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Local feature extraction based facial emotion recognition: A survey

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ABSTRACT

Notwithstanding the recent technological advancement, the identification of facial and emotional expressions is still one of the greatest challenges scientists have ever faced. Generally, the human face is identified as a composition made up of textures arranged in micro-patterns. Currently, there has been a tremendous increase in the use of Local Binary Pattern based texture algorithms which have invariably been identified to being essential in the completion of a variety of tasks and in the extraction of essential attributes from an image. Over the years, lots of LBP variants have been literally reviewed. However, what is left is a thorough and comprehensive analysis of their independent performance. This research work aims at filling this gap by performing a large-scale performance evaluation of 46 recent state-of-the-art LBP variants for facial expression recognition. Extensive experimental results on the well-known challenging and benchmark KDEF, JAFFE, CK and MUG databases taken under different facial expression conditions, indicate that a number of evaluated state-of-the-art LBP-like methods achieve promising results, which are better or competitive than several recent state-of-the-art facial recognition systems. Recognition rates of 100%, 98.57%, 95.92% and 100% have been reached for CK, JAFFE, KDEF and MUG databases, respectively.

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1. INTRODUCTION

With the development of artificial intelligence and pattern recognition, computer based facial expression recognition has attracted many researchers in the domain of computer vision. Several studies have shown that the facial expression contributes to better understand the conversations [1, 2], and it helps to express the individual's internal emotions, also, it is considered as the main modality for human communication.
Recent progresses in psychology and neuroscience fields give a more positive interpretation of the emotions role in human behavior [3]. The facial emotion recognition system resides of three important steps; face detection, feature extraction and classification. By taking image or series of images as input, the most important step is feature extraction that allows to describe the input images and calculate their characteristic vector using a given operator. Indeed, extracting poor features involves producing poor recognition quality even with the use of best classifiers. Because of the exceptional exhibition of LBP based techniques, they have developed as one of the most unmistakable local image descriptors. Although initially intended for texture analysis [4], the LBP descriptor has given excellent outcomes in different applications because of its invariance to monotonic global graylevel changes, furthermore, its better resistance against brightening changes property in real-world

applications including face recognition. Another equally important property is its computational effortlessness and the low length of its histogram vector, which make it ready to examine images in challenging real-time settings. The achievement of the LBP in numerous applications conceived an offspring of an immense number of LBP variations, which have been proposed and keep on being proposed. Without a doubt, since Ojala's work [4] and because of its adaptability and effectiveness, the general LBP-like way of thinking has demonstrated extremely well known, and an extraordinary assortment of LBP variations have been proposed in the writing to improve discriminative power, robustness, and appropriateness of LBP. The main objective of this study is to perform a large scale performance evaluation for facial emotion recognition, assessing 46 recent state-of-the-art texture features, on four widely-used benchmark databases. Performance of the adopted facial expression recognition system coupled with the best evaluated texture descriptor on each dataset is compared against those of state-of-the-art approaches. We disclose in the experimental section the fact that some descriptors originally proposed for applications other than facial emotional recognition allow outperforming several recent state-of-the-art systems. The remaining sections of this research work are arranged in the following way: Section 2. reviews the traditional LBP operator as well as some of its recent and popular variants. Section 3. reviews the few existing surveys on texture descriptor based classification and recognition as well as the evaluated state-of-the art LBP-like methods. Section 4. provides detailed explanation on the results of the experiments while comparing the performances of the best performing descriptors on each tested datasets with those of recent state-of-the-art facial emotional recognition systems. Finally, section 5. draw this paper to a close by proposing some future research perspectives.

2. BRIEF REVIEW OF EXISTING METHODS

The original Local Binary Pattern (LBP) operator proposed by Ojala et al [4] , which consists in coding the pixel-wise information in an image, is a powerful texture analysis descriptor. It aims to search micro-textons in local regions. The value $\mathbf{I}_p$ of the pixels in a 3×3 grayscale image patch around the central pixel $\mathbf{I}_c$ are turned into binary values (0 or 1) by comparing them with $\mathbf{I}_c$ (value of the central pixel). The obtained binary numbers are encoded to characterize a local structure pattern and then the code is transformed into decimal number. Once a LBP code of each pixel is obtained, a histogram is built to represent the texture image. For a 3×3 neighborhood, the definition of the kernel function of LBP operator is given in (cf. Eq (1)), where $\mathbf{I}_p$ (p $\in \{1, 2, ..., \mathrm{P}\}$) signifies the gray levels of the peripheral pixels, P corresponds to the number of neighboring pixels (P=8) and $\varphi(\cdot)$ is the Heaviside step function (cf. Eq (1)).

$$\mathbf{LBP}(\mathbf{I_c}) = \sum_{\mathbf{p=1}}^{\mathbf{P=8}} \varphi\left(\mathbf{I_p} - \mathbf{I_c}\right) \times \mathbf{2^{p-1}}, \quad \varphi\left(\mathbf{z}\right) = \begin{cases} 1 \ , \ \mathbf{z} \geq 0 \\ 0 \ , \ \mathbf{z} < 0 \end{cases} \tag{1}$$

Local binary patterns by neighborhoods (nLBPd) operator [5] consists in encoding the relationship between each pair of the peripheral pixels $\mathbf{I}_0$, $\mathbf{I}_1$, $\mathbf{I}_2$, ...,$\mathbf{I}_7$ around the central pixel $\mathbf{I}_c$ in a 3×3 square neighborhood. The pairs of pixels are compared with sequential neighbors or within neighbors possesing a distance length d. The kernel function of *nLBPd* code is defined by (cf. Eq. (2)). When d=1, the binary code of the central pixel $\mathbf{I}_c$ is gotten as below (Eq. (3)):

$$\mathrm{nLBP}_d(\mathbf{I_c}) = \sum_{p=0}^{P-1} \varphi(\mathbf{I_p}, \mathbf{I_{(p+d \ \mathrm{mod} \ P)}}) \times 2^p \tag{2}$$

$$\mathbf{I}_c = \varphi(\mathbf{I}_0 > \mathbf{I}_1), \varphi(\mathbf{I}_1 > \mathbf{I}_2), \varphi(\mathbf{I}_2 > \mathbf{I}_3), \varphi(\mathbf{I}_3 > \mathbf{I}_4), \varphi(\mathbf{I}_4 > \mathbf{I}_5), \varphi(\mathbf{I}_5 > \mathbf{I}_6), \varphi(\mathbf{I}_6 > \mathbf{I}_7), \varphi(\mathbf{I}_7 > \mathbf{I}_8) \tag{3}$$

The procedure of Local Graph Structure (LGS) descriptor introduced by Abusham et al. [6] is to exploit the dominant graph process in order to encode the spatial data for any pixel in the image. LGS is based on local graph structures in local graph neighborhood. The graph structure of LGS represents more left-handed neighbor pixels than right-handed ones. To overcome this defect, Extended Local Graph Structure (ELGS) operator is proposed [7]. The procedure for ELGS is based on using the LGS texture descriptor to build two descriptions (horizontally and vertically) and then combine them into a global description.

3. EVALUATED STATE-OF-THE-ART LBP VARIANTS

The pioneering LBP work [4] and its success in numerous computer vision problems and applications has inspired the development of great number of new powerful LBP variants. LBP descriptor is adaptable to suit in many different applications requirements. Indeed, after Ojala's work, e.g., Heikkila et al [8], several modifications and extensions of LBP have been developed with the aim to increase its robustness and discriminative power. These extensions and modifications of LBP, developed usually in conjunction with their intended applications (see Table 1), focus on several aspects of the LBP method such as, Quantization to multiple level via thresholding; sampeling local feature vectors and pixel patterns with some neighborhood topology; combining multiple complementary features within LBP-like and with non-LBP descriptors for both images and videos and finally, regrouping and merging patterns to increase distinctiveness.

Table 1. Summary of texture descriptors tested.

Ref	Year	Complete name	Abbreviation	Application
[4]	2002	Local Binary Pattern	LBP	Texture classification
[9]	2003	Simplified Texture Unit +	STU+	Texture classification
[10]	2004	Gradient texture unit coding	GTUC	Texture classification
[11]	2005	Difference Symmetric Local Graph Structure	DSLGS	Finger vein recognition
[8]	2006	Center-Symmetric Local Binary Patterns	CSLBP	Texture classification
[12]	2008	Centralized Binary Pattern	CBP	Facial expression recognition
[13]	2010	Local Ternary Patterns	LTP	Face recognition
[14]	2010	Directional Binary Code	DBC	Face recognition
[15]	2010	Improved Local Ternary Patterns	ILTP	Medical image analysis
[16]	2010	Local Directional Pattern	LDP	Face recognition
[17]	2011	Binary Gradient Contours (1)	BGC1	Texture classification
[17]	2011	Binary Gradient Contours (2)	BGC2	Texture classification
[17]	2011	Binary Gradient Contours (3)	BGC3	Texture classification
[18]	2011	Center-Symmetric Local Ternary Patterns	CSLTP	Feature description
[18]	2011	Extended Center-Symmetric Local Ternary Patterns	eCSLTP	Image retrieval
[19]	2011	Improved Local Binary Patterns	ILBP	Face detection
[6]	2011	Local Graph Structure	LGS	Face recognition
[20]	2012	Local Maximum Edge Binary Patterns	LMEBP	Image retrieval
[16]	2013	Improved binary gradient contours (1)	IBGC1	Texture classification
[21]	2013	Local Directional Number Pattern	LDN	Face expression analysis
[22]	2013	Local Gray Code Pattern	LGCP	Face expression analysis
[23]	2013	Rotated Local Binary Pattern	RLBP	Texture classification
[24]	2015	Adaptive Extended Local Ternary Pattern	AELTP	Texture classification
[5]	2015	Directional Local Binary Patterns	dLBPα	Texture classification
[5]	2015	Local Binary Patterns by neighborhoods	nLBPd	Texture classification
[25]	2015	Maximum Edge Position Octal Pattern	MMEPOP	Image retrieval
[26]	2015	Multi-Orientation Weighted Symmetric Local Graph Structure	MOW-SLGS	Finger vein recognition
[27]	2015	Orthogonal Symmetric Local Ternary Pattern	OSLTP	Image region description
[26]	2015	Symmetric Local Graph Structure	SLGS	Finger vein recognition
[28]	2015	eXtended Center-Symmetric Local Binary Pattern	XCS_LBP	Texture classification
[29]	2016	Adaptive Local Ternary Patterns	ALTP	Face recognition
[29]	2016	Center-Symmetric ALTP	CSALTP	Face recognition
[30]	2016	Diagonal Direction Binary Pattern	DDBP	Face recognition
[7]	2016	Extended Local Graph Structure	ELGS	Texture classification
[31]	2016	Local Extreme Sign Trio Patterns	LESTP	Image retrieval
[32]	2016	Quad Binary Pattern	QBP	Target tracking
[31]	2016	Sign Maximum Edge Position Octal Pattern	SMEPOP	Image retrieval
[33]	2016	Complete Eight Local Directional Patterns	CELDP	Face recognition
[34]	2017	Centre Symmetric Quadruple Pattern	CSQP	Facial image recognition and retrieval
[35]	2017	Local Directional Binary Patterns	LDBP	Texture classification
[36]	2017	Local neighborhood difference pattern	LNDP	Natural and texture image retrieval
[37]	2017	Local Quadruple Pattern	LQPAT	Facial image recognition and retrieval
[38]	2018	Local Diagonal Extrema Number Pattern	LDENP	Face recognition
[39]	2018	Local Concave-and-Convex Micro-Structure Patterns	LCCMSP	Texture classification
[40]	2018	Local Directional Ternary Pattern	LDTP	Texture classification
[41]	2018	Repulsive-and-Attractive Local Binary Gradient Contours	RALBGC	Texture classification

There are several researches reported in the literature that are devoted to surveying LBP and its variants. One can cite:

(a) Hadid et al. [42] reviewed 13 LBP variants and provided a comparative analysis on two different problems which are gender and texture classification.

(b) The work of Fernandez et al. [43] attempted to build a general framework for texture examination that the authors refer to as histograms of equivalent patterns (HEP). A set of 38 LBP variants and non LBP strategies are executed and experimentally assessed on eleven texture datasets.

(c) Huang et al. [44] displayed a survey of LBP variants in the application region of facial image processing. However, there is no experimental study of the LBP strategies themselves.

(d) Nanni et al. [45] examined the performance of LBP based texture descriptors in a fairly specific and narrow application, which consists in classifying cell and tissue images of five datasets.

(e) Michael Bereta et al. [46] highlighted many types of local descriptors including local binary patterns and their combination with Gabor filters. They examined only 14 LBP variants on FERET database.

(f) Lumini et al. [47] evaluated the effectiveness of LBP, HOG, POEM, MBC, HASC, GOLD, RICLBP, and CLBP descriptors. Each of these feature extraction methods is carried out only on two datasets: FERET and the Labeled Faces in the Wild (LFW).

(g) Liu et al. [48] provided a systematic review of LBP variants while regrouping them into different categories. 40 texture features including thirty two LBP-like descriptors and eight non-LBP methods are evaluated and compared on thirteen texture datasets.

(h) Slimani et al. [49] reviewed the performance of 22 state-of-the-art LBP-like descriptors and some of its recent variations and provides a comparative analysis on facial expression recognition problem using two benchmark databases.

It can be inferred that there is a limited number of state-of-the-art published works which are devoted to survey LBP-like methods in texture and face recognition and in particular facial emotion recognition which is practically nonexistent. Note that, most of these works remain limited in terms of number of LBP-like descriptors reviewed and tested datasets, suffer from lack of recent LBP variants and some of them do not include experimental evaluation. Since no broad assessment has been performed on an incredible number of LBP variations, and considering recent rapid increase in the number of publications on LBP-like descriptors, this paper aims to provide such a comparative study in facial emotion recognition problem and offers a more up-to-date introduction to the area. For that, 46 recent state-of-the-art LBP variants are evaluated and compared over four challenging representative widely-used facial expression databases. The performance of the best texture descriptor on each dataset is also composed to those of state-of-the-art facial emotion recognition systems. Note that for the descriptors, we utilized the original source code if it is freely accessible; otherwise we have built up our own implementation. The evaluated state-of-the-art texture descriptors and their intended applications are summarized in Table 1.

4. EXPERIMENTAL RESULTS AND DISCUSSION

In this section, the state-of-the-art LBP variants summarized in Table 1 are extensively evaluated and compared over four publicly available facial expression datasets (see section 4.2.). In addition, performance of the best performing method on each dataset has been compared against those of recent state-of-the-art facial emotion recognition systems. The following subsections describe: 1) the experimental configuration; 2) the datasets considered in the experiments, 3) the obtained results and 4) comparisons with other existing approaches.

4.1. Experimental configuration

In order to systematically evaluate the performance of the tested methods, we setup a comparative analysis through a supervised image classification task. Similar to most state-of-the-art facial expression recognition systems, the adopted system, shown in Figure 1, involves several steps including 1) image processing to alter and resize faces to have a common resolution; 2) feature extraction using the evaluated LBP variants; 3) histogram vector calculation. In this step, in order to incorporate more spatial information into the final feature vectors, the obtained feature images were spatially divided into multiple non-overlapping regions and histograms were extracted from each region. For example, the LBP code map is divided into m×n non-overlapping sub-regions, from each of which a sub-histogram feature is extracted and is normalized to sum one. By concatenating these regional sub-histograms into a single vector, a final LBP based facial emotion representation is obtained; and 4) image classification using the SVM classifier. In this step, the images of each dataset are preliminarily divided into a random split containing two sub-sets, one for the training and the other for testing. In the experiments, we tackled the 7-expression classification problems and overall results are computed as the average of the per-class accuracies and not the average accuracy of all samples, which avoids biasing toward expressions with more samples in the databases.

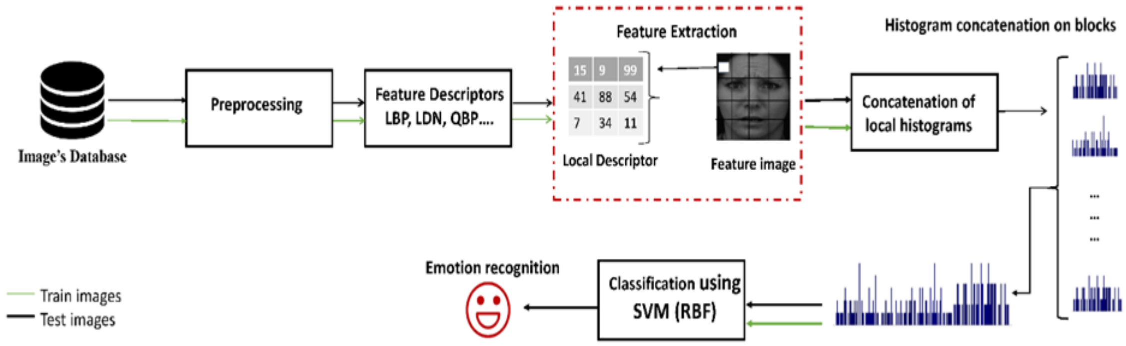

Figure 1. Outline of the adopted facial emotion recognition system.

4.2. Tested datasets

In our experiments, we used four benchmark databases; the Cohn Kanade (CK), the Japanese Female Facial Expression (JAFFE), the Karolinska Directed Emotional Faces (KDEF) and the Multimedia Understanding Group (MUG) databases. The main characteristics of each database are described herein below. The four datasets include facial expressions of six basic emotions; Anger, Disgust, Fear, Happiness, Sadness, Surprise and the neutral facial expression.

(a) The JAFFE database [50] contains 213 facial expression images from 10 Japanese females where every subject expresses three times the seven facial expressions. The images have a resolution of 256x256 pixels.

(b) The CK database [51] includes 2105 digitized image sequences (video) from 182 adults ranging from 18 to 30 years old. Each image has a resolution of 640x490 pixels with eight-bit accuracy for gray scale values.

(c) The KDEF dataset [52] contains two sessions of multi-view posed facial expression images from 70 amateur actors, with age ranging from 20 to 30 years old. The database has totally 4900 2D images of seven human facial expressions of emotions. The images have a resolution of 562x762 pixels, and each of the seven facial expressions is acquired from five different angles -90°, -45°, 0°, 45°, 90°.

(d) The MUG Database [53] contains 86 subjects, where 51 are males and 35 are females. All subjects are between 20 and 35 years old. Only 52 subject images are available for usage with this database. For each expression, a total of 50 to 160 images are existing. The images have a resolution of 896x896 pixels.

4.3. Results and analysis

Tables 2 and 3 report the average accuracy of each tested descriptor obtained on CK, JAFFE, KDEF and MUG Databases. The first column consists of the name of the descriptor along with the parameter used if that concerns a parametric descriptor. The other columns concern the abbreviation of emotion categories that we tested and the accuracy obtained; NE: NEUTRAL, HA : HAPPY, FE : FEAR, SA: SAD, AN: ANGRY, DI: DISGUST, SU: SURPRISE, Acc: Accuracy.

4.3.1. Performance analysis on Cohn-Kanade (CK) Database

For this database, we used a subset of 10 sequences that reflect only the samples expressing the seven categories of emotions, and then we selected the four latest frames of each sequence that have the highest expression intensity. The optimal number of non-overlapping sub-regions to compute the histogram features is 14x14 for all the tested descriptors. For each emotion expression, two images are used as training set and the two others are used as test set. Table 2 illustrates the obtained experimental results for the basic emotion recognition recorded on CK dataset using the 46 evaluated state-of-the-art texture descriptors. It can be inferred that almost all the tested descriptors produce good results on CK dataset where their average accuracy is above 96%. Tweenty-seven LBP-methods like RALBGC, BGC1, BGC2, BGC3, dLBPα, ELGS manage successfully to differentiate all classes perfectly (average accuracy equal to 100%), leaving then, essentially, no room for improvement. Note that, all the evaluated descriptors reached a score of 100% for "Happy" and "Surprise" classes.

4.3.2. Performance analysis on JAFFE Database

In this second experiment, each emotion in JAFFE database is designated into 10 females with three samples. One image is taken for each person and for each emotion expression in the test, making a total of 70 samples in the testing phase while the remaining 140 samples depict the training set. All faces are preprocessed to align them into a canonical images with a resolution of 128x128. The histograms are produced on the feature images spatially divided into 12x12 non-overlapping sub-regions. It is apparent from Table 2 that DSLGS, ELGS and SLGS operators yield the highest average rate as they reached a score of 98.57%. Then, come the eight descriptors: BGC2, CSLBP, dLBPα, ILBP, LCCMSP, LDENP, LGCP and OS_LTP which reached a recognition rate of 97.14%. It can be noticed that several tested LBP-like descriptors have perfectly recognized some classes by getting the accuracy of 100%.
Note that there is a significant performance drop for all the tested descriptors on the class of "sadness" where the reached accuracy is in the range [50%, 90%]. It also emerges from Table 2 that some methods like CSALTP, GTUC and LMEBP produce the worst performance on almost all the classes where their accuracy is sometime below 70%. We would also point out that although parametric methods like eCS_LTP, ILTP, GTUC, AELTP are regarded as "optimized" since their parameter values are tuned during the experiment, their performance is markedly weaker than the non-parametric ones.

4.3.3. Performance analysis on KDEF database

We choose the images of both sessions for each subject and only the view angle 0° is considered. The subset contains 70 subjects, each one expresses two times the seven emotion categories. Thus, in total we use 980 images. We altered the sizes of all the faces of KDEF database into a steady sized template, which have the same resolution of 256x256 and the faces were then split into 14x14 blocks for region-based feature extraction. Each subject express two times the seven categories, so we selected one facial image per subject for training phase and the other one for test phase.

It is apparent from Table 3 that the LGS operator is ranked as the top 1 descriptor in KDEF database as it achieves a recognition rate of 95.92%, with perfect recognition (100%) of happy and neutral categories, followed by DSLGS, SLGS and LBP descriptors which reached a score of 95.31%. Then, come seven descriptors like BGC2, BGC3, CSLBP, dLBPα, ELGS, ILBP and LQPAT which allowed to achieve accuracies between [94.08% - 94.90%]. Then tweenty-six LBP-methods attained accuracies between [90.20% - 93.88%] where three descriptors RLBP, BGC1 and SMEPOP reached 93.88% and two descriptors MMEPOP and DBC attained 90.20% and 90.41%, respectively. Accuracies between [80.61% - 86.53%] were achieved by eight LBP-like methods in which 80.61% was achieved by ALTP and 86.53% by XCS_LBP. We can observe from Table 3 that the worst performance of 59.39% was attained by CSALTP descriptor.

4.3.4. Performance analysis on Multimedia Understanding Group (MUG) Database

We have used 924 facial expression images, i.e., 132 images for each facial expression. All faces were altered and resized to have a common resolution of 256x256. Then, they were split into 18x18 blocks for region-based feature extraction. For this experiment, in each emotion category, we used four images per subject, two for training phase and two for test phase.

Table 3 gathers the obtained experimental results. Clearly, it can be observed that eight of the tested descriptors ELGS, LDTP, LDENP, LGCP, LNDP, LTP, LQPAT and SMEPOP manage to differentiate all classes perfectly 100% in accuracy leaving then, no room for improvement. In addition, thirty-one LBP-like methods give accuracies between [99.03% - 99.68%], LBP attained 98.73%, DBC reached 98.05%, XCS_LBP got 97.40% and finally, GTUC attained an accuracy of 97.08%.

As we can observe, all tested methods obtain very promising results on the MUG dataset, excpect three state-of-the-art methods AELTP, LMEBP and CSALTP attained the lowest accuracies comparing with the other methods tested. The undermost accuracy of 71.43% was achieved by CSALTP. Then an accuracy of 84.09% was attained by AELTP and finally 89.94% was obtained when testing LMEBP method.

Table 2. Experiments Results on CK and JAFFE Databases

	Cohn Canade Database								JAFFE Database							
	NE	HA	FE	DI	AN	SA	SU	Acc	NE	HA	FE	DI	AN	SA	SU	Acc
LDTP	100	100	100	95	95	100	100	98.57	90	90	80	90	60	70	100	82.86
RALBGC	100	100	100	100	100	100	100	**100**	90	100	80	90	80	80	100	88.57
RLBP	100	100	100	100	100	100	100	**100**	90	90	90	80	90	80	100	88.57
CELDP	100	100	100	100	100	100	100	**100**	90	80	80	80	100	80	100	87.14
AELTP{1}	95	100	100	100	95	95	100	97.86	80	80	90	80	90	80	100	85.71
ALTP{0.006}	90	100	100	100	95	95	100	97.14	100	100	90	90	100	80	100	94.29
BGC1	100	100	100	100	100	100	100	**100**	90	90	80	100	100	80	100	91.43
BGC2	100	100	100	100	100	100	100	**100**	100	100	100	100	100	80	100	97.14
BGC3	100	100	100	100	100	100	100	**100**	100	90	90	100	100	80	100	94.29
CBP 1	100	100	100	90	100	90	100	97.14	100	90	90	100	100	90	100	95.71
CSALTP{0.006}	100	100	100	100	100	95	100	99.29	70	90	80	80	50	60	100	75.71
CSLBP {1}	100	100	100	100	100	100	100	**100**	100	100	100	100	100	80	100	97.14
CSLTP {1}	100	100	100	100	100	100	100	**100**	100	100	90	100	90	80	100	94.29
CSQP	100	100	100	100	100	100	100	**100**	100	90	100	90	100	80	100	94.29
DBC {45}	100	100	100	95	95	100	100	98.57	100	100	90	90	90	90	100	94.29
DDBP	100	100	100	100	95	100	100	99.29	90	90	100	100	100	80	100	94.29
dLBP α {45}	100	100	100	100	100	100	100	**100**	100	100	100	90	100	90	100	97.14
DSLGS	100	100	100	100	100	100	100	**100**	100	100	100	100	100	90	100	**98.57**
eCS_LTP{1}	100	100	100	90	95	100	100	97.86	100	100	80	90	90	90	100	92.86
ELGS	100	100	100	100	100	100	100	**100**	100	100	100	100	100	90	100	**98.57**
GTUC {2}	100	100	95	95	100	100	100	98.57	100	90	60	70	80	50	80	75.71
IBGC1	100	100	100	100	100	100	100	**100**	90	90	70	90	90	70	100	85.71
ILBP {1}	100	100	100	100	100	**100**	100	**100**	100	90	100	100	100	90	100	97.14
ILTP {1}	95	100	100	100	95	95	100	97.86	90	100	80	90	80	80	100	88.57
LBP	100	100	100	100	95	100	100	99.29	100	100	100	90	90	80	100	94.29
nLBPd {1}	100	100	100	100	100	100	100	**100**	100	90	80	100	100	80	100	92.86
LCCMSP	100	100	95	90	95	95	100	96.43	100	90	100	100	100	90	100	97.14
LDBP	100	100	100	100	100	100	100	**100**	100	90	80	100	100	80	100	92.86
LDENP	100	100	100	100	100	100	**100**	**100**	100	100	100	100	100	80	100	97.14
LDN	100	100	100	100	100	100	100	**100**	100	100	90	100	100	80	100	95.71
LDP {1}	100	100	100	100	100	100	100	**100**	100	100	90	100	100	70	100	94.29
LESTP 10	100	100	100	100	95	100	100	99.29	90	100	90	90	100	80	100	92.86
LGCP	100	100	100	100	100	100	100	**100**	100	100	100	100	100	80	100	97.14
LGS	100	100	100	100	100	100	100	**100**	100	100	90	100	100	80	100	95.71
LMEBP	100	100	100	90	95	100	100	97.86	60	90	70	90	50	60	80	71.43
LNDP	100	100	100	100	95	100	100	99.29	90	100	100	100	100	80	100	95.71
LTP{1}	90	100	100	100	95	95	100	97.14	90	100	90	90	100	80	100	92.86
LQPAT	100	100	100	100	100	100	100	**100**	90	100	100	100	100	80	100	95.71
MMEPOP	100	100	100	100	100	100	100	**100**	100	100	90	90	100	80	100	94.29
MOW_SLGS	100	100	100	100	100	100	100	**100**	100	90	90	100	100	80	100	94.29
OS_LTP {1}	100	100	100	100	100	100	100	**100**	100	100	100	100	100	80	100	97.14
QBP {1}	100	100	100	95	100	100	100	99.29	100	100	90	100	100	70	100	94.29
SLGS	100	100	100	100	100	100	100	**100**	100	100	100	100	100	90	100	**98.57**
SMEPOP	100	100	100	100	100	100	100	**100**	90	100	100	90	100	80	100	94.29
STU+ {1}	100	100	100	95	100	100	100	99.29	100	100	80	100	100	70	100	92.86
XCS_LBP	100	100	100	100	95	100	100	99.29	90	100	90	70	90	80	100	88.57

Table 3. Experiments Results on KDEF and MUG Databases

	KDEF Database								MUG Database							
	AN	DI	FE	HA	NE	SA	SU	Acc	AN	DI	FE	HA	NE	SA	SU	Acc
LDTP	82.86	91.43	90	95.71	95.71	91.43	95.71	91.84	100	100	100	100	100	100	100	**100**
RALBGC	84.29	87.14	91.43	100	97.14	91.43	98.57	92.86	100	100	100	100	100	100	97.73	99.68
RLBP	88.57	92.86	91.43	97.14	98.57	92.86	95.71	93.88	100	100	100	100	97.73	100	100	99.68
CELDP	87.14	87.14	87.14	97.14	94.29	92.86	95.71	91.63	100	100	100	100	97.73	100	100	99.68
AELTP {10}	68.57	80	80	95.71	94.29	82.86	87.14	84.08	93.18	65.91	68.18	68.18	100	93.18	100	84.09
ALTP {0.006}	60	74.29	74.29	97.14	91.43	75.71	91.43	80.61	100	100	97.73	100	100	100	100	99.68
BGC1	85.71	92.86	90	100	98.57	92.86	97.14	93.88	100	97.73	100	100	100	100	97.73	99.35
BGC2	90	91.43	90	100	100	94.29	95.71	94.49	100	95.45	100	100	97.73	100	100	99.03
BGC3	94.29	92.86	90	98.57	97.14	91.43	94.29	94.08	100	100	97.73	100	100	100	100	99.68
CBP {10}	87.14	88.57	88.57	97.14	95.71	88.57	92.86	91.22	100	97.73	97.73	97.73	100	100	100	99.03
CSALTP {5}	40	41.43	34.29	65.71	82.86	55.71	95.71	59.39	65.91	68.18	68.18	63.64	65.91	68.18	100	71.43
CSLBP {1}	92.86	91.43	88.57	100	98.57	92.86	94.29	94.08	100	97.73	100	100	100	100	100	99.68
CSLTP {1}	91.43	88.57	87.14	100	98.57	92.86	94.29	93.27	100	95.45	100	100	100	100	100	99.35
CSQP	90	91.43	88.57	98.57	95.71	92.86	94.29	93.06	100	100	97.73	100	97.73	100	100	99.35
DBC {45}	85.71	87.14	87.14	100	94.29	87.14	91.43	90.41	100	95.45	97.73	97.73	97.73	100	97.73	98.05
DDBP	85.71	90	91.43	98.57	97.14	91.43	95.71	92.86	100	95.45	100	100	97.73	100	100	99.03
dLBPα {135}	87.14	90	91.43	98.57	98.57	95.71	97.14	94.08	100	100	100	100	100	100	97.73	99.68
DSLGS	87.14	94.29	92.86	100	98.57	95.71	98.57	95.31	100	97.73	97.73	100	97.73	100	100	99.03
eCS_LTP {1}	91.43	91.43	91.43	94.29	97.14	88.57	92.86	92.45	100	97.73	100	97.73	100	100	100	99.35
ELGS	85.71	94.29	92.86	100	100	92.86	98.57	94.90	100	100	100	100	100	100	100	**100**
GTUC {1}	78.57	81.43	87.14	95.71	90	85.71	85.71	86.33	97.73	95.45	95.45	93.18	100	100	97.73	97.08
IBGC1	82.86	88.57	90	100	95.71	91.43	97.14	92.24	100	97.73	97.73	100	100	100	97.73	99.03
ILBP	87.14	94.29	90	100	100	92.86	95.71	94.29	100	95.45	100	100	97.73	100	100	99.03
ILTP {1}	62.86	75.71	75.71	97.14	90	80	91.43	81.84	100	100	100	100	97.73	100	100	99.68
LBP	88.57	94.29	91.43	100	100	94.29	98.57	95.31	97.73	95.45	97.73	100	97.73	100	100	98.73
nLBP$_d$ {1}	81.43	90	91.43	100	98.57	92.86	95.71	92.86	100	100	100	100	97.73	100	100	99.68
LCCMSP	82.86	87.14	87.14	98.57	97.14	92.86	98.57	92.04	100	100	100	100	97.73	100	100	99.68
LDBP	81.43	88.57	87.14	100	98.57	91.43	98.57	92.24	100	97.73	100	97.73	100	100	97.73	99.03
LDENP	90	90	87.14	100	100	91.43	97.14	93.67	100	100	100	100	100	100	**100**	**100**
LDN	87.14	88.57	90	98.57	97.14	92.86	95.71	92.86	97.73	95.45	100	100	100	100	100	99.03
LDP {1}	88.57	90	91.43	97.14	97.14	91.43	94.29	92.86	100	97.73	100	100	100	100	100	99.68
LESTP {10}	64.29	78.57	77.14	97.14	91.43	80	91.43	82.86	100	100	100	100	100	100	97.73	99.68
LGCP	88.57	92.86	84.29	100	100	92.86	95.71	93.47	100	100	100	100	100	100	100	**100**
LGS	90	95.71	92.86	100	100	94.29	98.57	**95.92**	100	95.45	100	100	97.73	100	100	99.03
LMEBP	75.71	77.14	90	94.29	84.29	81.43	91.43	84.90	81.82	95.45	88.64	93.18	90.91	90.91	88.64	89.94
LNDP	77.14	87.14	90	100	97.14	91.43	97.14	91.43	100	100	100	100	100	100	100	**100**
LTP {10}	65.71	80	77.14	95.71	94.29	81.43	90	83.47	100	100	100	100	100	100	100	**100**
LQPAT	84.29	88.57	95.71	100	98.57	94.29	97.14	94.08	100	100	100	100	100	100	100	**100**
MMEPOP	74.29	87.14	90	98.57	95.71	91.43	94.29	90.20	100	100	100	100	97.73	100	100	99.68
MOW_SLGS	84.29	94.29	87.14	100	95.71	94.29	95.71	93.06	100	97.73	97.73	100	100	100	100	99.35
OS_LTP {1}	91.43	91.43	87.14	100	98.57	91.43	94.29	93.47	100	97.73	100	100	100	100	100	99.68
QBP {1}	91.43	90	88.57	97.14	97.14	92.86	87.14	92.04	100	95.45	100	100	100	100	100	99.35
SLGS	87.14	94.29	92.86	100	98.57	95.71	98.57	95.31	100	97.73	97.73	100	97.73	100	100	99.03
SMEPOP	87.14	94.29	90	100	97.14	94.29	94.29	93.88	100	100	100	100	100	100	100	**100**
STU+ {1}	88.57	88.57	92.86	98.57	98.57	94.29	90	93.06	100	100	100	93.18	100	100	100	99.03
XCS_LBP	82.86	84.29	80	98.57	94.29	78.57	87.14	86.53	100	93.18	95.45	93.18	100	100	100	97.40

4.4. Comparison with state-of-the-art methods

In this section, we compare the performance of the best performing descriptors on each database with those of existing state-of-the-art methods. We should note that the performance evaluation with other state-of-the-art approaches may not be directly comparable due to the differences in partitioning the dataset into training and testing sets, number of classes, number of subjects and features used. However, distinctive results of every approach still can be indicated. The extracted results from the reviewed state-of-the-art papers as well as the recognition rates reached by the best performing evaluated LBP-variants on each database are arranged in Table 4.

It can be observed from Table 4 that, except for both JAFFE and KDEF databases, where the number of the used samples is relatively the same for almost all the existing systems, the used number of samples on CK and MUG databases varies from one existing approach to another. Given two different systems to compare on a given database, two cases are possible to provide a fair and accurate comparison of their results. In the first one, the used number of samples and the configuration into train/test sets should be the same, whereas in the second case, the system using a less number of samples, must at least be tested with a delicate configuration into train/test sets compared to the other which uses a higher number of samples. We used the second case in our evaluation for comparing the state-of-the-art methods with the adopted system, which uses the most difficult configuration in terms of train/test sets. Indeed, almost all the existing state-of-the-art systems use a partition where the number of training images is superior to that of test images (e.g., 10-fold), while in this study, the half-half configuration is adopted.

Table 4. Comparison with state-of-the-art methods

Database	**Ref (Year)**	**Method**	**Samples**	**Classifier** (Measure train-test)	**Classes**	**Accuracy**
KDEF	[54] (2016)	Local dominant binary pattern	1168	SVM (10-fold)	7 class	83.51
	[55] (2017)	Facial landmarks + Center of Gravity (COG)	980	SVM (70%-30%)	6 class	90.82
	[56] (2017)	LBP + HOG	-	K-means + self-organizing map	6 class	85.8
	[57] (2017)	Low-Rank Sparse Error dictionary (LRSE)	980	CRC (leave one-subject-out 10-fold)	7 class	79.39
	[58] (2017)	LTP+HOG	280	SVM (10-fold)	7 class	93.34
	This paper	**LGS**	980	**SVM** (half-half)	**7 class**	**95.92**
MUG	[59] (2013)	Local Fisher Discriminant Analysis	567	1NN (leave-one-out)	7 class	95.24
	[60] (2014)	ASM	1260	LDA (2/3-1/3)	7 class	99.71
	[61] (2015)	Geometric features	324	SVM (five-fold)	6 class	95.50
	[62] (2017)	MRDTP+GSDRS	567	ELM (10-fold)	7 class	95.7
	[63] (2017)	GLBP	-	Random Forest (10-fold)	7 class	92.60
	This paper	**Several LBP variants including ELGS, LDTP, LDENP**	924	**SVM** (half-half)	**7 class**	**100**
JAFFE	[59] (2013)	Local Fisher Discriminant Analysis	213	1NN (leave-one-out)	7 class	94.37
	[64] (2016)	Curvelet transform	213	OSELM-SC	7 class	94.65
	[65] (2017)	HOG	182	SVM (70%-30%)	7 class	92.75
	[66] (2017)	DDL + CRC LBP	213	CRC (10-fold)	7 class	97.3
	[62] (2017)	MRDTP+GSDRS	213	ELM (10-fold)	7 class	94.3
	[67] (2017)	HOG + U-LTP	213	SVM (64%-36%)	7 class	97.14
	This paper	**DSLGS, ELGS and SLGS**	213	**SVM** (half-half)	**7 class**	**98.57**
Ck	[68] (2015)	IMF1 + KLFDA	404	SVM (10-fold)	7 class	99.75
	[69] (2015)	LGBP	150	SVM (57.2%-42.8%)	7 class	97.4
	[65] (2017)	HOG	1478	SVM (70%-30%)	7 class	98.37
	[58] (2017)	LTP+HOG	610	SVM (10-fold)	7 class	96.06
	[66] (2017)	DDL + CRC LBP	-	CRC (10-fold)	7 class	98.8
	This paper	**27 LBP variants including RALBGC, ELGS, DSLGS**	280	**SVM** (half-half)	**7 class**	**100%**

Examining Table 4, we could make the following findings :

(a) KDEF database: It can be easily observed that the LGS operator is the best performing method which achieved the higher performance over the recent state-of-the-art systems with a recognition rate reaching 95.92%.

(b) JAFFE database: It is easily found that the accuracy recorded by three LBP-like variants outperformed those obtained by the state-of-the-art approaches. Indeed, it emerges from Table 4that the top ranked method on JAFFE database is that presented in [66] as it reached a score of 97.3% which is lower than that obtained by DSLGS, ELGS and SLGS operators (98.57%).

(c) CK database: It is apparent from Table 4 that the highest score achieved on CK database is 99.75% obtained by the method presented in [68] while Table 2indicates that 27 LBP variants reached a score of 100%.

(d) MUG database: As for CK database, several evaluated LBP variants like ELGS, LDTP, LDENP, LGCP, LNDP LQP and SMEPOP descriptors reached a score of 100% outperforming the best performing state-of-the-art approach presented in [60] which reached a score of 99.71%.

The LGS, DSLGS and ELGS descriptors, which are based on the graph concept, manage to achieve remarkable accuracies over all the tested benchmarks. This fact is clearly highlighted on KDEF experiment where we find that few descriptors succeeded to record above 94% average accuracy. Then, the dominant graph encoding process justifies the robustness and effectiveness of LGS, DSLGS and ELGS descriptors. On the other hand, we remark that CSALTP descriptor suffers on KEDF experiment reaching just 59.39% also on JAFFE and MUG experiments, on which the results were very high by the majority of the tested descriptors, the reason behind is the user specified threshold used in this operator, which needs to be identified on each experiment based on testing many values requiring many computations. Rather than this, all the other descriptors record good performances proving the discriminative power of the local description concept.

5. CONCLUSION AND FUTURE WORKS

We reported in this present work a comprehensive comparative experimental analysis of a great number of recent state-of-the-art LBP-like descriptors on facial expression recognition. It is noteworthy that the choice of an appropriate descriptor is crucial and generally depends on the intended application and many factors, such as computational efficiency, discriminative power, robustness to illumination and imaging system used. The experiments presented herein significantly constitute a good reference model when trying to find an appropriate method for a given application. Our experiments on facial expression recognition included a detailed and comprehensive performance study of 46 texture descriptors of the literature covering numerous application areas like texture classification, image retrieval, finger vein recognition, medical image analysis, face recognition, face expression analysis, etc. To show descriptors performance over several challenging situations, the tested descriptors were applied on four famous and widely used datasets such as JAFFE, CK, KDEF and MUG databases. The main finding that can be drawn from the analysis of the overall performance from the experiments is that although some LBP-like features have been originally conceived and proposed for texture classification, they show considerable performance in facial expression recognition. Indeed, even though they were not specifically designed for facial expression recognition, some LBP variants outperform all state-of-the-art approaches over the tested databases. It is of great importance to note that the descriptors based on dominating set and graph present a significant performance stability against the other evaluated state-of-the-art descriptors as they are often found among the best performing LBP variants on the four tested databases. For KDEF database, LGS operator, which is based on dominating set and graph theory, is the best performing descriptor reaching a score of 95.92% outperforming the recent state-of-the-art systems. For JAFEE database, the better recognition rate which was 98.57% has been achieved by three descriptors based also on dominating set and graph theory such as DSLGS, ELGS and SLGS. 27 LBP variants including again those based on dominating set and graph theory reached a score of 100% on CK database. Finally, many evaluated LBP variants like LDTP, LDENP, LGCP, LNDP LQP and SMEPOP descriptors as well as the ELGS operator reached a score of 100% over MUG database. As future works, we look forward to extend this study to include the evaluation of deep features and deep classifiers. Furthermore, we wish to further explore the power of texture descriptors in other applications such as compound emotion recognition, gender classification, face recognition, texture classification, etc., in order to assess their ability to work with various classification problems.

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