A Robust and Dominant Local Binary Pattern and Its Application

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Abstract— Facial image analysis is a main challenge of image processing. Some techniques like Local Binary Pattern, Local ternary Pattern, modified LBP (MLBP),BRINT and extended LBP which can be used in image processing to overcome the challenge. Moreover in recent years interested area is image processing and computer vision and its has been shown in many application with seffiectively like facial image analysis, including tasks as diverse as face detection, face recognition and facial expression analysis. LBP is non-parametric descriptor for summarizes the local structure of imges. LTP classified the pain states from facial expression. CS-LBP are similar to LBP but it plays good to robustness in flat image. BRINT is used to build very fast, very compact while remaining robust to illumination variations, rotation changes and noise. So using all this technique facial analysis is better than other techniques through recent techniques.

Key words: Binary Rotation Invariant and Noise Tolerant, Local Binary Pattern, Local ternary Pattern, Modified Local Binary Pattern and Soft Local Binary Pattern

I. INTRODUCTION

Local binary patterns (LBPs) [1] have aroused increasing interest in image processing and computer vision. As a nonparametric method, LBP summarizes local structures of images efficiently by comparing each pixel with its neighboring pixels. The most important properties of LBP are its tolerance regarding monotonic illumination changes and its computational simplicity. LBP was originally proposed for texture analysis [2], and has proved a simple yet powerful approach to describe local structures. It has been extensively exploited in many applications, for instance, face image analysis [3], [4], image and video retrieval [5], [6], environment modeling [7], [8], visual inspection [9], [10], motion analysis [11], [12], biomedical and aerial image analysis [13], [14], and remote sensing [15] (see a comprehensive bibliography of LBP methodology online [16]). LBP-based facial image analysis has been one of the most popular and successful applications in recent years. Facial image analysis is an active research topic in computer vision, with a wide range of important applications, e.g., human–computer interaction, biometric identification, surveillance and security, and computer animation. LBP has been exploited for facial representation in different tasks, which include face detection[4], [17]–[19], face recognition facial [1] expression analysis ,demographic (gender, race, age, etc.) classification and other related applications. The development of LBP methodology can be well illustrated in facial image analysis, and most of its recent variations are proposed in this area. Some brief surveys on image analysis or face analysis which use LBP, were given, but all these studies[1] discussed limited papers of the literature, and many new related methods have appeared in more recent years. In this paper, we present a comprehensive survey of the LBP methodology, including its recent variations and LBP-based feature selection, as well as the application to facial image analysis. To the best of our knowledge, this paper is the first survey that extensively reviews LBP methodology and its application to facial image analysis, with more than 100 related reviewed literatures. The remainder of this paper is organized as follows. The LBP methodology is introduced in presents the recent variations of LBP. LBP-based feature-selection methods are discussed in describes different facets of its applications on facial image analysis. Section II describes about LBP,Section III describes about recent variations of Local Binary pattern, Section IV describes about local-binary-pattern feature selection,Section V describes about local-binary-pattern-based facial image analysis and finally Section VI is conclusion.

II. LOCAL BINARY PATTERNS

The original LBP operator labels the pixels of an image with decimal numbers, which are called LBPs or LBP codes that encode the local structure around each pixel. It proceeds thus, as illustrated in Fig. 1: Each pixel is compared with its eight neighbors in a 3 × 3 neighborhood by subtracting the center pixel value; the resulting strictly negative values are encoded with 0, and the others with 1. For each given pixel, a binary number is obtained by concatenating all these binary values in a clockwise direction, which starts from the one of its top-left neighbor. The corresponding decimal value of the generated binary number is then used for labeling the given pixel. The derived binary numbers are referred to be the LBPs or LBP codes. One limitation of the basic LBP operator is that its small 3 × 3 neighborhood cannot capture dominant features with large-scale structures. To deal with the texture at different scales, the operator was later generalized to use neighborhoods of different sizes [1]. A local neighborhood is defined as a set of sampling points evenly spaced on a circle, which is centered at the pixel to be labeled, and the sampling points that do not fall.

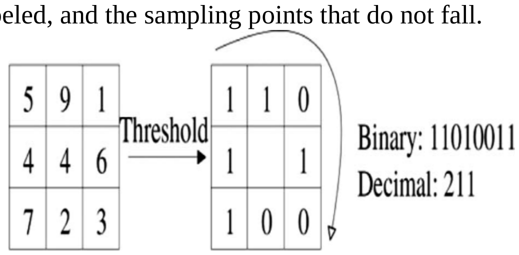

Fig. 1: Example of the basic LBP operator [1].

Within the pixels are interpolated using bilinear interpolation, thus allowing for any radius and any number of sampling points in the neighborhood. Fig. 2 shows some examples of the extended LBP (ELBP) operator, where the notation (P, R) denotes a neighborhood of P sampling points on a circle of radius of R.

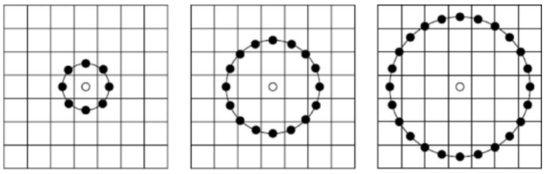

Fig. 2: Examples of the ELBP operator [1].

The circular (8,1), (16,2), and (24,3) neighborhoods. Next the recent variations of Local Binary pattern is discussed in Section III.

III. RECENT VARIATIONS OF LOCAL BINARY PATTERN

LBP methodology has been developed recently with large number of variations for improved performance in different applications. These variations focus on different aspects of the original LBP operator: 1) improvement of its discriminative capability; 2) enhancement of its robustness; 3) selection of its neighborhood; 4) extension to 3-D data; and 5) combination with other approaches. In this section, we review recent variations of LBP.

A. *Enhancing The Discriminative Capability:*

The LBP operator defines a certain number of patterns to describe the local structures. To enhance their discriminative capability, more patterns or information could be encoded. Jin *et al.* [17] modified the LBP operator to describe more local structure information under certain circumstances. Specifically, they proposed an improved LBP (ILBP), which compares all the pixels (including the central pixel) with the mean intensity of all the pixels in the patch (as shown in Fig. 3). For instance, the LBP(8,1) operator produces only 256 (2^8) patterns in a 3 × 3 neighborhood, while ILBP has 511 patterns ($2^9 - 1$, as all zeros and all ones are the same). Later, ILBP was extended to use the neighborhoods of any size instead of the original 3 ×3 patch [7]. Almost at the same time, a similar scheme was used to extend CT to modified CT [4], namely, modified LBP (MLBP) in [1] A mean LBP [1] is presented, which is similar to ILBP, but without considering the central pixels.

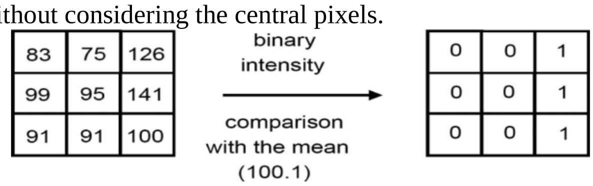

Fig. 3: Example of the ILBP

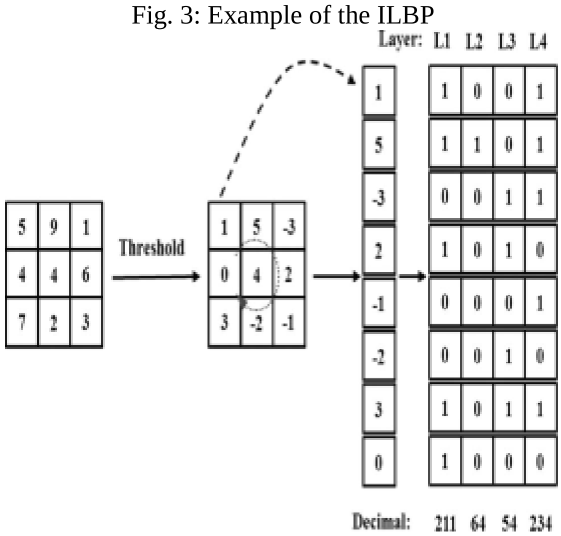

Fig. 4: Example of the ELBP operator

B. *Improving The Robustness:*

LBP is sensitive to noise, since the operator thresholds exactly at the value of central pixel. To address this problem, Tan and Triggs [21] extended the original LBP to a version with 3-value codes, which is called local ternary patterns (LTPs). The LTP codes are more resistant to noise, but no longer strictly invariant to gray-level transformations. A coding scheme is used to split each ternary pattern into two parts: the positive one and the negative one, as illustrated in Fig. 5. One problem of LTP is to set threshold *t*, which is not simple.

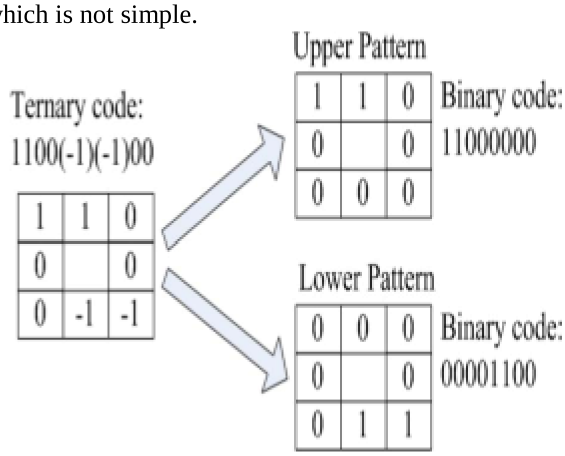

Fig. 5: Example of the LTP operator

The soft LBP (SLBP) was introduced in [4], which employs two fuzzy membership functionsWith SLBP, one pixel contributes to more than one bin, but the sum of the contributions of the pixel to all bins is always 1. SLBP enhances the robustness in the sense that a small change in the input image causes only a small change in output. However, it loses the invariance to monotonic variations, aswell as increases the computation complexity. As with LTP, a proper value of *d* should be set.

IV. LOCAL-BINARY-PATTERN FEATURE SELECTION

In most existing work, the input image is divided into small regions, from which LBP histograms are extracted, and the local histograms are further concatenated into a spatially enhancedfeature vector of the dimensionality of O (10^3). Moreover, some recent variations even increase the feature vector length dramatically, such as ELBP, VLBP, and Gabor-wavelets-based LBP. It is believed that the derived LBP-based feature vector provides an overcomplete representation with redundant information [7], which could be reduced to be more compact and discriminative. Furthermore, when building real-time systems, it is also desired to have LBP-based representation with reduced feature length. For all the reasons, the problem of LBP feature selection has recently been addressed in many literatures. We classify these techniques into two categories: The first one is to reduce the feature length based on some rules (like uniform patterns), while the other one exploits feature-selection techniques to choose the discriminative patterns. Both streams have their own merits and drawbacks: the first one is simple, but has limited feature selection ability; on the contrary, the second one has a better feature-selection capacity, but usually requires offline training that could be computationally expensive.

V. LOCAL-BINARY-PATTERN-BASED FACIAL IMAGE ANALYSIS

Machine-based face recognition involves two crucial aspects, i.e., facial representation [3], and classifier design [1] Facial representation consists in deriving a set of relevant features from original images to describe faces, in order to facilitate effective machine-based recognition. "Good" facial features are desired to have the following properties [4]: First, they can tolerate within-class variations, while discriminate different classes well; second, they can be easily extracted from the raw images to allow fast processing; finally, they lie in a space with low dimensionality to avoid computationally expensive classifiers. Since it was introduced for face representation [3], LBP has proved to be an efficient descriptor for facial image analysis, as it fulfills the aforementioned criteria quite well, and recent years have witnessed increasing interest in LBP features for facial representation. In this section, we first present the LBP-based facial description, and then review existing studies on different tasks, including face detection, face recognition, facial expression analysis, demographic classification, and other applications.

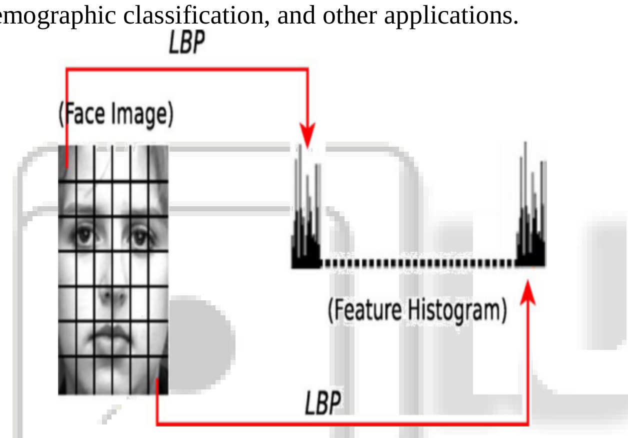

Fig .6: LBP-based face description

A. *Local-Binary-Pattern-Based Face Description:*

A face image can be considered as a composition of the micropatterns described by LBP. One can build an LBP histogram computed over the whole-face image. However, such a representation only encodes the occurrences of micropatterns without any indication about their locations. In addition, to consider the shape information of faces, Ahonen *et al*. [3] proposed to divide face images into *m* local regions, from which local LBP histograms can be extracted, and then to concatenate them into a single, spatially enhanced feature histogram (as shown in Fig. 7). The resulting histogram encodes both the local texture and global shape of face images. Most of the existing studies adopt the aforementioned scheme to extract LBP features for facial representation. However

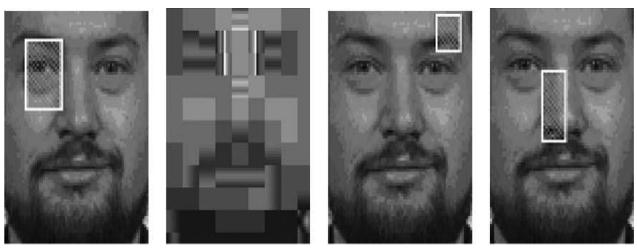

Fig. 7: Top four selected subregions

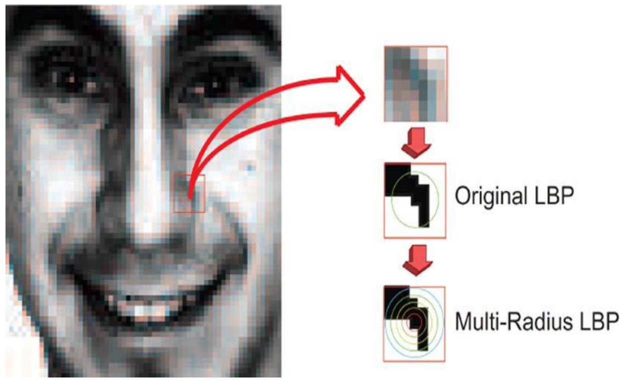

Fig. 8: Evolvement from the LBP to multi-radius LBP

Dividing face images into a grid of subregions is somewhat arbitrary, and the subregions are not necessarily well aligned with facial features. Moreover, the resulting facial description depends on the chosen size and the positions of these subregions. To address this issue, in [1] and [3], many more subregions are obtained by shifting and scaling a subwindow over the face images, and boost learning [1] is adopted to select the most discriminative subregions in terms of LBP histograms (as shown in Fig. 8).

B. *Face Detection:*

The purpose of face detection is to determine the locations and sizes of human faces in digital images. Hadid *et al*. [4] first used LBP for face detection. To describe low-resolution faces, a four-neighborhood LBP operator LBP(4,1) was applied to overlapping small regions. The support vector machine (SVM) classifier was adopted to discriminate faces from nonfaces. To compare with the state-of-the-art methods, they performed their experiments on the MIT-CMUdataset, and the proposed method detected 221 faces without any false positives. Later, they [1] proposed a hybrid method to address face detection under unconstrained environments. Their method first searched for the potential skin regions in an input image to avoid scanning the entire image, as was done in [1]. Then, a coarse-to-fine strategy is employed to determine whether the scanned regions are faces or not: In the coarse stage, LBP feature vector extracted from the whole region is utilized as the input to a polynomial SVM; patterns that are not rejected by the first SVM classifier are further analyzed by the second finer one whose inputs are extracted from overlapped blocks inside the region. The detection rate reported is 93.4% with 13 false positives.

C. *Face Recognition:*

Face recognition aims to identify or verify a person from a digital image or a video sequence. Ahonen *et al.* [3] introduced LBP in face recognition with nearest neighbor (NN) classifier and chi-square distance as the dissimilarity measure. The experimental results showed that their approach outperforms the PCA, the elastic bunch graph matching (EBGM), and the Bayesian intra-/extrapersonal classifier on all four probe sets of the FERET database. They later investigated whether these good results are due to the use of local regions or the discriminative capacity of LBP methodology [1]. Based on the comparisons with three other texture descriptors extracting features from the same local patches, the strength of LBP to represent faces was clearly confirmed. In [4], face recognition experimentswere also carried out on the MoBo database, which is quite challenging, since the images are in low resolution. As mentioned earlier, AdaBoost later was applied to select a few of the most effective LBP-based features for face recognition [1]. Compared with the approach in [3], the boosting LBP-based method achieves a slightly better recognition rate, while using fewer LBP features.

D. Facial Expression Analysis:

Machine-based facial expression recognition aims to recognize facial affect states automatically, and may depend on both audio and visual clues [1]. In this paper, we focus our attention on studies purely based on visual information, which use facial motion or facial features [1]. Most of these studies only consider the prototypical emotional states, which include seven basic universal categories, namely, neutral, anger, disgust, fear, happiness, sadness, and surprise. [1] exploited a coarse-to-fine classification scheme with LBP for facial expression recognition by making use of images. More precisely, at the coarse stage, a seven-class problem was first reduced to a two-class one, while at fine stage, a *k*-NN classifier performed the final decision. Their approach produced 77% average recognition accuracy on JAFFE dataset. In paper [1]with the same facial description, a linear programming technique was applied for expression classification. A seven-class problem was decomposed into 21 binary classifications by using the one-against-one scheme.With this method, they obtained over 90% accuracy both on the JAFFE database and some real videos. It [1] also investigated LBP for facial expression recognition. The template matching with weighted chi-square statistics and SVM were adopted to classify the basic prototypical facial expressions, and the best performance obtained on the Cohn–Kanade Database reached 88.4% by using SVM.

E. Face Analysis Systems:

Advantages of LBP make it very attractive to build real-time face analysis systems. Furthermore, related hardware designed for high-speed LBP computation [1] also boosts the development of LBP-based real-world applications. hun et al [1]. built an access control system by using LBP based face recognition [1]. In their system, a camera was set on a door to capture video frames; LBP features were extracted for both background subtraction and face recognition. The face detection approach in [1] was adopted for face detection in color images, and the face recognition method in [3] was applied for person identification. The face recognition accuracy of 71.6% was obtained on 20 video sequences of ten subjects. In hun et al [1] presented a system to detect multiple faces in video sequences, where faces are not limited to frontal views. An adaptive selection approach from two skin models in RGB and ratio RGB spaces is used to overcome the illumination problem by automatic focus of the camera. The experimental result of 93% accuracy was reported on the NRC-IIT database, which consists of 23 single-face video sequences of 11 persons with different poses. The system runs at 2.57 f/s for image sequences of 320 × 240 pixels on a standard PC (Pentium 4, 2.6-GHz, 512-MB RAM) in the Visual C++ environment. Based on the LBP features extracted from NIR faces, [1], designed an illumination-invariant face recognition system for cooperative users in an indoor situation. AdaBoost was used to learn Haar features for face detection and eye detection, and to select LBP features for face recognition. All three parts achieve outstanding results with low cost on a large dataset. The system can operate in real time with an EER below 0.3%. hun et al [1] introduced a portable face recognition system, which is deployed on a laptop using a standard webcam for image acquisition. On the basis of the relevant regions determine by skin color, the two eyes were first detected with a cascade AdaBoost classifier of Haar features. These were then used to register face images. LBP was used to preprocess facial regions to reduce illumination influences. Their system was evaluated on a small dataset consisting of 42 sequences from 14 subjects, and produced 79% accuracy.

VI. CONCLUSION

LBP is one of the most powerful descriptors to represent local structures. Due to its advantages, i.e., its tolerance of monotonic illumination changes and its computational simplicity, LBP has been successfully used for many different image analysis tasks, such as facial image analysis, biomedical image analysis, aerial image analysis, motion analysis, and image and video retrieval. During the development of LBP methodology, a large number of variations are designed to expand the scope of application, which offer better performance as well as improve the robustness in one or more aspects of the original LBP. ILBP, Hamming LBP, and ELBP enhance the discriminative ability of LBP; LTP and SLBP focus on improving the robustness of LBP on noisy images; MB-LBP, elongated LBP, change the scale of LBP to provide other categories of local information; Gabor-wavelet-based LBP, CS-LBP, and LBP-HF combine other methods with LBP to bring in new merits. However, the earlier extensions only operate on traditional 2-D data; the variant LBP should be highlighted, since both of them expand the scope of LBP applications: 3-D LBP extends the LBP operator to describe 3-D volume data, while LBP endows LBP with the ability to capture dynamic information. To obtain a small set of the most discriminative LBP-based features for better performance and dimensionality reduction, LBP-based representations are associated with some popular techniques of feature-selection schemes to reduce the feature length of LBP codes, which contain rule-based strategy, boosting and subspace learning, etc. As the most typical and important application of LBP, facial image analysis provides a very good demonstration of the use, development, and performance of LBP. From this comprehensive overview, following conclusions can be drawn: 1) local- or component-oriented LBP representations are effective representations for facial image analysis, as they encode the information of facial configuration while providing local structure patterns; and 2) using the local- or component-oriented LBP facial representations, feature selection is particularly important for various tasks in facial image analysis, since this facial description scheme greatly increases the feature length. Meanwhile, similar to most of the texture-based techniques, LBP is sensitive to severe lighting changes, and to blurred andnoisy images [1]. The former case can be regarded as nonmonotonic lighting variations, which normally occur in facial images due to 3-D facial volume structures, thereby leading to nonmonotonic transformations, e.g., shadows and bright spots can typically occur and change their positions depending on lighting directions. While the latter case is often caused by thebad quality of camera sensors and poor user cooperation of capture condition, etc. As a result, in such environments, it is necessary and useful to preprocess the images before applying LBP. In addition, some open questions for subregion-based LBP description, e.g., facial description, concern the relevant number of components and the corresponding neighborhood of a certain LBP operator for the best analysis result. Although these questions have been discussed in several papers, and even with machine-learning techniques, these conclusions drawn so far have always been dependent on the used databases and some given parameters.

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