Facial Expression Recognition Using Texture Description of Displacement Image

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Abstract

In recent years, facial expression recognition, as an interesting problem in computer vision has been performed by means of static and dynamic methods. Dynamic information plays an important role in recognizing facial expression in the image sequences. However, using the entire dynamic information in the expression image sequences is of higher computational cost compared to the static methods. To reduce the computational cost, instead of entire image sequence, only neutral and emotional faces can be employed. In the previous research, this idea was used by means of Difference of Local Binary Pattern Histogram Sequences (DLBPHS) method in which facial important small displacements were vanished by subtracting Local Binary Pattern (LBP) features of neutral and emotional face images. In this paper, a novel approach is proposed to utilize two face images. In the proposed method, the face component displacements are highlighted by subtracting neutral image from emotional image; then, LBP features are extracted from the difference image as well as the emotional one. Then, the feature vector is created by concatenating two LBP histograms. Finally, a Support Vector Machine (SVM) is used to classify the extracted feature vectors. The proposed method is evaluated on standard databases and the results show a significant accuracy improvement compared to DLBPHS.

Keywords: Facial Expression Recognition; Difference Image; Displacement Image; Local Binary Patterns; Support Vector Machine.

1. Introduction

Emotion expression in human face or facial expression is an important way of human emotional social interaction. Psychological studies show that the basic emotions have universal facial expressions in all cultures [1]. There are six basic emotions including anger, disgust, fear, happiness, sadness, and surprise which were proposed in [2]. Different subjects express these emotions differently. However, we can recognize facial expression of an unfamiliar face [3]. Due to various applications, such as human-computer interaction and producing robots with human-like emotions, automatic analysis of facial expression becomes an interesting and challenging problem in pattern recognition and machine vision studies.

Feature extraction plays an important role in the accuracy of recognizing facial expression. Facial expression recognition systems can be divided according to their feature extraction method [4]. Basically, there are three types of feature extraction methods: (1) appearance feature-based; (2) geometric feature-based; and (3) hybrids of appearance and geometric features. Geometric feature-based methods [5-7] use the location and geometric shape of facial components, such as mouth and

eyes, to represent a facial image. Appearance feature-based methods [8-11] employ the texture information of facial image [4,11]. In the hybrid methods [12-16], both geometric and appearance features are utilized to represent facial images. Though geometric features have similarity to or more accuracy than the appearance features [17,18], geometric feature extraction generally needs perfect facial fiducial point localization.

In [6,7], a geometric model of 30 fiducial points was proposed and several specific distances were used as facial features. In [5], a subset of the facial expressions was recognized by calculating the correlation functions from some geometric features of the lip regions, such as the relationship between the width and the height of the lips. In some studies [19-22], optical flow-based methods were used to track facial movements in the video sequences. However, optical flow-based methods suffer from the varying illumination and non-rigid facial motions and cannot be used in real-time applications due to their computational complexity [23].

In appearance feature-based methods, Gabor filter [24] was generally applied to the facial images [15,25-27]. However, convolving Gabor filters in different orientations and scales require a huge amount of

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calculations. In recent years, another type of texture descriptors as Local Binary Patterns (LBP) has been introduced [28], and its different versions have been used for facial appearance feature extraction in both static and dynamic approaches [9-11,15]. A survey of the exiting works on facial image analysis using LBP-based representation can be found in [29]. One important property of LBP is its tolerance against illumination changes [11]. In [11], facial images were normalized by manually labeling the eyes location, and then the face images were represented using LBP features. Volume Local Binary Patterns (VLBP) and Local Binary Patterns from Three Orthogonal Planes (LBP-TOP) were used for dynamic image texture description in [9,10]; as well as the recognition of facial expression. The disadvantage of VLBP is its long feature vector increasing computational cost.

In other categorization, the existing studies can be divided into static and dynamic methods [4]. Static methods use a single frame to recognize facial expression, while in the dynamic methods temporal changes in the video sequence are utilized [4]. Facial expression recognition using LBP presented in [11] is a static approach. However, VLBP and LBP-TOP used in [9,10] are dynamic methods. Psychological studies indicate that dynamic methods provide higher performance than the static approaches [30].

1.1 Database

In this paper, extended Cohn-Kanade database (CK+) [31], that is an extended version of original Cohn-Kanade dataset (CK) [32], is used to evaluate the proposed algorithm. CK+ database was presented in 2010 to overcome the limitations of CK database. The database consists of 123 subjects and all prototypic emotions; in addition, the dataset includes contempt facial expression. Moreover, 68 fiducial points were localized using Active Appearance Model (AAM) in the database [31]. Each data includes a sequence of images starting from neutral face to the peak of its emotion. For instance, Fig. 1 shows

an image sequence with surprise facial expression in CK+ database. In this paper, three peak frames of each sequence were labeled as one of the six basic emotions are used for our experiments. Besides, face regions are localized using AAM feature point localization. Fig. 2 shows some examples of CK+ facial image selected from peak frames.

1.2 A brief overview of this study

As mentioned previously, facial expression recognition using dynamic approaches provide better results than the static methods [30]. Therefore, this paper tries to utilize the dynamic information of facial expression. However, utilizing the whole dynamic information of an image sequence has a huge computational cost. For this reason, this paper compares the emotional image with neutral image to extract suitable facial features. In this study, LBPs are used as facial appearance features due to their accuracy in facial representation [29] and computational simplicity. All of the experiments are person-independent in such a way that the train persons are not present in the testing data. For this reason, a multiclass Support Vector Machine (SVM) classifier is used in different cross validation testing schemes. Support Vector Machine is a powerful classifier which has attracted much attention in pattern recognition and facial expression recognition problems [9-11,27].

The remainder of this paper is summarized as:

In the next section, LBP texture representation is described. The proposed feature extraction method using LBP is described in section 3. Evaluation of the proposed system on standard databases is presented in section 4. Finally, section 5 concludes this paper.

2. Local Binary Patterns

Basic Local Binary Patterns (LBP) operator was

Fig 1. One image sequence in CK+ database [31] with surprise expression. The sequence starts from neutral image (top left) to the peak of surprise emotion (bottom right).

Fig 2. Some samples of original CK database images and extended data in CK+ database are presented in the top and bottom rows, respectively. From top left to bottom right: Disgust, Happiness, Surprise, Fear, Angry, Contempt, Sadness, and Neutral facial expression [31]

introduced as a powerful texture descriptor in [28]. This operator describes each image pixel by an integer number on the interval {0-255}. For each pixel, LBP operator produces 8 labels by thresholding 3×3 neighborhood of the pixel with its gray-level value. The corresponding decimal value of generated binary number by 8 labels is then used to describe the given pixel. Fig. 3 shows the result of applying LBP operator to a pixel.
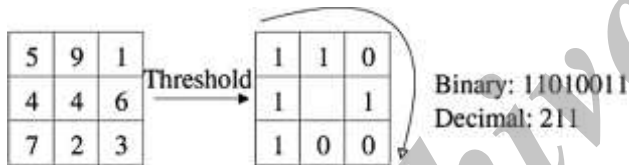

Fig 3. An example of the basic LBP operator on an image pixel [33].

Finally, the matrix of produced LBP codes is defined and the histogram of these codes is given as

$$h_i = \sum_{x,y} S(lbp_k(x, y) = i), \qquad i = 1,...,n-1 \tag{1}$$

Where lbp_k is the produced LBP code matrix of the kth image; n is the number of LBP codes (in basic LBP operator, n is equal to 256); and function S is defined as

$$S(x) = \begin{cases} 1 & x \ is \ True \\ 0 & x \ is \ False \end{cases} \tag{2}$$

The basic LBP operator produces 256 binary patterns. However, it can be shown that a subset of these binary patterns contains more information than others [34]. The most appeared binary patterns in facial images are uniform that contain at most two bitwise transitions from 1 to 0 or vice versa when the binary code string circulates [34]; for example 00011100 and 11111111 binary patterns are uniform. The number of uniform binary patterns in the basic LBP operator is 58; accumulating the non-uniform binary patterns into a single bin yields a 59 bin histogram (LBP^{u2} operator) which can be used as a texture descriptor [34]. LBP^{u2} histogram contains texture information over the image. Fig. 4 shows some examples of uniform binary patterns along with their micro-texture information.

The experiments show that 90.6% of the appeared binary patterns using basic LBP operator in facial images are uniform [36]. Consequently, this paper uses LBP^{u2} operator to represent facial images.
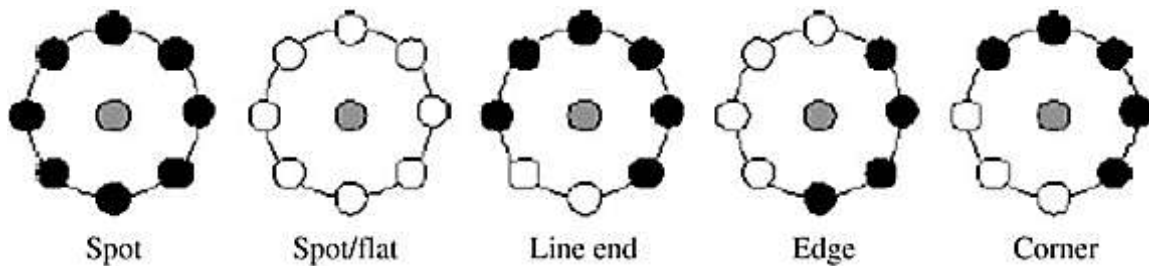

Fig 4. The experiments show that 90.6% of the appeared binary patterns using basic LBP operator in facial images are uniform [36].

3. Facial Representation using Displacement Image LBP (DI-LBP)

As mentioned previously, this study uses the dynamic information of facial images. Appearance-based features represent texture information, such as creases, wrinkles, and furrows in the facial image. Intuitively, we can say that a facial expression is a variation in the texture of facial image. This variation is individual in each expression; and it lies in some specific regions. In this paper, the facial regions containing expression-based

variation are detected in the video sequence. For this reason, the difference of emotional image and one of the previous frames (here: the first frame of image sequence) is calculated. Then, LBP^{u2} features are extracted from the difference or displacement image (DI). The block diagram of the proposed algorithm is shown in Fig. 5.

At first, three peak frames and the first frame of each sequence are selected from the database. All color images are converted to grayscale image. Next, face region is localized using AAM feature points. Then, all facial images are normalized to 150×110 pixels. In the next
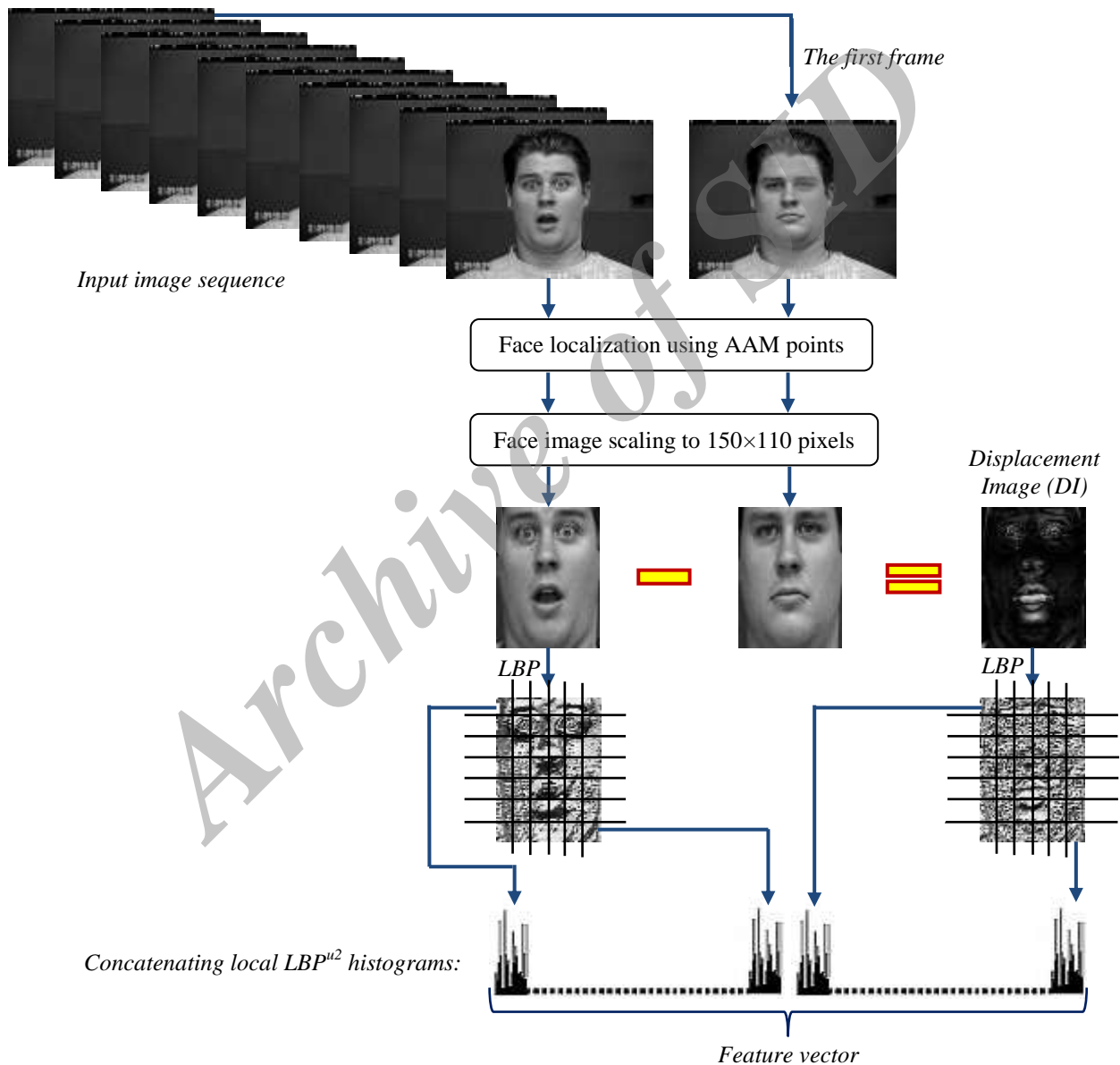

Fig 5. The general framework of proposed facial expression recognition system.

Step, the difference of three peak frames and the first frame is calculated. Then, LBP^{u2} histogram is extracted from difference/displacement image (DI-LBP). Thus, the facial regions being stationary in the image sequence are

appeared as flat areas in DI. Accordingly, facial stationary textures are accumulated in the flat area bin of LBP histogram. Holistic LBP histogram cannot represent any indication about location of binary patterns. To overcome

this problem, facial images are divided into 42(6×7) sub-region with the size of 21×18 pixels according to [11]. Then, the LBP[u2] histograms of these sub-regions are concatenated to a single feature vector with the length of 2478(59×42) to represent facial image. Each sub-region LBP histogram can be defined as

$$H_i = \sum_{x,y} S\{lbp_k(x,y) = i\}.S\{(x,y) \in R^{(j)}\}$$
$$i = 0,\dots,n-1, \qquad j = 0,\dots,m-1 \qquad (3)$$

where R(j) is *j*th sub-region in facial image; and m is the number of sub-regions (m = 42).

To keep all suitable information of facial image, the LBP histograms of emotional image is calculated in the same way. Finally, this LBP histograms and DI-LBP are concatenated into a final feature vector with the length of 4956(2×2478).

In [37], difference of LBP histograms which are calculated from emotional and neutral frames was used as DLBPHS (Difference of LBP Histogram Sequences) feature vector to represent facial images. One disadvantage of DLBPHS is the elimination of small displacement texture information from LBP histogram by subtracting LBP feature of two images. Small displacements which occurred in a single sub-region of facial image did not affect the LBP histogram of this sub-region. In other words, the LBP histogram is not changed by a small displacement in the facial component. Consequently, subtracting two LBP histograms eliminates the small displacement information of facial image. On the contrary, the effects of these small displacements are highlighted in DI. Calculating LBP histogram from DI can be appropriately used for texture description in facial image.

Another disadvantage of subtracting two LBP histograms in DLBPHS algorithm is the elimination of facial stationary region information. In contrast, in the proposed method, the difference of neutral and emotional images is calculated; thus, facial stationary regions are appeared as flat area in DI. Accordingly, the texture information of these regions lies in flat area bin in the LBP histogram. As a result, feature vectors are inherently normalized. Furthermore, any information is not eliminated from feature vector; and only lies in suitable bins in the LBP histogram.

4. Experiments

To evaluate the performance of the proposed algorithm, Support Vector Machine (SVM) [38] classifier is utilized on CK+ [31] database. For this reason, different testing schemes, including 10-fold cross validation and leave-one-subject-out are used for person-independent classification. To reduce the computational cost, some important regions in facial image can be used for feature extraction. For this reason, mouth and eyes regions are selected in our experiments. This method reduces computational complexity and enhances the accuracy of

the algorithm. A multi-class SVM classifier with linear and polynomial (degree = 2) kernel functions is used to classify the extracted features. Table 1 shows the result of different region selection in facial expression recognition. The confusion matrix of six-expression recognition on CK+ database using SVM (linear) is shown in Table 2. The results of different region selection are compared with [39] in Table 3.

Table 1. 6-class average recognition rate on CK+ database in case of different region selection

SVM kernel	Measure				
Linear	10-fold	91.45	93.72	89.5	79.44
	[1]LOSO	**93.16**	**94.68**	**91.97**	**80.24**
Poly.	10-fold	91.67	94.16	89.72	77.71
	LOSO	92.29	94.68	91.86	79.26

[1] LOSO: leave-one-subject-out

Table 2. Confusion matrix of six-expression recognition on CK+ database using SVM (linear) classifier and leave-one-subject-out testing scheme

Expression	An. (%)	Di. (%)	Fe. (%)	Ha. (%)	Sa. (%)	Su. (%)
Angry	**92.59**	5.19	0	0	2.22	0
Disgust	1.72	**97.70**	0	0.57	0	0
Fear	4.17	2.78	**88.89**	0	0	4.17
Happiness	0	2.42	1.45	**96.14**	0	0
Sadness	8.33	0	0	0	**88.10**	3.57
Surprise	0	1.20	1.20	1.2	0	**96.39**
Average	**94.68 %**					

Table 3. Comparison of the algorithm performance with [39] on CK+ database in case of different facial region selection

	whole face	Best region selection	mouth	eyes
Ours (%)	**93.16**	**94.68**	**91.97**	**80.24**
[39] (%)	88	91.4	81.0	64.8

CK+ database includes contempt facial expression, which makes it more challenging than the original CK database. In this section, 7-class facial expression recognition including contempt and six basic expressions is performed using SVM (polynomial kernel with degree = 2) classifier and leave-one-subject-out cross validation. Table 4 shows the confusion matrix of 7-class facial expression recognition. It can be seen from Table 4 that some classes have higher recognition rate than other ones. It can be due to different numbers of data in the CK+ database. Fig. 6 shows the recognition rate of each class along with the number of training data in such class. According to Fig. 6, in anger, disgust, happiness, and surprise expression, where training data are bigger than other ones, recognition rate is higher than three other expressions.

Table 5 compares the performance of the proposed method to other studies which used SVM classifier on CK+ dataset. In [39], the authors use Manifold based Sparse Representation (MSR) method and show that their method outperforms SVM classifier. As shown in Table 5,

the proposed algorithm has the highest accuracy on the database.

Table 4. Confusion matrix of 7-class recognition on CK+ database

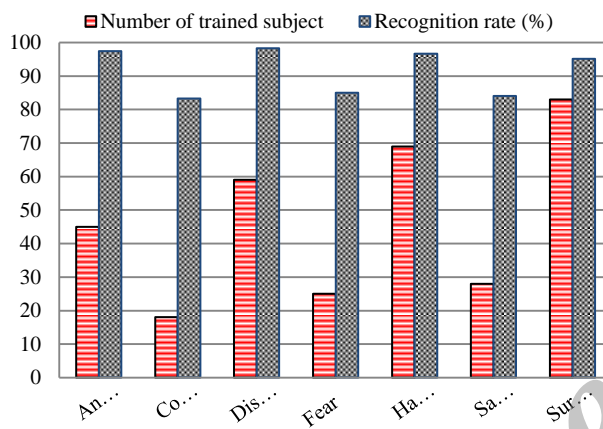| Exp.	An. (%)	Co. (%)	Di. (%)	Fe. (%)	Ha. (%)	Sa. (%)	Su. (%)
An.	**97.44**	0	1.71	0	0	0.85	0
Co.	0	**83.33**	0	0	8.33	8.33	0
Di.	1.72	0	**98.28**	0	0	0	0
Fe.	5	0	0	**85**	5	0	5
Ha.	0	0	1.93	1.45	**96.62**	0	0
Sa.	13.04	0	0	2.9	0	**84.06**	0
Su.	0	2.41	1.20	1.20	0	0	**95.18**
Average	**94.41 %**						

Fig 6. Recognition rate versus number of train data in each class.

Table 5. Comparison of the algorithm performance with the existing work on CK+ database

Method	Classes	Classifier	Cross Validation	Acc. (%)
Ours	6	SVM	leave-one-subject-out	94.68
Ours	6	SVM	10-fold	94.16
Ours	7	SVM	leave-one-subject-out	94. 41
Ours	7	SVM	10-fold	94. 05
[31]	7	SVM	leave-one-subject-out	88.33
[40]	7	SVM	10-fold	90.1
[41]	7	SVM	leave-one-subject-out	82.6
[42]	7	SVM	10-fold	89.3
[39]	7	MSR	leave-one-subject-out	91.4

5. Evaluation on JAFFE database

To provide a fair comparison of the proposed algorithm with DLBPHS [37], we conducted the experiments in the same ways as [37]. In [37], JAFFE database [43] was used in the experiments. JAFFE database consists of 10 Japanese female subjects. Each subject has 3 or 4 images for each basic facial expression

and the neutral face (totally 213 images with size of 256×256 pixels). Some samples of JAFFE facial expression images are shown in Fig. 7.

In [37], 2 images from each expression for each subject were selected in training step, and the rest of the images from each expression were used as test images. In this section, the experiments are conducted in the same way as [37]. The confusion matrix of six basic expressions is shown in Table 6. As can be seen in Table 6, sadness expression has lowest recognition rate in six classes. Recognition of sadness expression in JAFFE database is relatively difficult due to the dataset characteristics. We can see this issue in the reported results in [37]. Moreover, we implement the DLBPHS method [37] (which was discussed in section 3) with the same results as [37] on JAFFE database. Then, this method is experimented on CK+ database in a 10-fold cross validation person-independent testing scheme. Table 7 compares the results of our method with DLBPHS on both CK+ and JAFFE databases.

Table 1. Confusion matrix of 6-class expression recognition on JAFFE database

Expression	An.	Di.	Fe.	Ha.	Sa.	Su.
Angry	**90**	10	0	0	0	0
Disgust	0	**100**	0	0	0	0
Fear	0	10	**90**	0	0	0
Happiness	0	0	0	**100**	0	0
Sadness	0	0	20	10	**70**	0
Surprise	0	0	0	0	0	**100**
Average	**91.23 %**					

Table 7. Comparisons between DLBPHS method [37] and our method

Method	Database	6-calss recognition (%)
Our method	**CK+**	**94.16**
Our method	**JAFFE**	**91.23**
DLBPHS	CK+	82.36
DLBPHS [37]	JAFFE	80.33

6. Conclusions

In this paper, we present an approach for facial expression recognition which uses the dynamic information of neutral and emotional frames for feature extraction. For this reason, the first frame of each image sequence (neutral face) is subtracted from the emotional face instead of subtracting their feature vectors. Then, LBP texture descriptor is utilized to extract efficient facial features. From the experimental results on the standard databases, it can be concluded that feature extraction from difference/displacement image (DI) provides a better accuracy than subtracting LBP feature vectors.

In many dynamic facial expression methods, the whole facial expression image sequence is used. The proposed method can be used in these dynamic systems to reduce the computational cost. Moreover, DI can be computed from emotional face and one of the previous frames (which has low emotion intensity) instead of neutral face for real-world applications in future work.
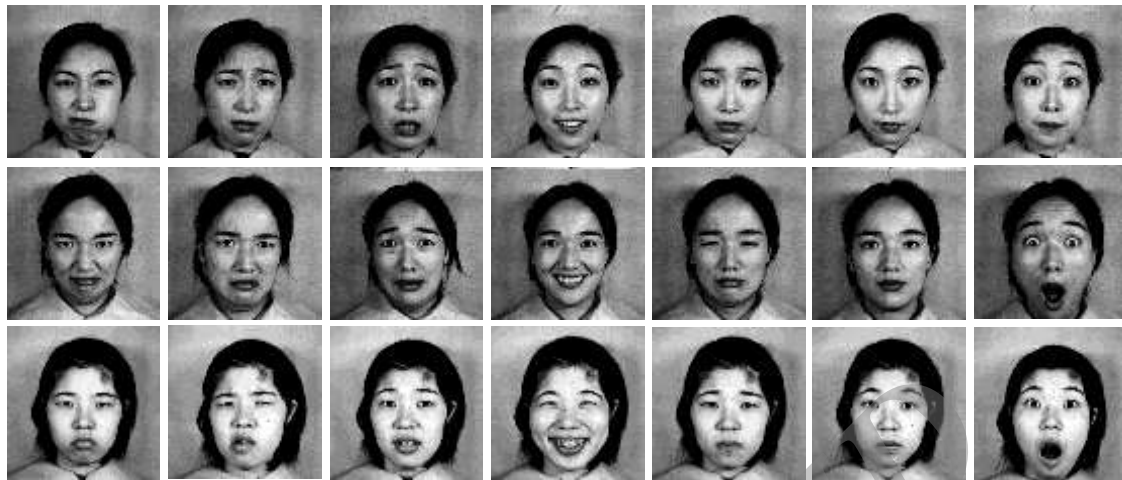
Fig 7. The example images from JAFFE database [43]; each row from left to right: anger, disgust, fear, happiness, sadness, neutral, and surprise.

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