New Technology for Developing Facial Expression Recognition in e-Learning

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Abstract--**This project develops a face expression recognition system based on facial expression features that extracted by FaceSDK in JAFFE database. To verify the performance of our facial expression recognition system, the system was tested on JAFFEE database among static picture environment and randomly moving picture environment. The system can real-time captures participants' facial features several times in one second and then records the information in database for further analysis. Research results shows that the high performance and generalizability of our system via various machine learning algorithms. We believe that the developed facial expression recognition system with algorithms is an effective mechanism for e-learning system or another research issues.**

INTRODUCTION

Nowadays, facial expression recognition has recently become a promising research area. The reason is that facial expression is able to provide a critical human behavioral measure for the area of emotion, cognitive processes, and social interaction[1]. It is now widely accepted that intelligent learning environments are expected to care about both learners and tutors, and to have a good understanding of the variety of learning contexts. Our aim is to develop a facial expression recognition system, which can get, recognize and analyze facial expression and emotion state when students learning.

Several areas include commerce, engineering industry, or digital content industry that could obviously benefit from an automatic understanding of human emotional experience [2]. In recent studies, psychologists, educators, and neurologists have shown how emotion influences cognitive activities (e.g., learning) [3]. However, scientific evidences from academic studies about understanding human emotions are still very limited [2]. The contributions of this study are that develops a facial expression recognition system to identify learners' seven emotion status and proposes a new algorithm to improve the accuracy of facial expression recognition. Therefore, the outcome of this study is able to develop an efficient facial expression recognition system for e-learning and system developer such as cyber security.

LITERATURE REVIEW

A. Affective Computing in Learning

Why human emotion is an important research area? The latest scientific findings indicate that emotions play an essential role in decision-making, perception, learning and more [4]. Facial expression recognition is one of the most well-studies emotion expression channels [2]. Human emotions can be classified into six archetypal emotions: surprise, fear, disgust, anger, happiness, and sadness that are widely accepted from psychological theory. Facial expressions is able to provide important clues about emotions [5]. Positive emotions, such as enjoyment, hope, and pride, have been positively associated with intrinsic motivation, effort, self-regulation, and more sophisticated learning strategies [6], whereas negative emotions such as anger/frustration, shame, anxiety, and boredom have been associated with reduced effort, lower performance, increased external regulation, and decreased self-regulated learning strategies[7].

B. Support Vector Machine

Support vector machine (SVM) is a new classification method based on statistical learning theory. The advantage of SVM is SVM does not need a large number of training samples to avoid over fitting [8]. The original SVM is a binary classification, but the large number problems in real life is multi-choose. For solving the multi-class classification, the combination approach that constructing several binary classifiers and combine them into one multi-class support vector machine is usually popular. Multi-class support vector machine (MSVM) had been practically used in several problems of pattern recognition, for example, machine vision [8, 9], corporate credit rating [10], alcohol identification [11] and EEG-based mental fatigue measurement [12], and real-time face recognition [13]. Currently, hybrid methods that used principle component analysis to extract critical facial features as input variables into various SVMs as a new classifier for facial expression recognition in various industry such as law enforcement, security application, or video indexing [14].

METHOD

A. Research procedure of our designed system

In this project, we develop a facial expression emotion recognition system with SVM and decision tree classifiers based on JAFFE facial expression database as training and test dataset. First, user's facial expression videos in JAFFE database are captured by webcam and analysis in Luxand face recognition software--FaceSdk software (http://www.luxand.com/facesdk/). The FaceSdk software will identify 66 facial expression feature points and then these feature points were handled in data preprocessing step. In data preprocessing step, we firstly calculate D_1~D_6 variables from 66 facial expression feature points based on our designed modified Ammar algorithm. After that, the D_1~D_6 variables were normalized via our proposed normalization algorithm. The features were as the input variables to build the facial expression recognition system via various types of machine learning algorithms to classify the type of emotion. Because each photograph has the type of facial expression in the JAFFE, so we used the database as our training and test data. SVM models' performance was evaluated in classification accuracy.

B. Descriptions of our designed algorithms

Based on Ammar's research, D_1~D_6 are six important variables for identify user's facial expression [4]. The definition of the D_1~D_6 is shown in Table 1.

TABLE 1. DEFINITION OF D_1~D_6

Di	Definition
D_1	Opening of the eye
D_2	Outdistance between the interior corner of the eye and the eyebrow
D_3	Opening of the mouth in width
D_4	Opening of the mouth in height
D_5	Outdistance between the eye and eyebrow
D_6	Outdistance between the corner of the mouth and the external corner of the eye

Reference: [4]

Based on *Di* evolution for every emotion (Table 2), it will be possible to be different between various emotions while being interested in priority in the *Di* distance which undertake significant modifications [4].

Assume two points x = $[x_1, x_2, \ldots, x_n]$ and y=$[y_1, y_2, \ldots, y_n]$ in *d* dimension space, then the Euclidean distance can be presented as follow:

$$dist(x,y) = \sqrt{\sum_1^d (x-y)^2} \quad (1)$$

C. Normalization process

Each participant exist individual differences in their facial features. In addition, these facial feature values will be changed while they move ahead or back to our webcam. Therefore, in order to increase classification accuracy of our facial emotion recognition system, this study proposed a new normalization process to deal with normalizing facial features. Fortunately, the participants' Euclidean distance between left eye inner corner and right eye inner corner (i.e. facial feature point 24 and 25 in Figure 3-3) will not change This study proposed a new variable *n* denotes the Euclidean distance between left eye inner corner (facial features point 24) and right eye inner corner (facial feature point 25). The equation is present as below:

$$n = dist(24,25) \quad (2)$$

where 24, 25 denotes the facial feature point 24 and 25 (i.e. participant's left eye inner corner and right eye inner corner).

D. Facial expression Database

This study selected the Japanese Female Facial Expression (JAFFE) database (http://www.kasrl.org/jaffe.html) as our training and testing dataset to verify our face cognition system. The facial expression database has been tested their proposed algorithms and be published in several academic journals [1, 15-17]. The database contains 213 images of 7 facial expressions (6 basic facial expressions + 1 neutral) observed by 10 Japanese female models (Figure 4). Each photograph has been rated on 6 emotion adjectives by 60 Japanese subjects. The photos were taken at the Psychology Department in Kyushu University.

TABLE 2. *DI* EVOLUTION FOR EVERY EMOTION

	D_1	D_2	D_3	D_4	D_5	D_6
Joy	=	=	↑	↑	=	↓
Sadness	↓	↑	=	=	↓	
Anger	↑	↓	=	↑or↓	=	=
Fear	?	↑	=	=	↑	=
Disgust	=	=	↑	↑	=	=
Surprise	↑	↑	=	↑	=	=

Reference: [4]

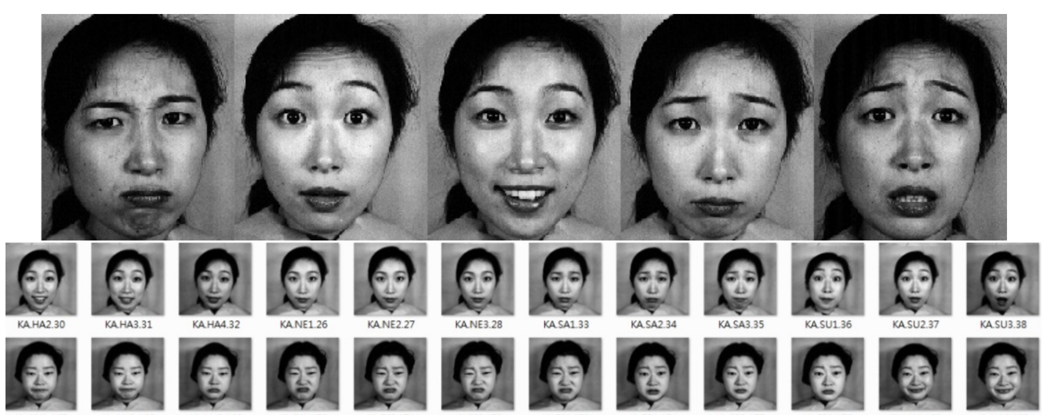

Figure 4. Example photographs in JAFFE face database

IV. DATA ANALYSIS

A. Developed Facial Expression Recognition System

Based on the abovementioned algorithm, our developed facial emotion recognition system was design in Java language with FaceSDK toolkit. The system can real-time identify important facial features and stored in database for further analysis. The database example of our proposed face recognition system was presented in Table 3.

B. Performance Analysis

To verify the performance of our facial expression recognition system, the system was tested on JAFFEE database. The FLASH program showed each picture 5 seconds in sequence. In fixed mode, each picture was showed in fixed size but it was showed in random picture size in random picture size mode. Our facial expression recognition captured total 213 pictures in each mode, and stored 3696 records (four records in one second). Our system calculated the average number during one second in the database for D_1-D_6 features and P1-P66 facial features. The final dataset included total 927 records with seven emotion status (happy, sad, surprised, angry, disgusted, fear, and neutral).The data were analyzed by various machine learning algorithms—CART and support vector machines. The comparison of performance of models was shown in Table 4.

Our system has stable prediction accuracy among various ratio of training and testing data. The SVM has the highest prediction accuracy in all the models.

V. CONCLUSION

Several areas include commerce, engineering industry, or digital content industry that could obviously benefit from an automatic understanding of human emotional experience [2]. This study develops an effective facial expression recognition system with high prediction accuracy and stability. The SVMs has the highest prediction accuracy and stability. Therefore, the outcome of this study is able to provide more helpful information for research and e-learning developer to improve learning achievement and accuracy of facial emotion recognition.

TABLE 3. THE DATABASE EXAMPLE OF OUR FACE RECOGNITION ALGORITHM

H:M:S	Emotion	n	D1	D2	D3	D4	D5	D6	P1_x	P1_y	P2_x	P2_y	P3_x	P3_y		P66_x	P66_y
14:26:00	0	48.00	-0.08	-0.28	0.00	-0.09	-0.10	-0.08	244	263	344	262	293	325	…	303	373
14:26:00	0	45.04	0.07	-0.18	0.10	-0.08	-0.15	0.04	241	261	345	260	292	326	…	303	375
14:26:01	0	45.04	0.14	-0.23	0.08	-0.08	-0.15	0.07	241	260	345	260	292	327	…	303	373
14:26:01	0	43.10	0.27	-0.27	0.13	-0.03	-0.11	0.27	244	261	345	262	292	328	…	302	373
14:26:01	0	45.04	0.16	-0.23	0.10	-0.11	-0.14	0.05	243	261	345	260	294	327	…	303	374
14:26:01	1	45.04	0.09	-0.20	0.04	-0.13	-0.09	0.01	245	263	345	260	291	327	…	303	374
14:26:01	1	47.01	0.02	-0.16	0.04	-0.15	-0.15	-0.10	241	261	345	260	292	327	…	303	375
14:26:01	1	51.01	-0.29	-0.24	-0.13	-0.21	-0.21	-0.34	240	262	345	261	291	327	…	302	373
14:26:01	1	46.04	0.08	-0.17	0.05	-0.11	-0.14	-0.08	242	262	344	261	293	327	…	303	373

Note: emotion 1=happy; 2=sad; 3=surprised; 4=angry; 5=disgusted; 6=fear; 7=neutral ….

TABLE 4. SVM PERFORMANCE OF FACIAL EXPRESSION RECOGNITION SYSTEM

Data	CART.	SVM
Training(90)	92.98 %	99.38 %
Test (10)	71.93 %	88.71 %
Training(80)	92.74 %	99.44 %
Test (20)	69.95 %	88.98 %
Training(70)	92.24 %	99.57 %
Test (30)	69.60 %	88.17 %

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