Indian Journal of Science and Technology, *Vol 8(35), DOI: 10.17485/ijst/2015/v8i35/86092, December 2015*
ISSN (Print) : 0974-6846
ISSN (Online) : 0974-5645

Recognition of Facial Emotion through Face Analysis based on Quadratic Bezier Curves

Yong-Hwan Lee[1], Hyochang Ahn[2], Han-Jin Cho[1] and June-Hwan Lee[1]*

[1]Department of Smart Mobile, Far East University, Korea; hwany1458@empal.com, hanjincho@hotmail.com, rainbow@kdu.ac.kr

[2]Department of Applied Computer Engineering, Dankook University, Korea; youcu92@dankook.ac.kr

Abstract

Emotion recognition is a challenging task of human-computer interface in wireless communication. Emotion recognition from speech has a problem with the quality of the input voice, which is difficult to ensure in the mobile environment. On the contrary, facial emotion recognition is one of the interesting subjects due to the relevance of the expressions on human emotions. This paper proposes an automatic extraction and interpretation method of facial expression using extraction of feature points and variation of the Bezier curve from still image. The proposed algorithm has three steps to recognize the facial emotion: (1) Detecting facial regions with feature map, (2) Drawing the Bezier curve on eye and mouth, and (3) Classifying the emotion of characteristic with Hausdorff distance. To evaluate the proposed recognition scheme, we estimate a success-ratio with emotionally expressive facial image repository. Experimental results show average 76.1% of success to interpret and classify the facial expression and emotion.

Keywords: Emotion Classification Model, Emotion Recognition, Facial Expression Analysis, Quadratic Bezier Curves

1. Introduction

Recognition and analysis of facial expression and its emotion have attracted a large number of interests in the last few years, and they have been researched extensively in neuroscience, cognitive sciences, computer sciences and engineering[1]. The researches focus on improving a quality of Human-Computer Interfaces (HCI), as well as enhancing a user feedback to computer. While interaction between user and computer traditionally occurs by using keyboard and/or mouse, in the recent, smart devices equipped with camera enable a system to see and trace a user's activities, and this leads that the user can easily utilize intelligent interaction. Human interacts with the others by speeches and/or gestures to emphasize a certain part of the speech, and to display the user emotions. Emotions are usually displayed by vocal, visual and/or other physiological means[6]. There are many ways to display human's emotion, and the most natural way to show the emotion is using facial expression, which are mostly based on video sequences[17].

Various methods have been used to detect and evaluate a human's emotions. The commonly used techniques for emotion recognition include the use of physiological signals, speeches, body gestures and facial expressions. Emotion recognition by speech has some problems by assuring the quality of the input voice and by identifying the context of the words being spoken, which are different to ensure under mobile environment[18]. On the contrary, recognition of facial expression and its emotion is very interesting subject due to the relevance of the expressions on human's emotions, which provides the most natural way to recognize an emotion of the user[2], relatively few restrictions on the wireless mobile environments.

**Author for correspondence*

The motivation of this work is to research the effect of facial landmark, and to implement an efficient recognition algorithm of facial emotion with still image, while most of researches are using video sequences due to utilize the differences between frames. This paper proposes a scheme to automatically segment an input still image, and to recognize facial emotion using detection of color-based facial feature map and classification of emotion with simple curve and distance measure is proposed and implemented. This paper is an extension[1] of the previous work[3]. This work not only extends rules of classification to recognize five types of human facial emotion, but also provides an enhanced performance by pre-processing.

This paper is organized as follows: Section 2 provides related works about recognition of facial emotion. Section 3 presents the proposed system that uses two main steps to recognize and classify the facial emotion from still image. Section 4 shows the experimental results for evaluation, and Section 5 concludes this work with future works.

2. Related Works

A number of recently papers exist on automatic affect analyze and recognition of human emotion[4]. Many literatures about face analysis and recognition decompose the facial expression, and then evaluate the emotional state of face with four main steps, as shown in Figure 1; (1) Localization of the face area on the input image, (2) Extraction of facial feature and representation of the extracted feature vector, (3) Analysis of facial expression, and (4) Interpretation and classification of facial expression by emotional model[18].

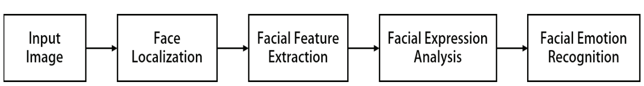

Figure 1. General workflow of facial emotion recognition[18].

Face localization step involves a detection of every face within the input image, by obtaining position of faces and by delimiting areas. The result of this step is a boundary rectangle of the detected face region. Anyway, face localization (similar meaning as *face detection*) algorithm is itself a research area with partial solutions, which has focus on locating face area with specific characteristics (such as eyes) within images and/or videos[22]. The next step is a facial feature extraction, which is the most computationally demanding task in the recognition process. In this step, the significant information of a face is obtained, which allows a recognizing the facial expression. As cited in[18], the process of feature extraction can roughly be categorized into three methods: feature-based approach, image-based approach and model-based approach. The third step is a classification of facial expression, which is built to accept a feature vectors calculated from original input data. Statistical pattern based approaches are commonly used to construct the classifier with some training schemes. The last step is an analysis and recognition of facial expressions and its emotions. The most commonly used schemes are Facial Action Coding System (FACS)[20] and Facial Animation Parameters (FAPS)[21].

Ekman[5] was a pioneer of research on facial emotion recognition through face analysis from psychology perspective. Ira[6] proposed architecture of Hidden Markov Models to automatically segment and to identify facial expression from video streams. Yashnari[7] investigated a scheme for recognizing facial expression from speaker by using combination of thermal image processing and speech recognition method. He improved speech recognition method to save thermal images through intentional facial expressions of five emotional categories, before and when a user speaks the phonemes of the first and last vowels. Spiros[8] proposed an emotional recognition method of extracting appropriate features of face, and consequently recognizing a state of user's emotion. His experimental results were robust on variations of facial expression among different users. However, these researches are based on videos using extracting frames.

Several researches were published that could recognize deliberately, which produced action units from face images in the frontal view[9] or in the profile view[10]. While Riazur[9] employed an expert rules based on neural networks and utilized a feature based image representation, Pantic[10] included a machine learning method and used an appearance based image representation. Valstar[11] provided a probabilistic ensemble learning technique for automatic action unit of facial recognition from images. Chakraborty[27] proposed an emotional recognition system based on fuzzy relational approach from facial expression

These improvements are due to three changes: First, we extend clear distinguishable rules on the classification of entered images as shown in Table 1[1]. Second, an improved method is applied in the pre-processing step and on the generation of feature curve to enhance computational time. Last, image database was prepared more large and reasonable, focusing on the five basic emotions (happy, angry, surprise, sad and neutral).

and control. He used external stimulus to excite specific emotions in human subjects by segmenting and localizing the individual video frames into regions of interest. He utilized the selected features (such as eyes, mouth and eyebrow), and mapped them to an emotional rule by employing Mamdain-type relational models. Cowie[28] proposed and implemented an intelligent emotion recognition system, which could interweave psychological findings about emotional presentation of facial expressions. He created a fuzzy rule for classifying facial expressions with six archetypal emotional categories. Valstar[29] proposed an automatic facial recognition method, which could be fast and robust on recognizing facial expression from video stream. He analyzed subtle changes in facial expression and their temporal behavior by recognizing action units of facial muscle.

One of other approaches for emotion recognition is to use a user's speech. Speech not only includes an information what user said, but also contains an information about speaker's emotion and intention[30]. Razak[31] proposed a voice-driven emotion recognizer for automatic identifying user's speech, running on smart phone. He utilized linear predictive coding algorithm for feature extraction, and selected 18 speech features to represent each emotion. English and Malay are supported for training and recognition purpose. Pao[32] proposed a speech emotion recognition method using whole sentence based segmentation, which detects a transition point of human emotion from continuous input speech. He investigated five emotions (happy, sad, bored, anger and neutral), and employed two classifying schemes (traditional K-nearest neighbor and weighted discrete K-NN) in recognition step. Kamaruddin[33] proposed a method to find a correlation between driver behavior states and speech emotion states. He used three different classifiers (multiple layer perceptron, adaptive neuro fuzzy inference and generic self-organizing fuzzy neural network), coupled with extracting features of Mel Frequency Cepstral coefficient. However, using on application, pitch plays an important vocal characteristic of parameter in speech, and it is produced through periodic vibration of vocal-cords[23]. In mobile environment, speech-based applications still have a big problem that is hard to get a clear voice due to noises and external factors. Furthermore, application is no longer globally used, since it is dependent on the language.

Physiological signal is another way for obtaining human expressive emotion. Bio-sensors have an advantage of monitoring physiological parameters of the body, which are directly controlled by nervous system[25]. Zhai[34] proposed a stress detection method using physiological signals from non-invasive and non-intrusive sensors. He monitored four signals (galvanic skin response, blood volume pulse, pupil diameter and skin temperature), and analyzed the collected data to differentiate affective states for a user. He used support vector machine learning to classify a various status and to find out that physiological signals have a strong correlation with changes in emotional state. Maaoui[35] proposed an emotion recognition scheme using physiological signals from multiple subjects. He selected five physiological signals (blood volume pulse, electromyography, skin conductance, skin temperature and respiration) to extract 30 features for recognition. He used two classification methods (fisher discriminant and support vector machine), and compared an emotional state as classified. Danny[26] proposed an emotion recognition scheme using brain query electroencephalogram personal efficiency trainer, which actually takes a look inside human head to observe user's mental state.

3. Proposed Method

The proposed method for interpretation and classification of facial expression and emotion is composed of three major steps: first one is a detecting and analysis of facial area from original input image, and second is a drawing the Bezier curve on the facial feature region, and last is a verifying of the facial emotion of characteristic features in the region of interest. A flow depicting main steps of the proposed method is shown in Figure 2.

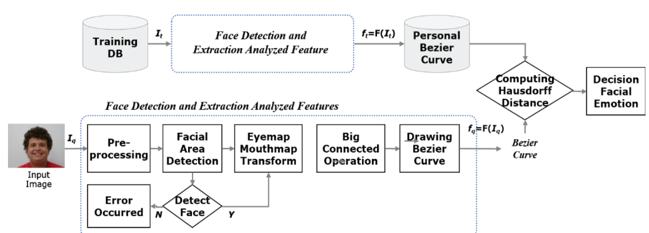

Figure 2. Diagram of the proposed scheme.

In the first step of face detection, the proposed method finds and points out a facial area within input image using detection algorithm of skin color and eye/mouth region. The proposed system first extracts pixels for skin color using initialization of spatial filtering, due to the results from lighting compensation. Then, the proposed method evaluates a face position and region of facial location for eye and mouth with their feature map. After obtaining the region of interest, we extract points of the feature map to apply Bezier curve on both eyes and mouth. Then, interpretation and classification of facial emotion are performed through training and measuring a difference of Hausdorff distances with quadratic Bezier curve between input face image and facial images in database.

3.1 Detection of Facial Area and Extraction of Feature Map

First step of our scheme is color space transformation and lighting compensation. Although skin color appears to vary, we assume that there exists underlying similarities in the chromatic properties of all faces and that all major differences lie in intensity rather than in the facial skin color as its own. In this case, we utilize a skin-color based approach using YCbCr color model. To convert color model, the following equation is applied[12].

$$\begin{bmatrix} Y \\ C_b \\ C_r \end{bmatrix} = \begin{bmatrix} 16 \\ 128 \\ 128 \end{bmatrix} + \begin{bmatrix} 65.481 & 128.553 & 24.966 \\ -37.797 & -74.203 & 112.000 \\ 112.000 & -93.786 & -18.214 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{1}$$

After converted color model, an illumination calibration is pre-requisite during the pre-processing for the accurate face detection. Since the illumination condition is an important factor to effect on the performance of detection, we execute pre-processing to equalize the intensity value in an image as follow:

$$Y' = \left(\frac{y - \min_1}{\max_1 - \min_1}\right)(\max_2 - \min_2) + \min_2 \quad \mathit{if} \quad (y \le K_l \; and \; K_h \le y) \tag{2}$$

Where min_1 and max_1 are minimum and maximum value of Y component on input image, min_2 and max_2 are the value of the transformed space, K_l and K_h are given with 30 and 220, respectively. The values of these experiential parameters are estimated from training data sets of skin fetching from sample database.

Histogram equalization enhances the performance which brightness is second into one direction, Frequency cumulativeness is dependent on r_k, and the following equation is then used for the intensity equalization.

$$E(r_k) = \sum_{j=0}^{k-1} P_r(r_j) = \sum_{j=0}^{k-1} \frac{n_j}{n} \quad, 0 \le r_k \le 1 \tag{3}$$

Where k is the number of discrete values for the intensity, n is the number of total pixels in image, r_k is the k th intensity, and n_k is the number of pixels whose intensity is r_k.

After reducing the illumination impact to the brightness component, we attempt to extract the region of eye and mouth on an image using *eyemap* and *mouthmap* in Equation (4) and Equation (5)[13]. Region of eyes would be easily found due to its intrinsic feature, namely symmetry. This paper restricts that both eyes should be present inside the image to detect the skin region. As cited in[14], eyes are characterized by low red component and high blue one in the CbCr planes. Thus, transformation of *eyemap* is constructed by the following equation.

$$eyemap = \frac{1}{3}\left\{\alpha \cdot (C_b)^2 + \beta \cdot (\hat{C}_r)^2 + \left(\frac{C_b}{C_r}\right)\right\} \tag{4}$$

where $(C_b)^2, (\hat{C}_r)^2$ and C_b/C_r are the normalized to the range [0,255], $\hat{C}_r$ is the negative value of C_r (i.e., 255 - C_r), and α is greater than 1, β is less than 1 of positive constant which emphasizes to increase or decrease the red and blue component. Fig. 3 (c) shows an example of detecting interest points (two eyes) using *eyemap*. We set the parameter values as $\alpha = 1.2$ and $\beta = 0.8$, which are the experiential values.

The mouth is characterized by a high red component and low blue one, thus the mouth region has a relatively high response in the $(C_b)^2$ feature, low response in the (C_b/C_r) Thus, *mouthmap* is constructed with the following equation.

$$mouthmap = (C_r)^2 \times \left\{C_r - \alpha \cdot \left(\frac{C_r}{255 \cdot C_b}\right)\right\} \tag{5}$$

Figure 3 (d) shows an example of detecting mouth point using mouthmap with $\alpha = 0.80$.

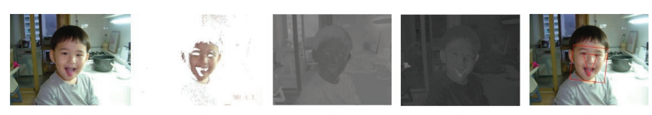

Figure 3. Detection of face boundary and features using eyemap and mouthmap; (a) Original input image, (b) Skin-tone extracted image, (c) Eyemap, (d) Mouthmap, and € Face boundary map.

After extracting the eye-mouth points with two eyes and one mouth, the feature region and the boundary points are detected by computing the density of transition pixels. To find a particular region, the relative contrast between the feature region and facial skin is an important clue for the processing. To detect the regions from background skin pixels, a morphology based approach is used to extract high-contrast feature.

Let assume that $I(x,y)$ is a gray-level image, and $S_{m,n}$ denotes a structuring element with $m \times n$ size, where m and n are odd integers and larger than zero. To obtain the morphological binary pattern, closing and opening operations are performed on structural element. Closing and opening are operated by Equation (6) and (7), respectively.

$$I(x,y) \bullet S_{m,n} = \left(I(x,y) \oplus S_{m,n}\right) \otimes S_{m,n} \tag{6}$$

$$I(x,y) \circ S_{m,n} = \left(I(x,y) \otimes S_{m,n}\right) \oplus S_{m,n} \tag{7}$$

Where $\otimes$ indicates a dilation operation, and $\otimes$ denotes an erosion operation.

The difference, obtained from subtracting both images, is calculated by Equation (8) to get the result of the following.

$$D\left(I_1, I_2\right) = \left| I_1(x,y) - I_2(x,y) \right| \tag{8}$$

Then, threshold procedure with Equation (9) is applied by labeling process to extract a longest binary pattern. To convert the skin pixels in the boundary rectangle to white pixels, and rest of them to black, a parameter T is dynamically defined by the background image, which is responsible for determining the threshold of the binarization operation.

$$T\left(I(x,y)\right) = \begin{cases} 255, & if\ I(x,y) \geq T \\ 0, & otherwise \end{cases} \tag{9}$$

3.2 Quadratic Bezier Curve on Eye and Mouth

Quadratic Bezier curve generates contour points considering global shape information with the curve passing through first and last control points[15]. If there are $L+1$ control points, position is defined as $P_k : \left(x_k, y_k\right), 0 \leq k \leq L$ considering 2D shapes. Then, these coordinate points are blended to form $P(t)$ given in Equation (10), which represent a path of Bezier polynomial function between P_0 and P_L.

$$P(t) = \sum\nolimits_{k=0}^{L} P_k BEZ_{k,L}(t) \tag{10}$$

Where Bezier blending function $BEZ_{k,L}(t)$ is described as Bernstein polynomial, defined in[14].

$$BEZ_{k,L}(t) = \left(\frac{1}{k}\right) \cdot t^k (1-t)^{L-k} \tag{11}$$

The recursive formula which are used to decide coordinate location is obtained by Equation (12)

$$BEZ_{k,L}(t) = (1-t) \cdot BEZ_{k,L-1}(t) + t \cdot BEZ_{k,L+1}(t) \quad t\ BEZ_{k-1,L-1}(t) + t \cdot BEZ_{k-1,L-1}(t) \tag{12}$$

Where $BEZ_{k,k}(t)=t^k$ and $BEZ_{0,k}(t)=(1-t)^k$.

Each of the coordinates of the Bezier curve is expressed by the following pair of the parametric formulas:

$$x(t) = \sum\nolimits_{k=0}^{L} x_k BEZ_{k,L}(t)$$
$$y(t) = \sum\nolimits_{k=0}^{L} y_k BEZ_{k,L}(t) \tag{13}$$

An example for construction of quadratic Bezier curve with three control points is shown in Figure 4[37].

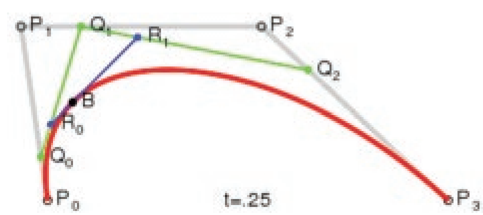

Figure 4. Example of construction of quadratic Bezier curve.

For applying the quadratic Bezier curve, we need to extract some control points of each interest regions, where locate in the area of left eye, right eye and mouth. Thus, we apply big connected operation for finding the highest connected area within each interest regions from the *eyemap* and *mouthmap*, and longest binary pattern using morphology-based operation. Then, we find four boundary points of the regions, which are the starting pixels and the ending pixels in horizontals, and the top and bottom pixels of the central points in verticals. After getting four boundary points of each region, the Bezier curves are obtained by drawing tangents to a curve over the four boundary control points. Figure 5 shows how to move the control points across different subjects, and to interpret the facial features with the quadratic Bezier curve, and to interpolate the extracted feature points.

3.3 Training and Recognizing Facial Emotion with Hausdorff Distance

In training database, there are two tables which are storing for personal information and indexes of three emotions with user's own curves of facial expression analysis. For detection of facial emotion, we need to compute the

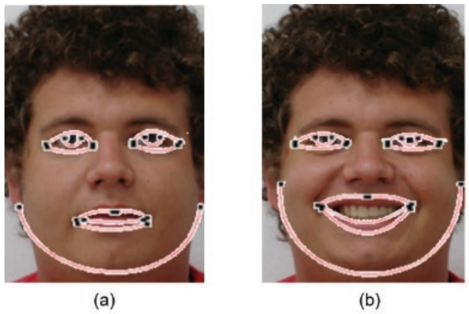

Figure 5. Quadratic Bezier curve and the extracted feature points interpliation across different subjecdts; (a) Line fitting over example image in neutral condition (normal), and (b) in happy condition (smiling).

distance as one-to-one correspondence of each interest regions between input image and the images in database. The quadratic Bezier curves are drawn and fitted over principal lines of facial features. To estimate a similarity matching, at first, we normalize the displacements that convert each width of the Bezier curve to 100 and height according to its width. Then, we apply Hausdorff distance to compare the shape metric between them. Distance $d_H(p,q)$ between two curves $p(s), s \in [a,b]$ and $p(t), t \in [c,d]$ is calculated with Equation (14)[16].

$$d_H(p,q) = \max\left(\max_{s\in[a,b]}\min_{t\in[c,d]}\left|p(s)-q(t)\right|, \max_{t\in[c,d]}\min_{s\in[a,b]}\left|p(s)-q(t)\right|\right)$$

4. Experiments and Results

Five expressions such as smile, sad, surprise, angry (Table 1) and neutral (otherwise) are considered for the experiments of facial emotion recognition. Face expressions are compared against the model of facial database consisting of neutral face. All of facial images are normalized by option parameters, and the Bezier points are interpolated over the principal lines of the extracted facial features. These points for each curve form an adjacent curve segments. Hausdroff distances are estimated based on the curve segments. Then, interpretation and classification of facial emotion is chosen by measuring similarity in faces. The ground truth set for estimating the performance of the algorithm is provided with the categories in the experiments, which are correct if the decision is belonged to the correct category.

In order to categorize facial emotion, at first, we need to determine some expressions from movements and changes of facial control points. Ekman[5] had been produced a system which describes visually distinguishable facial movements (called Facial Action Coding System, FACS). Those movements are based on enumeration of all Action Units (AUs). There are 46 AUs in FACS that account for movements of control points and changes of feature points in facial expression. He provided combination rules of the AUs, which are considered to determine form defining emotion-specified expressions. The rules for facial emotion (given in Table 1) are created by basic AUs from FACS, and decision of recognition is determined from their rules. The rules of variances in parametric model describe an emotional pattern for each facial expression. Figure 6 illustrates a temporal deformation template for face shape of different emotions. The method used to encode the emotional pattern takes into account the total variance for each parametric points in the temporal analysis from long time video stream through the experiments.

Table 1. rules of classification for facial emotion

Emotion	Movements of AUs
Smile	Eye opening is narrowed, Mouth is opening, and Lip corners go up obliquely.
Sad	Eye is slightly closed, Lower lip corner and Eyebrows go down, and Mouth is stretched.
Surprise	Eye and Mouth are opened, Upper eyelid raises, Mouth is stretched, and Chin line is sharpened.
Angry	Eyebrows go down and are centerizing, and Mouth is slightly opened.

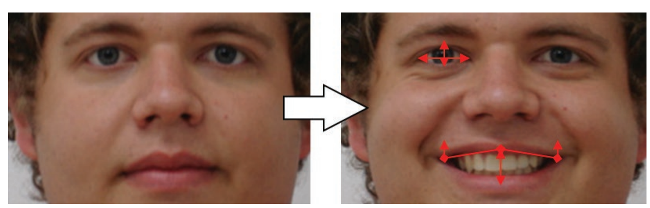

Figure 6. Shape deformation templates for the prototypic emotions.

In this work, the facial expressions have interpreted and classified only by static image. Testing of the algorithm is performed on a database of passport image, which is obtained from FEI face database[2], MMI Facial expression database[3], and Radboud Faces database[4].

2 http://fei.edu.br/~cet/facedatabase.html
3 http://mmifacedb.eu/
4 http://www.socsci.ru.nl:8180/RaFD2/RaFD?p=main

FEI database have total of 2,800 images, which consist of 14 images for each of 200 individuals. All images are colorful and are taken against a white homogenous background in an upright frontal position. Additionally, they provide a subset of facial images, totally 400 images, and each subject has two frontal images (one with neutral and the other with smiling facial expression). MMI database consists of over 2900 videos and high-resolution still images of 75 subjects. It is fully annotated for the presence of AUs in videos (event coding), and partially coded on frame-level, indicating for each frame whether an AU is in either the neutral, onset, apex or offset phase. MMI has a set of data recorded were posed displays of the six basic emotions with still images. Radboud database is a high quality faces database, which contain a set of pictures of 67 models, displaying 8 emotional expressions. Accordingly to the Facial Action Coding System, each model was trained to indicate the following expressions: Anger, disgust, fear, happiness, sadness, surprise, contempt, and neutral. Each emotion was represented by three different gaze directions and all pictures were taken from five camera angles simultaneously.

Figure 7. Example images for two subjects (neutral and happy) from sample database.

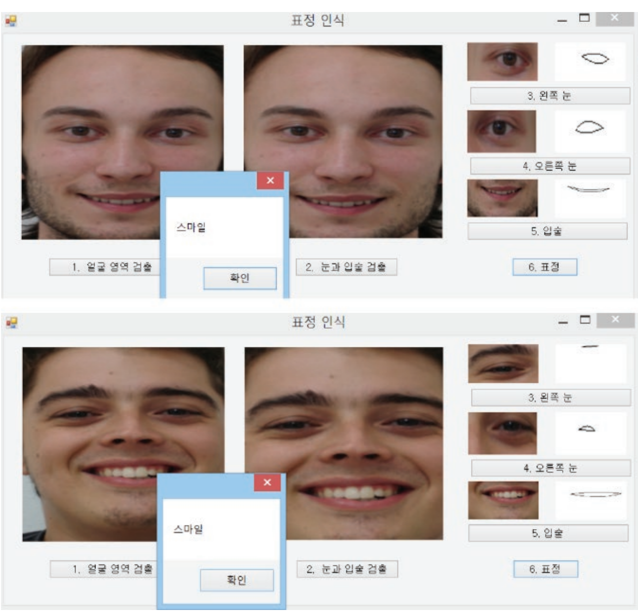

Figure 8. Screenshot of the implemented prototype system: Face interpretation and classification.

We used a subset of facial images from the database which consisted of 580 images and five categories (neutral, happy, angry, surprise, sad). Figure 7 shows sample facial images by FEI database which express an emotion, for example, by neutral and smiling expression.

We have experimented the algorithm presented in previous section under Windows 7 Enterprise as OS with the Intel Core 3.2 GHz PC with 4 GB RAM and have implemented with visual C#. Figure 8 shows a screen shot of the implemented system.

The experiments show the recognition results under different facial expressions such as smile, sad, surprise and neutral. The proposed method recognizes 463 of the 580 faces, which means that a successful recognition ratio of 76.1% is achieved, as shown in Table 2.

Table 2. Emperimental results of facial expression classification

Emotion Classification	Corrects/Misses	Success Ratio[%]
Happy	97/23	80.8%
Sad	48/22	68.6%
Surprise	84/16	84.0%
Angry	46/34	57.5%
Neutral	188/22	89.5%
Total Count and Average	**463/117**	**76.1%**

5. Conclusions

In this paper, we have proposed and implemented a simple approach for interpretation and classification of the facial emotion. The algorithm is performed three major steps: one is a detection of facial region with skin color segmentation and calculation of feature-map for extracting two interest regions, focused on eye and mouth. And second is a drawing the Bezier curves fitting on eye and mouth, and last is a verification of the facial emotion of characteristic features with the Bezier curve and the Hausdorff distance. Experimental results shows average successful ratio of 76.1% to recognize the facial expression, and this indicates the good performance and enough to applicable to mobile devices.

The main contribution of this paper is that the new model were implemented, which is convenient and can be adapted for usage on applications of user interaction and recognition in the wireless mobile environments. This approach opens up new applications in the field of computer vision and wireless application.

How to make the proposed method robust to facial pose variation and complex background under wireless mobile environments, and how to improve the computing time for real-time application are an interesting direction for future research effort.

6. References

1. Ralph A. Recognizing Emotion from Facial Expressions: Psychological and Neurological Mechanisms. Behavioral and Cognitive Neuroscience Reviews; 2002.
2. Thomaz CE, Giraldi GA. A New Ranking Method for Principal Components Analysis and its Application to Face Image Analysis. Image and Vision Computing. 2010; 28(6):902–13.
3. Yong-Hwan L, Hyochang A, Han-Jin C, June-Hwan L. Facial Emotion Recognition using Bezier Curves. International Conference on Convergence Technology. 2015.
4. Gunes H, Piccardi M. Automatic Temporal Segment Detection and Affect Recognition from Face and Body Display. IEEE Transactions on Systems, Man, and Cybernetics - Part B. 2009; 39(1):64–84.
5. Ekman P, Friesen WV. Facial Action Coding System (FACS): Investigator's Guide. Conculting Psychologists Press; 1978.
6. Ira C, Ashutosh G, Thomas SH. Emotion Recognition from Facial Expressions using Multilevel HMM. Neural Information Processing Systems; 2000.
7. Yasunari Y. Facial Expression Recognition for Speaker using Thermal Image Processing and Speech Recognition System. WSEAS, International Conference on Applied Computer Science. 2010. p.182–6.
8. Spiros VI, Amaryllis TR, Vasilis AT, Theofilos PM, Kostas CK, Stefanos DK. Emotion Recognition through Facial Expression Analysis based on a Neurofuzzy Network. Neural Networks. 2005; 18:423–35.
9. Riazur RM, Ameer AM, Sorwar G. Finding Significant Points for Parametric Curve Generation Techniques. Journal of Advanced Computations. 2008; 2(2):107–16.
10. Pantic M, Rothkrantz LJM. Facial Action Recognition for Facial Expression Analysis from Static Face Images. IEEE Transactions on Systems, Man and Cybernetics - Part B. 2004; 34(3):1449–61.
11. Valster MF, Pantic M, Ambadar Z, Cohn JF. Spontaneous vs. Posed Facial Behavior: Automatic Analysis of Brow Actions. ACM International Conference on Multimodal Interfaces. 2006. p.162–70.
12. Rafael CG, Richard EW, Steven LE. Digital Image Processing using Matlab. Prentice Hall; 2004.
13. Yong-Hwan L, Tae-Kyu H, Young-Seop K, Sang-Burm R. An Efficient Algorithm for Face Recognition in Mobile Environments. Asian Journal of Information Technology. 2005; 4(8):796–802.
14. Rein-Lien H, Abdel-Mattaleb M, Jain AK. Face Detection in Color Images. IEEE Transactions on Pattern Analysis and Machine Intelligence. 2002; 24(5):696–701.
15. Buss S, Buss RS. 3D Computer Graphics - A Mathematical Introduction with OpenGL. Cambridge University Press; 2003.
16. Seon-Hong K, Young Joon A. An Approximation of Circular Arcs by Quartic Bezier Curves. Computer-Aided Design. 2007; 39(6):490–3.
17. Nicu S, Ira C, Theo G, Thomas SH. Multimodal Approaches for Emo-tion Recognition: A Survey. Proceedings of SPIE - International Society for Optical En-gineering. 2005; 5670.
18. Andoni B, Manuel G. Emotion Recognition based on the Analysis of Facial Expressions: A Survey. New Mathematics and Natural Computation. 2009; 5(2):513–34.
19. Fatma N. Adaptive Intelligent User Interfaces with Emotion Recognition [Ph.D. Dissertation]. University of Central Florida. 2000.
20. Paul E, Wallace VF, Joseph CH. Facial Action Coding System (FACS). A Human Face. 2002.
21. Pardas M, Bonafonte A, Landabaso JL. Emotion Recognition based on MPEG-4 facial animation parameters. In proceeding on Acoustics, Speech and Signal Processing; 2002; 4:3624–7.
22. Muhammad IR, Muhammad KK, Khaled A, Jong HP. Energy Efficient Distributed Face Recognition in Wireless Sensor Network. Wireless Personal Communications. 2011; 60(3):571–82.
23. Jong KK, Hern SH, Myung JB. On a Speech Multiple System Implementation for Speech Synthesis. Wireless Personal Communications. 2009; 49(4):533–43.
24. Peter A, Petri P, Tomohire K, Dan B, Seamus H, Hiroshi S. Wireless User Perspectives in Europe: HandSmart Mediaphone Interface. Wireless Personal Communications. 2002; 22(2):161–74.
25. Andreas H, Silke G, Peter S, Jason W. Emotion Recognition using Bio-Sensors: First Steps towards an Automatic System. Affective Dialogue Systems. Lecture Notes in Computer Science. 2004; 3068:36-48.
26. Danny OB. EEG-based Emotion Recognition [Online published]; 2006. Available from: http://hmi.ewi.utwente.nl/verslagen/capita-selecta/CS-Oude_Bos-Danny.pdf
27. Chakraborty A, Konar A, Chakraborty UK, Chatterjee A. Emotion Recognition from Facial Expressions and its

Control using Fuzzy Logic. IEEE Transactions on Systems, Man and Cybernetics Part A: Systems and Humans. 2009; 39(4):726-43.

28. Cowie R, Cowie ED, Taylor JG, Ioannou S, Wallace M, Kollias S. An Intelligent System for Facial Emotion Recognition. IEEE International Conference on Multimedia and Expo; 2005.
29. Valster M, Pantic M. Fully Automatic Facial Action Unit Detection and Temporal Analysis. Proceedings of Conference on Computer Vision and Pattern Recognition Workshop; 2006.
30. Jeon JH, Xia R, Liu Y. Sentence Level Emotion Recognition based on Decisions from Sub-sentence Segments. IEEE International Conference on Acoustics, Speech and Signal Processing; 2011. p. 4940-3.
31. Razak AA, Zainalabidin MI, Komiya R. Comparison between Fuzzy and NN Method for Speech Emotion Recognition. Proceedings of International Conference on Information Technology and Applications; 2005.
32. Pao TL, Yeh JH, Tsai YW. Recognition and Analysis of Emotion Transition in Mandarin Speech Signal. International Conference on Systems Man and Cybernetics. 2010. p. 3326-32.
33. Kamaruddin N, Wahab A. Driver Behavior Analysis through Speech Emotion Understanding. IEEE Intelligent Vehicles Symposium. 2010. p. 238-43.
34. Zhai J, Barreto A. Stress Detection in Computer Users based on Digital Signal Processing of Non-invasive Physiological Variables. Proceedings of Annual International Conference of IEEE Engineering in Medicine and Biology Society; 2006. p. 1355-8.
35. Maaoui C, Pruski A, Abdat F. Emotion Recognition through Physiological Signals for Human-Machine Communication. IEEE/RSJ International Conference Intelligent Robots and Systems. 2008. p. 1210-5.
36. Anis Y, Ole-Christoffer G, John O, Martin G, Frank R. A User-Centric Approach for Personalized Service Provisioning in Pervasive Environments. Wireless Personal Communications. 2011; 61(3):543-66.
37. Available from: http://en.wikipedia.org