RESEARCH ARTICLE OPEN ACCESS

Effect of Different Occlusion on Facial Expressions Recognition

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ABSTRACT
Occlusions around facial parts complicate the task of recognizing facial expressions from their facial images. We propose facial expressions recognition method based on local facial regions, which provides better recognition rate in the presence of facial occlusions. Proposed method uses Uniform Local Binary pattern as a feature extractor, which extract discriminative features from some important parts of facial image. Feature vectors are classified using simplest classifier that is template matching with chi square distance measure. Extensive experiments are performed on JAFFE database**.**
Keywords- Chi Square Distance Measure, Facial Expressions, Feature Vectors, Template Matching, Uniform Local Binary Pattern.

I. INTRODUCTION

In recent years, there has been a growing interest in improving all aspects of the interaction between humans and machines .Facial expression recognition become an active research topic in fields, like computer vision, image processing, psychology, medical science etc[1]. One such problem which arises in facial expression recognition is effect of occlusion on different parts of facial image.

Occlusions give different effects on facial image [2]. Occlusions occur on face image by sunglasses, scarves, caps etc. As we know occlusion is one kind of difficulty arises in facial expression. The ability to handle occluded facial features is important for achieving robust recognition.

There are two important steps for successful facial expression recognition method. First step is extraction of effective features from facial image and second is to design classifier. There are several methods for feature extraction such as Principal Component Analysis (PCA), 2D-PCA, Linear Discriminant Analysis (LDA), Local Binary pattern (LBP) etc. We have used LBP, because of its low computation and high discrimination capability.

LBP is applied on whole face image to get effective feature vector. As we know, LBP histogram gives only occurrence of LBPs; they do not provide locations of LBPs. So it is beneficial to divide the whole face image into different parts and calculate histogram of each part separately and then concatenate all histograms. The image can be divided into equal or unequal sized sub images. We know that different sub images contain varying amount of information. We take only those parts which provide maximum amount of information. We are taking forehead, eyes, nose and mouth; these four parts somehow give more information compare to other parts.

After getting effective feature vectors, our next step is to design a classifier. There are several classifiers such as neural network, template matching, support vector machine (SVM), adaBoost etc, used for classification. Some classifier has generalization ability, some has strong machine learning technique, some has excellent classification accuracy etc. We are using template matching because of its simplicity. In template matching, a template is formed for each class of face expression by concatenating the LBP histograms of a above mentioned parts. In training phase, one template is formed and stored for each expression and in the testing phase, a test image is compared with all stored templates.

As we know occlusion is common difficulty, arises generally in facial expression. Effect of occlusion around forehead, eyes, nose, and mouth somehow decrease the system performance. Different experiments with various occlusions are performed and evaluated on JAFFE database. .

II. LOCAL BINARY PATTERN

Nowadays, LBP receives huge attention because of its low computation and high discrimination capability [3, 4]. The original LBP operator labels the pixels of an image with decimal numbers, which are called LBPs.

Formally, given a pixel at (x_c, y_c), the resulting LBP can be expressed in decimal form as follows:

$$LBP_{P,R}\,(x_c, y_c) = \sum_{P=0}^{P-1} s(i_P - i_c)2^P \qquad (1)$$

Where i_c and i_P are gray-level values of the central pixel and surrounding pixels in the circle neighborhood with a radius R, and function S(x) is defined as:

$$S(x) = \begin{cases} 1, & if x \geq 0 \\ 0 & otherwise \end{cases} \quad (2)$$

Each pixel is compared with its 3x3 neighborhood by comparing the center pixel value with neighborhood pixel value, if neighborhood pixel value is greater than or equal to center pixel value then assign 1 to neighborhood pixel otherwise assign 0 .For each pixel a decimal number is obtained by concatenating all these binary values in a clockwise direction, which starts from one of its top-left neighbor. The corresponding decimal value of the generated binary number is then used for labeling the given pixel. The derived binary numbers are called LBPs or LBP code as shown in Fig. 1.

200	215	95
150	100	100
115	90	98

1	1	0
1		1
1	0	0

Pattern: 11010011
Decimal: 211

Fig.1 LBP Transformation

With the help of LBP code whole image can be converted into LBP image, as shown in Fig. 2.

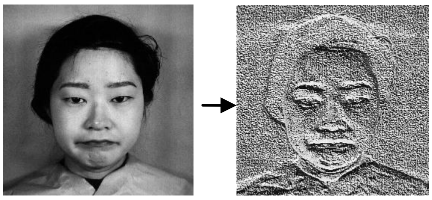

Fig.2 Conversion of an Image to LBP Image

The limitation of LBP is its small 3x3 neighborhood, which cannot capture the dominant features. To overcome this we have used neighborhood of radius 2.

2.1. UNIFORM LBP

Some LBP patterns contain more information than others [5, 6]. It is beneficial to use only those patterns which contain more information, called uniform patterns. A LBP is called uniform, if binary pattern contains at most 2 bitwise transitions from 0 to 1 or 1 to 0, when the bit pattern is traversed circularly. For example, 00011000 is a uniform pattern but 01101111 are not, as it has four bitwise transitions.

The LBP operator that accumulates only uniform patterns is denoted by $LBP^{U2}_{P,R}$ .The number of patterns for $LBP^{U2}_{8,1}$ is only 59 as compared to number of patterns for $LBP_{8,1}$ is 256 ,the reason is, assign separate label for each uniform pattern and a single label for all non-uniform patterns.

Selecting only uniform patterns reduce length of LBP histogram and also improve the performance of classifier.

III. TEMPLATE MATCHING

We have used template matching as a classifier. In template matching; a template is formed for each class of face expression by concatenating the LBP histograms of separate parts of image. There are seven types of facial expressions in JAFFE database such as anger, disgust, fear, happy, sad, surprise and neutral. In training phase, we have stored all these seven templates, one for each expression. In the testing phase, a test image is compared with all stored templates. Comparison is based on Chi square distance. It is represented by:

$$X^2(A, B) = \sum_i (Ai - Bi)^2 / (Ai + Bi) \quad (3)$$

Here A is the LBP histogram of template image and B is the LBP histogram of test image respectively.

IV. DATABASE

There are several databases used for facial expression recognition. We have used JAFFE (Japanese Female Facial Expression) database for our experiments [7].JAFFE is a very popular database for facial expression recognition. It contains 213 gray scale images with seven kinds of facial expressions such as anger, disgust, fear, happy, sad, surprise and neutral, each expression has three or four images, which are posed by 10 Japanese female models, having dimension of 256x256. Some images of JAFFE database is shown below.

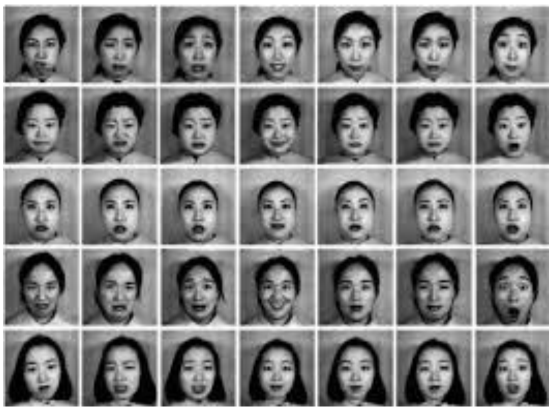

Fig.3 Images from JAFFE Database

V. PROPOSED METHOD

In this method, images are taken from JAFFE dataset and applied occlusion on images such as occlusion around forehead, eyes, nose, and mouth. We have also taken images without any occlusion.

Firstly, we have performed feature extraction. For effective feature extraction uniform LBP is applied on images.

Now, instead of taking complete image, we have divided an image into different subparts such as forehead, eyes, nose, and mouth. As every part of face does not contain equal amount of information, so we have used these four parts and applied uniform LBP operator ($LBP^{U2}_{8,2}$) on these parts. We have calculated the histogram of these parts separately and concatenated them to form a feature vector. Using uniform LBP, the length of feature vector gets reduced.

To improve the performance of our system, we have used template matching with chi square distance as a classifier. We have used template matching because of its simplicity.

VI. EXPERIMENTS AND RESULTS

We have performed experiments on images from JAFFE database. Uniform LBP has applied on separate parts such as forehead, eyes, nose, and mouth of facial image (with and without occlusion on parts) for feature extraction. And finally for classifier we have used template Matching. Experiments for evaluating the importance of different facial parts in expressions recognition are performed and results are shown in form of confusion matrices.

6.1 Examining the importance of all facial parts (without any occlusion)

Instead of taking whole image, we have divided the image into sub parts. So, we have chosen some important facial parts like forehead, eyes, nose and mouth. An image with no occlusion is shown in Fig. 4.

Fig.4 An image with No Occlusion

A concatenated histogram of all facial parts such as forehead, eyes, nose and mouth worked as an input to the classifier. And confusion matrix is shown in table 1.

Table1. Confusion Matrix of all Facial Parts without Any Occlusion

	AN	**DI**	**FE**	**HA**	**NE**	**SA**	**SU**
AN	**100**	0	0	0	0	0	0
DI	0	**100**	0	0	0	0	0
FE	0	0	**87.5**	0	0	12.5	0
HA	0	0	0	**88.88**	11.11	0	0
NE	0	0	0	0	**100**	0	0
SA	0	0	0	0	11.11	**88.88**	0
SU	0	0	0	0	0	0	**100**

Above confusion matrix has achieved recognition rate of 94.82%. All facial parts such as forehead, eyes, nose, and mouth are playing their role in expressions recognition. Here, expressions such as anger, disgust, neutral, surprise has achieved 100% recognition rate.

6.2 Examining the importance of facial parts when occlusion around forehead

Forehead is an important facial part of human face. The movements of the muscles in the forehead produce characteristic wrinkles, which help in recognize expressions. If forehead has occluded, then it may affect the system performance. An image with occlusion around forehead is shown in Fig. 5.

Fig.5 An image with Occlusion around Forehead

A concatenated histogram of facial parts such as eyes, nose, and mouth with occlusion around forehead worked as an input to the classifier. And confusion matrix is shown in table 2.

Table2. Confusion Matrix of Facial Parts with Occlusion around Forehead

	AN	**DI**	**FE**	**HA**	**NE**	**SA**	**SU**
AN	**100**	0	0	0	0	0	0
DI	0	**100**	0	0	0	0	0
FE	0	0	**87.5**	0	0	12.5	0
HA	0	0	0	**88.88**	0	11.11	0
NE	0	0	0	0	**100**	0	0
SA	0	0	0	0	11.11	**88.88**	0
SU	0	0	0	0	0	0	**100**

Above confusion matrix has achieved recognition rate of 94.82%. Here, we have observed that recognition rate remain the same when forehead has occluded, forehead has played very insignificant role in expression recognition.

6.3 Examining the importance of facial parts when occlusion around eyes

Eyes play a very significant role in recognizing person's expressions. The eyes are often viewed as important features of facial expressions. A person's eyes reveal much about how they are feeling, or what they are thinking. An image with Occlusion around eyes is shown in Fig. 6.

Fig.6 An image with Occlusion around Eyes

A concatenated histogram of facial parts such as forehead, nose, and mouth with occlusion around eyes worked as an input to the classifier. And confusion matrix is shown in table 3.

Table3. Confusion Matrix of Facial Parts with Occlusion around Eyes

	AN	DI	FE	HA	NE	SA	SU
AN	**100**	0	0	0	0	0	0
DI	0	**100**	0	0	0	0	0
FE	0	0	**87.5**	0	0	12.5	0
HA	0	0	0	**88.88**	11.11	0	0
NE	0	0	0	0	**100**	0	0
SA	0	0	0	0	22.22	**77.77**	0
SU	0	0	0	0	0	0	**100**

Above confusion matrix has achieved recognition rate of 93.10%.Here, we have observed that eyes play less important role in expression recognition. Due to occlusion around eyes performance of the system has degraded.

6.4 Examining the importance of facial parts when occlusion around nose

As every part of the face does not contribute equally in face expressions, some parts contain more information than other parts. Nose, is one of the most important part of human face and plays a significant role in expression recognition. An image with Occlusion around nose is shown in Fig. 7.

Fig.7 An image with Occlusion around Nose

A concatenated histogram of facial parts such as forehead, eyes, mouth with occlusion around nose worked as an input to the classifier. And confusion matrix is shown in table 4.

Table4. Confusion Matrix of Facial Parts with Occlusion around Nose

	AN	DI	FE	HA	NE	SA	SU
AN	**100**	0	0	0	0	0	0
DI	0	**100**	0	0	0	0	0
FE	0	0	**87.5**	0	0	12.5	0
HA	0	0	0	**88.88**	11.11	0	0
NE	0	0	0	0	**100**	0	0
SA	0	0	0	0	33.33	**66.66**	0
SU	0	0	0	0	0	0	**100**

Above confusion matrix has achieved recognition rate of 91.37%.Here, we observed that nose play important role in expression recognition. Due to occlusion around nose performance has degraded from 94.82% to 91.37%.

6.5 Examining the importance of facial parts when occlusion around mouth

Mouth plays a very significant role in expressions recognition and an important part of human face. An image with occlusion around mouth is shown in Fig. 8.

Fig.8 An image with Occlusion around Mouth

A concatenated histogram of facial parts such as forehead, eyes, nose with occlusion around mouth worked as an input to the classifier. And confusion matrix is shown in table 5.

Table5. Confusion Matrix of Facial Parts with Occlusion around Mouth

	AN	DI	FE	HA	NE	SA	SU
AN	**100**	0	0	0	0	0	0
DI	0	**100**	0	0	0	0	0
FE	0	0	**87.5**	0	0	12.5	0
HA	0	0	0	**77.77**	22.22	0	0
NE	0	0	0	0	**87.5**	0	12.5
SA	11.11	0	0	0	11.11	**77.77**	0
SU	0	0	0	0	0	0	**100**

Above confusion matrix has achieved recognition rate of 89.65%.We have observed that mouth play a very important role in expression recognition. Mouth has affected so much on recognition rate.

VII. CONCLUSION AND FUTURE WORK

A method for recognizing facial expressions in the presence of occlusion has been presented. In this paper, we have extracted effective features based on uniform local binary pattern. As every part of the face does not contain equal amount of information, we have chosen some important facial parts like forehead, eyes, nose, and mouth. After feature extraction, we have classified expressions with the help of template matching and used chi square distance as measure of similarity. Experimental results demonstrated that the proposed method has reliably recognized occluded faces with higher recognition rate than the existing methods. Proposed method has outperformed other methods as listed in Table6. We will extend our work to different classifiers and different databases.

Table6. Comparison of Proposed Method with Existing Methods

S.NO.	Method (features + classifier)	Recognition Rate (%)
1	LBP + Template Matching[1]	79.1
2	Geometric Features + TAN[24]	73.2
3	LDA + NN[1]	73.4 ± 5.6
4	LBP + SVM(RBF)[1]	88.9 ± 3.5
5	Gabor + SVM(RBF)[1]	86.8 ± 3.6
6	Proposed Method	94.82

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