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A Sparse Representation Approach to Facial Expression Recognition Based on LBP plus LFDA

Ritesh Bora, V.A.Chakkarvar

Computer science and Engineering Department,
Government College of Engineering, Aurangabad [Autonomous]
Station Road, Aurangabad, Maharashtra, India.

***Abstract*— Human facial expressions plays an important role in interaction and communication between each other. Automatic facial expression recognition is most interesting and challenging subject in areas like signal processing, pattern recognition, artificial intelligence etc. Its applications include human-computer interfaces, human emotion analysis and medical care and cure. In this paper, a new method of facial expression recognition based on local binary patterns (LBP) and local fisher discriminant analysis (LFDA) is presented. The high dimensional LBP features are firstly extracted from the original facial expression images. Then low dimensional discriminative embedded data representations are produced from high dimensional LBP features with striking performance improvement on facial expression recognition task by using LFDA .Finally, sparse representation classifier is used for facial expression classification.**

***Keywords*— Facial Expression Recognition, Image Processing, LFDA, LBP, Sparse Representation.**

I. Introduction

The expression is the basic way to express human emotions in everyday interaction with others. Recent psychology research has shown that most expressive way of human display emotions is through facial expressions. Mehrabian [1] show that the facial expression has more impact than the verbal part of the message while communication. Automatic facial expression recognition has increasingly attracted much attention due to its important applications to human-computer interaction, data driven animation, video indexing, etc.

An automatic facial expression recognition system made of two main parts: facial feature extraction and facial expression classification. The generic facial expression recognition flow is given in fig 1.

Facial feature extraction phase extracts a set of appropriate features from original face images for describing faces. Two types of approaches to extract facial features are found: geometric-based methods and appearance based methods [2]. In geometric feature extraction system, the shape and location of various face components are considered. The geometry-based methods require accurate and reliable facial feature detection, which is different to achieve in real time applications. Reverse seen in the appearance-based methods, image filters are applied to either the whole face image known as holistic representation or some specific region of the face image known as analytic representation to extract appearance change in the face image so far, there are many traditional methods such as principal component analysis (PCA) [3], Linear discriminant analysis (LDA) [4] and Gabor wavelet analysis [5] have been applied to either the whole face or specific face regions to extract the facial appearance changes. Nevertheless, it is computationally expensive to convolve the face images with a set of Gabor filters to extract multi-scale and multi-orientation coefficients. It is thus inefficient in both time and memory for high redundancy of Gabor wavelet features.

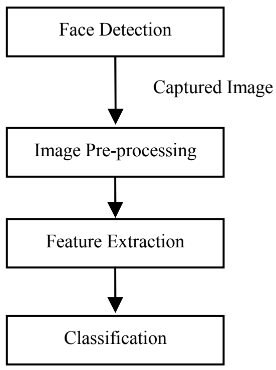

Fig. 1 Generic FER flow

Local binary patterns (LBP) [6], originally proposed for texture analysis [14] and a non parametric method efficiently summarizing the local structures of an image, have received increasing interest for facial image representation. The most important property of LBP features is their tolerance against illumination changes and their computational simplicity. Currently, LBP has been successfully applied as a local feature extraction method in facial expression recognition [7]-[11]. Extracted LBP features represented by a set of high dimensional data sets to train and test a classifier and removing irrelevant feature data, as a pre-processing step to a classifier, is needed. To solve this problem, one usually feasible way is to perform dimensionality reduction for generating few new features containing most of the valuable facial expression information. The two widely used traditional dimensionality reduction methods are PCA and LDA. However, these two methods PCA and LDA still have their respective inherent drawbacks, resulting in decreasing their performance on facial expression recognition tasks to some extent. In detail, PCA is an unsupervised learning method, fails to extract the discriminative embedded information from high dimensional data. In reverse case, LDA is a supervised learning method, but still has an essential limitation. That is, maximum of embedded features by LDA must be less than the number of data classes due to the rank deficiency of the between-class scatter matrix [4].

A new dimensionality reduction method called local Fisher discriminant analysis (LFDA) [12] has been proposed to overcome the limitation of LDA in recent years. LFDA effectively combines the ideas of LDA and locality preserving projection (LPP) [13], LFDA maximizes isolation between-class and preserves within-class local structure at the same time. LFDA is capable of extracting the low dimensional discriminative embedded data representations. We firstly use LFDA to extract the low dimensional discriminative embedded data representations from the original extracted high dimensional LBP features. Then sparse representation is adopted for facial expression classification into seven categories happy, sad, anger, fear, surprise and disgust and neutral identified by Paul Ekman [14].

A. *Review of LBP, LFDA and Sparse Representation*

1) Local Binary Pattern (LBP): LBP is a very powerful method to describe the texture and shape of a digital image. Ojala et al. [15] first introduced LBP operator and showed its high discriminative power for texture classification. At a given pixel position (x_c, y_c), LBP is defined as an ordered set of binary comparisons of pixel intensities between the centre pixel and its eight surrounding pixels (Fig 2). The decimal form of the resulting 8-bit word (LBP code) can be expressed as follows:

$$\text{LBP}(x_c, y_c) = \sum_{n=0}^{7} s(i_n - i_c)2^n$$

Where i_c *corresponds* to the grey value of the centre pixel (x_c,y_c), in to the grey values of the 8 surrounding pixels, and function s(x) is defined as:

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

By definition, the LBP operator is unaffected by any monotonic gray-scale transformation which preserves the pixel intensity order in a local neighbourhood. Each bit of the LBP code has the same significance level and that two successive bit values may have a totally different meaning. The LBP code may be interpreted as a kernel structure index.

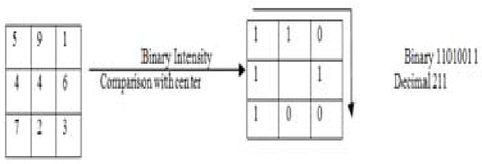

Fig. 2 an example of basic LBP operator

Let us consider LBP opeator was extended to use neighbourhood of different sizes [15]. The $LBP_{P,R}$ notation refers to *P* equally spaced pixels on a circle of radius *R*. In this paper, we use the $LBP_{P,R}$ operator which is illustrated in Fig 3.

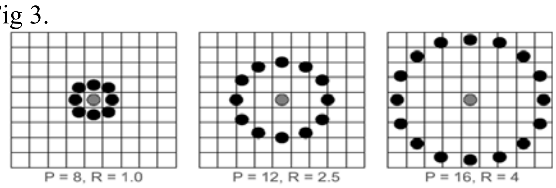

Fig. 3 Circularly neighbour-sets for three different values of P and R

Another extension to the original operator is called uniform patterns. A local binary pattern is called uniform if the binary pattern contains at most two bitwise transitions from 0 to 1 or 1 to 0 when the bit pattern is considered circular. For example, the patterns 00000000 (0 transitions) and 11001111 (2 transitions) are uniform whereas the patterns 11001001 (4 transitions) is not. In the computation of the LBP histogram, uniform patterns are used so that the histogram has a separate bin for every uniform pattern and all non-uniform patterns are assigned to a single bin. For uniform patterns with *P* sampling points and radius *R* the notion $LBP_{P,R}^{u2}$ is used. The superscript *u*2 stands for using only uniform patterns. Ojala et al. [15] noticed that in their experiments with texture images, uniform patterns account for a bit less than 90 % of all patterns when using the (8, 1) neighbourhood and for around 70 % in the (16, 2) neighbourhood. The image after LBP uniform pattern is illustrated in Fig 4.

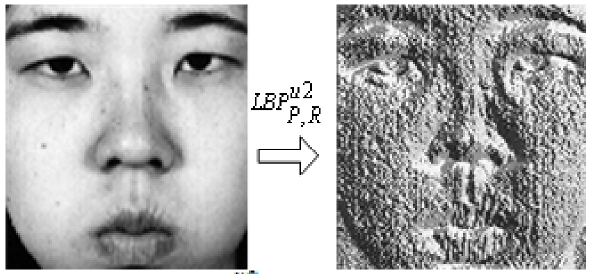

Fig. 4 The instance of $LBP_{P,R}^{u2}$ processing of facial expression image

To extract the features of the facial expression, the images are divided into local regions R_0, R_1, R_{m-1} and texture descriptors are extracted from each region independently. For every region a histogram with all possible labels is constructed. This shows that every bin in a histogram represents a pattern and contains the number of its appearance in the region. A histogram of the labelled image $f_l(x, y)$ can be defined as:

$$H_i = \sum_{x,y} T\{f_l(x,y) = i\}\, T\{(x,y) \in R_j\},\ i = 0,1,\ldots,n-1\ \ j = 0,1,2,\ldots,m-1$$

Where n is referred to as number of label generated by LBP operator. The m is referred to the local region number of the divided image. The function of *T* (*B*) can be defined as:

$$T(B) = \begin{cases} 1 & B \text{ is true} \\ 0 & B \text{ is false} \end{cases}$$

The feature vector is constructed by concatenating the regional histograms to a one big histogram shown in Fig 5.

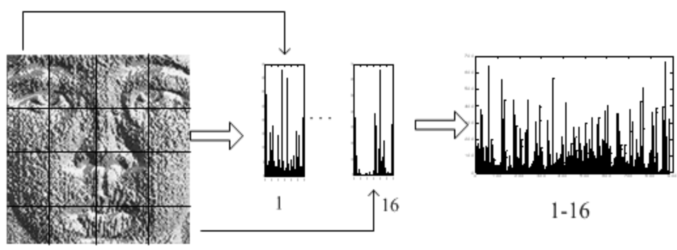

Fig. 5 The example of regional histograms and global histograms construction

2) *LFDA (Local Fisher Discriminant Analysis):* LFDA [12] finds a transformation matrix T such that an embedded representation y_i of a sample x_i is given by

$$y_i = T^T x_i$$

Where T^T denotes the transpose of a matrix T and Let n_l be the number of samples in class *l*. Let $S^{(lw)}$ and $S^{(lb)}$ be the local within-class scatter matrix and the local between-class scatter matrix.

$$S^{(lw)} = \frac{1}{2}\sum_{i,j=1}^{n} W_{i,j}^{(lw)} (x_i - x_j)(x_i - x_j)^T$$

$$S^{(lb)} = \frac{1}{2}\sum_{i,j=1}^{n} W_{i,j}^{(lb)} (x_i - x_j)(x_i - x_j)^T$$

The LFDA transformation matrix $\mathbf{T}_{LFDA}$ is defines as

$$T_{LFDA} = \underset{T \in \mathbb{R}^{d \times r}}{\operatorname{argmax}} \left[trace\left(T^T S^{(lb)} T \left(T^T S^{(lw)} T\right)^{-1}\right)\right]$$

That means, LFDA seeks a transformation matrix **T** such that nearby data pairs in the same class are made close and the data pairs in different classes are separated from each other; far apart data pairs in the same class are not imposed to be close.

3) *Sparse Representation:* The primary goal of sparse representation algorithm was not for classification but compression of signals. Sparse representation uses sampling rate lower than the Shannon-Nyquist bound. From theory of sparse representation it has sown that sparse signals can be reconstructed from a small number of linear measurements [17]-[18]. Therefore, performance of algorithm is measure in terms of sparsity of the representation and fidelity to original signals.

Let given n training samples: $v_1, v_2, \ldots, v_n$. We can construct the matrix $A = [v_1, v_2, \ldots, v_n] \in \mathbb{R}^{m \times n}$, the test sample $y \in \mathbb{R}^m$ can be linearly represented by all training samples as $y = Ax \in \mathbb{R}^m$. The equation $y = Ax$ is usually over-determined. The minimum l^0 – norm solution is NP hard and given as:

$$x_0 = \operatorname{argmin} \|x\|_0 \quad subject\ to\ Ax = y$$

Where $\|x\|$ is l^0 norm of x..The equivalent l^1 norm solution given by

$$\hat{x}_1 = \operatorname{argmin} \|x\|_1\ subject\ to\ Ax = y$$

II. RELATED WORK

A. Automatic Analysis of Facial Expressions : The State of the Art[2000,IEEE]

This paper was submitted Majapantic and Leon J. M. Rothkrantz [19]. They did survey of past work to solve problems related to face detection, extraction of facial expression and classification of the expression. Capability of human visual system with respect to these problems and it served as goal for development of an automatic facial expression analyzer.

B. Performance Comparisons of Facial Expression Recognition in JAFFE database [2008, IJPRAI]

This paper was submitted by Frank Y. Shih and Chao-fa Chuang [20]. They investigated various feature representation and classification schemes to recognize seven different facial expressions such as happy, neutral, angry, disgust, sad, fear and surprise in the JAFFE database. The proposed method 2D-LDA and SVM shows better result 95.71% by using leave one out strategy and 94.13% by using cross validation strategy than PCA, LDA and RBF network.

C. Robust Face Recognition via Sparse Representation [2009, IEEE]

This paper was submitted by John Wright, Allen Y. Yang [21] and colleagues. They considered problem of automatically human faces recognition from frontal views with varying expressions and illumination as well as occlusion and disguise. The proposed method based on sparse representation which solves the problem of feature extraction and robustness to occlusion.

D. A New method For Facial Expression Recognition Based On Sparse Representation Plus LBP [2010, IEEE]

This paper was submitted by Ming-Wei Huang, Zhe-wei Wang and Zi-Lu Ying [22]. Proposed method sparse representation plus LBP has better performance than using sparse representation based classification plus PCA or LDA. They used JAFFE database for experimental evaluation. Compare proposed method with SRC, PCA, LDA, KPCA, Gabor Histogram feature +MVBoost and proposed method gives result 62.9%.

E. Facial Expression Recognition Based on Gabor Features and Sparse Representation [2012, IEEE]

This paper was submitted by Weifeng Liu, Caifeng Song [23] and Colleague. Gabor + Sparse representation which extract Gabor feature from facial image and solve recognition on facial parts, Recognition with occultation but not solve mixed facial Expressions analysis problem.

F. Facial Expression Recognition Based on Local Binary Patterns and Local Fisher Discriminant Analysis [2012,WSEAS]

This paper was submitted by Shiqing Zhang, Xiaoming Zhao, Bicheng Lei [24]. Propose method LBP+LFDA with SVM for facial expression classification on JAFFE database gives accuracy of 90.7% with 11 reduced features in person dependent case as well as 65.91% in person independent case. Compare with PCA, LDA, LPP methods gives better results than that.

III. PROPOSED METHOD LBP+LFDA WITH SRC

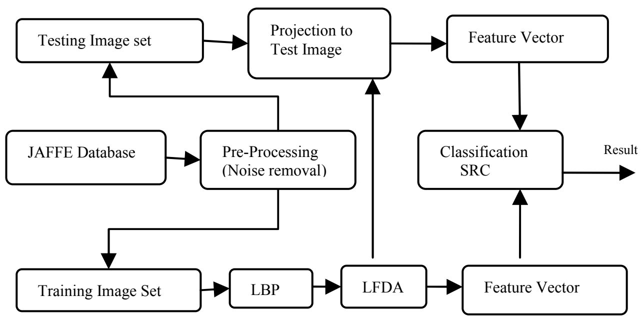

Fig. 6 Proposed method uses following Algorithm flow

A. Algorithm Steps:

Step 1 (JAFFE database) – In our FER system we use JAFFE database which contains 213 facial images from 10 Japanese female. Each image has a resolution of 256×256 pixels. The head is almost in frontal pose.

Step 2 (Pre-processing / Normalization) – Removal of noise, illumination from images.

Step 3 (Testing and Training dataset) – Add images to training and testing dataset as per person dependant /independent case of execution.

Step 4 (Feature extraction) – In the feature extraction first high dimensional features are extracted from given image using LBP and then reduce features with extraction of low dimensional features using LFDA.

Step 5 (Classification) – In this phase sparse representation method is used and output the correct result.

IV. CONCLUSIONS

Facial expression recognition has importance in many areas including medical science and psychology for identification of patient's mental state. One of the crucial stage in this system is feature extraction which extracts features from high dimensional LBP feature to low dimensional feature before fed to Sparse classification.

The Proposed method of facial recognition is innovative in this area with combination of LBP+LFDA and SRC for identification of seven different facial expressions sad, disgust, anger, happy, surprise, fear and neutral with reduced features for storage of JAFFE database work for both person dependant and independent mode.

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