel is lower than -t, then assigns value -1 and assigns value 0 if the pixel value is between -t and t. Upon the threshold step, upper and lower patterns are created to eliminate the negative values. LTP is obtained by upper and lower pattern concatenation and its working process is shown in Fig. 1. (Upper LTP is 01101000 and lower LTP is 100000101).

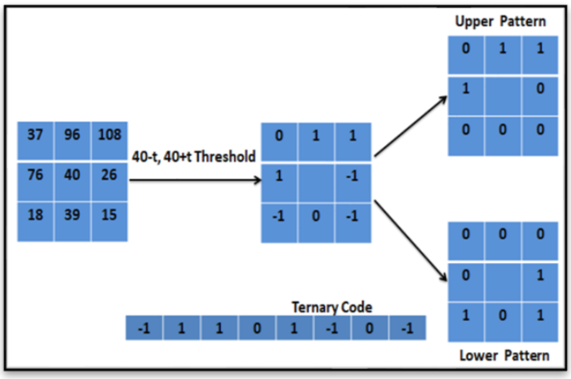


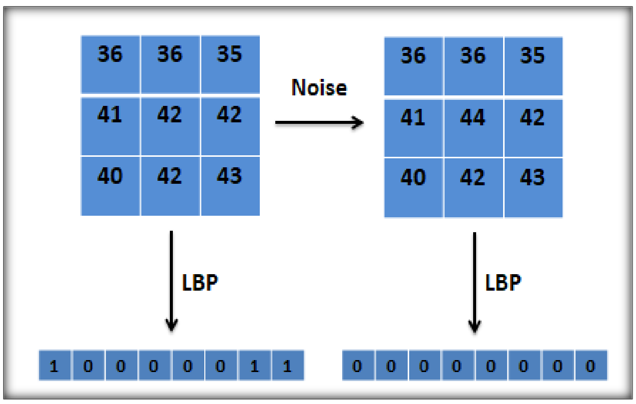
Fig. 1. Working procedure of basic LTP

LTP is mathematically defined as

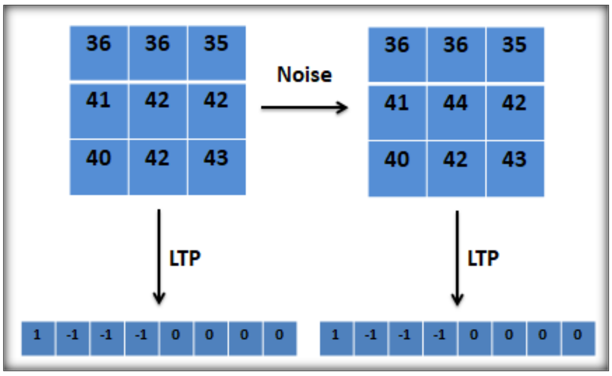
$$LTP_{S,P} = \sum_{y=0}^{S-1} 2^y h(i_y - i_c) \quad (8)$$

$$\text{Where} \quad h(i_y - i_c) = \begin{cases} 1 & i_y - i_c \geq t \\ 0 & -t < i_y - i_c < t \\ -1 & i_y - i_c < -t \end{cases} \quad (9)$$

Where i_c represents central pixel value and i_y represents the value of the neighboring pixel in the P radius circle. S is the circle's number of neighbors.



(a)



(b)

Fig. 2. LBP and LTP code (a) without noise (b) with noise

If neighbors do not exactly lie in the middle of the pixel, then bilinear interpolation is used to estimate the neighbor. This step is called encoding step. After encoding step histogram is created based on the equation:

$$H(m)=\sum_{i=0}^{I}\sum_{j=0}^{J} f(\, LTP_{S,P}(i,j),m)\ ,\ m\epsilon[0,M] \quad (10)$$

$$f(x,y)=\begin{cases}1 & x=y\\ 0 & otherwise\end{cases} \quad (11)$$

Where, M is the maximal LTP pattern value.

Fig. 2., shows that the calculated LBP pattern will change due to noise if there is a slight change in the intensity of the central pixel. The code calculated without noise is 10000011 and if suppose central pixel intensity value has changed from 42 to 44 due to noise then the code changes to 00000000. But LTP codes are more resistant to noise. The user defined threshold t = 5 is used here, and the calculated code is same for both cases (with and without noise).

3.2 Preprocessing

Preprocessing involves a series of steps to address the effect of illumination variation. Gamma correction is being used here has a preprocessing. When an image isn't properly corrected, it may appear bleached out or too dark. Gamma correction controls overall brightness of an image. This is a nonlinear transformation of each pixel, which improves the image's local dynamic range in dark or shadowed areas.

The basic concept is that the incoming illumination and surface reflectance combine to determine the intensity of light reflected from an object. To recover information at the object level regardless of illumination, here α=0.5 is used in the Gamma Correction equation (12).

$$G(x,y) = \alpha * f(x,y) \quad (12)$$

Histogram equalization is used in the final step, to globally rescale the image intensities to standardize overall contrast. This adjusts the contrast by equalizing the histogram. The effects of GC and HE on ORL dataset is shown in the Fig. 3.

(a) (b) (c)

Fig. 3. Results of Pre-processing using GC and HE on ORL dataset (a) Original Image (b) Image after Gamma Correction (c) Image after Histogram Equalization

3.3 Enhanced LTP (ELTP)

Consider the input face image I(x,y) and preprocess the input image I(x,y) using Gamma Correction and Histogram Equalization. Then apply LTP method on pre-processed image and calculate the Lower and Upper LTP (LTP-L & LTP-U). Concatenation of 256 LTP-L and LTP-U are the final feature vector for further processing. Recognition of the face is done using Euclidean Distance (ED).

The ED classifier is used to compare the similarity of the test image with the stored dataset. The straight-line distance between two points m and n in Euclidean space is given as,

$$Dist = \sqrt{\sum_{i=1}^{N}(\, m_i,\ n_i)^2} \quad (13)$$

In the equation (13), the number of features is N, the feature vectors of the test and stored images are m and n, and the distance is Dist. The images with the least distance are regarded to be recognized images.

4 Results and discussion

The face recognition tests were performed using the face dataset of ORL, UMIST and VTU (VISA). The results of the proposed ELTP algorithm is compared to that of the LTP, LBP and DCT algorithms. The ORL face dataset is a collection of a series of 400 images consisting of 10 samples of 40 different people, images taken at various times, different lighting, facial expressions such as open or closed eyes and facial features such as glasses or no glasses. The Face Dataset UMIST is a collection of 400 images of 20 people, each with 20 faces. The VTU dataset (VISA) contains 500 images of 100 persons, each with 5 samples.

Table 1. Recognition rate on ORL Dataset.

Test Cases	ELTP	LTP	LBP	DCT
1	93.00	91.00	89.00	88.50
2	93.50	92.50	89.50	86.50

3	97.50	96.00	94.50	94.00
4	96.00	95.50	94.50	93.00
5	98.00	97.50	96.00	94.50

Table 1 shows the experimental setup of face recognition using ORL dataset. In Test Case-1, a training set is made up of samples 1st to 4th and 5th to 10th samples are considered as test set for the individual in the dataset. Similarly, in Test Case-2, 1st to 5th samples were considered as training set and 6th to 10th samples as test set and in Test Case-3, 1st to 6th samples as training set and 7th to 10th samples as test set for each individual. For training, odd numbered index (1, 3, 5, 7 and 9) and testing even numbered index (2, 4, 6, 8 and 10) images are considered in the Test Case-4. Likewise, in Test Case-5, for training, even numbered index images were utilized and for testing odd numbered index images.

Table 2. Recognition rate on UMIST Dataset.

Test Cases	ELTP	LTP	LBP	DCT
1	91.00	90.00	80.00	75.50
2	91.00	91.00	75.50	73.00
3	95.50	95.00	94.00	94.50
4	94.50	94.50	92.00	89.50
5	95.50	93.50	91.00	94.50

Table 2 shows the experimental setup of face recognition using UMIST dataset. In Test Case-1, a training set is made up of samples 1st to 8th and 6th to 20th samples are considered as test set for the individual in the dataset. Similarly, in Test Case-2, 1st to 10th samples were considered as training set and 11th to 20th samples as test set and in Test Case-3, 1st to 12th samples as training set and 13th to 20th samples as test set for each individual. For training, odd numbered index and testing even numbered index images are considered in the Test Case-4. Likewise, in Test Case-5, for training, even numbered index images were utilized and for testing odd numbered index images.

Table 3. Recognition rate on VISA (VTU) Dataset.

Test Cases	ELTP	LTP	LBP	DCT
1	90.50	91.50	88.00	89.50
2	97.33	95.00	89.00	85.50
3	98.00	94.50	91.00	90.00
4	98.00	98.00	94.50	93.00
5	99.50	98.50	95.00	94.00

Table 3 shows the experimental setup of face recognition using VISA dataset. In Test Case-1, a training set is made up of samples 1st to 4th and one samples as test set for the individual in the dataset. Similarly, in Test Case-2, 1st and 2nd samples are considered as training set and 3rd to 5th samples as test set and in Test Case-3, 1st to 3rd samples as training set and 4th and 5th samples as test set for each individual. For training, odd numbered index and testing even numbered index images are considered in the Test Case-4. Likewise, in Test Case-5, for training, even numbered index images were utilized and for testing odd numbered index images.

From the tables 1, 2 and 3, it is observed that ELTP based Face recognition gives more recognition rate compared to LTP, LBP and DCT based face recognition on ORL/UMIST/VTU(VISA) datasets.

5 Conclusion

Face biometric traits are the most common biometric traits and are easily available. This paper discusses four approaches to face recognition: Discrete Cosine Transformation (DCT), Local Binary Pattern (LBP), Local Ternary Pattern (LTP) and Enhanced Local Ternary Pattern (ELTP) respectively. The LBP generates code using central pixels as a threshold while LTP generates ternary code using user defined +/- t threshold. LTP improves resistance to noise. From the experimental observations, it is concluded that ELTP based face recognition is a better method when it is compared with other approaches. As a future research, combination of various algorithms and multimodal framework along with biometric fingerprint traits can be introduced to enhance the accuracy.

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