

Facial Expression Feature Extraction Based on FastLBP

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Abstract—The methods of facial expression feature extraction based on traditional LBP have some drawbacks such as complexity, high dimension of feature vectors, which may reduce the efficiency of subsequent recognition process. To solve the above problems, this paper proposes an improved LBP algorithm—FastLBP (FLBP). FLBP compresses the feature vectors described by LBP histogram to decrease the complexity of the algorithm. This method increases the efficiency of training and testing in facial expression recognition and ensures the accuracy of recognition at the same time. The experimental results show that FLBP proposed by this paper is fast and effective.

Index Terms—LBP, fastPCA, Facial expression feature extraction, Facial expression recognition

I. INTRODUCTION

Facial Expression Recognition (FER) extracts expression features [1] through related computer technology to recognize different facial expressions. The research of facial expression recognition originated from 1970s. The key points of early research discussed and analyzed two aspects which are biology and psychology. Ekman and Friesen [2] developed Facial Expression Coding System (FACS), adopting 44 Action Units (AU) to describe the change of facial expression, defining 6 basic expression categories: anger, happiness, sadness, surprise, disgust, fear. Most subsequent research created facial expression data model based on the FACS.

In general, there are two kinds of expression feature extraction methods: method based on static image and method based on dynamic image [3]. Expression feature extraction of static image includes global approach and local approach. Global approach includes Principal Component Analysis (PCA) [4], Independent Component Analysis (ICA) [5], Linear Discriminant Analysis (LDA) [6], etc. Global approach describes global feature of facial expression image, which can overcome geometric invariance whereas decrease the information of classes change. Local approach includes Gabor [7] and Local Binary Pattern (LBP) [8], etc. Local approach has the ability to characterize facial expression image in different scale, however, it may lead to high dimension feature

vectors, which would make it impossible in real-time processing and bring about some degree of information redundancy.

This paper proposes an improved local feature extraction approach—FastLBP (FLBP) to figure out the existing questions of global approach and local approach. FLBP can not only extract the facial expression feature effectively, but also overcome the shortage of LBP operator, which may have passive effect on real-time processing of algorithm due to its high feature vectors. Firstly, this method divides facial expression image into different part; Secondly, FLBP extracts the expression feature vectors histogram of different part; Then, FLBP amalgamates all of the histogram; Lastly, FPCA is used to reduce the dimension of merged and complete facial expression feature vectors histogram. The experimental results indicate that FLBP has retained the advantages of LBP operator—greyscale invariance. What's more, it decreases the complexity of the algorithm and increases the efficiency of facial expression feature.

First part of this paper is introduction, which mainly introduce the definition of facial expression, the meaning of facial expression recognition and put forward an improved local feature extraction approach; Second part describes FLBP algorithm in detail, including specific processing of facial expression feature extraction; Third part gives out the experimental results and analyzes the FLBP algorithm; The final part is the summary of the whole paper.

II. FLBP ALGORITHM

FLBP is an improved LBP algorithm; it derives from the traditional LBP operator. First of all, FLBP utilizes the circular neighbor $LBP_{p,r}$ operator to extract facial expression features; Then, FLBP adopts fastPCA to reduce the high dimension of feature vectors. FLBP is an approach which combines the two methods mentioned above, and it provides more accurate and more valid feature vectors to the following recognition work. An illustration of facial expression recognition based on FLBP algorithm is shown in Figure 1.

Procedure:

- 1) Locate and detect the input image to make sure correct face position
- 2) Grayscale treat and normalize the facial expression image
- 3) Divide regions and Extract the LBP feature
- 4) Gather all of the blocks to generate a complete histogram of expression image
- 5) Reduce dimension of LBP feature vectors by fastPCA
- 6) Adopt related algorithm to recognize and match

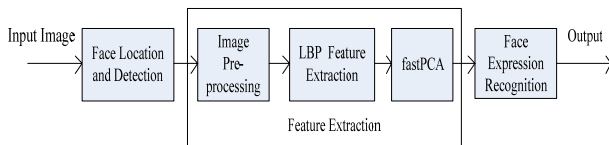


Figure1. Facial expression Recognition Based on FLBP

A. Original Expression Image Pre-processing

Pre-processing of expression image before feature extraction is essential. It includes grayscale processing and normalization. First, according to the eyes, label the position of feature points artificially[9]; Next, both of the distance between two eyes and between forehead and

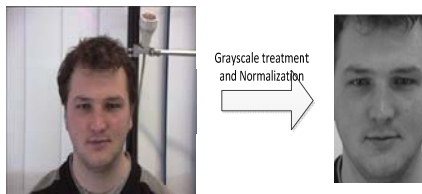


Figure2. Normalized Grayscale Image

brow are 55 pixels, positioning face direction on same level and ensuring consistency of the face position; And then, normalize the facial expression image processed above. T. Kanade [10] pointed out that most of the methods of facial expression were based on the following 5 size: 288×384, 144×192, 72×96, 36×48, 18×24 pixels,

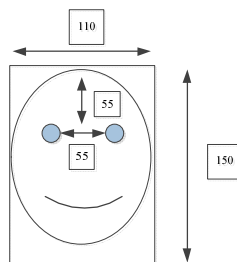


Figure3. Normalized Geometric Model

however, through the 6 size (110×15, 55×75, 36×48, 27×37, 18×24, 14×19 pixels) chosen by Caifeng Shan

[11] compared with previous 5 size, the author found that image size of 110×150 would provide better performance for subsequent recognition. Therefore, this paper adjusts the size of all expression images to 110×150 pixels;

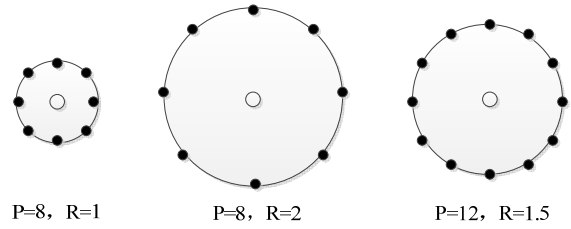


Figure4. 3 Common LBP_{P,R} Operators

Geometric model is shown in Figure 2. At last, the normalized image is converted to a grayscale image through histogram equalization to eliminate the light effect. Processed image is shown in Figure 3.

B LBP Blocks Feature Extraction

Next step, this paper will extract the expressional feature by block-based LBP method. Local binary pattern (LBP) was introduced by Ojala et al[12], which is an efficient texture descriptor. Original LBP operator is similar to template operation while extracting image features.

Original LBP operator can be extended to neighbor of different size and shape. Circular neighbor LBP operator is often noted as LBP_{P,R}. P represents there are P neighbors and R represents the radius of circular neighbor. For different (P, R), there are corresponding different LBP operators. See Figure 4 for examples of the common extended LBP operators.

Each facial expression image can be regarded as a composition by every part of sub-regions and each sub-region can be represented by LBP histogram. LBP histogram is a global statistical vector, which can be defined as:

$$H_{i,j} = \sum_{x,y} I(f(x,y) = i), (i = 0, 1, \dots, n-1) \quad (1)$$

Where n is the number of different labels produced by the LBP operator and

$$I(A) = \begin{cases} 1 & A \text{ is true} \\ 0 & A \text{ is false} \end{cases} \quad (2)$$

Divide the original image $f(x,y)$ into different parts as $R_0, R_1, \dots, R_{m-1}$. The LBP features extracted from each sub-region are concatenated into a single, spatially enhanced feature histogram defined as:

$$H_{i,j} = \sum_{x,y} f_i(x,y) \cdot I((x,y) \in R_j), (i=0,1,\dots,n-1, j=0,1,\dots,m-1) \quad (3)$$

Where m is the amount of blocks, and n is LBP template number, for example: if the number equal to 3, then $n=2^8=256$.

In the end, put all these feature histogram vectors of sub-region images to create facial expression feature vectors. Figure 5 is an example of LBP histogram on

facial expression. This paper selects the Chi square statistic (χ^2) as dissimilarity measure for histogram:

$$\chi^2(S, M) = \sum_i \frac{(S_i - M_i)^2}{S_i + M_i} \quad (4)$$

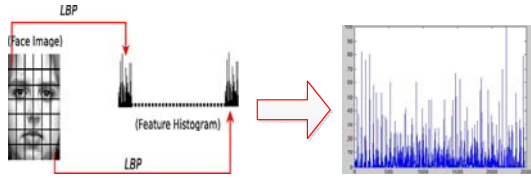


Figure5. Facial Expression Feature Histograms Based on LBP

Theoretically, smaller blocks will have better ability to describe feature, meanwhile, the high dimension histogram vectors will lead to redundant information and to some extent have negative effect on real-time performance of the algorithm. However, LBP histogram describes the feature of sub-region expression image respectively, which may cause so much binary modern data as consequence, making the histogram lost its statistical significance. In view of these problems, researchers put forward the conception of uniform patterns to improve original LBP operator.

Uniform patterns [13], which describe the facial expression image by LBP binary strings and the transformation between 1 and 0 is less than two, such as: the pattern 00000000, 00111000 and 11001111 are uniform patterns. The patterns 01010011 and 11001001 are not. In the process of histogram, it will only allocate histogram bins to uniform patterns, but all of the non-uniform patterns are put in a bin. The number through the calculated uniform LBP operator of bins (features) is 59 (58 uniform patterns bins and a non-uniform patterns bin), so that solve the high dimensional histogram characteristics of redundancy effectively.

The parameters of $LBP_{p, R}$ selected by this paper are $P=8$ and $R=2$, hence, there are $2^P = 2^8 = 256$ sub-binary numbers to describe facial expression texture feature. The choice of LBP blocks has direct relation with histogram feature vectors. While blocks are equal to 6×7 on an expression image, the dimensions of it are 2478 ($59 \times 6 \times 7 = 2478$).

C. fastPCA

FLBP reduces the dimensions of LBP histogram feature vectors through the method fastPCA. The process of decreasing the dimensions of feature vectors is vital because 2478 dimensions of expression feature vectors will lower the efficiency of following recognition on training and testing. In consideration of the distribution of facial expression database is balanced, which means that most face images take over same region on coordinate system, and less different posture and the positions of eyes, nose and mouth are general alike. Therefore,

according to the numbers of image data, the average dimensions of FLBP are from 300 to 500.

Give a training image D, each size of it is $m \times n$ and the dimensions are $N = m \times n$. Transpose the training image of the i -th image to a one-dimensional column vector, then the D images training sample set are:

$$X = \{x_1, x_2, \dots, x_N\} \quad (5)$$

Sample mean for the training samples are:

$$\bar{X} = \frac{1}{N} \sum_{i=1}^N x_i \quad (6)$$

Since the size of the sample matrix X is $d \times n$, (d n -dimensional feature vectors), then the covariance matrix S is an $n \times n$ phalanx, when the dimensions d are large, the computation is very complex. Therefore, this paper chooses fastPCA to compute nonzero eigenvalues of the matrix S corresponds to the intrinsic vectors. Set $Z_{d \times n}$ is the matrix, which comes from each sample of matrix X subtracting sample means $\bar{X}$, then the covariance matrix S is $(Z^T Z)_{d \times d}$. Now discuss the intrinsic matrix $(ZZ^T)_{n \times n}$. Under normal circumstances, the number of samples is less than the sample number of dimensions, the size of R is less than the covariance matrix S , and however, it has the same nonzero eigenvalues.

Given n -dimensional column vectors $\vec{v}$ are eigenvectors of R , then:

$$(ZZ^T)\vec{v} = \lambda\vec{v} \quad (7)$$

Both sides multiply Z^T , and apply matrix multiplication associative law, then:

$$(Z^T Z)(Z^T \vec{v}) = \lambda(Z^T \vec{v}) \quad (8)$$

Formula (7) explains that $Z^T \vec{v}$ is the eigenvalue of covariance matrix $S = (Z^T Z)_{d \times d}$. It implies that the eigenvector $Z^T \vec{v}$ can be obtained by commuted the tiny eigenvector $\vec{v}$ of matrix $R = (ZZ^T)_{n \times n}$ and multiplied Z^T getting the covariance matrix $S = (Z^T Z)_{d \times d}$.

Define abbreviations and acronyms the first time they are used in the text, even after they have been defined in the abstract. Do not use abbreviations in the title unless they are unavoidable.

III. EXPERIMENTS AND RESULTS

In order to validate the effectiveness of our method, the extensive experiments are carried out by the platform of Matlab 2008a. Moreover, the test environment of this section is the Intel Core 2 Duo CPU, 2.4GHz, 2G RAM, and the operation system is Windows XP.

A. Data Pre-processing

The database used in this paper is FEED Database [14], which contains the 6 basic expressions defined by Eckman& Friesen from facial expressions and emotions database of the Technical University Munich. This

database is gradually completed and attempts to assist researchers to investigate different facial expressions. What's more, it has been part of the Face and Gesture Recognition Research Network of European Union.

This database contains 18 different individuals. Each individual performed three times to constitute whole video sequences. In addition, there are another 3 expressionless performing and then all of the sequences were recorded to express neutral emotion. The number of images in each expression sequences is 399 and the overall number is 3×399 .

The size of each image in this database is 320×240 pixels and color depth is 24 bits. The 6 basic expressions and expressionless images are shown in Figure 6.

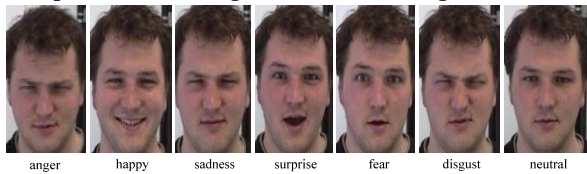


Figure6. Facial Expression Images

Through the Metadata from FEED database, the details of the images used in this paper are shown in Table 1.

TABLE II.
DETAILS OF THE IMAGE DATABASE

Class Label	Emotion	Number of Image instances
1	anger	539
3	disgust	600
4	fear	459
5	happy	486
6	sadness	444
7	surprise	577
8	neutral	280

B. Experimental Results

The FLBP algorithm expounded previously is mainly focused on the theoretical analysis, the following experiment further verify rapidity, accuracy and reliability of the proposed algorithm. The FLBP method proposed in this paper is compared with traditional circular neighborhood $LBP_{p,R}$ operator and $LBP + PCA + LDA$ method in feature extraction time. The experimental results are shown in Table 2.

It can be seen from Table 2 that the proposed FLBP method uses much less time in feature extraction than

TABLE I.
COMPARISON IN FEATURE EXTRACTION TIME

Emotion	LBP	LBP+PCA+LDA	FLBP
Anger	34.687846	4.343404	3.828604
Disgust	40.618099	5.467082	4.624682
Fear	25.201078	3.141922	2.923522
Happy	26.602098	3.415321	3.087721
Sadness	25.554298	3.103957	2.776357
Surprise	34.318814	4.993683	4.556883
Neutral	16.271732	2.071317	1.525317
Average	29.03628	3.790955143	3.331869429

traditional LBP algorithm. It is also slightly better than $LBP + PCA + LDA$ method. Therefore, FLBP is very rapid in the process of feature extraction.

This paper employs KNN algorithm to classify images. The training time and testing time of feature vectors are calculated. The training time and testing time are treated as time complexity factors which are used to compare performance between different algorithms and different expressions. The results of proposed algorithm (FLBP) compared with traditional LBP on the time are shown in Table 3.

From Table 3 we can see if traditional $LBP_{p,R}$ algorithm is employed in the experiment, namely training the expression feature vectors directly, the average of training time will be about 3s. However, if FLBP method used in this paper is employed in the experiment, the training time will be about 0.6s. It is superior to traditional $LBP_{p,R}$ algorithm. What's more, the testing time is also in a way superior to $LBP_{p,R}$. Hence, in the time complexity, FLBP overmatch circular neighborhood LBP algorithm.

Recognition accuracy is also tested using KNN method. This paper takes 80% of the images as training samples and the other 20% as testing samples. The labels of testing expression samples marked by us will be compared with the test labels training by KNN algorithm, and then the comparison results are defined as the accuracy of the recognition process. Through the comparison of different algorithm, the efficiency and accuracy of feature extraction in different algorithm can be known. The recognition accuracy of FLBP and LBP algorithm is shown in Table 4.

The recognition accuracy of disgust expression using FLBP is significantly higher than that using traditional $LBP_{p,R}$ algorithm. The recognition accuracy of sadness expression using FLBP is slightly lower. However, the average accuracy of FLBP in expression recognition is

TABLE III.
COMPARISON IN RECOGNITION ACCURACY

Emotion	LBP	FLBP
Anger	79.4%	79.7%
Disgust	65.8%	82%
Fear	71.4%	71.7%
Happy	92.7%	93.4%
Sadness	44.3%	42.2%
Surprise	74.8%	75.9%
Neutral	100%	100%
Average	75.5%	77.8%

higher than circular neighborhood LBP algorithm, which means that FLBP method is more effective and accurate in the feature extraction performance.

From the three experiment results---Table 2, Table 3 and Table 4, we can see that FLBP algorithm proposed in this paper can improve the efficiency of the expression feature extraction.

An important feature of FBP algorithm is that It reduces the dimension of big feature vectors in order to ensure the reliability. The experiment reduces the 2478 dimensions of feature vectors histograms to different degrees, including 30, 50, 80, 100, 200, 300, 400, and

TABLE IV.
COMPARISON IN TRAINING TIME AND TESTING TIME

Emotion	LBP		FLBP	
	Training (s)	Testing (s)	Training(s)	Testing(s)
Anger	2.2466	0.1678	0.5028	0.0786
Disgust	5.1721	0.0031	1.3677	0.0029
Fear	2.0442	0.6812	0.3466	0.0090
Happy	2.9238	0.0087	0.4740	0.0047
Sadness	1.5356	0.0033	0.2199	0.0041
Surprise	4.2342	0.0030	1.1323	0.0038
Neutral	1.0961	0.0016	0.1455	0.0168
Average	2.7504	0.1241	0.5984	0.0379

500. The results have illustrated that FLBP algorithm has small effect on facial expression recognition accuracy when the dimensions are greater than 100 or equal to 100. If the dimensions are below 100, the recognition accuracy will decrease relatively. Therefore, it can be concluded

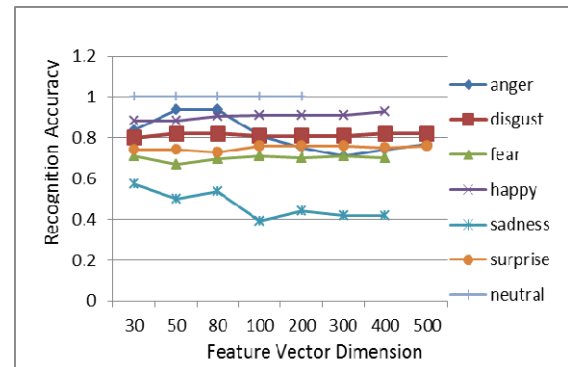


Figure7. Recognition Accuracy on Different Expression under Different Dimensions

that FLBP is reliable in facial expression feature extraction. Figure 7 shows the experiment results of the recognition accuracy under different dimensions.

IV. CONCLUSION

This paper presents an improved local feature extraction algorithm used on facial expression feature extraction method---FLBP, which is based on traditional LBP operator. In addition, FLBP compresses the high dimension feature vectors histograms and keeps the essential information of expression images. It is no doubt that FLBP method can decrease the algorithm complexity as well. Through the experimental validation, FLBP algorithm is superior to traditional circular neighbor LBP_{p, R} operator. It has better performance, is more effective and more accurate in expression feature extraction than traditional LBP. In the end, this paper compares the recognition accuracy under different dimensions, confirming that FLBP is a reliable compressed processing algorithm. In conclusion, FLBP is a fast, accurate, effective and reliable facial expression feature extraction method.

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