Neural Comput & Applic
DOI 10.1007/s00521-014-1637-6

ORIGINAL ARTICLE

Fuzzy model of dominance emotions in affective computing

Kaveh Bakhtiyari · Hafizah Husain

Received: 7 March 2014 / Accepted: 19 May 2014

Abstract To date, most of the human emotion recognition systems are intended to sense the emotions and their dominance individually. This paper discusses a fuzzy model for multilevel affective computing based on the dominance dimensional model of emotions. This model can detect any other possible emotions simultaneously at the time of recognition. One hundred and thirty volunteers from various countries with different cultural backgrounds were selected to record their emotional states. These volunteers have been selected from various races and different geographical locations. Twenty-seven different emotions with their strengths in a scale of 5 were questioned through a survey. Recorded emotions were analyzed with the other possible emotions and their levels of dominance to build the fuzzy model. Then this model was integrated into a fuzzy emotion recognition system using three input devices of mouse, keyboard and the touch screen display. Support vector machine classifier detected the other possible emotions of the users along with the directly sensed emotion. The binary system (non-fuzzy) sensed emotions with an incredible accuracy of 93 %. However, it only could sense limited emotions. By integrating this model, the system was able to detect more possible emotions at a time with slightly lower recognition accuracy of 86 %. The recorded false positive rates of this model for four emotions were measured at 16.7 %. The resulted accuracy and its false positive rate are among the top three accurate human emotion recognition (affective computing) systems.

Keywords Fuzzy emotion · Dominance emotion · Multilevel emotion · Human–computer interaction · Affective computing

K. Bakhtiyari (✉)
Department of Computer and Cognitive Science, Faculty of Engineering, University of Duisburg-Essen, 47048 Duisburg, North Rhine-Westphalia, Germany
e-mail: academic@bakhtiyari.com

K. Bakhtiyari · H. Husain
Department of Electrical, Electronics and Systems Engineering, Faculty of Engineering and Built Environment, Universiti Kebangsaan Malaysia (UKM), 43600 Bangi, Selangor, Malaysia

H. Husain
e-mail: hafizah@eng.ukm.my

1 Introduction

Computer systems are now attempting to interact more naturally with the users as human beings. Graphical user interface (GUI) is becoming more flexible and intelligent to be adapted with human interests. The adaptive systems applications learn the user interactions to make a user friendly platform. Human emotions are the other user parameters which are being considered in a wide area.

The importance of affective computing (AC) is reflected by its wide applications in different areas such as computer games (entertainments), computer-based tutors (e-learning), machine and system controlling (industrial areas), criminology and computer privacy/security. [1]. For instance, the emotional states of students during a presentation in an online tutor reflect the usability and performance of the class with students. This information even can help teachers or intelligent systems to adapt to the training system for a better educational ambiance to deliver knowledge as much as possible to the students [1, 2].

Nowadays, most of the digital device manufacturers are trying to soften the gap between human and computer by designing more natural and real interfaces. They work based on gesture recognitions, and some new smart phones respond to its users' questions by employing voice recognition techniques. These interactions are simulated from the human–human interactions in the social life. Beside all these technology improvements, the lack of emotions is very clear. If digital systems feel our emotions, they can be replaced with pets or even friends. Future digital handheld devices would be smart by recognizing the human emotions to understand environment, situations, users and people. Therefore, they would be able to interact properly with human. From the aspect of social science, the replacement of human with digital systems can be a serious threat to human life. However, it is a great mutation in technology and human–computer interaction (HCI).

Recently, the accuracy of human emotion recognition has been improved by utilizing advanced analysis methods and techniques including image processing, voice recognition, natural language processing (NLP), keystroke dynamics, mouse movements, touch screen interactions, electroencephalography (EEG) devices, measuring heart rates, body heat, blood pressure and so on [3–7]. Some of these methods (e.g., image processing, voice recognition and NLP) are time- and resource-consuming. They need some special perquisites such as availability of video camera (webcam) or microphone, and some other methods require highly technical equipment such as EEG or heart rate measuring devices [2]. These are medical machines that need technical training to be installed and used, and sometimes, the part of skin for installation should be shaved because of the inferences and noises. Processing and analyzing of keyboard keystroke dynamics, mouse movements and touch screen interactions are the three methods which are mostly available on every computer [8]. They are also available in portable digital devices such as handhelds, tablets and mobile phones. This research has focused on these three methods for affective computing to evaluate the presented fuzzy model because of their availability, popularity and efficiency in cost and resources.

1.1 What are the emotions and research challenges?

Emotions are discussed by three factors in psychology: Valence (Pleasure), Arousal and Dominance (Control) also known as PAD [1, 9–11]. The first factor is *Valence* or *Pleasure*, which shows the pleasure level, whether it is a positive or a negative emotion. The second factor is *Arousal* which talks about the amount of energy of emotions. In literature, different amount of energy has been named such as happiness, sadness and so on. And the third factor is *Dominance*, which describes the strength level of each emotion. It says how strong an emotion is.

The last factor of *Dominance* (*Control*) is usually ignored in most of the research. Many scholars in affective computing only considered the Arousal and Valence of emotion. The lack of dominance factor is due to complexity of recognition systems by analyzing a broader set of probable emotions. Dominance is also a very important factor; therefore, it cannot be simply ignored in affective computing. Firstly, human emotions are not constant and they do not occur and exist in one single level. For example, if you feel happy for 2 days, the level and strength of feeling would not be the same for every moment that you have the same emotion. In the other words, emotions are more than the binary values of 0 and 1. All the eight basic emotions (*Joy*, *Anticipation*, *Anger*, *Disgust*, *Sadness*, *Surprise*, *Fear* and *Acceptance*) according to the Sanskrit texts and the other sub-emotions are following the dominance definition [12]. Emotions have a fuzzy basis, and discrete calculation would not be a proper solution for evaluation and detection. Figure 1 has illustrated the three dimensions of Arousal, Valence (Pleasure) and Dominance (Control).

Secondly, users as human beings may not have only one emotion at a time; they may have different emotions in different strengths. This fact is usually neglected in the currently developed human emotion recognition systems as they attempt to find only one current emotion and perhaps the strongest emotion at a time [13]. It is very clear that our lifestyle is affected by various emotions, and we are living with the combination of them. The happiness at the time of receiving a gift and the happiness at the time being in a theme park can be at a same level (dominance). However, they are presented in two different qualities, because the combinations of other possible emotions are different in those two cases [14].

Thirdly, psychological research showed a difference in human emotional change pattern based on cultural and language backgrounds of people [15]. These differences say that a specific emotional pattern which is extracted from a person from a specific geographical area cannot be extended to the other part of the world.

This research attempts to analyze human emotions based on a fuzzy model which is able to recognize the human

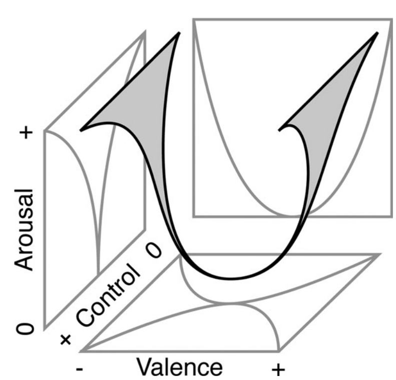


Fig. 1 The three dimensions of Valence (Pleasure), Arousal and Dominance (Control) for an emotion

emotions at five levels. Also, it estimates the other possible emotions with their dominance levels at the same time.

2 Related works

There are lots of research that concentrate on affective computing using various methods as mentioned earlier: keyboard keystroke dynamics, mouse movements analyzing, touch screen interactions processing, facial expression recognition, voice recognition, NLP, gesture recognition, EEG signal processing, etc. None of these methods alone could overcome the discussed problems in Sect. 1.1. Despite these deficiencies, there are still some valuable studies on human emotions in HCIs. In this section, very few highlighted studies are reviewed to provide a better understanding of the current challenges. It also tries to present an outlook of affective computing in the future.

2.1 Facial expression recognition

Facial expressions are the result of muscle changes on a human face, which show specific emotions. Human face by itself is a complete emotion expressing system. Facial expressions processing can find out how a person feels and what his/her emotion is. Facial expression is classified as a nonverbal communication. People can communicate by their face without saying a word.

Facial expression recognition is a method based on image processing technique. An image of human face is captured by a camera, and then, the software would process it to extract the feature points and analyze them to recognize the proper emotion. Kao and Fahn [16] exercised different machine learning methods, and they finally accessed the accuracy of 90 % on emotion recognition. Researchers, such as Kao and Fahn, usually tried to detect the emotion without defining its dominance level to show how strong it is. Despite the classical research, Konar et al. used type-2 fuzzy in facial expression recognition to recognize the emotions at different levels. He was successful in gaining the accuracy up to 88.66 %, but they could only recognize the emotions in three discrete levels. Same as the other researchers, they ignored the cultural and language differences on various people. Training the system based on a specific user may not guarantee its usability on the other people [17].

High processing time-, resource-consuming and cultural differences are the main challenges of facial expression recognition techniques. Facial expression usually presents the one and only strongest emotion at a time, so finding the other possible emotions is still a challenge. These problems make it an open research area. This paper covers the last two problems about different cultural backgrounds and the coincidence of emotions at a time.

2.2 Body gesture recognition

Body gesture is the different poses of body parts such as hands, feet, head, lips, eyes and so on. It is a nonverbal communication like facial expression. Body gesture recognition uses image processing techniques like facial expression recognition. So, this method inherits the main challenges and problems of image processing such as high resource and time consumption.

The history of body gestures goes back to more than 500 years ago. Body gesture also follows the cultural and societal rules and regulations to express the emotions. In some countries, people rarely use body gestures, and in some other countries, it is very often. Even though it is popular to use body gesture in our social experience, the gestures are different in style among different cultures, countries and societies. Understanding the level of emotions by gestures is usually mixed with facial expressions. The combination of facial expression and body gestures can represent a clearer emotion and its appropriate level.

Body gesture recognition is becoming more popular in the digital industry. For instance, some new smart TVs are the example of this technology, which has replaced the remote control with the hand gestures. Glowinski et al. presented one of the most recent researches in body gesture recognition, but they were not truly successful in accurate recognition of major emotions. Their best achieved accuracy was 81 % resulted on a few emotions [18]. This level of vision recognition with intensity criteria is a new research topic that it is just taken off.

2.3 Natural language processing (NLP)

Natural language processing is a verbal communication that processes the text by analyzing the words and the structure of the sentence to recognize the author emotional state. It is also another sample of not a very successful method of affective computing. This idea was emerged when the number of SMS increased as today SMS is becoming one of the important communication channels [19]. Li et al. tried *Ortony*, *Clore* and *Collins* (*OCC*) model with 16 rules to enhance the original model of 22 rules. However, they only achieved the highest accuracy of 74.1 % for the emotion of *Anger* and least accuracy in *Pity* for 58.1 % [20]. But their research still suffers from the discussed challenges in this paper.

2.4 Voice recognition

The voice recognition method works on processing the user's voice and tries to understand how he/she feels. The analysis of the sound spectrum and tone changes is extracted as features and then marked as fingerprint to be matched with emotions.

Lots of research has been done on this methodology for affective computing, but still they could not get any better accuracy of 78.64 % that Xiao et al. achieved in 2007 [21]. Xiao et al. used a hierarchal classification to analyze the sounds, but they neither used any fuzzy model nor dominance level recognition. Most of the affordable studies were on mixing voice recognition with the other methods such as mixing with body gesture recognition [7], NLP [22, 23] and facial expression recognition [24, 25].

2.5 Electroencephalography (EEG) signal processing

Electroencephalography (EEG) measures and records the voltage of ionic current flows in neuron (electrical activities of neurons) along the human scalp. As a matter of fact, this device was only used in medical and neurology purposes. As its price decreased over time, it has become an affordable research tool in various research areas including computer science and artificial intelligence. The idea of recognizing the human emotions was experienced by EEG in many research papers [3, 26]. One of the best researches in human emotion recognition was done by Schaff and Schultz [27] with 66 % of accuracy. Of course, this accuracy is not that impressive, but they proved the possibility and the ability of obtaining high accuracy in emotion recognition using EEG machines.

One of the most impressive results of EEG was the real-time processing and analyzing of human emotions conducted by Liu et al. They addressed and covered the challenge of the time-consuming process of the other methods by EEG signal processing [3].

2.6 Mouse movements

The users of computer and digital systems equipped with mice may have noticed that they move the mouse randomly and without any specific purpose when they are bored, and sometimes very fast and straight when they are in a rush. Researchers monitored the mouse movements and tried to extract some features and parameters to process and analyze if they can detect the users' emotions.

A mouse features are usually limited to maximum combinations of three buttons and some movements. There is only a few research in this topic. In addition, they have gotten pretty much similar results with the other mentioned methodologies [28].

2.7 Keyboard keystroke dynamics

Keyboard typing has its own timing features, which describes the time differences between *key presses*, *key ups* and *key downs* of different keys on the keyboard. Keyboard keystroke dynamics were being discussed as an authentication system from 1980s. Monrose et al. were one of the groups who could achieve a very good and reliable accuracy in authentication through the keyboard keystroke dynamics in 2000 by 92.14 % [19]. They presented the human emotion changes as their own problem for authentication. It implied that human emotions can directly impact on keystroke dynamics. So, later on, other researchers tried to recognize human emotions by analyzing keystroke dynamics. In some research, facial expression recognition, body gesture and the other methods are also joint with keyboard keystroke dynamics to make more reliable results in affective computing systems [2, 29, 30].

2.8 Touch screen interactions

"Touch Communicates Distinct Emotions" is a title of one psychological research paper. It says that people can communicate by touching each other in the social life. This is a nonverbal communication channel [31]. This touch can be either on a human or an object. What if the object would be the computer touch screen monitor?

In addition to mouse and keyboard, touch screen displays have also been used as a mean of affective computing. Touch screens are growing faster from desktop computers to digital handheld devices such as PDAs and cellular phones. Nowadays, it has been replacing classic mouse and keyboard.

This research area is pretty much similar to mouse movements as human fingers play as the mouse pointer. Also, while the user is typing on touch keyboard, the same rules and analysis of keyboard keystroke dynamics can be extended to the touch screen keyboard interactions.

But still beside all those similarities, touch screen displays have their own specific feature: z-index value, which measures the intensity of pressure that it is not available in mouse and keyboard. Even though finger is like the mouse pointer, the users do not necessarily touch the monitor constantly as they are moving from one object to another.

There is also some research individually only on touch screen displays to recognize human emotions that they were less successful with higher false positive rates than the other methods [28].

2.9 General background

All of the reviewed literature in affective computing shows that the discussed challenges in Sect. 1 are still addressed.

As a matter of fact, a very few research has been done so far to detect the dominance of emotions. This paper presents a fuzzy model to provide a solution toward multilevel affective computing (ML-AC) with the ability of detecting other possible emotions with their levels of dominance.

3 Research methodology

In this paper, fuzzy recognition of human emotions has been investigated to detect emotions in different dominance levels and energy. It gives a relative answer to the question of "How much happy am I?" The answer may not be very accurate, but it differentiates *very extremely happy* and *normal happy* people from each other [32]. This research has used keyboard keystroke dynamics, mouse movements and touch screen displays for data collection. Two types of methodologies were also employed to analyze the collected data. The first methodology was experience sampling methodology (ESM) that it is using prototype software to collect the required data from keyboard, mouse and touch screen monitors [8]. Later, we used a survey based on PANAS standard on human emotions to design the fuzzy model.

At the first stage, a prototype application was developed to record the keyboard keystroke dynamics of the users. The keystroke dynamics are including the time duration of key down-to-down, up-to-down and down-to-up. Also, finger printings of the users were collected to identify and differentiate the users [2]. Keyboard fingerprint is the time interval of the keystroke dynamics for 20 specific words which are common in English such as "the", "an" and "is". [2, 19].

The developed application was also programmed to record the mouse movements and touch screen interactions of the users while working on the computer. The selected features for mouse movements were time intervals between two clicks, mouse travel pixels, the direct distance between two clicks, keystroke dynamics of the right clicks, left clicks and double clicks [28].

Touch screen interactions have the same features of the mouse movement plus one more feature: "*z-index,*" which refers to the pressure amount of the finger on the screen which is usually between 0 and 255. This value varies from one touch screen manufacturer to another. However, not all touch screen monitors are able to detect the z-index value. Also, on the tested touch screen, despite mouse movements, the finger travel distance between two touches was not measurable and detectable, and only the direct distances were recorded [31].

At the time of recording the above features of keyboard keystroke dynamics, mouse movements and touch screen interactions, the users were asked every 4 h to select their appropriate emotions (only one at a time) and their dominance levels in the scale of 5 (from 0 to 4) through the prototype application. At the end of the data collection, which took about 2 months, support vector machine (SVM) with non-linear Gaussian Kernel was chosen as the classification and machine learning technique on the recorded data in RapidMiner software for evaluation. Split ratio for learning/training and testing was set to 80–20 %, respectively. In this system, the users had a chance to select a very few emotions; therefore, the recognition process by SVM usually came out with one single emotion as the result. Then, a fuzzy model was required to be integrated into the system. Therefore, the system can detect more emotions with their appropriate levels at the time of existence of each other emotions.

This emotions' fuzzy model classifies the emotions into five different levels from 0 to 4. Zero (0) shows 0 % of the emotion, or in the other word, it does not exist; however, four shows the highest level of emotion. PANAS is a standard to find negative or positive emotions of people [33]. PANAS uses 20 emotions, and we included the seven missed basic emotions in this list which are not listed in PANAS and used this standard to evaluate the system. The list of these 27 emotions is as follows:

Joy	Surprise	Excited	Enthusiastic
Inspired	Active	Anticipation	Fear
Upset	Proud	Nervous	Afraid
Anger	Acceptance	Strong	Irritable
Determined	Disgust	Interested	Guilty
Alert	Attentive	Sadness	Distressed
Hostile	Ashamed	Jittery	

One hundred and thirty people from different domains participated in this project to have their emotional states recorded in the system. Recorded data features through the survey were users' age, sex, birth location, current location, language as well as the emotional scales of 27 emotions. The participants were distributed as follows:

Men: 51 %—average age: 30.13 years old
Women: 49 %—average age: 28.29 years old
People were originally from:
Europe: 18.37 %
Middle East: 44.18 %
South East Asia: 13.17 %
East Asia: 7.75 %
People were living in:
Europe: 27.90 %

South East Asia: 34.88 %
East Asia: 16.37 %
Middle East: 11.62 %

Forty-five percent of people were living in different regions of their own country.

Through the collected data, we found that men's emotions (self-reported) were stronger than women's, or at least they felt them stronger. The strongest emotion was *Active* in a range of 3.24 out of 4, and the least one was *Unfriendly* with the value of 1.62 out of 4. It showed that most of the people thought that they were super active and less unfriendly in their normal life.

Later, the generated model based on the emotional states of 130 volunteers was integrated into a binary affective computing system based on keyboard keystroke dynamics, mouse movements and touch interactions in order to recognize the user's emotions while they are interacting with computer. The initial binary affective computing system was successful in emotion recognition with the best accuracy of more than 90 % for one emotion at a time. At this stage, the integration of this model into this existing system was intended to provide the detection of more than one possible emotion at a time with their relevant dominance level. For this section of research, 50 users were selected for testing the fuzzy system while they interact with computers.

4 Results and analysis

Here, the results of the research are discussed in two parts. First, the individual change pattern of each emotion is explained and graphed, and finally, the model was evaluated on a human emotion recognition system based on a hybrid of keyboard keystroke dynamics, mouse movements and touch screen interactions [8].

4.1 Analysis of emotions

Here, we have discussed only eight basic emotions according to the psychological studies, and the other emotions are related and categorized under these eight emotions. These are *Joy*, *Anticipation*, *Anger*, *Disgust*, *Sadness*, *Surprise*, *Fear* and *Acceptance*.

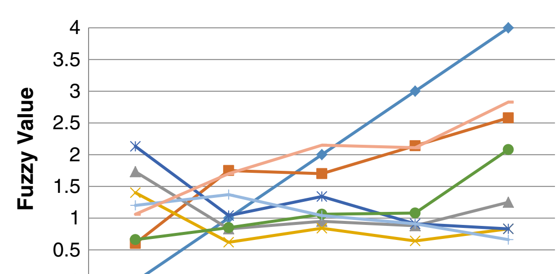
In this research, some similar change patterns were found among some emotions. Basically, both negative and positive emotions have similar change patterns, but among those basic emotions, some of them were closely related. For instance, *Disgust* and *Anger* have a similar change rate pattern with each other, and *Sadness* is closer to them in comparison with the other emotions. On the other hand, *Acceptance* and *Anticipation* have very similar change patterns with each other. As it can be seen, these emotions are in a same group in terms of positive and negative emotions (valence). Figure 2 shows a similar change pattern for emotions, when the level of *Joy* is increasing from 0 to 4 from the first row to the fifth. Figure 2 is also included with the tabular data.

Conversely, the above values demonstrate the probability of existence of the other emotions. For example, when *Joy* is about 50 % (*Joy* = 2), it can be estimated that *Disgust* may exist at the dominance level of 21 % (*Disgust* = 0.84/4) or even *Fear* at the level of 26 % (*Fear* = 1.04/4), but *Acceptance* can be accepted at this level at the same time about 53.75 % of *Joy* (*Acceptance* = 2.15/4), as we also experienced that convincing people are easier when they feel joy. The following membership function rules are only the samples which can be reasoned based on Fig. 2.

F1: IF Joy **INCREASES** FROM 2 TO 3, THEN Anticipation **INCREASES** FROM 1.7 TO 2.14.
F2: IF Joy **INCREASES** FROM 2 TO 3, THEN Acceptance **STAYS AT THE AVERAGE** OF 2.13.
F3: IF Joy **DECREASES** FROM 4 TO 3, THEN Surprise **DECREASES** FROM 2.08 TO 1.08.

The following figures show the extracted analyzed data from our research based on the growth of basic emotions (Figs. 3, 4, 5, 6, 7, 8, 9).

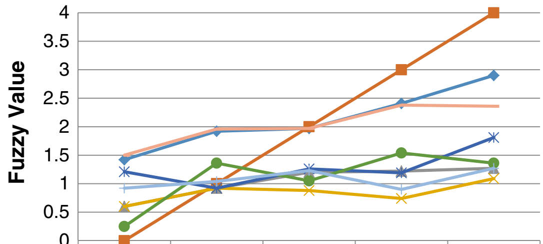
All the above values range between 0 and 4. Furthermore, we compared the emotions change pattern of people in different regions of the world. As mentioned in Sect. 1.1, some psychological research indicates different emotions' concepts in different parts of the world. We have used our



	1	2	3	4	5
Joy	0	1	2	3	4
Anticipation	0.6	1.75	1.7	2.14	2.58
Anger	1.73	0.83	0.95	0.88	1.25
Disgust	1.4	0.62	0.84	0.64	0.83
Sadness	2.13	1.04	1.34	0.91	0.83
Surprise	0.66	0.85	1.06	1.08	2.08
Fear	1.2	1.37	1.04	0.91	0.66
Acceptance	1.06	1.7	2.15	2.11	2.83

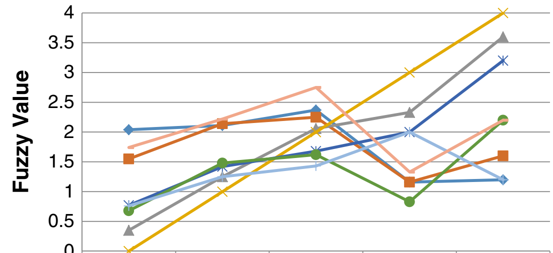
Time

Fig. 2 Emotions change pattern based on the growth of "Joy"



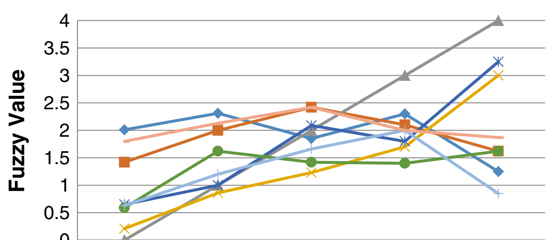
	1	2	3	4	5
Joy	1.42	1.92	1.97	2.41	2.9
Anticipation	0	1	2	3	4
Anger	0.6	0.92	1.2	1.22	1.27
Disgust	0.6	0.92	0.88	0.74	1.09
Sadness	1.21	0.92	1.26	1.19	1.81
Surprise	0.25	1.36	1.05	1.54	1.36
Fear	0.92	1.04	1.23	0.9	1.27
Acceptance	1.5	1.96	1.97	2.38	2.36

Fig. 3 Emotions change pattern based on the growth of “Anticipation” from 0 to 4



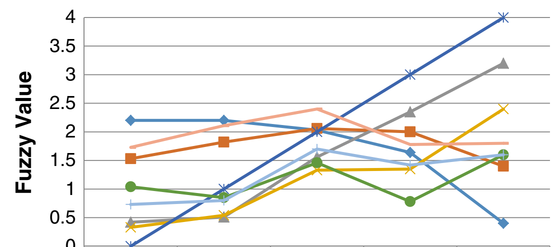
	1	2	3	4	5
Joy	2.04	2.11	2.37	1.16	1.2
Anticipation	1.55	2.14	2.25	1.16	1.6
Anger	0.35	1.25	2.06	2.33	3.6
Disgust	0	1	2	3	4
Sadness	0.77	1.42	1.68	2	3.2
Surprise	0.68	1.48	1.62	0.83	2.2
Fear	0.76	1.25	1.43	2	1.2
Acceptance	1.74	2.22	2.75	1.33	2.2

Fig. 5 Emotions change pattern based on the growth of “Disgust” from 0 to 4



	1	2	3	4	5
Joy	2.01	2.31	1.85	2.3	1.25
Anticipation	1.42	2	2.42	2.1	1.62
Anger	0	1	2	3	4
Disgust	0.21	0.86	1.23	1.7	3
Sadness	0.65	1	2.09	1.8	3.25
Surprise	0.59	1.62	1.42	1.4	1.62
Fear	0.63	1.2	1.66	2	0.85
Acceptance	1.8	2.13	2.42	2	1.87

Fig. 4 Emotions change pattern based on the growth of “Anger” from 0 to 4



	1	2	3	4	5
Joy	2.2	2.2	2.03	1.64	0.4
Anticipation	1.53	1.82	2.06	2	1.4
Anger	0.42	0.51	1.56	2.35	3.2
Disgust	0.33	0.54	1.33	1.35	2.4
Sadness	0	1	2	3	4
Surprise	1.04	0.85	1.46	0.78	1.6
Fear	0.73	0.8	1.7	1.42	1.6
Acceptance	1.73	2.11	2.4	1.78	1.8

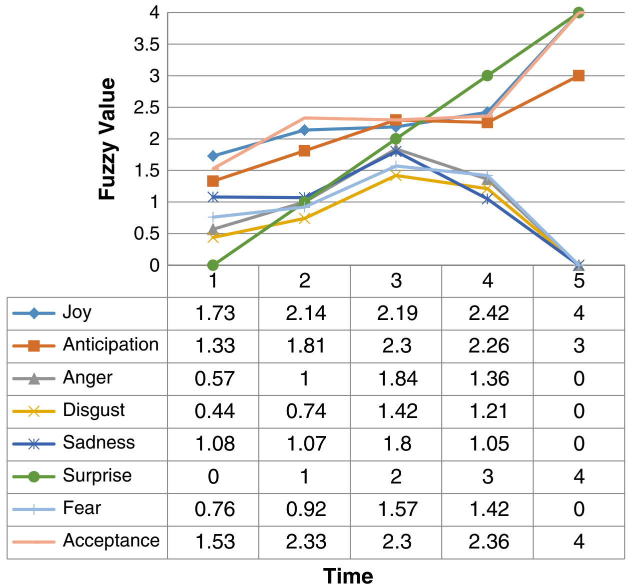
Fig. 6 Emotions change pattern based on the growth of “Sadness” from 0 to 4

research data to confirm whether the different emotions' concepts cause different emotions change pattern or not. For this purpose, three regions, namely Europe, Middle East and South East (SE) Asia were selected. Then, the users' data with the emotion of *Joy* at the dominance value equal to 2 (or 50 %) were analyzed. Table 1 shows the classified values by regions.

Figure 10 demonstrates the graphed values in Table 1. The emotional pattern of Europe and Middle East are similar; however, South East Asia follows a very different pattern of changes to these two regions. This graph proves the psychological studies based on the influences of cultural and language backgrounds on emotions. This graph might even predict the approximate location of the user who is interacting with computer by tracking his/her emotional pattern, which has not been yet investigated.

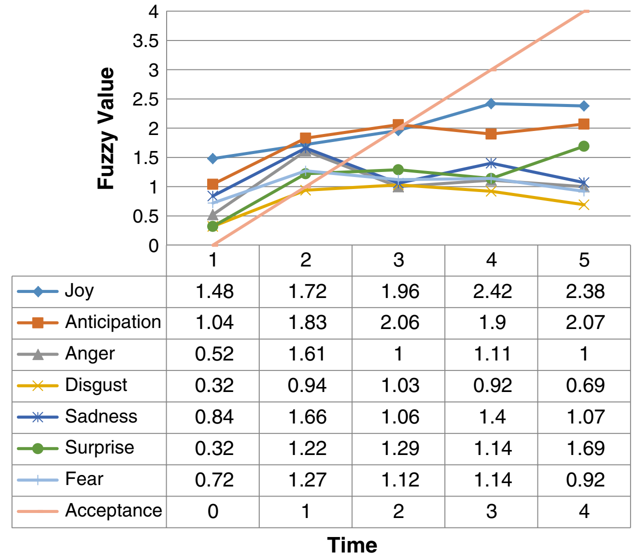
4.2 Fuzzy model on human emotion recognition

The above data and classification were used as a fuzzy model in our affective computing system using 50 participants for emotion recognition. Besides the detected emotions by the system, the other possible emotions with their dominance values were also



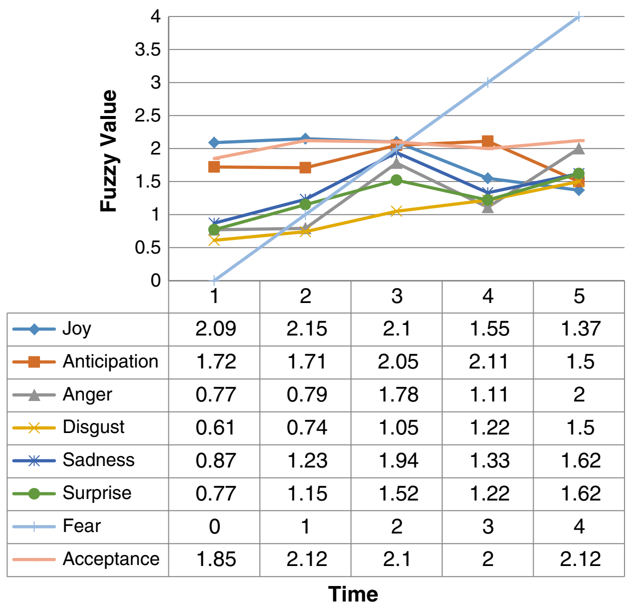
	1	2	3	4	5
Joy	1.73	2.14	2.19	2.42	4
Anticipation	1.33	1.81	2.3	2.26	3
Anger	0.57	1	1.84	1.36	0
Disgust	0.44	0.74	1.42	1.21	0
Sadness	1.08	1.07	1.8	1.05	0
Surprise	0	1	2	3	4
Fear	0.76	0.92	1.57	1.42	0
Acceptance	1.53	2.33	2.3	2.36	4

Fig. 7 Emotions change pattern based on the growth of "Surprise" from 0 to 4



	1	2	3	4	5
Joy	1.48	1.72	1.96	2.42	2.38
Anticipation	1.04	1.83	2.06	1.9	2.07
Anger	0.52	1.61	1	1.11	1
Disgust	0.32	0.94	1.03	0.92	0.69
Sadness	0.84	1.66	1.06	1.4	1.07
Surprise	0.32	1.22	1.29	1.14	1.69
Fear	0.72	1.27	1.12	1.14	0.92
Acceptance	0	1	2	3	4

Fig. 9 Emotions change pattern based on the growth of "Acceptance" from 0 to 4



	1	2	3	4	5
Joy	2.09	2.15	2.1	1.55	1.37
Anticipation	1.72	1.71	2.05	2.11	1.5
Anger	0.77	0.79	1.78	1.11	2
Disgust	0.61	0.74	1.05	1.22	1.5
Sadness	0.87	1.23	1.94	1.33	1.62
Surprise	0.77	1.15	1.52	1.22	1.62
Fear	0	1	2	3	4
Acceptance	1.85	2.12	2.1	2	2.12

Fig. 8 Emotions change pattern based on the growth of "Fear" from 0 to 4

Table 1 Classified values of "Joy" at 50 % for different regions

	Europe	Middle East	SE Asia
Anticipation	1.14	1.8	1.66
Anger	0.42	1.09	1.5
Disgust	0.71	0.71	1.16
Sadness	1	1.66	0.5
Surprise	0.57	1.33	1.33
Fear	0.85	1.33	0.66
Acceptance	2	2.09	2.33

detected and tested via the prototype application [8]. SVM classification method with the non-linear Gaussian kernel at the split ratio of 80 % for training and 20 % for testing has been used. The accuracy of the detected emotions was evaluated from two different aspects. The first aspect evaluated whether the names of the recognized emotion or emotions are correct or not. From the second aspect, it evaluated the system by the dominance percentage of detected emotions [34, 35]. For example, consider a user with two emotions: *Joy*—50 % and *Fear*—20 %. From the first aspect of the evaluation, if the system could detect *Joy* and *Fear*, then the evaluation is successfully accomplished. However, from the second aspect, not only *Joy* and *Fear* should be detected correctly, but also the detected dominance level of the other emotions would be considered in the precision of the system [36].

To evaluate the results, the result of the system was compared with the binary (non-fuzzy) human emotion recognition. Bakhtiyari et al. [8] gained an accuracy of 93 % on a binary affective computing system. Later, the fuzzy model was applied to detect dominance level and other possible related emotions. After applying the fuzzy model, the accuracy of the system from the first aspect decreased a bit to 86 % (as seen in Table 2) in comparison with the binary detection as it was dependent on the emotions. This model estimated more than one emotion at

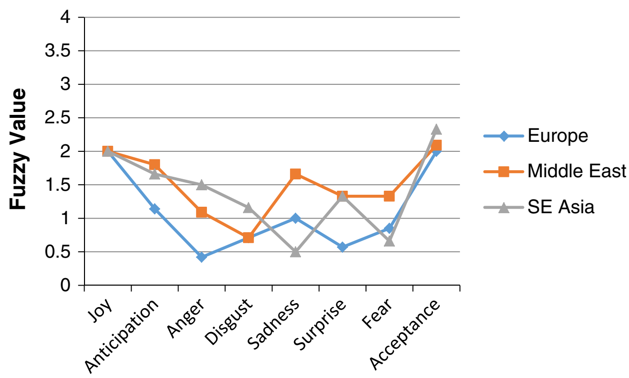


Fig. 10 Classified graph of "Joy" at 50 % for different regions

Table 2 Human emotions classification accuracy after applying the fuzzy model

Selected emotion	Detected emotion			
	Neutral	Afraid	Sadness	Nervous
Neutral	0.68	–	–	–
Afraid	–	0.85	–	–
Sadness	–	–	0.86	–
Nervous	–	–	–	0.65

a time, which can be possible in parallel with the other emotions.

By integrating the fuzzy model, a lower false positive rate from 0 to 16.7 % has been achieved in detecting the emotions' dominance level.

4.3 Outliers handling

In order to improve the reliability of the research result, outliers were also handled in the research methodology. Outliers could happen in two sections of this research: (1) data collection via survey and (2) data collection via prototype.

Data collection via *survey*: At this stage, all collected data were normalized to check if there are any out of range outliers. In our 130 participants with 27 recorded emotions (3,510 data entity), there were less than 4 % of outliers which were ignored for the rest of research.

Data collection via *prototype:* The prototype application was developed to not only record the required data, but also to monitor the input data. In the recorded data set, there was no missing value or incomplete records due to the application control. In order to detect the outliers, each individual user's recorded data had to be normalized separately. Due to the atomic emotional changes while interacting with computer, the normalization and removing the outliers would generate a perfect emotional data; however, the atomic changes could not be ignored easily, and they

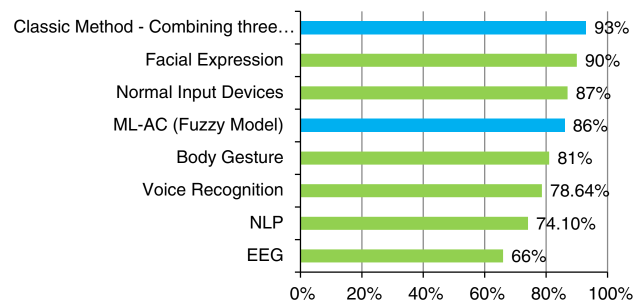


Fig. 11 Comparison between the proposed model and other related works

play an import role in classification section. Therefore, the data were maintained as is for the classification.

5 Discussion

Binary (non-fuzzy and non-dominance) affective computing by combining three methods of analysis of keyboard keystroke dynamics, mouse movements and touch screen interaction showed 93 % of accuracy, which is among the best achievements [8]. Facial expression and then using the normal input devices (such as keyboard, mouse and touch screen) independently got then next best accuracies in our test. Then by applying the fuzzy model, the accuracy has been decreased to 86 %. Still it is among the top accuracies in affective computing. Meanwhile, it has the advantage of representing the strength level of the emotions as it is shown in Fig. 11. The measured false positive rate in this system was maximum 16.7 %, which was less than the other methods in average.

Although fuzzy model decreased the accuracy of recognition, it provided a solution to available research problems in affective computing. The fuzzy model enables affective computing systems to detect the level of emotions and to estimate the other possible emotions of the users. This fuzzy model can be extended by intensity to open a new era of computing to bring the analog life into the digital world. This intensity can be used in terms of interaction intensity. This approach is a new outlook in the computing area in the future of HCIs.

6 Conclusion and future work

A fuzzy model was presented through a new solution based on the statistics and probability for human emotion recognition. It overcomes some of the problems of emotion detection at different levels and other possible emotions at a same time. This model is able to recognize the other possible emotions simultaneously and worked more naturally by recognition of arousal, valence and dominance of emotions. This fuzzy model detected the emotions with the accuracy of 86 %. In addition, it gained a maximum 16.7 % of false positive rate for recognizing the dominance level of the emotions in scale of 5.

This model can be extended, improved and even integrated into different recognition methods. Future research work will be expanded on human emotion recognition by the extracted model for each region of the world by comparing the accuracies and error rates of different regions. This model can also be extended for affective computing in recommender systems which is still an open challenge [37].

Fuzzy affective computing can be applied in many wide areas, and this model can be a step forward into the more real emotion understanding for digital systems in order to interact with human naturally. For the next step in our research, we intend to integrate this model into a hybrid recommender system for an e-commerce purpose. Another ongoing research using this model is building a computational investing system. This system recommends the possible decisions to the investors by considering multiple factors including the fuzzy affective computing [38].

Acknowledgments We thank the students of Universiti Kebangsaan Malaysia (The National University of Malaysia) and University of Duisburg-Essen for their collaborations and participations in this research and emotions' survey. Special thanks to Mona Taghavi for her initial review and comments on this paper.

References

1. Cowie R, Douglas-Cowie E, Tsapatsoulis N, Votsis G, Kollias S, Fellenz W, Taylor JG (2001) Emotion recognition in human-computer interaction. IEEE Signal Process Mag 18(1):32–80
2. Epp C, Lippold M, Mandryk RL (2011) Identifying emotional states using keystroke dynamics. Paper presented at the Proceedings of the 2011 annual conference on Human factors in computing systems, Vancouver, BC, Canada
3. Liu Y, Sourina O, Nguyen MK (2010) Real-time EEG-based human emotion recognition and visualization. In: International conference on cyberworlds, Alberta, Canada. IEEE, pp 262–269
4. Milanova M, Sirakov N (2008) Recognition of emotional states in natural human–computer interaction. In: IEEE international symposium on signal processing and information technology (ISSPIT), Ho Chi Minh City, Vietnam. IEEE, pp 186–191
5. Bashir MG, Nagarajan R, Hazry D (2010) Facial emotion detection using GPSO and Lucas-Kanade algorithms. Paper presented at the international conference on computer and communication engineering (ICCCE)
6. Kao ECC, Liu CC, Yang TH, Hsieh CT, Soo VW (2009) Towards text-based emotion detection. In: International conference on information management and engineering (ICIME), Kuala Lumpur, Malaysia. IEEE, pp 70–74
7. Amarakeerthi S, Ranaweera R, Cohen M (2010) Speech-based emotion characterization using postures and gestures in CVEs. In: International conference on cyberworlds, Alberta, Canada. IEEE, pp 72–76
8. Bakhtiyari K, Taghavi M, Husain H (2014) Implementation of emotional-aware computer systems using typical input devices. In: Nguyen NT, Attachoo B, Trawiński B, Somboonviwat K (eds) 6th Asian conference on intelligent information and database systems, Bangkok, Thailand, 7-9 April 2014. Springer International Publishing, pp 364–374. doi:10.1007/978-3-319-05476-6_37
9. Strongman KT (2003) The psychology of emotion. Department of Psychology, University of Canterbury, 5th edn. Wiley, Christchurch
10. Derks D, Fischer AH, Bos AER (2008) The role of emotion in computer-mediated communication: a review. Comput Hum Behav 24(3):766–785. doi:10.1016/j.chb.2007.04.004
11. Mehrabian A (1996) Pleasure-arousal-dominance: a general framework for describing and measuring individual differences in temperament. Curr Psychol 14(4):261–292. doi:10.1007/BF02686918
12. Griffiths PE (2003) Basic emotions, complex emotions, Machiavellian emotions. R Inst Philos Suppl 52:28. doi:10.1017/S1358246100007888
13. Gendron M, Barrett LF (2009) Reconstructing the past: a century of ideas about emotion in psychology. Int Soc Res Emotion 1(4):24. doi:10.1177/1754073909338877
14. Hartel CEJ, Ashkanasy NM, Zerbe WJ (2007) Functionality, intentionality and morality, vol 3. Research on emotion in organization, 1st edn. Elsevier, Amsterdam
15. Lewis M, Haviland-Jones JM, Barrett LF (2010) The cultural psychology of the emotions—ancient and renewed. In: Richard A. Shweder JH, Horton R, Joseph C (eds) Handbook of emotions, 3rd edn. Guilford Press, New York, p 19
16. Kao CY, Fahn CS (2012) A design of face detection and facial expression recognition techniques based on boosting schema. Appl Mech Mater 121:617–621
17. Konar A, Chakraborty A, Halder A, Mandal R, Janarthanan R (2012) Interval type-2 fuzzy model for emotion recognition from facial expression. Percept Mach Intell 114–121
18. Glowinski D, Camurri A, Volpe G, Dael N, Scherer K (2008) Technique for automatic emotion recognition by body gesture analysis. In: IEEE computer society conference on computer vision and pattern recognition workshops, Providence, RI, USA
19. Monrose F, Rubin AD (2000) Keystroke dynamics as a biometric for authentication. Futur Gener Comput Syst 16(4):351–359
20. Li H, Pang N, Guo S, Wang H (2008) Research on textual emotion recognition incorporating personality factor. In: IEEE international conference on robotics and biomimetics, Sanya, China. IEEE, pp 2222–2227
21. Xiao Z, Dellandrea E, Dou W, Chen L (2007) Automatic hierarchical classification of emotional speech. In: Ninth IEEE international symposium on multimedia workshops, pp 291–296
22. Klecková J (2009) Important nonverbal attributes for spontaneous speech recognition. In: Fourth international conference on systems. IEEE, pp 13–16
23. Pittermann J, Schmitt A, El Sayed NF (2008) Integrating linguistic cues into speech-based emotion recognition. In: 4th International Conference on Intelligent Environments, University of Washington, Seattle, USA. IET, pp 1–4
24. Wang Y, Guan L (2008) Recognizing human emotional state from audiovisual signals*. IEEE Trans Multimed 10(5):936–946
25. Huang T (2008) Audio-visual human computer interface. In: IEEE international symposium on consumer electronics, University of Illinois, USA. IEEE
26. Guangying Y, Shanxiao Y (2010) Emotion recognition of electromyography based on support vector machine. In: Third international symposium on intelligent information technology and security informatics, Jinggangshan, China. IEEE, pp 298–301

27. Schaaff K, Schultz T (2009) Towards emotion recognition from electroencephalographic signals. In: Affective computing and intelligent interaction and workshops (ACII), Memphis, TN, USA. IEEE, pp 1–6
28. Schuller B, Rigoll G, Lang M (2004) Emotion recognition in the manual interaction with graphical user interfaces. In: IEEE international conference on multimedia and expo. IEEE, pp 1215–1218
29. Seniuk A, Blostein D (2009) Pen acoustic emissions for text and gesture recognition. In: 10th international conference on document analysis and recognition. ACM, pp 872–876
30. Wang R, Fang B (2008) Affective computing and biometrics based HCI surveillance system. In: International symposium on information science and engineering, China. IEEE, pp 192–195
31. Hertenstein MJ, Keltner D, App B, Bulleit BA, Jaskolka AR (2006) Touch communicates distinct emotions. Emotion 6(3):528
32. Jaimes A, Sebe N (2007) Multimodal human–computer interaction: a survey. Comput Vis Image Underst 108(1–2):116–134. doi:10.1016/j.cviu.2006.10.019
33. Watson D, Clark LA, Tellegen A (1988) Development and validation of brief measures of positive and negative affect: the PANAS scales. J Personal Soc Psychol 54(6):1063–1070. doi:10.1037/0022-3514.54.6.1063
34. Yusoff N, Salim S (2010) SCOUT and affective interaction design: Evaluating physiological signals for usability in emotional processing. In: 2nd international conference on computer engineering and technology (ICCET). IEEE, pp V1-201-V201-205
35. Kong X, Yang Y (2009) Measuring emotions in interactive contexts. In: IEEE 10th international conference on computer-aided industrial design and conceptual design. IEEE, pp 526–530
36. Mower E, Mataric M, Narayanan S (2010) A framework for automatic human emotion classification using emotion profiles. IEEE Trans Audio Speech Lang Process 99:1
37. Rajaraman A, Ullman J (2011) Recommendation systems. In: Mining of massive datasets. Cambridge University Press, Cambridge
38. Taghavi M, Bakhtiyari K, Scavino E (2013) Agent-based computational investing recommender system. Paper presented at the Proceedings of the 7th ACM conference on recommender systems, Hong Kong, China. doi:10.1145/2507157.2508072