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An Efficient Facial Expression Recognition Using Curvelet Transform Based RLBP and Distinct LBP Feature

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Abstract: The project presents human emotion recognition from face images based on textural analysis and knn classifier. Automatic facial expressionrecognition (FER) plays an important role in HCI systems for measuring people's emotions has dominated psychology by linking expressions to a group of basic emotions (i.e., anger, disgust, fear, happiness, sadness, andsurprise). The recognition system involves face detection, features extraction and finally classification. The face detection module will be used to obtain face images, which have normalized intensity, are uniform in size and shape anddepict only the face region. The distinct LBP is used to extract the features texture from face regions to discriminate the illumination changes also RLBP for texture feature extraction. These features are useful to distinguish the maximum number of samples accurately and the KNN classifier based on discriminant analysis is used to classify the six different expressions. The simulated results will be shown that the DLBP and RLBP based feature extraction with used classifier gives much better accuracy with lesser algorithmic complexity than other facial expression recognition approaches.

Keywords: Pre-processing, Curvelet Transform, Distinct LBP, RLBP, KNN classifier.

I. INTRODUCTION

Recently, many sparse and dense descriptors (e.g., SIFT, Gabor, MR8 and LBP) have been proposed for different kinds of applications. There are several studies to evaluate their performance, e.g., [13, 14]. LBP [15] is perhaps the best performing dense descriptor and it has been widely used in various applications, such as texture classification, human detection and face recognition [18]. It has been proven to be highly discriminative and its key advantages, namely its invariance to monotonic gray level changes and computational efficiency, make it suitable for demanding image analysis tasks.

However, one issue of LBP is that it is not so robust to the noise present in images when the gray-level changes resulting from the noise are not monotonic, even if the changes are not significant [2]. To this end, we propose a new descriptor based on LBP, i.e., robust local binary pattern (RLBP). The idea is to locate the possible bit in LBP pattern changed by the noise and then revise the changed bit of the LBP pattern. The idea is very simple, but it works very well. For example, the performance of LBP decreases significantly when we add white Gauss noise in the Brodatz texture dataset [1]. However, the performance of RLBP almost does not change. We also add noise in UIUC texture [7] and FRGC face datasets [17] to testify the performance of RLBP.

Extraction of proper and sufficient features from the facial image is the most important step for effective FER. Facial feature extractors should be selected in such a way that they help to derive a set of features from original facial image which would minimize the intra-class differences and maximize the inter-class variations. Two main types of approaches have been used by researchers for extracting facial features in FER, one is based on face geometry while the other uses textural information of the facial image. In geometry based feature extraction techniques, face shape and location of facial components are used for defining feature vectors. Various 2D, 3D models and Facial Action Coding Systems (FACS) are used to describe the face structure [3] [4] [5]. The geometry based models require reliable and accurate feature detection / tracking [6]. They exhibit high recognition efficiency but are time and memory demanding. Appearance based techniques extract and use either holistic or local features for FER.

Holistic features are extracted using various techniques such as Gabor filters [7] [8], Principle Component Analysis (PCA) [1] [4], Independent Component Analysis (ICA) [9], Linear Discriminant Analysis (LDA) [10], etc. Local feature extraction approaches predominantly use Local Binary Patterns (LBP) [11] or its variants [12] [13] [14] [15] to describe texture of the face. Higher order autocorrelation like features [16], Local PCA [1], Local LDA [1], etc. have also been used by researchers besides LBP. Amongst all the feature extraction techniques, LBP method has become quite popular due to its simplicity, impressive computational efficiency and good texture discriminative property [17].

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II. LITERATURE SURVEY

Recently, many different image descriptors have been proposed. For example, Loweintroduced the sparse scale-invariant feature transform (SIFT) descriptor [11], whichperforms elegantly [13]. Several attempts to improve SIFT have been reported [3, 7, 10, 13,19].A highly popular dense image descriptor is LBP [18]. Many variants of it have beenproposed recently, achieving considerable success in various tasks. Ahonen et al. exploitedthe LBP for face recognition [18], and Tan and Triggs proposed local ternary patterns(LTP) [21]. Zhao and Pietikäinen introduced the spatiotemporal LBP [24]. Liao et al.proposed the dominant local binary pattern (DLBP) [8], and Guo et al. proposed acompleted modeling of the local binary pattern (CLBP) operator [4].

III. PROPOSED METHOD

The proposed system has divided into few modules: Pre-processing, Face detection, Curvelet transform (CT), DLBP, RLBP, K-NN Classifier. Initially we had taken test image and apply preprocessing technique like rgb to gray conversion, filtering and face detection and all, later we had applied Curvelet transform, once if you apply transform means you will get four sub bands like Low and High. In that we had taken Low freq for applying DLBP and RLB, at last we had used KNN classifier for classification. Same process we are applying for all database images.

A. Proposed Method Block diagram:

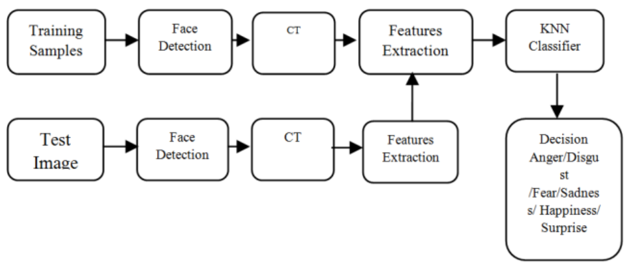

Fig.3 block diagram of proposed method

A. Preprocessing

In Preprocessing of the proposed system the following steps namely Gray scale conversion, Noise removal is involved. In computing, a gray scaledigital image is an image in which the value of each pixel is a single sample, it carries only intensity information. Images of this sort, also known as black-and-white, are composed exclusively of shades of gray, varying from black at the weakest intensity to white at the strongest.Gray scale images are distinct from one-bit bi-tonal black-and-white images, which in the context of computer imaging are images with only the two colors, black, and Gray scale images have many shades of gray in between. Gray scale images are often the result of measuring the intensity of light at each pixel in a single band of the electromagnetic spectrum, and in such cases they are monochromatic proper when only a given frequency is captured. And the gray scale conversion of image is given by [17].

$$\mathrm{gray}(i,j) = \{0.29 * \mathrm{rgb}(:,:,1) + 0.59 * \mathrm{rgb}(:,:,2) + 0.11 * \mathrm{rgb}(:,:,3)\}; \quad (1)$$

Generally we are using median filter to suppress the noise. The procedures are

(i) Arranging matrix pixel value in the form of ascending order.
(ii) Find the median value of that matrix.
(iii) Replace that value into that noisy pixel location.

B. Face Detection

A face detector has to tell whether an image of arbitrary size contains a human face and if so, whereit is. One natural framework for considering this problem is that of binary classification, in which a classier is constructed to minimize the misclassification risk. Since no objective distribution candescribe the actual prior probability for a given image to have a face, the algorithm must minimize both the false negative and false positive rates in order to achieve an acceptable performance.

This task requires an accurate numerical description of what sets human faces apart from otherobjects. It turns out that these characteristics can be extracted with a remarkable committee learningalgorithm called Adaboost, which relies on a committee of weak classifiers to form a strongone through a voting mechanism. A classifier is weak if, in general, it cannot meet a predefined classification target in error terms.An operational algorithm must also work with a reasonable computational budget. Techniquessuch as integral image and attention cascade make the Viola-Jones algorithm [10] highly efficient:fed with a real time image sequence generated from a standard webcam, it performs well on astandard PC.

C. Curvelet Transform

Curvelet were first introduced in [8] and have been around for a little over five years by now.Soon after their introduction, researchers developed numerical algorithms for their implementation[37, 18], and scientists have started to report on a series of practical successes, see [39, 38, 27, 26, 20]for example. Now these implementations are based on the original construction [8] which uses apre-processing step involving a special partitioning of phase-space followed by the ridgelet transform[4, 7] which is applied to blocks of data that are well localized in space and frequency.In the last two or three years, however, curvelets have actually been redesigned in aeffort to makethem easier to use and understand. As a result, the new construction is considerably simpler andtotally transparent. What is interesting here is that the new mathematical architecture suggests.

The algorithm of the Curvelet transform of an image P can be summarized in the following steps [8–10]: The algorithm of the Curvelet transform of an image P can be summarized in the following steps [8–10]:

A) The image P is split up into three sub bands Δ1,Δ2 and P3 using the additive wavelet transform
B) Tiling is performed on the sub bands Δ1 and Δ2.

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C) The discrete ridgelet transform is performed on each tile of the subbands Δ1 and Δ2. A schematic diagram of the curvelet transform is depicted in Fig. 2.

A schematic diagram of the curvelet transform is depicted in Fig. 2.

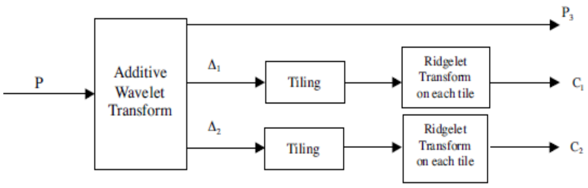


Figure 2. Discrete curvelet transform of an image *P*.

D. DLBP

The structural method like LBP suffers from illumination effect. To avoid these problems in the statistical and structural methods, the present paper combined structural and statistical methods using the proposed DLBP.
Conversion of 5×5 window into 3×3 window

STEP 1: Formation of nine overlapped sub 3 x 3 neighborhoods from a 5 x 5 neighborhood: A neighborhood of 5x5 pixels is denoted by a set containing 25 pixel elements: P= {P11… P15: P21….. P25:P31 ...P35: P41… P45: P51…. P55}, here P33 represents the intensity value of the central pixel and remaining values are the intensity of neighboring pixels as shown in Fig. 3.

STEP 2: Formation of ―First order Compressed Image Matrix (FCIM)‖ of size 3 x 3 from 5 x 5: In step four, from each overlapped 3 x 3 sub matrix of step three , a pixel value for the FCIM of size 3 x 3 is obtained as given in equation 1.1. The FCIM is a 3 x 3 matrix with nine pixel elements (FCP1 to FCP9) as shown in the Fig. 4. The FCIM maintains the local neighborhood properties including edge information.

P_{11}	P_{12}	P_{13}	P_{14}	P_{15}
P_{21}	P_{22}	P_{23}	P_{24}	P_{25}
P_{31}	P_{32}	P_{33}	P_{34}	P_{35}
P_{41}	P_{42}	P_{43}	P_{44}	P_{45}
P_{51}	P_{52}	P_{53}	P_{54}	P_{55}

Figure 3. Representation of a 5 x 5 neighborhood

P_{11}	P_{12}	P_{13}		P_{12}	P_{13}	P_{14}		P_{13}	P_{14}	P_{15}
P_{21}	P_{22}	P_{23}		P_{22}	P_{23}	P_{24}		P_{23}	P_{24}	P_{25}
P_{31}	P_{32}	P_{33}		P_{32}	P_{33}	P_{34}		P_{33}	P_{34}	P_{35}
	n1				n2				n3	
P_{21}	P_{22}	P_{23}		P_{22}	P_{23}	P_{24}		P_{23}	P_{24}	P_{25}
P_{31}	P_{32}	P_{33}		P_{32}	P_{33}	P_{34}		P_{33}	P_{34}	P_{35}
P_{41}	P_{42}	P_{43}		P_{42}	P_{43}	P_{44}		P_{43}	P_{44}	P_{45}
	n4				n5				n6	
P_{31}	P_{32}	P_{33}		P_{32}	P_{33}	P_{34}		P_{33}	P_{34}	P_{35}
P_{41}	P_{42}	P_{43}		P_{42}	P_{43}	P_{44}		P_{43}	P_{44}	P_{45}
P_{51}	P_{52}	P_{53}		P_{52}	P_{53}	P_{54}		P_{53}	P_{54}	P_{55}
	n6				n7				n8	

Figure 4. Formation of nine overlapped 3 x 3 neighborhoods {n1, n2, n3… n9} from Fig. 2.

$$FCP_i = \text{Avg of } (n_i) \text{ for } i = 1, 2, \ldots 9 \qquad (1.1)$$

FCP_1	FCP_2	FCP_3
FCP_4	FCP_5	FCP_6
FCP_7	FCP_8	FCP_9

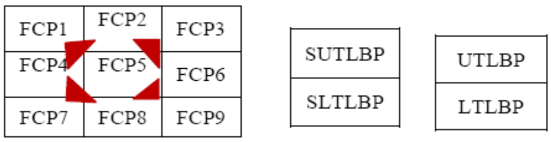
Figure 5 .Representation of grey level FCIM

STEP 3: LBP on FCIM: The FCIM of Fig.4 is converted in to binary based on LBP method as given the equations 1.2 and 1.3

$$FCPi = 0 \text{ if } FCPi < FCP5 \qquad (1.2)$$
$$FCPi = 1 \text{ if } FCPi >= FCP5 \qquad (1.3)$$

STEP 4: Formation of two Distinct LBP‘s (DLBP) on FCIM of Step 3: From the binary FCIM of 3 x 3 neighborhoods four Triangular LBP unit values are derived as shown in Fig.5. Each Triangular LBP unit value contains only three pixels, thus it can have a maximum value of seven. To have rotationally invariance the minimum value is chosen for each Triangular LBP. The Upper TLBP‘s (UTLBP) i.e TLBP1 and TLBP2 are formed from the combination of pixels FCP1, FCP2, FCP4 and, FCP2, FCP3, FCP6 respectively. The Lower TLBP‘s (LTLBP) i.e TLBP3 and TLBP4 are formed from the combination of pixels FCP4, FCP7, FCP8 and, FCP6, FCP8, FCP9 respectively. Based on this, two DLBP‘s are evaluated. The two DLBP‘s are formed from sum of UTLBP (SUTLBP) and sum of LTLBP (SLTLBP) values of FCIM as given in equations 1.4 and 1.5

$$SUTLBP = TLBP1 + TLBP2 \qquad (1.4)$$
$$SLTLBP = TLBP3 + TLBP4 \qquad (1.5)$$



E. RLBP

The RLBP produces code, which is invariant to monotonic gray scale transformation and insensitive to noise. The gray value of centre pixel in 3x3 local area is replaced by its average local gray value of the neighbourhood pixel values instead of the gray value of centre pixel value, in which the RLBP is calculated. The Average Local Gray value (ALG) is defined as

$$ALG = \frac{\sum_{i=1}^{8} g_i + g}{9},$$

where g is the gray value of the centre pixel and (i=0,1,…8) represents the gray value of the neighbor pixels. ALG is the average gray level of local area, which is obviously more robust to noise than the gray value of the centre pixel. This can be defined as

$$RLBP_{P,R} = \sum_{p=0}^{P-1} s(g_p - ALG_c)2^p$$
$$= \sum_{p=0}^{P-1} s\left(g_p - \frac{\sum_{i=1}^{8} g_{ci} + g_c}{9}\right) 2^p,$$

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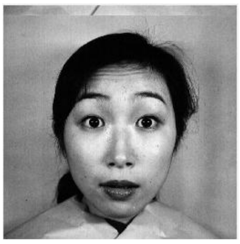
The LBP process is applied by using ALG as the threshold instead of the gray value of central pixel, named as Robust Local Binary pattern (RLBP).
where gc is the gray value of central pixel and □□(p=0,1,…P- 1) represents the gray value of the neighbor pixel on 3x3 local area of radius R, P is the number of neighbors and □□□(i=0,1,…8) is the gray values of the neighbor pixel of gc Average local gray level of pixel is used as threshold, therefore RLBP is insensitive to noise and also two different patterns with same LBP code may have different RLBP code, because that neighbors of each neighbor pixel are considered. The RLBP can overcome mentioned demerits of LBP.

F.KNN- Classifier

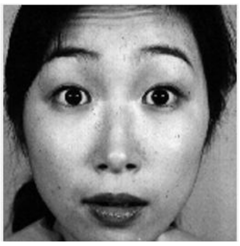
k-nearestneighbor algorithm [12,13] is a method for classifying objects based on closest trainingexamples in the feature space. k-nearestneighbour algorithm is among the simplest of all machinelearning algorithms. Training process for thisalgorithm only consists of storing feature vectorsand labels of the training images. In theclassification process, the unlabelled query point issimply assigned to the label of its k nearestneighbors.
Typically the object is classified based on thelabels of its k nearest neighbors by majority vote. Ifk=1, the object is simply classified as the class ofthe object nearest to it. When there are only twoclasses, k must be a odd integer. However, there canstill be ties when k is an odd integer whenperforming multiclass classification. After weconvert each image to a vector of fixed-length withreal numbers, we used the most common distancefunction for KNN which is Euclidean distance:

$$d(x,y) = ||x-y||^2 = \sum_{i=1}^{k}(x_i - y_i)^2$$

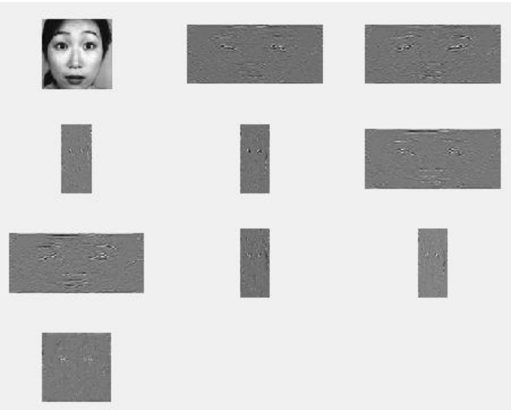
VI. RESULTS AND DISCUSSION



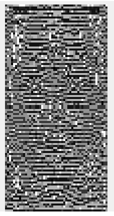
a) Test image



b) Cropped image

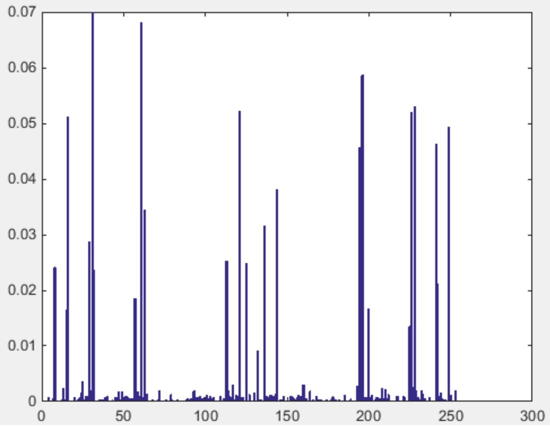


c) Curvelet Transform subbands

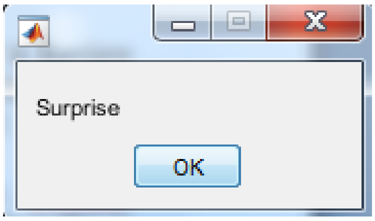


d) DLBP

e) RLBP



f) Histogram Features



g) Result

Expression	Angry	Disgust	Surprise	Fear	Sad	Hap-py	Neutral
Angry	**100**	0	0	0	0	0	0
Disgust	0	**96**	0	0	0	0	0
Surprise	0	0	**100**	0	0	0	0
Fear	0	0	0	**100**	4	0	0
Sad	0	4	0	0	**96**	0	0
Happy	0	0	0	0	0	**100**	0
Neutral	0	0	0	0	0	0	**100**
Recognition	**100**	**96**	**100**	**100**	**96**	**100**	**100**

V. CONCLUSION

The present paper developed an integrated approach by combining the DLBP and RLBP on FCI that output performs the statistical and other face analysis methods in terms of recognition performance and the robustness to illumination change. Thus the proposed integrated method represents complete information of the facial image. The proposed DLBP & RLBP of FCI is a three phase model for recognizing facial expressions. In the first Phase it, reduced the 5x 5 image in to a 3x 3 sub image without losing any significant information. In the second and third phases Distinct LBP. Then apply RLBP at last we had used KNN classifier to find the expression of input image. The proposed method overcomes the unpredictable distribution of the face images in real environment caused by statistical methods and illumination problems caused by LBP. Comparison of the recognition performance with different methods shows the superiority of the proposed method.

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