# Facial Expression Recognition Based on Histogram Sequence of Local Gabor Binary Patterns

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*Abstract*—**During the driving, the good emotion can benefit the vehicle safety. The good emotion will result in the certain facial expressions and vice versa. The facial expression is used as a useful cue to perform the surveillance of driver's status. Considering the characteristics of driving safety, the facial expressions of anger, happiness, sadness and fear are investigated. The main contribution of this paper is to present a new facial expression recognition method based on the histogram sequence of local Gabor binary patterns. First, the Gabor Coefficients Maps (GCM) are extracted by convolving the face image with the multi-scale and multi-orientation Gabor filters. Then, the local binary pattern operator is performed on each GCM to extract the local Gabor binary pattern. Next, the face image is described using the histogram sequence of all these local Gabor binary patterns. Finally, the multi-class Support Vector Machine (SVM) is used to perform the feature classification. The experimental results show that the facial expression recognition algorithm proposed in this paper is effective and superior to the other similar methods both in the recognition rate and speed.**

*Keywords*—**facial expression recognition, Gabor coefficients maps, local Gabor binary pattern, support vector machine**

## I. INTRODUCTION

Facial expression, as a kind of body language, can reflect the human emotion effectively [1]. Based on the emotion observation of one person, we can get to know some information about his or her mood, feeling and personality etc. In 1971, Ekman and Friesen presented that the human emotion can be divided into six types, including the happiness, sadness, fear, disgust, surprise and fear. Each of these six basic emotions corresponds to a certain type of facial expression. Besides the neutral expression, these seven types of expressions have been studied widely in the world. So far the facial expression recognition, as an important technology, has been applied in many domains, such as psychology, image understanding, vehicle driving safety, video retrieval, virtual reality and human computer interaction. Our research domain is the vehicle safety and the facial expression is used as a useful cue to perform the surveillance of driver's status. Considering the characteristics of driving safety, the facial expressions of anger, happiness, sadness and fear are investigated in this paper. Our objective is to recognize these four types of facial expressions effectively and efficiently.

According to [2], the techniques of facial expression recognition can be divided into two types, one is based on the static image and another is based on the dynamic video. To the former type, we recognize the facial expression just from the single static image and the available information is very limited. The corresponding methods include the Principal Component Analysis (PCA) [3], Independent Component Analysis (ICA) [4] and the one based on wavelet transformation. To the latter type, the facial expression can be recognized based on the multiple frames of video. The model of optical flow [5], as one of the latter corresponding methods, can extract the dynamic features of facial expression. According to the existing practical applications, it can be learned that the former technique is simple and can be used in the real-time situation. The latter technique costs the high computation and cannot satisfy the real-time requirement.

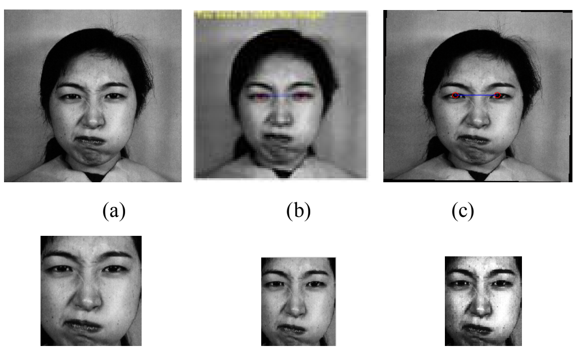
This paper performs the facial expression recognition based on the static image. Zhu et al. [6] proposed a method combining the Gabor filter and Support Vector Machine (SVM). The achieved recognition rate is high, but the computational cost is also high and only the local texture information is adopted. In [7], the local binary patterns and SVM are applied in the expression recognition. Due to the dimension of local binary patterns being lower than the one of Gabor features, the computational cost of the proposed method in [7] has been reduced quite a lot. To combine the advantages of the two methods proposed in [6] and [7], this paper proposes a new facial expression recognition method combining the Gabor coefficients with the histogram of Local Binary Pattern (LBP) [8].

First, the Gabor Coefficients Maps (GCMs) are extracted by convolving the face image with the multi-scale and multi-orientation Gabor filters. The usage of GCM can reduce the dimension of feature vectors. Then, the Local Binary Pattern (LBP) operator is performed on each GCM to extract the Local Gabor Binary Pattern (LGBP). Next, the face image is described using the Histogram Sequence of all these Local Gabor Binary Patterns (HSLGBP) [9]. By combing the Gabor transformation, LBP and local histogram, the proposed method is robust to the illumination variation, image rotation and deformation. Finally, the multi-class SVM is used to perform the feature classification, considering that SVM can achieve the good performance in the case of small samples [10]. According to the training samples, the prior knowledge of

HSLGBP in each scale and each orientation can be achieved. The final recognition result is based on the combination of prior knowledge and estimation result of testing samples.

## II. IMAGE PREPROCESSING

The image preprocessing includes the image segmentation, size normalization and histogram equalization. We take Fig. 1(a) as an example to describe how to perform the image preprocessing. The size of Fig. 1(a) is 256 x 256 in pixels. Generally speaking, the human face in an image is slanting to some extent, which will influence the precision of expression recognition. So the image needs to be rotated to make the human face perpendicular to the horizontal line. We use the method of template matching to locate the two eyes of human face in the image, as shown in Fig. 1(b). Connect these two eyes into a line and compute the angle between this line and the horizontal line. According to the achieved angle, rotate the image so that the line connecting the two eyes is horizontal. The rotation result is shown in Fig. 1(c). Next, we need to extract the principal face region from the background region, and here the geometrical feature of human face is used. The segmentation result is shown in Fig. 1(d), whose size is 123 x 135 in pixels. Following the image segmentation is the size normalization, i.e. the image zooms in or out to a constant size. Here all the face region images are normalized to the size of 112 x 96 in pixels. The size normalization result is shown in Fig. 1(e). To reduce the influence of illumination variation, the histogram equalization is applied to perform the illumination compensation, as shown in Fig. 1(f).



(a) (b) (c)

(d) (e) (f)

Figure 1. Example of image preprocessing

## III. FEATURE EXTRACTION

### A. Gabor Filter

It is common to use the base points instead of the entire image to extract the target features. The Gabor filter can be viewed as a sinusoidal plane at the certain frequency and orientation, modulated by a Gaussian envelope [11]. The Gabor filter has been applied in many domains, such as texture segmentation, object detection, fractal dimension management, document analysis, edge detection, retina identification, image coding and representation. Due to the characteristics of Gabor filter, we use the multiple Gabor filters in the different scales and orientations to perform the feature extraction. Based on the consideration of Gabor filters' spatial locality and orientation selectivity, we design a group of Gabor filters in four scales and six orientations.

The Gabor filter is a linear filter whose impulse response is defined by a harmonic function multiplied by a Gaussian function. Because of the multiplication-convolution property (Convolution theorem), the Fourier transform of a Gabor filter's impulse response is the convolution of the Fourier transform of the harmonic function and the Fourier transform of the Gaussian function. The two-dimensional Gabor filter is composed of the real part and imaginary part, donated as

$$G_k(x,y) = G_r(x,y) + iG_i(x,y). \tag{1}$$

The real part can be calculated as follows

$$G_r(x,y) = \frac{K_v^2}{\sigma}\exp\left(-\frac{K_v^2(x^2+y^2)}{2\sigma}\right)$$

$$*[\cos(K_v\cos(Q_u)\cdot x + K_v\sin(Q_u)\cdot y) - \exp(-\frac{\sigma}{2})]. \tag{2}$$

And the imaginary part is calculated as follows

$$G_i(x,y) = \frac{K_v^2}{\sigma}\exp\left(-\frac{K_v^2(x^2+y^2)}{2\sigma}\right)$$

$$*[\sin(K_v\cos(Q_u)\cdot x + K_v\sin(Q_u)\cdot y) - \exp(-\frac{\sigma}{2})], \tag{3}$$

where $K_v = \pi\exp(-(v+2)/2)$ , $Q_u = \pi * u/6$.

In (3), the multiplicative factor $K_v^2$ ensures that the filters tuned to the different spatial frequency bands have the approximately equal energies. The term $\exp(-\frac{\sigma}{2})$ is subtracted to make the filters insensitive to the overall level of illumination. The terms $Q_u$ and $K_v$ have defined the orientation and scale of the Gabor wavelets respectively. The parameter $\sigma$ is the ratio of the Gaussian window's width to the Gabor wavelets' length and the parameter $u$ is the orientation of Gabor wavelets. In this paper $\sigma$ is set to be $\pi^2$.

### B. Gabor Feature Extraction

With the different scales and orientations, a filter bank consisting of several Gabor filters is built. The filters are convolved with signal, resulting in the Gabor space. This process is closely related to the activity in the primary visual cortex. The Gabor space is very useful in several domains such as iris recognition. To an image whose size is 256 x 256 in pixels, the four scales are denoted as $v$=0, 1, 2, 3 and the six orientations are denoted as $u$=1, 2, 3, 4, 5, 6, i.e. from 30 to 180 degrees by the step of 30 degrees. The face image is convolved with the Gabor filters and the convolution result is called the Gabor Coefficient Map (GCM). The corresponding convolution equation is following

$$G(x, y, v, u) = G_k(x, y) * I(x, y), \quad (4)$$

where $G_k(x, y)$ is the Gabor filter and $I(x, y)$ is the face image.

After the preprocessing the face image is set to be 112 x 96 in pixels. With four scales and six orientations, the number of Gabor filters is 24 (=4*6). So the dimension of Gabor features is very high and equals 258048 (=24*112*96). Fig. 2 illustrates the Gabor features of the face image.

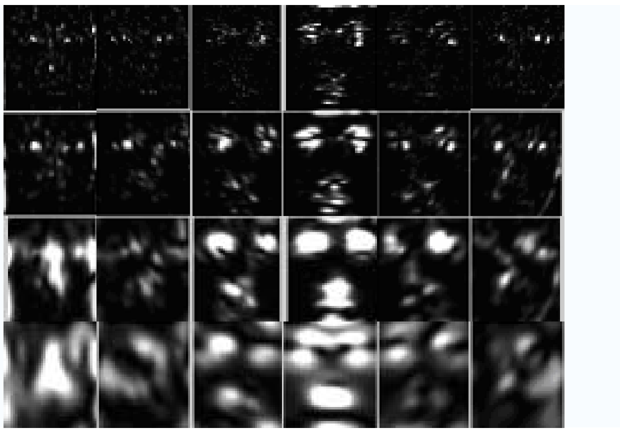


Figure 2. Gabor features of face image

### C. Local Gabor Binary Pattern

The features extracted based on the Gabor filter are usually high-dimensional, but their information is rather redundant. There are two classic methods which can be used to perform the dimension reduction. One method is to use the sparse points to extract features, e.g. the sparse points are achieved every several lines and rows. The example of this method is PCA [12] and the shortage of this method is that it is possible to lose some principal information. Another method, e.g. the elastic bunch graph matching [13], applies the Gabor filter to the feature points of the face image. Here, the shortage is that the method depends too much on the selection of feature points. Against the shortage of the existing methods, the Local Binary Pattern (LBP) operator [14] [15] [16] is applied in the neighborhood region to get the Gabor coefficients and the histogram technique is used to solve the partial variation. By extracting the GCM we can reach two goals, one is to avoid losing principal information and anther is to reduce the dimension simultaneously.

The LBP as a novel low-cost image descriptor for texture classification has been applied in many domains [7]. To a pixel, its intensity is denote as $f_c$, where c=4. From top to bottom and from left to right, except the central pixel, each pixel in the 3 x 3 neighborhood region is labeled to be 0 to 8 except 4. The intensity of each pixel is denoted as $f_p$, where p= 0, 1,2,3,5,6,7,8. To each pixel, the LBP operator is computed as follows

$$LBP = \sum_{p=0}^{8} S(f_p - f_c)2^p, \quad (5)$$

where

$$S(f_p - f_c) = \begin{cases} 1, f_p \geq f_c \\ 0, f_p < f_c \end{cases}. \quad (6)$$

Fig. 3 illustrates how to compute the LBP operator. In Fig. 3, the left part gives the neighborhood information and the right part gives the computational result of (6). The sequence of binary result is 10011110 and the computational result of (5) is 121 (=1*1+0*2+0*4+1*8+1*16+1*32+1*64+0*128).

| | | |
|---|---|---|
| 9 | 2 | 3 |
| 4 | 5 | 6 |
| 7 | 8 | 9 |

Threshold $\longrightarrow$

| | | |
|---|---|---|
| 1 | 0 | 0 |
| 0 | | 1 |
| 1 | 1 | 1 |

Figure 3. An example of LBP operator

In this paper, the LBP operator is applied to the output of GCM and the result is denoted as

$$LGBP = \sum_{p=0}^{8} S(G_p(x, y, v, u) - G_c(x, y, v, u))2^p. \quad (7)$$

### D. Histogram Sequence of Local Gabor Binary Patterns

Considering that the histogram technique has many good characteristics, the histogram is applied to the LGBP. If the histogram is computed based on the entire face image, it is possible to lose some detailed information. So, before computing the histogram the face image is divided into several non-intersectional regions. Then the histogram is applied to each region's LGBP of the face image respectively. Meanwhile, the dimension of LGBP can be reduced by dividing the entire face image into several regions.

To the image $f(x, y)$ whose gray-level is between 0 and L-1, the histogram can be computed as

$$h_i = \sum I\{f(x, y) == i\}, i = 0,1,......L-1, \quad (8)$$

where $i$ is the gray-level, $h_i$ means the number of pixels whose gray-level is $I$, and

$$I\{X\} = \begin{cases} 1, X \quad is \quad ture \\ 0, X \quad is \quad false \end{cases}. \quad (9)$$

We divide the face image into $m$ regions ($R_0, R_1, ......R_{m-1}$, as shown in the left part of Fig. 4) and compute the histogram of each region, as shown in the right part of Fig. 4. Here the histogram is denoted as

$$H_{v,u,R_j,i} = \sum_{(x,y)\in R_j} I\{LGBP(x, y, v, u)\} I\{(x, y) \in R_j\}, \quad (10)$$

where $i$ =0,1,…...L-1, $v$ =0,1,2,3, $u$ =1,2,….6, $j$ =0,1,…..m-1.

In the scale $v$ and orientation $u$, all the histograms are cascaded as the final feature, denoted as

$$HSLGBP(v,u) = (H_{v,u,0}, H_{v,u,1}, \ldots\ldots H_{v,u,m-1}), \quad (11)$$

where $v = 0,1,2,3$, $u = 1,2,\ldots.6$.

In this paper the face image is divided into 42(=7x6) regions and each region is 16 x 16 in pixels. Fig. 4 illustrates the computation of HSLGBP.

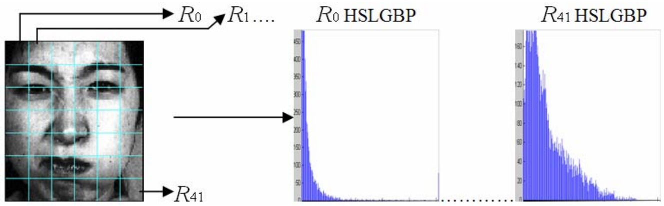



Figure 4. The computation of HSLGBP

## IV. FEATURE CLASSIFICATION

### A. Support Vector Machine

As the last step the expression classification must be based on a certain pattern classifier. All the classifiers can be divided into two types, one is the linear and another is the non-linear. Support Vector Machine (SVM) belongs to a family of generalized linear classifiers [17] and has proved to be more effective than other classifiers in the case of small samples. Moreover, SVM is a statistical learning method based on the minimum structural risk criterion. Considering that the facial expression is the high-dimensional problem with the samples being relatively small, we use the method of SVM to perform the expression classification.

SVM is a very effective binary classification algorithm. Given a linearly separable binary classification problem $\{(X_i, Y_i)\}_{i=1}^{n}$ (as shown in Fig. 5), where $Y_i = \{+1, -1\}$, $X_i$ is an n-dimension vector and $Y_i$ is the label of the class that the vector belongs to. SVM separates the two classes of points by a hyper plane, donated as $\omega^T x + b = 0$, where $\alpha$ is an input vector, $x$ is an adaptive weight vector and $b$ is a bias. SVM finds the parameters $\alpha$ and $b$ for the optimal hyper plane to maximize the geometric margin $2/\|\omega\|$, subject to $y_i(\omega^T x_i + b) \geq +1$. The solution can be found through a Wolfe dual problem with the Lagrangian multiplied by $\alpha_i$ : $Q(\alpha) = \sum_{i=1}^{n} \alpha_i - \sum_{i,j=1}^{n} \alpha_i \alpha_j y_i y_j (x_i \cdot x_j)/2$, subject to $\alpha_i \geq 0$ and $\sum_{i=1}^{n} \alpha_i y_i = 0$.

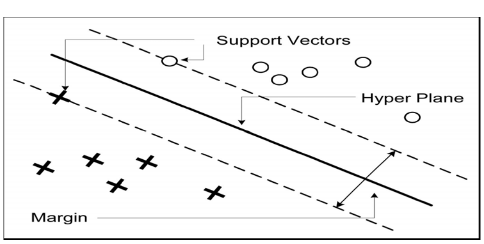



Figure 5. SVM for a linearly separable binary classification problem

In the dual format, data points only appear in the inner product. To get a potentially better representation of the data, the data points are mapped into a Hilbert Inner Product space through a replacement $x_i \cdot x_j \rightarrow \phi(x_i) \cdot \phi(x_j) = K(x_i, x_j)$, where $K(\cdot)$ is a kernel function. We then get the kernel version of the Wolfe dual problem

$$Q(\alpha) = \sum_{i=1}^{n} \alpha_i - \sum_{i,j=1}^{n} \alpha_i \alpha_j y_i y_j K(x_i \cdot x_j)/2 . \quad (12)$$

Thus, for a given kernel function, the SVM classifier is given by $F(x) = \mathrm{sgn}(f(x))$, where $f(x) = \sum_{i=1}^{n} \alpha i y i K(xi, x) + b$ is the decision function of the output hyper plane of the SVM.

Some common kernels include:

1. Polynomial (homogeneous): $K(x, x') = (x \cdot x')^d$
2. Polynomial (inhomogeneous): $K(x, x') = (x \cdot x' + 1)^d$
3. Gaussian Radial basis function:

$$K(x, x') = \exp\left(-\frac{\|x - x'\|^2}{2\sigma^2}\right)$$

4. Sigmoid: $K(x, x') = \tanh(kx \cdot x' + c)$, for some (not every) k>0 and c<0
5. Radial Basis Function (RBF):

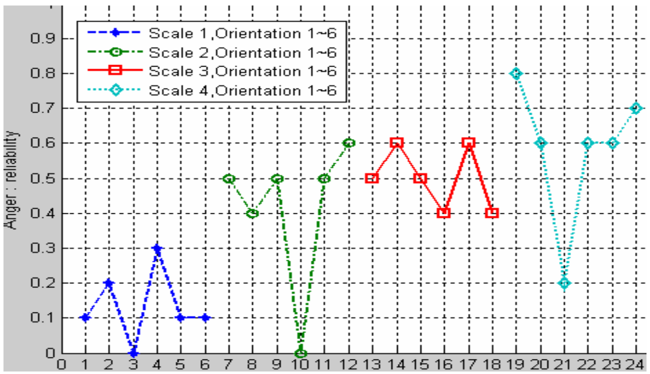
$$K(x, x') = \exp(-\gamma \|x - x'\|^2) \text{ ,for } \gamma > 0$$

In this paper, we choose the RBF kernel function to perform the SVM classification of two classes. It is noticeable that SVM makes the binary decision. Here, the multi-class classification is accomplished by a cascade of binary classifiers together with a voting scheme. If there is not a single maximum value of the voting result, we will use the algorithm of Nearest Neighborhood Classifier to make the final judgment.

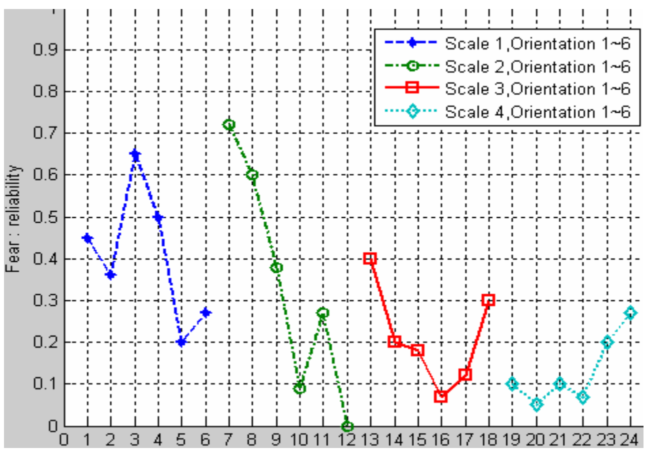
### B. Classification Result

If we cascade all the $HSLGBP(v,u)$ as the final feature to perform the sample training, we will find that the feature dimension is too high. Through the large-scale experiments, we discover that the Gabor wavelet coefficient in the different scale and orientation has the different contribution to the recognition result. The reason may be that the different expression results in the different orientation and degree of face organ deformation, such as eyebrow, mouth, eye and so on. If one expression causes the large deformation in one orientation, the recognition rate based on the Gabor wavelet coefficient at that orientation will be high.

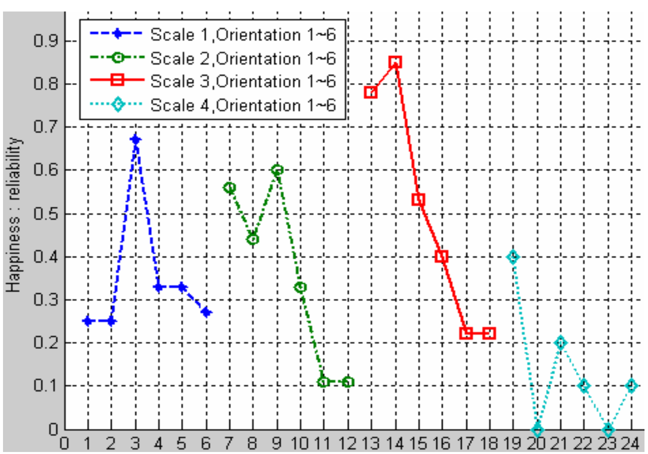
Based on the above observation, we design the experiments to investigate the relationship between the recognition rate and the Gabor wavelet coefficient in the different scale and orientation. If we determine all the relationships, we can assign the different weight to the expression in the different scale and orientation properly. The final recognition result is achieved by fusing all the recognition results based on the different Gabor wavelet coefficients. This method is superior to the one of using the wavelet coefficient in a single scale and orientation, or the one of using all the wavelet coefficient sequence in the different scale and orientation. The relationship between HSLGBP(v,u) and the recognition result is given in Fig. 6.



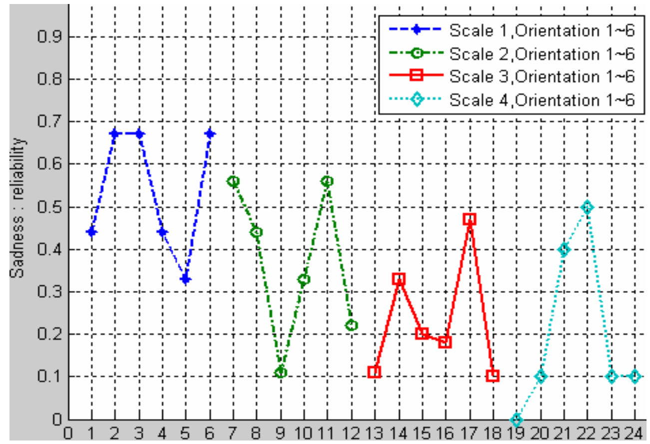

(a)




(b)




(c)




(d)

Figure 6. The relationship between HSLGBP(v,u) and recognition result (a) Anger, (b) Fear, (c) Happiness, (d) Sad

The term $R(v,u,i)$ is used to denote the recognition result of the $i$ th expression in the scale $v$ and orientation $u$. We get $R(v,u,i)$ through the sample training. The term $r(v,u,i)$ is the recognition result based on the testing samples. The final recognition result can be got by fusing $R(v,u,i)$ and $r(v,u,i)$, i.e.

$$R = \max_i [\sum_v \sum_u R(v,u,i) r(v,u,i)]. \tag{13}$$

## V. EXPERIMENTAL RESULT

In experiments the JAFFE facial expression database is used, which includes 213 images of ten persons. Each person has six basic expressions and two to four neutral expressions. Fig. 7 gives two examples of different expressions, which are the anger, disgust, fear, happiness, neutral, sadness and surprise.

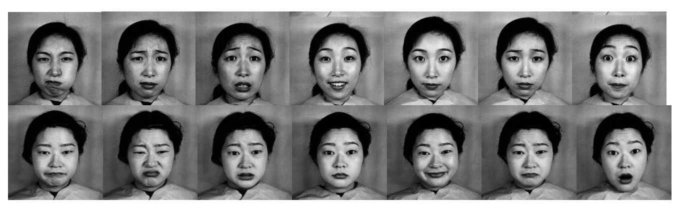


Figure 7. Two groups of images in the JAFFE facial expression database

Considering the case of small samples, the method of tenfold cross validation is applied. That is to say, the database is divided randomly into ten equal-sized parts, from which nine parts are used as training samples and the other as testing sample. The above process is repeated ten times so that each part has an opportunity to be used as testing sample. The experimental results show that the facial expression recognition algorithm proposed in this paper is effective and superior to the other similar methods.

Table I compares the recognition results among the different methods. The comparative study is carried out based on the same facial expression database, i.e. JAFFE, as the ones adopted by the other methods listed on the table. The recognition results of Gabor+SVM, LBP+SVM and LBP+Template Matching can be found in [6] [7] [18]. From the table we can see that the recognition result of our method is best. The facial features extracted based on Gabor + LBP is more effective than the ones based just on the Gabor filter or LBP operator. The dimension of features extracted based on the Gabor filter is rather high and equals 258048 (=24×112×96). Zhu et al. [6] applied the technique of AdaBoost to perform the feature selection and achieved the relatively good result. But it is possible for this method to lose some principal information about the face image. Fig. 8 compares the recognition results of four classic expressions between our proposed method based on Gabor+LBP+SVM and the one based on Gabor+AdaBoost+SVM. It can be seen that the method based on Gabor+LBP+SVM is superior to the one based on Gabor+AdaBoost+SVM . The dimension of features based on LBP is 10752 (=7×6×256), which is much lower than the one based on the Gabor filter. The average processing time per image with our proposed method is 32 seconds, which outperforms the average time of 38 seconds with Gabor+Adaboost+SVM. So it can be said that our proposed method is more efficient.

TABLE I. RECOGNITION RESULT COMPARISON AMONG DIFFERENT METHODS

| Mehthod | Recognition Result |
|---|---|
| Gabor+LBP+SVM | 97.28% |
| Gabor+SVM [18] | 95.18% |
| Gabor+Adaboost+SVM [6] | 97.1% |
| LBP+SVM [7] | 87.6% |
| LBP+Template Matching [7] | 79.1% |
| Gabor+LBP+Template Matching | 85.14% |

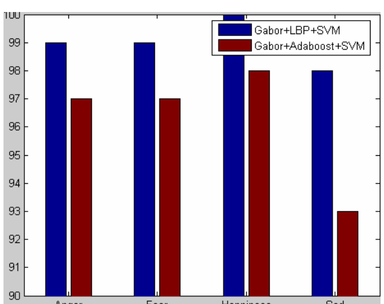



Figure 8. Recognition result comparison between two methods

## VI. CONCLUSION

Compared with the expression recognition method based on the video sequence, the one based on the static image is more difficult due to the lack of temporal information. The main contribution of this paper is to investigate the facial expression recognition based on the static image and to propose a new recognition method based on the histogram sequence of local Gabor binary patterns. The experimental results show that the facial expression recognition algorithm proposed in this paper is effective and superior to the other similar methods. The good performance of our proposed method depends on the variability of Gabor filter in representing expressions, the effectiveness of LBP in getting the global information and reducing dimension, the discrimination of SVM in the case of small samples.

## ACKNOWLEDGMENT

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