An improved local pattern descriptor for biometrics face encoding: a LC–LBP approach toward face identification

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ABSTRACT

Local binary pattern (LBP) has proved to be an efficient local image descriptor used in computer vision. LBP operator has successfully been applied in many biometrics applications. Face recognition is one such application where performance degrades due to varying illumination, facial expressions and head pose changes. To address these issues effectively, LBP operator can be used to represent face images during feature extraction. However, due to the limited number of discriminative characteristics, the LBP operator cannot address these issues properly. It seeks more distinctive and well-structured local feature representation. This paper reports a face identification system which makes use of a novel LBP variant called Logically Concatenated LBP in which the basic notion of Modified LBP is exploited and combined with three logical operations, viz. AND, OR and XOR. These logical operations are used to produce three different labeled face patterns from a single face. Further, these patterns are used for face matching and identification. The proposed face identification is tested on FEI, UMIST and Extended Yale Face B databases and identification accuracies have been determined. Experimental results are found to be encouraging and convincing. The experimental results are also compared with some existing local descriptors.

1. Introduction

Dynamic attributes of face images and degraded environments often make the face recognition (Li and Jain 2011) task a most challenging one. Traditional face recognition systems involve various feature representation and encoding techniques. These techniques have been tried to address the problems which occur due to changes in illumination, facial expressions, head pose, facial texture, face alignment, occlusion, etc. Even in the presence of clutter, cosmetics, glasses and noise in face image degrade the performance. To overcome these shortcomings (Li and Jain 2011), a large number of feature-based and appearance-based techniques have been presented in the literature. Among them, local binary pattern (LBP) (Maturana, Mery, and Soto 2009), SIFT (Kisku et al. 2009), SURF (Du, Su, and Cai 2009), EBGM (Wiskott et al. 1997) and PCA (Jerritta et al. 2014) approaches are found to be popular in face recognition as well as in other biometrics applications (Baskhi, Sa, and Majhi 2014a, 2014b; Damer and Fuhrer 2012). Some of them have been claimed to be robust to face dynamics, however, most of them have not been able to find a suitable and stable solution of these long standing problems (Klare and Jain 2013; Liao et al. 2009), especially varying illumination, facial expressions (Patil, Kothari, and Bhurchandi 2016), face rotation and local face structure representation (Alelaiwi et al. 2016; Liao et al. 2009). However, these face recognition systems can recognize faces under certain conditions with limited constraints. Beyond that, systems, so far, are not able to perform well and overall accuracy slows down quickly.

In biometrics, face recognition (Li and Jain 2011) is more advantageous than any other biometric systems because it does not require subject’s active participation in the recognition process. This advantage makes the face recognition unique in identity verification through biometric evidence. An automatic face recognition system is able to ascertain individuals among the crowd in airports, railway stations, super markets, multiplexes and in other places where security is susceptible to attack. Therefore, a high performance face recognition system is required which contains discriminative and well-structured information to deal with such attacks.

There exist several LBP-based face recognition systems which are used to minimize the effect of face dynamics at the cost of low performance. Such an LBP-based face recognition system is discussed in (Maturana, Mery, and Soto 2009) which addresses the problems of head pose variations and misalignment of faces. To deal with these problems, the authors have applied illumination normalization and LBP is used as a local feature descriptor. Later, spatial pyramid matching and the Naïve Bayes nearest neighbor are used for recognition. Utilizing LBP for face recognition is presented in another work (Tan and Triggs 2007) where a kernel-based system is proposed under the constraints of illumination changes. LBP and its derivatives such as multivariate LBP, center symmetric LBP, LBP variance, dominant LBP, advanced LBP, local texture pattern (LTP) and local derivative pattern (LDP) are used to minimize the effect of face dynamics at the cost of low performance. Such an LBP-based face recognition system is discussed in (Maturana, Mery, and Soto 2009) which addresses the problems of head pose variations and misalignment of faces. To deal with these problems, the authors have applied illumination normalization and LBP is used as a local feature descriptor. Later, spatial pyramid matching and the Naïve Bayes nearest neighbor are used for recognition. Utilizing LBP for face recognition is presented in another work (Tan and Triggs 2007) where a kernel-based system is proposed under the constraints of illumination changes. LBP and its derivatives such as multivariate LBP, center symmetric LBP, LBP variance, dominant LBP, advanced LBP, local texture pattern (LTP) and local derivative pattern (LDP) are successfully used in (Surulidani, Meena, and Rose 2012) for face recognition. These LBP derivatives address the problems which
occur due to illumination changes, face image transformations, image rotation, and facial expressions.

The proposed face identification system is greatly motivated by Modified LBP (MLBP) and it is used to compute two components – sign and magnitude. Later, these two components of each face block are converted into two separate binary patterns. Finally, these two binary patterns are concatenated using three logical operations (Mano 2008), viz. logical AND, logical OR, and logical XOR. As these two binary patterns are logically fused together in order to obtain three labeled face patterns, therefore, this novel LBP variant is called Logically Concatenated LBP or LC–LBP in short. LC–LBP is used to achieve three improved and distinctive representations of a single face image. The main advantage of this novel variant is that it can label a face image by three different binary patterns which are produced by three logical binary operations.

The rest of the manuscript is organized as follows. Section 2 presents the motivation behind introducing the novel LBP variant LC–LBP. The novel LBP variant LC–LBP and fusion of three logical operations are introduced in Section 3. Section 4 reports the experimental results of the proposed face identification system conducted on FEI, UMIST, and Extended Yale Face B face databases. Concluding remarks are made in the last section.

2. Motivation

The proposed face identification system uses the novel LBP variant LC–LBP as a local face descriptor and it is greatly inspired by the principles of basic LBP and MLBP. LBP (Ojala, Pietikäinen, and Harwood 1996; Ojala, Pietikäinen, and Mäenpää 2002) is a useful and computationally efficient operator used to extract local features from a face image. Prior to local feature extraction, a face image is divided into small regions or image blocks. Then, the LBP operator is applied to each image block. Considering all pixels in an image block, a binary pattern is obtained. LBP converts the face image into an array of integer labels that describe the scales of the face image. These integer-scales form histograms and all local histograms obtained from image blocks are then concatenated together to produce a concatenated histogram which represents global features of the whole face image.

In basic LBP, each image block is described by 9 pixels which constitute the 3 × 3 pixels region where every neighboring pixel is assigned the numeric value 0 or 1 depending on the sign of the difference value calculated over center pixel and neighborhood pixels. The threshold value of neighboring pixels represents an eight-bit binary pattern which is then multiplied by a power of two to the corresponding pixels and summed up to give the label value of the center pixel. The LBP code is given by

$$LBP_{	ext{ls}} = \sum_{j=0}^{L-1} f(p_i - p_j)2^j$$

where $f(x) = \begin{cases} 1, & \text{if } x \geq 0 \\ 0, & \text{if } x < 0 \end{cases}$

(1)

where $p_c$ denotes the gray value of the center pixel and $p_i$ represents the gray value of neighboring pixels around the center. Here, $L$ is the total number of neighboring pixels and $R$ is the radius of the neighborhood. An illustration of basic LBP operator is shown in Figure 1.

An extended LBP, known as MLBP (Brahnam et al. 2014) can be applied to improve the face classification performance, which utilizes both sign and magnitude features. In order to extend the

3. Logically concatenated LBP (LC–LBP)

3.1. Feature extraction and label face construction

In the proposed face identification system, a novel LBP variant called Logically Concatenated LBP (LC–LBP) is used to represent the local textures of a face image and encode the face characteristics into a fused feature set. LC–LBP uses basic notions of MLBP and extracts three different face patterns rather than generating a single pattern of concatenated histograms. After geometric normalization, the face image is divided into a number of image blocks of the same size, $3 \times 3$. The LC–LBP operator is then applied to each block and binary values 0 and 1 are assigned to the neighboring pixels around the center pixel of each image block. 0 and 1 are assigned based on the sign of the difference between center pixel and neighborhood pixels. The sign component preserves discriminative characteristics in labeled face pattern. However, it can add an advantage if more distinctive and relevant characteristics can be integrated with sign component. Thus, the fused information can produce a more convincing solution. In order to obtain a fused set of features from a face image, magnitude component can also be computed from the difference vector of sign component.

Let the pixel intensity difference between the center pixel ($p_c$) and the neighborhood pixels ($p_i$) be denoted by $Dist_i$. Hence, the distance would be given by $Dist_i = p_c - p_i$, where $i = 0, 1, \ldots, L - 1$. So, the local structure of an image centered at pixel $p_c$ is obtained with a distance vector $D_{\text{ls}} = \langle Dist_0, Dist_1, \ldots, Dist_{L-1} \rangle$. Now, from the distance vector $D_{\text{ls}}$, two disjoint component can be obtained, viz. sign and magnitude components. Further, the component vectors can be represented by $\langle S_{\text{ls}}, S_{\text{ls}}^\prime, \ldots, S_{\text{ls}}^\prime \rangle$ and $\langle M_{\text{ls}}, M_{\text{ls}}^\prime, \ldots, M_{\text{ls}}^\prime \rangle$, respectively. Moreover, Sign-LBP and Magnitude-LBP patterns can be constructed from sign vector and magnitude vector. It is assumed that each element in the distance vector is composed of sign and magnitude component. Therefore, it is given by

![Figure 1. Basic LBP operator.](attachment:image.png)
From Equation (2), it is observed that when distance is found positive, 1 is assigned, otherwise 0 is assigned. After Sign-LBP is obtained, Magnitude-LBP binary pattern is obtained from Equation (2). The pictorial representation of LC–LBP is shown in Figure 2. Magnitude-LBP binary pattern can now be constructed from Equation (4). It is given by

$$M_{avg} = \frac{1}{L} \sum_{i=0}^{L-1} M_i \quad \forall i = 0, 1, ..., L - 1$$

Since Equation (3) has produced a real number, therefore, it can be converted to an integer for the sake of experiment. $M_{avg}$ is then converted into a gray scale value for a center pixel either by applying the ceiling function or floor function.

To make a meaningful association of Sign-LBP with Magnitude-LBP, Sign-LBP binary pattern is obtained from Equation (2). The pictorial representation of LC–LBP is shown in Figure 2. Magnitude-LBP binary pattern can now be constructed from Equation (4). It is given by

$$\text{Magnitude-LBP}_{LR} = \sum_{i=0}^{L-1} f(i - M_{avg}) 2^i$$

where $f(x) = \begin{cases} 1, & \text{if } x \geq 0 \\ 0, & \text{if } x < 0 \end{cases}$

Figure 2 shows the computation of two binary patterns which are obtained from sign and magnitude components. These two binary patterns are then considered for logical concatenation using logical AND, OR, and XOR operations. Concatenation produces three new binary patterns. These three binary patterns contain varying image-scale information about the local face structure. At the end of this process, three labeled face images are obtained. Figure 3 shows three labeled face images, including the original face images and corresponding concatenated histograms. Each of these labeled face images represents a local structure and exhibits various discriminative characteristics on a set of common facial features. However, since LBP mainly deals with local structure of face image irrespective of varying illumination and facial expressions change, therefore these three labeled face representations would be able to contribute a good number of distinctive features to the final feature set. LC–LBP algorithm is shown in Figure 4.

3.2. Problem formulation

Let, $U_i = \{x_i\}$ and $U_j = \{y_j\}$ be two binary patterns where, $r = 0, 1, ..., l - 1$ and $x, y = 0/1$. $U_i$ and $U_j$ are generated from a pair of face images of two different subjects or from the same subject. Further, let $U_1$ and $U_2$ be determined from sign ($S$) and magnitude ($M$) components by separating these two components of an image block ($I'$) of a face ($I$) where, $|U_1| = |U_2|$ and $|I'| < |I|$. The binary elements of $S$ and $M$ are determined by taking the difference of each neighborhood pixel from the center pixel. Three logical operations, viz. OR, AND and XOR on $U_1$ and $U_2$ are applied and obtain three independent face patterns.

Let, $U_i = \{x_i\}$ and $U_j = \{y_j\}$ be two binary patterns of $r$ bits ($r = \text{total number of neighborhood pixels in a sub region}$) representing the sign and magnitude components. $U_i$ and $U_j$ can have some common as well as inverse characteristics. If $C_i \in U_i$ and $C_j \in U_j$ where $i = 1, 2, ..., n$ and $j = 1, 2, ..., m$ denote various characteristics such as scale, illumination, angle, etc. and if $C_i \approx C_j$ in terms of bit, then we can say that $C_i$ and $C_j$ are most familiar features both
of which are available in binary patterns \(U_s\) and \(U_M\). Otherwise, if \(c \in U_s\) and \(c \notin U_M\) or vice versa, then we can conclude that \(c\) is available in \(U_s\), but not in \(U_M\), or vice versa. Now, if any one bit-wise logical operation OR, XOR, or AND is applied to both \(U_s\) and \(U_M\), it results in a new binary pattern of an identical number of bits of distinct characteristics. Let us consider, \(R_1\) to be the resultant binary pattern and any logical operation is represented by \(\Theta\). Then, the interpretation can be written as

\[
R_1(z_j) = \left\{ \begin{array}{ll}
\phi, & \text{if } U_s = \{\phi\}, U_M = \{\phi\} \\
U_s \text{ or } U_M, & \text{if } U_s = \{x_s\}, U_M = \{\phi\} \text{ or } U_s = \{\phi\}, U_M = \{x_M\} \\
U_s \Theta U_M = \{x_s\} \Theta \{y_M\}, & \text{if } U_s = \{x_s\}, U_M = \{y_M\} \\
\forall r = 0, 1, \ldots, l - 1 & 
\end{array} \right.
\]

Figure 4 shows LC–LBP algorithm where \(H\) is an input face of size \(m \times n\). LC–LBP algorithm is applied to every pixel on the face image. ‘scale’ is a \(3 \times 3\) matrix used to compute Sign-LBP and Magnitude-LBP patterns and ‘mat’ are \(3 \times 3\) neighborhood used to compute concatenated LBP patterns of a pixel at \(H(i, j)\).

4. Evaluation

In this section, experimental results of the proposed face identification system (see Figure 5) are presented. In addition, face databases, experimental setup and protocols are also discussed. Finally, the performance in terms of experimental results is compared with another local descriptor known as LTP reported in (Suruliandi, Meena, and Rose 2012). Experiments are conducted on the FEI (Thomaz and Giraldi 2010), the UMIST (Kisku et al. 2011) and the Extended Yale Face B (Faraji and Qi 2015) face databases and identification accuracies are determined using Chi-square statistics (Kimberly 2005) and sum of squared differences (SSD) (Bieszczad, Sosnowski, and Madura 2011) for Rank 1, Rank 5, Rank 10, Rank 15, and Rank 20 identification strategies. Rank 1 strategy retrieves a face image from database having highest matching proximity. Similarly, the rest of the strategies retrieve face images from the database having similarity to probe face. In this experiment, a novel variant LC–LBP is used for local face as well as global face representation. During experiments face images do not pass through image enhancement prior to feature encoding. However, semi-automatic face localization is used for extracting the face region and further, face image is then resized to 46 \(\times\) 40 pixels from original size.

Initially, the training face image is divided into a number of image blocks of same size, \(3 \times 3\). Then both LC–LBP and LTP operator are applied separately to each block to extract the local texture features. The local texture features extracted from each block are then concatenated together separately to construct the global texture features of a face image. During testing, the same LC–LBP and LTP techniques are used to extract the local and global textural features of the probe faces. Texture features of probe face images are compared with the textural features of training images using Chi-square statistics and SSD metrics by computing matching proximity. Finally, identification accuracy is computed using Equation (6).

\[
\text{Identification accuracy} = \frac{(\text{No. of correct matches at rank K})}{(\text{No. of probe faces})} \times 100\%
\]
An important paper, (Suruliandi, Meena, and Rose 2012) evaluates the performance of LBP and derivatives along with LDP and LTP for face recognition. The experimental results (Suruliandi, Meena, and Rose 2012) determined on the JAFFE, the Yale and the FRGC V2 face databases show that LDP and LTP perform much better than other LBP variants. At the same time, LTP outperforms LDP.

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**Algorithm: Logically Concatenated–LBP**

| Algorithm LC-LBP \((H, m, n)\) | \[\text{if } (k == 2 \&\& l == 2)\] continue; 
| \[\text{else}\] | \[su \leftarrow su + K(k, l);\] 
| | end if 
| | end for 
| | end for 
| | \[\text{avg} \leftarrow su / 8;\] 
| | \[\text{Magnitude} \leftarrow K \geq \text{avg};\] 
| | \[M \leftarrow \text{Magnitude} \times \text{scale};\] 
| | \[se \leftarrow 0\] 
| | \[\text{for } k \leftarrow 1 \text{ to } 3\] 
| | \[\text{for } l \leftarrow 1 \text{ to } 3\] 
| | \[\text{if } (k == 2 \&\& l == 2)\] continue; 
| | | \[\text{else}\] 
| | | \[se \leftarrow se + M(k, l);\] 
| | | end if 
| | | end for 
| | | end for 
| \[K \leftarrow |\text{mat} - \text{temp}|\] 
| \[\text{Initialize } su \text{ to } 0\] 
| \[\text{for } k \leftarrow 1 \text{ to } 3\] 
| \[\text{for } l \leftarrow 1 \text{ to } 3\] 
| \[\text{if } (k == 2 \&\& l == 2)\] continue; 
| | \[\text{else}\] 
| | \[si \leftarrow si + S(k, l);\] 
| | end if 
| | end for 
| | end for 
| \[B(i,j) \leftarrow (si \text{ OR } se)\] 
| \[C(i,j) \leftarrow (si \text{ AND } se)\] 
| \[D(i,j) \leftarrow (si \text{ XOR } se)\] 

---

![Figure 4. Logically concatenated LBP (LC-LBP) algorithm.](image1)

![Figure 5. The proposed face identification system.](image2)
10% and the original size of each image is 640 x 480 pixels. The face images show distinct appearances, hairstyles, and adornments. The numbers of male and female subjects are exactly the same and equal to 100. Figure 6 shows some examples of face images from the FEI face database.

4.1.2. UMIST face database

The UMIST Face Database (Kisku et al. 2011) consists of 564 images of 20 people. Each covers a range of poses from profile to frontal views. Subjects cover a range of race, sex and appearance. Each subject exists in a separate directory with labeled 1a, 1b, ..., 1t and images numbered sequentially as they were taken. The images are all in PGM format, approximately 220 x 220 pixels in 256 shades of gray. Sample face images from UMIST database are shown in Figure 7.

4.1. Face databases

4.1.1. FEI face data-set

The FEI face database (Thomaz and Giraldi 2010) is a Brazilian face database that contains a total of 2800 face images captured from 200 subjects and each subject contributes 14 face images. All face images are in color and taken against a white homogenous background in an upright frontal position with profile rotation of up to about 180 degrees. Scale might vary about

Figure 6. Sample face instances of one subject from the FEI face database are shown.

Figure 7. Sample face images of one subject from the UMIST face database are shown.
4.1.3. Extended YALE face database B
The extended YALE Face Database B (Faraji and Qi 2015) contains 16,128 images of 28 human subjects under 9 poses and 64 illumination conditions. Sample face images from Extended YALE face database B are shown in Figure 8.

4.2. Experimental setup and protocol
To conduct the experiment on the FEI face database the whole database is divided into two groups – a training set of 2160 faces and a probe set of 640 faces. Training set contains face images with neutral expressions, pose changes and low lighting conditions. The extended YALE Face Database B contains 16,128 images of 28 human subjects under 9 poses and 64 illumination conditions. The UCSD pedestrian database contains 1,937 images of 57 human subjects, with different walking speeds and background variations. Sample face images from the extended Yale face database B are shown in Figure 8.

Table 1. Experimental results using LC-LBP local descriptor determined on FEI, UMIST and extended Yale face database B databases for different identification strategies are shown.

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Database</th>
<th>Challenges</th>
<th>No. of faces in training set</th>
<th>No. of faces in probe set</th>
<th>Rank</th>
<th>Identification accuracy (%)</th>
<th>Error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chi-square statistics</td>
<td>FEI face database</td>
<td>Facial expression, pose changes, low lighting conditions</td>
<td>2160</td>
<td>640</td>
<td></td>
<td>AND 73</td>
<td>OR 73</td>
</tr>
<tr>
<td>SSD</td>
<td>FEI face database</td>
<td>Facial expression, pose changes, low lighting conditions</td>
<td>2160</td>
<td>640</td>
<td></td>
<td>AND 83</td>
<td>OR 81</td>
</tr>
<tr>
<td>Chi-square statistics</td>
<td>UMIST face database</td>
<td>Pose changes, wearing glasses</td>
<td>544</td>
<td>20</td>
<td></td>
<td>AND 65</td>
<td>OR 65</td>
</tr>
<tr>
<td>SSD</td>
<td>UMIST face database</td>
<td>Pose changes, wearing glasses</td>
<td>544</td>
<td>20</td>
<td></td>
<td>AND 76</td>
<td>OR 80</td>
</tr>
<tr>
<td>Chi-square statistics</td>
<td>Extended Yale face database B</td>
<td>Illumination variation</td>
<td>950</td>
<td>190</td>
<td></td>
<td>AND 81</td>
<td>OR 84</td>
</tr>
<tr>
<td>SSD</td>
<td>Extended Yale face database B</td>
<td>Illumination variation</td>
<td>950</td>
<td>190</td>
<td></td>
<td>AND 85</td>
<td>OR 87</td>
</tr>
</tbody>
</table>

Figure 8. Sample face images from the extended Yale face B database are shown.
condition, and probe set contains face images with facial expressions (smile) and pose changes. On the other hand, in order to conduct the experiment on the UMIST face database, the whole database is again divided into two sets – probe and training sets. The probe set contains both frontal view and rotated face images and 20 such face images corresponding to 20 subjects are chosen for the probe set. Training set consists of the rest of 544 face images. A total of 1140 images of Extended YALE Face B database are used for evaluation. Only the face images with illumination variations are considered for the experiment. The probe set contains 190 face images and training set contains 950 face images.

During the experiment, every face image in probe set is compared with all the face images in the training set. The system generates three labeled face patterns each from the probe and training face images using novel LC–LBP variant. Then, similarity scores are measured between the encoded faces of training and probe sets using two metrics, viz. Chi-square and SSD. After computing matching proximity, identification accuracies are determined based on three logical operations for each identification strategy.

### 4.3. Experimental results

To demonstrate the efficacy of the proposed LC–LBP based face identification system, three databases viz. the FEI, the UMIST and the Extended Yale Face B face databases are used. The system is developed based on the concept of rank order statistics as the system retrieves most similar faces from the database according to the number of faces which are matched to probe face image at rank 'k'; for $k = 1, 5, 10, 15, 20$. In case of Top 1 rank strategy, only the most similar face is retrieved. The rank is decided by the similarity measures which are used to produce the matching scores while a pair of labeled face patterns is compared. Similarly, the other rank strategies retrieve the same number of similar faces from the database based on the order of face images. The identification performance of the proposed system is shown using graphical representation of cumulative match characteristics (CMC) curves determined on the FEI, the UMIST and the Extended Yale Face B databases.

It has been observed that when experiments are performed on the UMIST and the Extended Yale Face B databases, SSD outperforms Chi-square statistics except for a few cases like Top 1 and Top 5 for logical AND, OR, and XOR operations where performance of both metrics is found to be almost the same. However, in the case of the FEI database, Chi-square statistics is superior to SSD at all ranks except Top 20 for logical XOR where the system achieves 99% identification accuracy. The summary of the experimental results of the proposed system is shown in Table 1. In case of Top 1 rank, logical AND outperforms both the logical OR and XOR when logical AND is used with LC–LBP and Chi-square is applied for classification of faces in FEI database. The system achieves 73, 83, 87, 90, and 91% accuracies with 27, 17, 13, 10, and 9% errors on the FEI database for Top 1, Top 5, Top 10, Top 15, and Top 20 ranks, respectively, when Chi-square is used. On the other hand, when the SSD is applied for all strategies on the FEI database, logical XOR outperforms both logical AND and OR. Logical concatenation of Sign-LBP and threshold binary pattern (obtained from Magnitude-LBP) reveal more discriminative information about facial expression changes and pose changes by increasing the richness of the labeled face image as relevant facial characteristics which have contributed to classification task. This effect can be seen in the case of logical AND and logical XOR when Chi-square and SSD are applied respectively for all identification strategies. In cases when Chi-square statistics and SSD are used, the performance of LC–LBP in the proposed face identification is found to be very encouraging and challenging as no image enhancement techniques are used, rather semi-automatic cropped face images.

The experimental results of the proposed face identification system determined on the UMIST face database are shown in the same Table 1. In this case, LC–LBP variant with logical OR outperforms other logical operations when Chi-square is used. Both logical AND and XOR operations achieve the same accuracies at most of the ranks when the UMIST database is used. On the other hand, SSD performs well when logical operation AND is used with LC–LBP variant and as a result, it outperforms logical OR and XOR operations. For Top 15 and Top 20 ranks, the AND operation achieves 100% identification accuracy and for Top 1 and Top 5 ranks, performances are not found satisfactory when the SSD classifier is used. AND operation retains few facial characteristics as LC–LBP local features which help with correlation-based SSD measures to find homologous features between a pair of face images. SSD has the ability to minimize the associated errors and maximize the similarity followed by aggregation and optimization of the matching process. Chi-square tests whether there exists a relationship between a pair of probe and training face images and it also reveals whether these faces belong to the same class or not. However, SSD outperforms Chi-square as this metric is not able to provide more information about the strength of the relationship between faces.

As can be seen in Table 1, the proposed face identification system determines 100% accuracy on the faces with illumination variations of Extended Yale Face B database. Moreover, this performance has been recorded for all identification strategies, viz. Top 1 to Top 20 when Chi-square and SSD are applied.

Identification performance can also be exhibited by CMC curve. Figure 9 shows CMC curves which are determined on the FEI, the UMIST and the Extended Yale Face B face databases for various combinations of logical operations (i.e. OR, XOR and AND) with LC–LBP variant. It can be observed from the CMC curves shown in the first row of Figure 9 that when both Chi-square and SSD are applied on the combination of logical XOR with LC–LBP, SSD outperforms Chi-square. In case of logical OR, both SSD and Chi-square go almost hand in hand. When LC–LBP is combined with logical AND, Chi-square is found better than SSD. On the other hand, the combination of LC–LBP with logical XOR, OR, and AND may exhibit incremental accuracies for all strategies while Chi-square and SSD are used. However, SSD performs better than Chi-square except in a few cases. The CMC curves of the third row in Figure 9 reveal that the proposed system achieves 100% accuracy on the Extended Yale Face B database for all identification strategies when illumination variations of face images are considered for the experiment.

### 4.4. Comparison with other descriptor

This section reports comparison of novel LC–LBP based face identification when compared with LTP (Suruliandi, Meena, and Rose 2012) based system. As face identification systems which use LBP operator cannot be found in the literature, a direct
values as $\Delta g = 4$ and $\Delta g = 3$ ($\Delta g$ represents small positive value of desirable gray scale and related to uniform pattern) (Suruliandi, Meena, and Rose 2012) at each rank $k$ using the same distance metric mentioned in Sections 4.2 and 4.3. However, the better of these two parameters is taken for comparison. Table 2 shows the comparison table where accuracies are determined in the context of face identification on three well-known databases, viz. the FEI, the UMIST and the Extended Yale Face B databases.

Table 2. Comparison of LC–LBP with LTP descriptors in the context of face identification. Identification accuracies are determined on three face databases, namely, the FEI, the UMIST and the extended Yale face B database.

<table>
<thead>
<tr>
<th>Rank</th>
<th>Identification accuracy (%) on FEI face database</th>
<th>Identification accuracy (%) on UMIST face database</th>
<th>Identification accuracy (%) on extended Yale face database B</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Chi-square statistics</td>
<td>SSD</td>
<td>Chi-square statistics</td>
</tr>
<tr>
<td>Top1</td>
<td>LC–LBP</td>
<td>LTP</td>
<td>LC–LBP</td>
</tr>
<tr>
<td>Top5</td>
<td>73</td>
<td>56</td>
<td>74</td>
</tr>
<tr>
<td>Top10</td>
<td>83</td>
<td>77</td>
<td>81</td>
</tr>
<tr>
<td>Top15</td>
<td>90</td>
<td>83</td>
<td>88</td>
</tr>
<tr>
<td>Top20</td>
<td>91</td>
<td>86</td>
<td>99</td>
</tr>
</tbody>
</table>

Comparison of the proposed system cannot be ruled out. Thus, in this paper, LTP is being simulated and it is then tested on the same databases on which the proposed system has been evaluated. The accuracy achieved at rank $k$ by LC–LBP is compared with the accuracy achieved by LTP at the corresponding rank. With each identification strategy, the three different combinations of logical operators with LC–LBP are evaluated using the distance metrics mentioned in Sections 4.2 and 4.3. LTP achieves identification accuracies along with two parameters with different
10, Top 15, and Top 20. When evaluation is performed on the FEI database, it can be seen from Table 2 that LTP yields 86% accuracy at rank 20, however, LC–LBP gives improved accuracy of 91% at the same rank when Chi-square is used. LTP yields 87% accuracy at rank 20, however, LC–LBP achieves 99% accuracy at the same rank using SSD. In the next step, LC–LBP is compared with LTP and evaluation is made on UMIST database. For each strategy, LC–LBP gives better performance than LTP. Table 2 presents experimental results determined on the UMIST database and SSD outperforms Chi-square when the two are compared. Among all strategies, Top 10, Top 15, and Top 20 achieve 95, 100, and 100% accuracies respectively for LC–LBP when SSD is applied and on the other hand, 85, 90, and 95% accuracies are achieved when Chi-square is applied. The proposed LC–LBP based system gives better accuracies than LTP when both the descriptors are exposed to face images with pose changes and with the subject wearing glasses for evaluation. Contrary to the first two experiments performed on the FEI and the UMIST face databases, both LC–LBP based and LTP based face identification give 100% accuracy for all identification strategies when evaluation is made on the Extended Yale Face Database B and when both the descriptors are exposed to face images with illumination variations. Thus, the comparison shows that the novel LC–LBP outperforms LTP when they are evaluated on the face databases with varying illuminations, changes in facial expressions and pose, and occluded facial features.

5. Conclusion
In this paper, an efficient face identification system which uses a novel variant, LC–LBP, has been presented. In the proposed approach, face encoding is performed with three different labeled face patterns obtained from LC–LBP variant that uses three logical operations. After local feature representation using LC–LBP, Chi-square and SSD metrics are used to obtain the matching proximities. In order to determine identification accuracy, various identification strategies have been used. Evaluation has been conducted on the FEI, the UMIST and the Extended Yale Face B databases. In this experiment, sign and magnitude components are concatenated together using logical operators and the produced labeled face patterns are proved to deal with face images, head pose changes, and varying illuminations effectively. Moreover, the labeled face characteristics have made potential contributions to identification accuracy by minimizing associated errors and optimizing the matching process. Experimental results of the proposed face identification system are found to be encouraging and exploiting LC–LBP is proved to be an important advance toward efficient and robust face identification.

Nomenclature

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>AND</td>
<td>logical operator</td>
</tr>
<tr>
<td>CMC</td>
<td>cumulative match characteristic</td>
</tr>
<tr>
<td>Dist;</td>
<td>difference between center pixel and ith neighboring pixel</td>
</tr>
<tr>
<td>Dv</td>
<td>distance vector of length v</td>
</tr>
<tr>
<td>H</td>
<td>input face image</td>
</tr>
<tr>
<td>H(i,j)</td>
<td>pixel value at (i,j)th position in a face image</td>
</tr>
<tr>
<td>K</td>
<td>rank of identification</td>
</tr>
<tr>
<td>L</td>
<td>total number of neighboring pixels</td>
</tr>
<tr>
<td>LBP_{LR}</td>
<td>local binary pattern with radius R and L neighboring pixels</td>
</tr>
<tr>
<td>LC–LBP</td>
<td>logically concatenated local binary pattern</td>
</tr>
<tr>
<td>LTP</td>
<td>local texture pattern</td>
</tr>
<tr>
<td>m</td>
<td>total number of rows in an image</td>
</tr>
<tr>
<td>M_{avg}</td>
<td>average magnitude value of neighboring pixels</td>
</tr>
<tr>
<td>M_i</td>
<td>magnitude component of Dist_i</td>
</tr>
<tr>
<td>n</td>
<td>total number of columns in an image</td>
</tr>
<tr>
<td>OR</td>
<td>logical operator</td>
</tr>
<tr>
<td>p_c</td>
<td>center pixel</td>
</tr>
<tr>
<td>p_i</td>
<td>neighboring pixel at ith position</td>
</tr>
<tr>
<td>R</td>
<td>radius of an operator</td>
</tr>
<tr>
<td>S_i</td>
<td>sign component of Dist_i</td>
</tr>
<tr>
<td>SSD</td>
<td>sum of squared differences</td>
</tr>
<tr>
<td>U_M</td>
<td>magnitude binary pattern</td>
</tr>
<tr>
<td>U_S</td>
<td>sign binary pattern</td>
</tr>
<tr>
<td>XOR</td>
<td>logical operator</td>
</tr>
<tr>
<td>Θ</td>
<td>any logical operation (AND/OR/XOR)</td>
</tr>
<tr>
<td>Δg</td>
<td>small positive value of desirable gray scale</td>
</tr>
</tbody>
</table>

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References


