Face Identification using Local Ternary Tree Pattern based Spatial Structural Components

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Abstract. This paper reports groundbreaking results of a face identification system which makes use of a novel local descriptor called Local Ternary Tree Pattern (LTTP). Devising deft and feasible local descriptors for a face image plays an emergent preface in face identification task when the system performs in presence of lots of variety of face images including constrained, unconstrained and plastic surgery images. The LTTP has been proposed to extract robust and discriminatory spatial features from a face image as this descriptor can be used to best describe the various structural components of a face. To extract the most useful features, a ternary tree is formed for each pixel with its eight neighbors. LTTP pattern can be generated in four ways - LTTP-Left Depth (LTTP-LD), LTTP-Left Breadth (LTTP-LB), LTTP-Right Depth (LTTP-RD) and LTTP-Right Breadth (LTTP-RB). The encoding schemes of these four patterns generation are very simple and efficient in terms of computational complexity as well as time complexity. The proposed face identification system is tested on six face databases, namely, the UMIST, the JAFFE, the extended Yale face B, the Plastic Surgery, the LFW and the UFI. The experimental evaluation demonstrates the most outstanding results which will have long term impact in designing face identification systems considering a variety of faces captured under different environments.

Keywords: Face Identification, Local Descriptor, Ternary Tree, cosine similarity, sum of absolute differences, classifier.

1 Introduction

Face recognition [7] is an ongoing research field in computer vision and has been attained a significant attention due to extensive range of infliction of automatic face
recognition (AFR) in surveillance, law enforcement and information security. The wide application area of face recognition has motivated the researchers to enrich the reliability and robustness of automatic face recognition (AFR) system. Recognizing a face in a controlled environment is not a difficult task, however it raises an adverse situation in unconstrained environment which decrease the overall performance of automatic face recognition (AFR) system. The success of face recognition technology relies on the choice of a robust face representation as well as a suitable classifier, which can deal with various challenges of face recognition system. The local descriptor is a powerful approach and it is already used successfully in feature extraction phase of a face recognition system. Face recognition can be performed in three different modes – face verification, face identification and face matching. The face verification task validates an asserted identity of a face image, and either accept or abdicate the asserted identity. This is a one-to-one matching procedure. In face verification the probe face image is compared with all face templates of the asserted identity from the database. The face matching task does not require any pre-enrolled face database. This task examines whether two given face images are of the identical person or not. Out of these three tasks face identification is the most challenging one. The main objective of face identification task is to identify an individual based on the image of a face. In face identification, to find the identity of an unknown person, the input face image is compared with all face templates of the registered persons present in the database. This is a one-to-many matching procedure. The face identification is more demanding in crime inquisition, law enforcement, identification of suspicious person in public places like school, bank, railway station, airport and border of a country.

Therefore, the main objective of this paper is to propose a robust face identification framework which can be able to handle different real life situations efficiently and to ensure the robustness of the proposed face identification system, this paper proposed a novel local descriptor (LTTP) for discriminatory facial feature extraction.

1.1 Related Works

To handle varied worst situations during face recognition procedure, a large number of local descriptor based feature extraction approaches [3, 12, 10, 18, 16, 19, 5, 2, 1] have been presented in the literature. The existing local descriptors are principally examined for face verification do not experimented for face identification. The local descriptors have the competency to extract detailed discriminatory and static information from a face images more effectively under degraded and unconstrained environments.

Some local descriptors those already used for face recognition are Local Binary Pattern (LBP) [3,12], Multi scale-Local Binary Pattern (MS-LBP) [10], Multi block-Local Binary Pattern (MB-LBP) [18], Local Texture Pattern (LTP) [16], Local Derivative Pattern (LDP) [19], Local Vector Pattern (LVP) [5], Local Graph Structure (LGS) [2], Symmetric Local Graph Structure (SLGS) [1].

Among above mentioned local descriptors, the Local Binary Pattern (LBP) [3, 12] is a widely used local descriptor which encodes the local relationship of the pixels. The Local Binary Pattern operator works with the eight neighbors of a pixel, using the
value of the center pixel as a threshold. A binary pattern is generated for every pixel of the face image and produces a transformed image (TI). Histogram generated from the transformed image (TI) is used as feature vector. The LBP operator is able to extract micro-patterns from face images and these micro-patterns are invariant with respect to monotonic grey scale transformations. The attainment of LBP in face recognition as well as in other applications invigorated researchers to propose many improvements of the LBP. The scale variation is an important factor which affects the redaction of face recognition system due to variations of texture in different scale. To handle this undeniable situation, Multi-scale Local Binary (MS-LBP) [10] is presented which is an improvement of the Local Binary Pattern (LBP). The MS-LBP is able to extract micro-structures from the face images at different scales. Its accuracy is better than the single scale LBP due to the increased neighborhood size of the operator. The Multi-block Local Binary Pattern (MB-LBP) [18] is an improvement over LBP which compute average value of a sub region of face images and then apply LBP operator on it. The MB-LBP operator is more powerful than LBP due its encoding schemes. MB-LBP provides more discriminatory feature representation as it is able to extract macrostructures as well as microstructures from images. Local Texture Pattern (LTP) [16] is a local descriptor which uses a threshold constant to threshold pixels into three values. After thresholding a ternary pattern is generated for every pixel and form a transformed image. The LTP operator is more discriminative and less sensory to noise in identical regions. The directional patterns are more useful in face recognition. The Local Derivative Pattern (LDP) [19] uses local derivative to encode directional pattern. The more discriminatory facial information can be captured using LDP as it is able to extract high-order local information from a facial region. Local vector Pattern (LVP) is a local descriptor which extracts discriminatory features from a high-order derivative space. To increase the robustness of the structure of micropatterns, LVP encodes different pair-wise directions of vectors and generate invariant facial description. The encoding schemes used in LVP to generate a vector for a pair-wise direction is known as comparative space transform (CST) which is able to reduce feature length and high redundancy. Different local descriptors used different encoding schemes. Some existing local descriptors - Local Graph Structures (LGS) [2] and Symmetric Local Graph Structure (SLGS) [1] are used local directional graph for a pixel to generate a binary pattern. During pattern generation a source node is compared with its destination node in the directed local graph and assign a binary (0 or 1) label on that edge. These graph based local descriptors are also very powerful tool for face recognition.

All above mentioned local descriptors are successfully applied on face recognition, but still there is a need to develop more robust local descriptor which can able to capture more discriminatory information.

1.2 Major Contributions

The local descriptors are very powerful tool which can able to extract discriminatory information from a face. This work has been proposed an efficient local descriptor called Local Ternary Tree Pattern (LTTP) which has the ability to identify the strength of a face through the structural pattern that it devises. This is very simple in
terms of computational complexity as well as time complexity. Further, the identification performance on unknown faces captured under complicated environments is found to be outstanding. With a single or look-alike representations of LTTP, any face identification system can achieve its superiority. This work also proposes a robust face identification framework using LTTP in its feature extraction phase to handle different real life situations.

1.3 Paper Organization

The rest of the paper is organized as follows: Section 2 describes the proposed Local Ternary Tree Pattern (LTTP). Section 3 presents the proposed face identification framework which uses Local Ternary Tree Pattern in its feature extraction phase. The experimental results are provided in the next section. Finally, a conclusion is drawn in the last section.

2 Local Ternary Tree Pattern (LTTP)

This section describes the tree like structure and mathematical formulation of the novel local descriptor called Local Ternary Tree Pattern (LTTP). The Local Ternary Tree Pattern is an efficient feature extraction approach which is used to represent the invariant local textures of a face image in the way of extracting structural components of a face image. Unlike LBP, the LTTP generates a ternary tree for each pixel of an image with its 8 neighbors and extracts four different patterns rather than generating a single pattern.

To extract the discriminatory information and structural components from a face image, an image \( I(P) \) of size \( h \times v \) is divided into a number of smaller sub regions with dimension \( h' \times v' \), where \( h' << h \) and \( v' << v \). Then LTTP operator is applied on each pixel of the gray scale face image and generates transformed value for each pixel. To determine the transformed value for a pixel, at first a ternary tree is formed for a pixel with its eight neighbors in a 3x3 region. Then binary labeling of edges is performed. During labeling of edges of the ternary tree of a pixel, the root node is compared with its child nodes and computes the difference between the root node and child nodes. If the difference is found positive or equal to 0, then assign 1 to the edge between the root node (source pixel) and child node (neighborhood pixel), otherwise assign 0 to that edge. Finally, binary labels (0 or 1) of edges of the ternary tree are concatenated together using four rules to form 8-bit binary pattern which is then converted to a decimal number and assigned to the target pixel. The four concatenation rules are: Left oriented-Depth First Traversal (LTTP-LD), Left oriented-Breadth First Traversal (LTTP-LB), Right oriented-Depth First Traversal (LTTP-RD), and Right oriented-Breadth First Traversal (LTTP-RB). A ternary tree for a target pixel 'A' is shown in Figure 1. To generate the LTTP-LD pattern, at first starts from root node, goes to the depth in left side then goes to depth in right side and one by one concatenate all eight labels of edges. According to Figure 1, the sequence of edges to generate LTTP-LD is AB, BE, AC, CF, CG, CH, AD, DI. To generate the LTTP-LB pattern, at first starts from root node, goes to breadth from left side to right side,
covers all levels of the tree and one by one concatenate all eight labels of edges. According to Figure 1, the sequence of edges to generate LTTP-LB is AB, AC, AD, BE, CF, CG, CH, DI. To generate the LTTP-RD pattern, at first starts from root node, goes to the depth in right side then goes to depth in left side and one by one concatenate all eight labels of edges. According to Figure 1, the sequence of edges to generate LTTP-RD is AD, DI, AC, CH, CG, CF, AB, BE. Lastly, to generate the LTTP-RB pattern, at first starts from root node, goes to breadth from right side to left side, covers all levels of the tree and one by one concatenate all eight labels of edges. According to Figure 1, the sequence of edges to generate LTTP-RB is AD, AC, AB, DI, CH, CG, CF, BE. The encoding scheme of LTTP considers the direct relationship of a target pixel with its neighbors as well as the relationship between the pixels that form the local ternary tree of the target pixel. This encoding scheme enables the LTTP to generate unique face representation and subsequently the improved identification performance.

Fig. 1. An Image Block with a Ternary Tree formation for a Target Pixel ‘A’.

To produce the decimal number by applying LTTP operator for a pixel \( I(P_t) \), a binomial weight \( 2^q \) is multiplied to each label of edges of the ternary tree and then all multiplied labeled values are added.

The LTTP code for a target pixel \( I(P_t) \) is given by

\[
LTTP(I(P_t)) = \sum_{q=0}^{L-1} f(P_r - P_c) \times 2^q \quad \text{where} \quad f(x) = \begin{cases} 1, & \text{if } x \geq 0 \\ 0, & \text{if } x < 0 \end{cases}
\]  

(1)

where \( P_r \) denotes the gray value of root node (source pixel) and \( P_c \) denotes the gray value of child node (neighboring pixel). In Equation (1), \( L \) is the total number of neighboring pixels of the target pixel. The pictorial representation of basic LTTP operator is shown in Figure 2.
3 Proposed Face Identification Framework

The aim of this paper is to present a robust face identification system which uses the proposed local descriptor – LTTP in its feature extraction phase to improve the overall performance of the system in multiple environments including unconstrained environments. The system consists of two main phases – feature extraction and classification. A block diagram of the proposed framework is shown in Figure 3.

3.1 Problem formulation

The face identification [13, 14] is a 1:N matching that assimilates a probe image with all templates of face images present in a face database to infer the identity of the probe face.
Suppose, a probe face image $I_p$ is considered for testing and a full set of gallery images $G$ is considered for training. The feature vector $F(I_p)$ is generated for a probe image $I_p$. Then the objective function of the proposed face identification system can be defined as:

$$f(I_p) = \min\{D(F(I_p), F(G_i))\} \text{ where } i=1,2,3,\ldots, N$$

(2)

Where $D(.)$ is the distance function used to measure the similarity between two feature vectors $F(I_p)$ and $F(G_i)$. $F(G_i)$ is the feature vector of $i^{th}$ gallery image.

### 3.2 Feature Extraction

The robust and discriminatory facial feature extraction is the key to the success of a face identification system. This phase transforms a raw face image into a transformed image and generates the feature vector. In this phase, the proposed Local Ternary Tree Pattern (LTTP) is applied on all pixels of a face image to generate the transformed image (TI) and finally, the feature vector is generated from the transformed image by flattening it. The proposed LTTP is capable to handle different challenges of a face image like changes in photometric condition, facial expression, head pose, facial accessories (makeup glasses etc.), imaging modality and unconstrained environment. An input face image and its transformed patterns generated using LTTP variants are shown in Figure 4.

Suppose, an input face image is $I(P)$ with size $h \times v$. After applying LTTP on each pixel of the input face image $I(P)$, a transformed image $I'(P)$ is generated with size $h \times v$. Then a feature vector is generated from $I(P)$ by flattening it and the size of the feature vector would be $1 \times hv$.

![Proposed Face Identification Framework](image)
3.3 Classification

The classification plays an important role in the proposed face identification system. Classification phase can be divided into two sub-phases such as matching and identity generation.

During matching, the template generated from a probe face image is compared with all templates produced from gallery face images and computes their similarity scores. The cosine similarity measure (CS) [11] and the sum of absolute differences (SAD) [4] are used to measure the similarity between the feature of the probe image and the feature of the gallery images.

During identity generation, the similarity scores produced by matching are used to generate a rank order list for each probe image. The gallery feature which has the maximum similarity to the probe feature is selected and the identity of the corresponding gallery image is considered as the identity of the probe image.

![Input Face Image and Transformed Images generated by Applying LTTP Operator.](image)

4 Experimental Evaluation

The proposed face identification system is evaluated on six most challenging face databases, namely, the UMIST [8], the extended Yale face B [17], the JAFFE [16], the Plastic Surgery [15], the LFW [6] and the UFI [9] databases. The experiments are conducted on 1:N matching strategy and Rank-1 identification accuracy is determined on six face databases. To generate probe set and gallery set, random partition is used in all databases during experiments. A brief description of six databases is listed in Table 1 and sample images of these databases are shown in Figure 5.
| Name of Database | No. of Subjects | Total no. of images | File format | Resolution | Description |
|------------------|----------------|---------------------|-------------|------------|-------------|
| JAFFE            | 10             | 213                 | .tiff       | 121x146    | Facial Expression variations |
| UMIST            | 20             | 564                 | .pgm        | 92x112     | Pose variations (profile to frontal) |
| Extended Yale face B | 38         | 2432                | .pgm        | 40x46      | Illumination variations |
| LFW              | 1680           | 13000               | .pgm        | 64x64      | Unconstrained face images |
| UFI              | 605            | 4910                | .pgm        | 128x128    | Unconstrained face images |
| Plastic Surgery  | 900            | 1800                | .jpg        | 238x273    | Post surgery variations |

Fig. 5. Sample Images from the UMIST [8], the JAFFE [16], the extended Yale face B [17], the Plastic Surgery [15], the LFW [6] and the UFI [9] Face Databases.

The experimental results are shown in Table 2. The identification accuracy \( IA \) is computed using Equation (2) and Equation (3). For a probe image \( I_p \), the Identification Accuracy \( IA \) of the proposed system is defined as

\[
IA = \left( \frac{1}{|M|} \sum_{i=1}^{M} \sum_{j=1}^{M} \Delta(\Phi(I_p), \Phi(G), R(I_p, G_j))) \right) \times 100 \tag{2}
\]

where \(|M|\) is the size of probe set, \(|N|\) is the size of the gallery, and \( \Delta(.) \) computes \( k \)th best match for the probe image \( I_p \) as
\[
\Delta(\Phi(I_p), \Phi(G_i), R(I_p, G_i)) = \begin{cases} 
1, & \text{if } \Phi(I_p) = \Phi(G_i) \text{ and } R(I_p, G_i) = k \\
0, & \text{else} 
\end{cases}
\]

\(\Phi(\cdot)\) is a function which returns the class of an image and \(R(I_p, G_i)\) returns the ranked position of a gallery image \(G_i\) with respect to the test image \(I_p\) from the probe set.

### 4.1 Experimental Evaluation on the UMIST face database

To evaluate the efficacy of the proposed descriptor LTTP in face identification framework, the UMIST [8] face database is used as subjects present in the database covers a range of poses from profile to frontal views. From the experimental outcome, it has been observed that the proposed LTTP as well as the face identification system perform satisfactory while handling pose variations of face images on the UMIST [8] face database. The experimental outcomes in terms of identification accuracy (IA) are shown in Table 2. In the framework, the LTTP has achieved 100% accuracy using cosine similarity (CS) and sum of absolute differences (SAD) at Rank-1 on the UMIST face database. The result reveals that the novel LTTP is not only robust to the frontal face images; it is also robust to the different pose variations of the face images which occur during our normal face movement.

### 4.2 Experimental Evaluation on the extended Yale face B database

To test the robustness of LTTP in abrupt illumination variations, the extended Yale face B database [17] is used in experimental evaluations. The experimental outcomes determined with LTTP are shown in Table 2. From the experimental outcome it can be seen that the proposed LTTP has achieved 100% accuracy at Rank-1 in face identification framework while cosine similarity (CS) and sum of absolute differences (SAD) classifiers are used. The experimental outcome proves that the LTTP is capable to handle effect of illumination variations on face images during identification procedure.

### 4.3 Experimental Evaluation on the JAFFE database

To test the effectiveness of the LTTP in facial expression variations, the JAFFE [16] database is used as the subjects present in this database covers 7 facial expressions (6 basic facial expressions and 1 neutral facial expression). The experimental outcomes determined from the JAFFE dataset are found to be encouraging and shown in Table 2. The proposed face identification system with LTTP has achieved 100% identification accuracy at Rank-1 while cosine similarity (CS) and sum of absolute differences (SAD) classifiers are used. The experimental outcomes reveal that the proposed LTTP could capture variations in facial appearance due to expression changes very efficiently.
4.4 Experimental Evaluation on the Plastic Surgery Face Database

The post-surgery variations on a face create a challenging situation for a face identification system. The Plastic Surgery face database [15] contains pre-surgery and post-surgery face images of 900 subjects. To test the effect of post-surgery variations in face identification system, the Plastic Surgery face database [15] is used for evaluation. The experimental outcomes are found to be exceptional. It is very difficult to capture invariant facial information from a post-surgery face images, but the experimental outcomes prove that the novel LTTP is also capable to capture post-surgery variations efficiently form a face image. The proposed face identification system has achieved 100% identification accuracy at Rank-1 using LTTP as a feature extractor and cosine similarity (CS) and sum of absolute differences (SAD) as classifiers. The experimental outcomes are shown in Table 2.

4.5 Experimental Evaluation on the LFW database

The performance of the face identification system falls abruptly in an unconstrained environment. The LFW [6] face database is mainly designed for studying the problem of unconstrained face recognition. During the experimental evaluation the LFW [6] database is used to address the unconstrained face recognition problem. The proposed face identification system has achieved 100% accuracy on the LFW face database using both the classifiers (cosine similarity and sum of absolute differences). The experimental outcomes reveal that the proposed LTTP also shows the robustness in unconstrained environment. The experimental results are shown in Table 2.

4.6 Experimental Evaluation on the UFI database

The UFI [9] is another unconstrained face database and mainly designed to be used for benchmarking of the face identification methods. When the proposed face identification system is tested on the UFI database, it has achieved 99.66% identification accuracy at Rank-1 while cosine similarity (CS) and sum of absolute differences (SAD) classifiers are used for classification. The experimental outcomes prove the robustness of the proposed local descriptor (LTTP) in unconstrained environments.

| Name of Databases         | LTTP-LD CS | LTTP-LD SAD | LTTP-LB CS | LTTP-LB SAD | LTTP-RD CS | LTTP-RD SAD | LTTP-RB CS | LTTP-RB SAD |
|---------------------------|------------|-------------|------------|-------------|------------|-------------|------------|-------------|
| UMIST                    | 100        | 100         | 100        | 100         | 100        | 100         | 100        | 100         |
| JAFFE                     | 100        | 100         | 100        | 100         | 100        | 100         | 100        | 100         |
| Extended YALE face B     | 100        | 100         | 100        | 100         | 100        | 100         | 100        | 100         |
| Plastic Surgery          | 100        | 100         | 100        | 100         | 100        | 100         | 100        | 100         |
| LFW                      | 100        | 100         | 100        | 100         | 100        | 100         | 100        | 100         |
| UFI                      | 99.66      | 99.66       | 99.66      | 99.66       | 99.66      | 99.66       | 99.66      | 99.66       |


5 Conclusion and Future Works

This paper has presented a groundbreaking work on face identification which has used a novel local descriptor (LTTP) for facial feature extraction. The proposed descriptor LTTP as well as the face identification system have validated through variety of face images captured under extensive experiments including plastic surgery faces. The LTTP is a ternary tree based local descriptor where a pixel is represented by a ternary tree with its eight neighbors. Then using a thresholding rule a binary pattern is generated for the target pixel. The experiments illustrated that the use of LTTP in feature extraction phase of the face identification system has enabled it with greater discriminative power. The proposed LTTP is more robust than other local descriptors because its ternary tree structure is able to capture more discriminatory information from a face. The LTTP descriptor might have a huge impact if it is used for sustainable facial recognition systems. However, a few more tests on vibrant databases such as low resolution as well as heterogeneous face images will establish its usefulness as an unconquerable feature representation tool.

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