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# Face Recognition Using Completed Local Ternary Pattern (CLTP) Texture Descriptor

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**ABSTRACT**

Nowadays, face recognition becomes one of the important topics in the computer vision and image processing area. This is due to its importance where can be used in many applications. The main key in the face recognition is how to extract distinguishable features from the image to perform high recognition accuracy. Local binary pattern (LBP) and many of its variants used as texture features in many of face recognition systems. Although LBP performed well in many fields, it is sensitive to noise, and different patterns of LBP may classify into the same class that reduces its discriminating property. Completed Local Ternary Pattern (CLTP) is one of the new proposed texture features to overcome the drawbacks of the LBP. The CLTP outperformed LBP and some of its variants in many fields such as texture, scene, and event image classification. In this study, we study and investigate the performance of CLTP operator for face recognition task. The Japanese Female Facial Expression (JAFFE), and FEI face databases are used in the experiments. In the experimental results, CLTP outperformed some previous texture descriptors and achieves higher classification rate for face recognition task which has reached up 99.38% and 85.22% in JAFFE and FEI, respectively.



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## 1. INTRODUCTION

Automatic face recognition has been a focus research topic in past few decades. This is due to the advantages of face recognition and the potential need for high security in commercial and law enforcement applications. Today, the face is the most common biometric used by humans. Face recognition is a task that humans perform routinely and effortlessly in our daily lives. Humans are very good at recognising faces and complex patterns. Humans often use faces to recognise individuals and advancements in computing capability over the past few decades now enable similar recognitions automatically. Face Recognition more easily to apply instead of using fingerprint detection, iris recognition, signature recognition etc. because this sort of biometric also has some disadvantages for non-collaborative individuals. Many features have been proposed and used to design face recognition systems such as Principal Component Analysis (PCA) [1], Linear Discriminant Analysis (LDA) [2], Independent Component Analysis (ICA) [3], Local Binary Pattern (LBP) [4], etc.

LPB is one of the famous texture descriptor proposed in 2002 by Ojala [5] for texture classification. LBP descriptor and many of its variants are used for different computer vision tasks, such as object and scene recognition [6], human detections [7], object tracking [8], and face recognition [4],[9]-[10]. The LBP histogram is computed over user-defined patterns (grid of cells). The first step is the thresholding step where the centre of the pattern is compared with its pixel neighbourhood to convert their values to binary values (0 or 1). This step aims to find the binary differences. The next step is the encoding step, which encodes the binary number of each pattern and converts it to the equivalent decimal number that characterises a structural pattern. The LBP is one distribution-based descriptor because all the patterns' decimal values are then represented as a histogram. In addition to that, the LBP is computationally simple, showing good performance and excellent results in texture classification. Examples of LBP variants are Local Ternary Pattern (LTP) [11], Completed LBP (CLBP) [12], and Completed Local Binary Count (CLBC) [13]. In [4], the LBP is used for face description. The face is dividing into several blocks, LBP as a local descriptor is extracted from each block, and then all blocks descriptors are combined as a global descriptor. The nearest neighbour algorithm is used as a classifier. In [14], the authors have proposed a face recognition system based on CLBP. They used Multi-Class Support Vector Machine as a classifier to achieve a high face recognition accuracy. The combination of CLBP and sparse representation is used in to propose a new face recognition system in [15]. A brief evaluation of different face recognition systems based on LBP and different variants of LBP texture descriptors had been done in [16].

Although the LBP showed a good response and performance in many fields, it suffers from some drawbacks. Many of texture features are proposed based on LBP and inherit the drawbacks. The LBP is sensitive to noise, and different patterns of LBP may be classified into the same class that reduces its discriminating property [12]. To overcome LBP drawbacks, we proposed a new texture descriptor, called Completed Local ternary Pattern (CLTP) [17]. CLTP showed good accuracy rates in many fields rather than LBP and CLBP [17]-[18]. In [17], the CLTP outperformed LBP, CLBP, and CLBC in term of texture classification accuracy. Moreover, in [18], the CLTP is used for image, event, scene and medical image classification and achieved higher classification accuracy compared with LBP, CLBP, and CLBC.

In this paper, the CLTP texture descriptor is studied and investigated for face recognition system. Different standard face datasets are used in this study such as JAFFE and PEI datasets. The experimental results illustrate that CLTP is more robust and achieves higher face recognition accuracy rate compared with CLBP.

The rest of this paper is organised as follows. Section 2 briefly reviews the LBP and CLBP. Our proposed CLTP texture descriptors are explained in Section 3. Then in Section 4, the experimental results of proposed face recognition system using CLTP are reported and discussed. Finally, Section 4 concludes the paper.

## 2. RELATED WORKS

In this section, a brief review of the LBP and CLBP are provided.

### 2.1. Local Binary Pattern (LBP)

The LBP calculation can be described mathematically as follow:

$$LBP_{P,R} = \sum_{p=0}^{P-1} 2^p s(i_p - i_c), \qquad s(x) = \begin{cases} 1, & x >= 0, \\ 0, & x < 0, \end{cases} \tag{1}$$

Where $i_c$ and $i_p$ (p = 0, . . . , P − 1) denote the grey values of the centre pixel and the neighbour pixel on a circle of radius R, respectively, and P denotes the number of the neighbours. To estimate the neighbours that do not lie exactly in the centre of the pixels, the bilinear interpolation estimation method is used. The LBP is shown in Figure 1. In addition to LBP, Ojala et al. [5] also improved the original LBP to rotation invariant LBP ($LBP_{P,R}^{ri}$) and uniform rotation invariant LBP ($LBP_{P,R}^{riu2}$). After doing the encoding step in any of these LBP types; i.e., LBP, $LBP_{P,R}^{ri}$ and $LBP_{P,R}^{riu2}$, the descriptor histogram is constructed according to Equation (2) as follows:

$$H(k) = \sum_{i=0}^{I}\sum_{j=0}^{J} f(LBP_{P,R}(i,j),k), \qquad k \in [0,K], \qquad f(x,y) = \begin{cases} 1, & x = y, \\ 0, & otherwise \end{cases} \tag{2}$$

Where K is the maximal LBP pattern value.

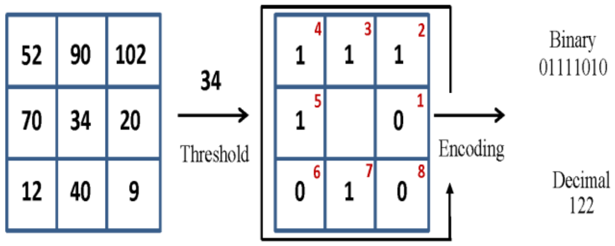


Figure 1. LBP descriptor

Although, many researchers targeted the LBP and did many improvements on it. The drawbacks of the LBP are inherited to all texture descriptors inspired from the LBP descriptor. The first drawback is sensitivity to noise as shown in the example in Figure 2 while the second drawback is shown in Figure 3 where different patterns of LBP may be wrongly classified into the same class that reduces its discriminating property.

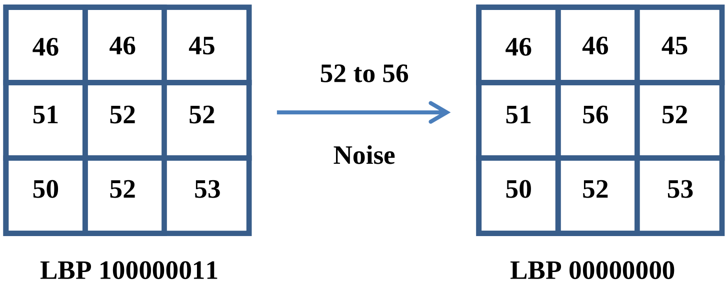


Figure 2. The example for LBP operator's noise sensitivity

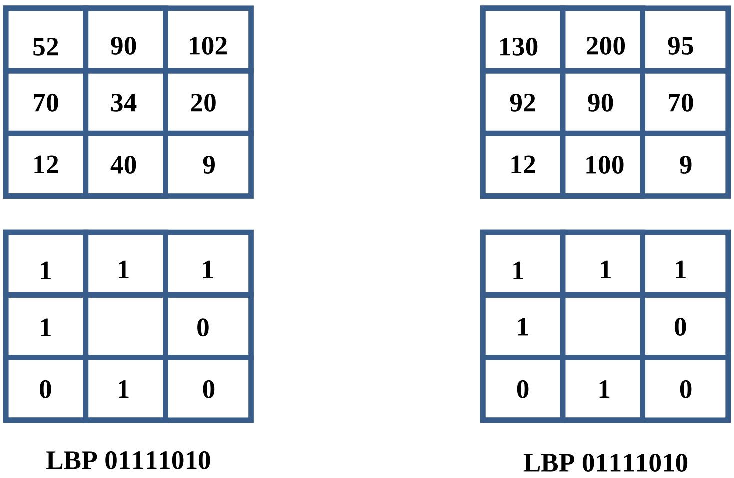


Figure 3. Similar LBP codes for two different texture patterns

## 2.2. Completed Local Binary Pattern (CLBP)

In 2010, Guo et al. [12] proposed the completed LBP (CLBP) descriptor. In CLBP, the image local difference is decomposed into two complementary components; the sign component $s_p$ and the magnitude component $m_p$.

$$s_p = s(i_p - i_c), \qquad m_p = |(i_p - i_c)| \tag{3}$$

Then, the $s_p$ is used to build the CLBP-Sign (*CLBP_S*), whereas the $m_p$ is used to build CLBP-magnitude (*CLBP_M*). The *CLBP_S* and *CLBP_M* are mathematically described as follows:

$$CLBP\_S_{P,R} = \sum_{p=0}^{P-1} 2^p s(i_p - i_c) \qquad s_P = \begin{cases} 1, & i_p \geq i_c, \\ 0, & otherwise, \end{cases} \tag{4}$$

$$CLBP\_M_{P,R} = \sum_{p=0}^{P-1} 2^p t(m_p, c) \qquad t(m_p, c) = \begin{cases} 1, & |(i_p - i_c)| \geq c, \\ 0, & |(i_p - i_c)| < c, \end{cases} \tag{5}$$

Where $i_c$, $i_p$, R and P are defined before in Equation (1), while c denotes the mean value of $m_p$ in the whole image.

The *CLBP_S* is equal to LBP whereas the *CLBP_M* measures the local variance of magnitude. Furthermore, Guo et al. [12] used the value of the grey level of each pattern to construct a new operator, called CLBP-centre (CLBP_C). The *CLBP_C* can be mathematically described as follows:

$$CLBP\_C_{P,R} = t(i_c, c_I) \tag{6}$$

Where $i_c$ denotes the grey value of the centre pixel and $c_I$ is the average grey level of the whole image.

Guo et al. [12] combined their operators into joint or hybrid distributions and achieved remarkable texture classification accuracy. They combined *CLBP_S* and *CLBP_M* in two ways. In the first way, they concatenated their histogram to build *CLBP_S_M*, while in the second way they calculated the 2D joint histogram. This 2D joint histogram is known as *CLBP_S/M*. The *CLBP_C* also combined with the *CLBP_S* and *CLBP_M* in two ways. In the first way, both of them are combined as 3D joint histogram and denoted as *CLBP_S/M/C*. In the second way, the *CLBP_C* is first combined jointly with the *CLBP_S* or *CLBP_M* to build 2D joint histogram denoted *CLBP_S/C* or *CLBP_M/C*, respectively. Then, this 2D joint histogram has to convert to 1D histogram and has to be concatenated with *CLBP_M* or *CLBP_S* to build the final histogram that denoted by *CLBP_M_S/C* or *CLBP_S_M/C*.

## 3. COMPLETED LOCAL TERNARY PATTERN (CLTP)

In CLTP [17], local difference of the image is decomposed into two sign complementary components and two magnitude complementary components as follows:

$$\begin{aligned} s_p^{upper} &= s(i_p - (i_c + t)), & s_p^{lower} &= s(i_p - (i_c - t)) \\ m_p^{upper} &= |i_p - (i_c + t)|, & m_p^{lower} &= |i_p - (i_c - t)| \end{aligned} \tag{7}$$

Where $i_c$, and $i_p$ are defined before in (1) while $t$ denotes the user Threshold. Then, the $s_p^{upper}$ and $s_p^{lower}$ are used to build the $CLTP\_S_{P,R}^{upper}$ and $CLTP\_S_{P,R}^{lower}$, respectively, as follows:

$$CLTP\_S_{P,R}^{upper} = \sum_{p=0}^{P-1} 2^p s(i_p - (i_c + t)) \qquad s_P^{upper} = \begin{cases} 1, & i_p > i_c + t, \\ 0, & otherwise, \end{cases} \tag{8}$$

$$CLTP\_S_{P,R}^{lower} = \sum_{p=0}^{P-1} 2^p s(i_p - (i_c - t)) \qquad s_P^{lower} = \begin{cases} 1, & i_p > i_c - t, \\ 0, & otherwise, \end{cases} \tag{9}$$

Then $CLTP\_S_{P,R}$ is the concatenation of the $CLTP\_S_{P,R}^{upper}$ and $CLTP\_S_{P,R}^{lower}$, as follows:

$$CLTP\_S_{P,R} = [CLTP\_S_{P,R}^{upper} \quad CLTP\_S_{P,R}^{lower}] \tag{10}$$

Similar to $CLTP\_S_{P,R}$, the $CLTP\_M_{P,R}$ is built using the two magnitude complementary components $m_p^{upper}$ and $m_p^{lower}$ , as follows:

$$CLTP\_M_{P,R}^{upperr} = \sum_{p=0}^{P-1} 2^p t(m_p^{upper}, c) \qquad t(m_p^{upper}, c) = \begin{cases} 1, & |i_p - (i_c + t)| >= c, \\ 0, & |i_p - (i_c + t)| < c \end{cases} \tag{11}$$

$$CLTP\_M_{P,R}^{lower} = \sum_{p=0}^{P-1} 2^p t(m_p^{lower}, c) \qquad t(m_p^{lower}, c) = \begin{cases} 1, & |i_p - (i_c - t)| >= c, \\ 0, & |i_p - (i_c - t)| < c \end{cases} \tag{12}$$

$$CLTP\_M_{P,R} = [CLTP\_M_{P,R}^{upper} \quad CLTP\_M_{P,R}^{lower}] \tag{13}$$

Moreover, the $CLTP\_C_{P,R}^{upper}$ and $CLTP\_C_{P,R}^{lower}$ can be described mathematically as follows:

$$CLTP\_C_{P,R}^{upper} = t(i_c^{upper}, c_I) \tag{14}$$

$$CLTP\_C_{P,R}^{loerr} = t(i_c^{lower}, c_I) \tag{15}$$

Where $i_c^{upper} = i_c + t,\ i_c^{lower} = i_c - t$ and $c_I$ is the average grey level of the world image.

The proposed CLTP operators are combined into joint or hybrid distributions to build the final operator histogram like the CLBP and CLBC [12],[13]. In the CLTP, the operators of the same type of pattern; i.e., the upper and the lower pattern, are combined first into joint or hybrid distributions. Then, their results are concatenated to build the final operator histogram.

## 4. EXPERIMENTS AND DISCUSSIONS

In this section, series of experiments are performed to study and investigate the performance of the CLTP for face recognition task. JAFFE [19] and FEI [20] standard databases are used in this study. Empirically, the threshold value t is set to 5 in all CLTP experiments. Different datasets were used in order to find the suitable threshold value which will be used in the CLTP evaluation experiments. The values were ranged from 0 to 25, and 5 was the suitable threshold value [17]-[18]. In all experiments, the LBP, CLBP, and CLTP are extracted based on three different texture patterns, namely, (P = 8 and R = 1), (P = 16 and R = 2), and (P = 24 and R = 3).

### 4.1. Dissimilarity Measuring Framework

In this study, the nearest neighbourhood classifier as well as the chi-square statistic is used to measure the dissimilarity of the histograms. Equation (16) describes the $\chi^2$ distance between two histograms $H = h_i$ and $K = k_i$ where $(i = 1,2,3,...B)$

.

$$Dissimilarity_{\chi^2}(H, K) = \sum_{i=1}^{B} \frac{(h_i - k_i)^2}{h_i + k_i} \tag{16}$$

### 4.2. Experimental Results of JAFFE dataset

The JAFFE database includes 10 classes and total 213 images. Each class has 20 JPEG images of different Japanese female in a different view of face expression which has angry, smile, sad, worry, nervous, neutral and etc. These images are grey and 256 x 256 in size. Examples of these images are shown in Figure 4. Table 1 shows the average of classification results of face recognition dataset of 100 random splits. In each class, $N$ = (2, 5, 10) is used as training images, while the remaining images are used as testing images. The best classification accuracy has obtained by $CLTP\_S/M/C_{3,24}$ operator, which has reached up 99.38% while the $CLBP\_S/M/C_{3,24}$ has achieved the best classification accuracy, which has reached up to 98.77%. From the Table X, all CLTP descriptors outperformed the CLBP descriptors in term of accuracy rate.

Figure 4. Some images from JAFFE Database

Table 1. Classification rates (%) on JAFFE Database

| Descriptors | R=1, P=8 | | | R=2, P=16 | | | R=3, P=24 | | |
|---|---|---|---|---|---|---|---|---|---|
| | 2 | 5 | 10 | 2 | 5 | 10 | 2 | 5 | 10 |
| CLBP_S | 56.43 | 63.97 | 70.52 | 47.62 | 53.54 | 58.78 | 48.59 | 56.34 | 61.76 |
| CLTP_S | 74.27 | 81.37 | 85.74 | 80.41 | 86.63 | 90.50 | 84.61 | 89.88 | 94.00 |
| CLBP_M | 70.29 | 74.37 | 76.58 | 74.93 | 79.97 | 83.94 | 73.47 | 79.31 | 83.76 |
| CLTP_M | 78.20 | 84.67 | 88.76 | 80.59 | 85.61 | 87.72 | 78.74 | 85.03 | 89.02 |
| CLBP_M/C | 87.26 | 91.53 | 94.03 | 88.03 | 92.73 | 94.89 | 89.09 | 94.14 | 96.27 |
| CLTP_M/C | 86.42 | 91.88 | 95.42 | 90.44 | 95.25 | 97.88 | 91.99 | 96.12 | 98.24 |
| CLBP_S_M/C | 86.24 | 90.71 | 93.98 | 85.79 | 91.97 | 94.68 | 89.73 | 95.00 | 97.19 |
| CLTP_S_M/C | 88.24 | 93.40 | 96.66 | 92.13 | 96.56 | 98.54 | 93.10 | 96.51 | 98.10 |
| CLBP_S/M | 73.34 | 81.60 | 87.70 | 72.54 | 81.73 | 88.34 | 79.78 | 86.51 | 90.70 |
| CLTP_S/M | 84.20 | 90.33 | 93.74 | 87.67 | 93.51 | 96.54 | 90.00 | 93.93 | 97.18 |
| CLBP_S/M/C | 86.39 | 92.29 | 94.60 | 88.28 | 93.55 | 96.02 | 92.54 | 96.65 | 98.77 |
| CLTP_S/M/C | 89.21 | 95.08 | 97.46 | 94.57 | 97.25 | 98.74 | 95.44 | 98.53 | 99.38 |

### 4.3. Experimental Results of FEI Face Database

The FEI face database is one of the standard faces databases. This database collected includes faces for 200 Brazilian persons captured on 2005 and 2006 at Artificial Intelligence Laboratory of FEI in São Bernardo do Campo, São Paulo, Brazil. FEI face database has a 2800 face image in total from the student and staff in the FEI from 19 years old to 40 years old. The images in FEI database are organised in 200 classes and each class contains14 images for the same person in different face view, rotation of almost 180 degrees and with different facial expression. The size of faces image is 640 x 480 pixels. Figure x shows some examples of FEI face database.

Figure 5. Some images from FEI Face Database

Table 2 shows the average of classification results of face recognition dataset of 100 random splits. In each class, $N$ = (2, 5, 10) is used as training images, while the remaining images are used as testing images. The best classification accuracy has obtained by $CLTP\_S/M/C_{2,16}$ operator, which has reached up 85.22% while the $CLBP\_S/M/C_{3,24}$ has achieved the best classification accuracy, which has reached up to 76.15%. Aside from *CLTP_ M* operator when N = (2, 5, 10) at P = 24, R = 3, all CLTP operators have achieved higher performance than CLBP operators for all N numbers of training images at radiuses 1, 2, 3.

Table 2. Classification rates (%) on FEI Face Database

| FEI database | R=1, P=8 | | | R=2, P=16 | | | R=3, P=24 | | |
|---|---|---|---|---|---|---|---|---|---|
| | 2 | 5 | 10 | 2 | 5 | 10 | 2 | 5 | 10 |
| CLBP_S | 12.13 | 16.90 | 21.03 | 9.09 | 11.98 | 15.15 | 12.18 | 16.25 | 20.12 |
| CLTP_S | 30.55 | 38.53 | 46.66 | 43.17 | 54.82 | 66.74 | 47.16 | 59.34 | 72.58 |
| CLBP_M | 18.98 | 26.47 | 33.29 | 22.87 | 32.93 | 41.00 | 26.96 | 36.90 | 45.16 |
| CLTP_M | 25.14 | 32.82 | 42.81 | 26.81 | 35.03 | 47.25 | 26.34 | 34.63 | 45.19 |
| CLBP_M/C | 33.46 | 46.17 | 55.61 | 35.22 | 49.76 | 59.66 | 40.97 | 53.87 | 61.16 |
| CLTP_M/C | 43.21 | 54.20 | 68.04 | 45.93 | 56.87 | 71.10 | 42.78 | 54.48 | 68.96 |
| CLBP_S_M/C | 32.82 | 44.16 | 53.64 | 37.24 | 49.30 | 59.31 | 44.33 | 56.92 | 66.47 |
| CLTP_S_M/C | 47.81 | 60.36 | 76.84 | 51.19 | 63.57 | 77.22 | 48.45 | 61.38 | 76.71 |
| CLBP_S/M | 23.47 | 34.15 | 42.31 | 29.68 | 42.11 | 50.52 | 40.58 | 55.40 | 64.22 |
| CLTP_S/M | 43.58 | 57.56 | 71.91 | 48.17 | 62.28 | 76.20 | 46.83 | 60.26 | 76.52 |
| CLBP_S/M/C | 37.07 | 50.97 | 60.29 | 47.10 | 60.70 | 70.23 | 55.02 | 68.80 | 76.15 |
| CLTP_S/M/C | 55.07 | 68.22 | 82.05 | 58.36 | 71.46 | 85.22 | 56.72 | 70.82 | 84.32 |

## 5. CONCLUSIONS

In this paper, the proposed Completed Local Ternary Pattern (CLTP) texture descriptor are studied and evaluated for face recognition task. Two standard face datasets are used in the experiments in this study which are JAFFE and PEI datasets. Different numbers of training images with a different size of the descriptors are used in the experiments. The experimental results showed the superiority of the proposed CLTP against CLBP in both JAFFE and PEI databases. This is due to the properties of CLTP compared with CLBP.


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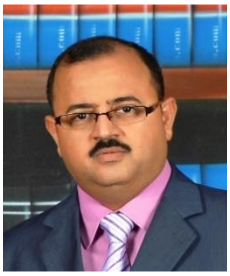
## BIOGRAPHIES OF AUTHORS



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