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Data mining in emotion color with affective computing

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Abstract This research applies an innovative way to measure and identify user's emotion with different ingredient color. How to find an intuitive way to understand human emotion is the key point in this research. The RGB color system that is widely used of all forms computer system is an accumulative color system in which red, green, and blue light are added together showing entire color. This study was based on Thayer's emotion model which classifies the emotions with two vectors, valence and arousal, and gathers the emotion color with RGB as input for calculating and forecasting user's emotion. In this experiment, using 320 data divide to quarter into emotion groups to train the weight in the neural network and uses 160 data to prove the accuracy. The result reveals that this model can be valid reckon the emotion by reply color response from user. In other hand, this experiment found that trend of the different ingredient of color on Cartesian coordinate system figures out the distinguishing intensity in RGB color system. Via the foregoing detect emotion model is going to design an affective computing intelligence framework try to embed the emotion component in it.

Keywords Data mining · Affective computing · FCM · Neural network · Detecting emotion · Color · Emotion classification

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1 Introduction

Data mining is an interdisciplinary computer-based information system [43] applied to process huge data repositories, generate information, discover knowledge [29], discovers hidden patterns and information from the existing data, too [30]. One of the data mining method, Fuzzy cognitive map (FCM) [20] is an effective knowledge presentation, inference and data mining model that is based on mankind knowledge. FCM is also a tool for design intelligent systems, which integrate components of neural network and fuzzy set. Moreover, FCM can be showed with the graph form, in which notions are showed as nodes and weighted edges represent concept relations about associations between the notions [38]. Affective computing was included in Artificial intelligence domain; it is computing that related to, cause, or obviously affection emotion [31], which is firstly proposed by Professor Picard at MIT in 1997. Affective computing is a kind of newly research domain and focuses the emotion activities and processes from human. The real class environment seems centralize on the cognitive capacities of the human and makes a fitness knowledge system for themselves [4, 42, 17]. The recent researches of psychologists and neurologists point out the major key of the motivation and the affectivity in cognitive activities, especially learning [7, 16, 11]. In another hand, Cloud learning is a new topic, extended by cloud computing, strengthening learner-centered, resource distributing and collaboration among learners, to unitedly build a unique learning environment for each learner [27]. This research will combine the affective computing and clouding computing to create an intelligence information system for human behavior detecting.

This research has been inspired by a creative idea. It proposes a framework that develops color response in natural interaction in order to seize the emotion expressed in the content. In this paper, the related work is summarized and the frame construction of artificial emotional model process is proposed according to the FCM framework simulating the emotional response. Then the model of emotion of intelligent system is given which is learned in its interaction with intuitive color feedback. The structure of this model was designed according to the Thayer's emotion model [42] one of the emotion classification. In the end, experimental research is used to test the effectiveness of the model.

2 Research related literatures

2.1 Data mining

Data mining is a powerful tool and newly method for sifting through one or multi-layers of externally unrelated data for meaningful process and the imminent need for turning such data into useful information and knowledge. New tendency emphasize on the role of the emotions in the interactive understanding, although the emotions are not lucidly visible as facial expression, tone inflections, body dynamics and gesture. Web content computing, is an innovative example that aims at gaining the content in network [24].

The innovative technology inspect expect affective states using predictable models from an alliance of traits refined from physiological measures [46, 32, 26, 22, 1, 13, 10].

The basic steps for data mining processes are [13]:

- Data clean: to clean noise and inconsonant data.
- Data integration: to integrate the resemble data sources.
- Data selection: to select the pertinent analysis work from the database.
- Data transformation: to transform the data suitably for the analysis need.

- Data mining: to mine and extra the anticipative information from database
- Pattern evaluation: to distinguish the data pattern from the detected result.
- Knowledge presentation: to presentation the mined knowledge to user and make it visualization.

In this research uses the one of data mining model to investigate the different color ingredient how to effect emotion classification.

2.2 Affective computing

Affective computing is an interdisciplinary field spanning computer sciences, psychology, and cognitive science [41]. And Picard in 1997 described that an affective computing system must have a few of the following capacities: 1. recognize, 2. express, or 3. Possess emotions. It focuses on creating personal computing systems having ability to sense, recognize and understand significantly after the positive interventions than the conditions with no intervention [34]. At present there are multiform ways of current study to detect for emotion status.

- Automatic detection of cognitive-affective states by computers [6, 18].
- Recent progress in real time affects detection [28] and fuzzy logic analyzer [25].
- Progress on affect detection through body movement and gestures [3, 5].
- Through acoustic-prosodic cues [12], lexical features [44] and physiological features [19].

2.3 Emotion and classification

Emotions are naturally part of our internal activity and perform a crucial role decision-making and cognitive relation processes. The definition of oxford dictionary online mentioned that "emotion is a strong feeling deriving from one's circumstances, mood, or relationships with others." [15]. Emotion was defined in "Taxonomy of Learning" that is a complex psycho-physiological experience of an individual's state of mind as interacting with biochemical (internal) and environmental (external) influences [33]. Emotion is the complex inside processing of an individual's state of mind. Leland Beaumont states that every emotion includes mood, motivation, temperament, personality, and disposition [14].

Basic emotions are claimed to be biologically fixed, innate and as a result universal to all humans and many animals as well. Complex emotions are then either refined versions of basic emotions, culturally specific or idiosyncratic [8]. The basic categories of emotion are joy, angry, sad, and happy. The categories of complex emotions can be combined or associated from basic emotions in emotions conditioning. In Table 1, Emotion classifications collected from early scholars. Since ancient times, many scholars proposed their emotion classifications. The researchers used their aspect to define the emotion expression making many varieties in emotion classification.

In 1972, Ekman devised a list of basic emotions that are not culturally determined, but universal. The six basic emotions are: 1. Anger, 2. Disgust, 3. Fear, 4. Happiness, 5. Sadness, and 6. Surprise. The newly included emotions are: Amusement, Contempt, Contentment, Embarrassment, Excitement, Guilt, Pride in achievement, Relief, Satisfaction, Sensory pleasure, Shame [9].

2.4 Thayer's emotion model

Thayer's emotion model was defined from the book, Biopsychology of Mood and Arousal that is based on mood analysis as biopsychological notion [2]. Thayer's emotion model is often

Table 1 Different emotional classification from scholar

Scholar	Emotion classification
Rene Descartes (1956–1690)	Love, hate, desire, joy, sadness and admiration
Baruch de Spinoza (1632–1677)	Joy, sorrow and desire
Thomas Hobbes (1588–1679)	Appetite, desire, love, aversion, hate, joy, and grief
A. Jorgensen (1894–1977)	Fear, happiness, sorrow, want, and angry shyness
Silvan Solomon Tomkins (1911–1991)	Interest, surprise, joy, anguish, fear, shame, disgust, and rage
Paul Ekman (1934-Now)	Anger, disgust, fear, happiness, sadness and surprise

adopt to avert ambiguous description [45]. This emotion model clarifies the emotion classification in a two-dimensional way according to valence quantity (positive to negative) and arousal quantity (exciting to sleepy). The emotion classifications are allotted into the four quadrants of a two-dimensional coordinate system, x axis is valence; y axis is arousal as shown in Fig. 1. Each model's quadrant includes three emotions. The first quadrant with positive valence and arousal emotions are pleased, happy and excited. The second quadrant with negative valence and positive arousal emotions are annoying, angry and nervous. The third quadrant with negative valence and arousal emotions are of sad, bored and sleepy. The fourth quadrant with positive valence and negative arousal emotions are calm, peaceful and relaxed. Those emotions was composed the Thayer's emotion space.

2.5 Fuzzy cognitive maps

The traditional FCM decision support technologies suppose that decision making can build a precise indication of a decision issue. The real-world problems, there are usually random event components with complex relations in the solving case. Hence, the application with FCM needs the new properties which are flexible, dynamic and swift. The FCM is a network, showed in Fig. 2, that every node describes the event, condition or status and every line

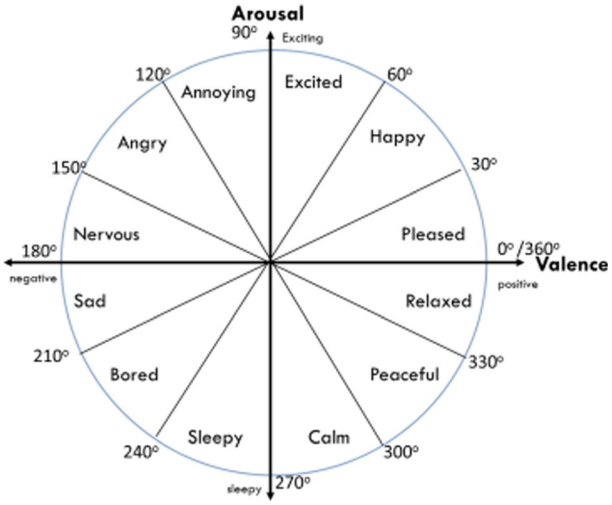


Fig. 1 Thayer's emotion model

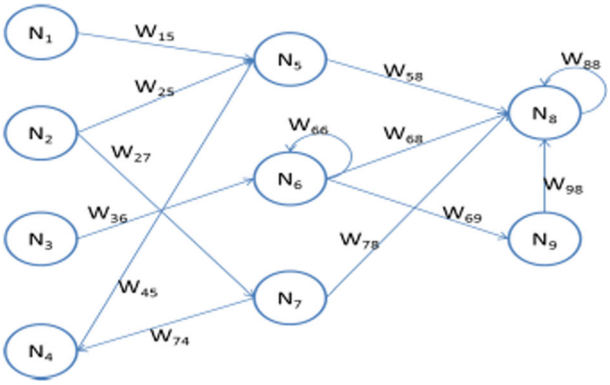


Fig. 2 Fuzzy cognitive map network

between nodes draw the relation, weight, value and sequence. The nodes in FCM would represent such concepts as events, physical components, investment, or risks, and so on.

2.6 Neural network model

The backpropagation neural network (BPNN) one kind of neural network model is the most widely applied neural network technique to classify or predict [21]. BPNN is layered feed-forward supervised network and the popular tool to solve wide range of problems like classification, recognition and control. The architecture of BPNN is a multilayer neural network with one layer of hidden units is shown in Fig. 3. BPNN due to its good strong and fault endure is extensively used in optimization and question approximation [40]. The serious defect involved in the BPNN model is convergent to a local area with ease [36, 35]. BPNN models is used frequently in membrane filtration process, to forecast the solution of membrane fouling [39, 23, 37] or membrane performances under diverse division parameters.

3 Method

This detecting emotion model with color in backpropagation model is an innovative framework for emotion status forecast. This experiment model adopts the two emotion models' (Thayer's model) merit to approach the human's emotion status by RGB color from user's choice.

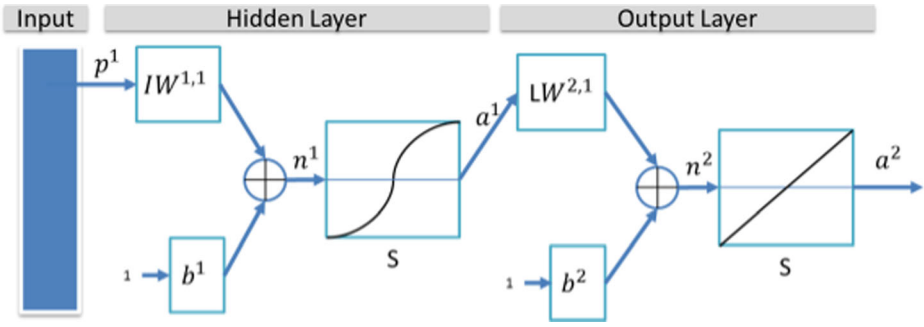
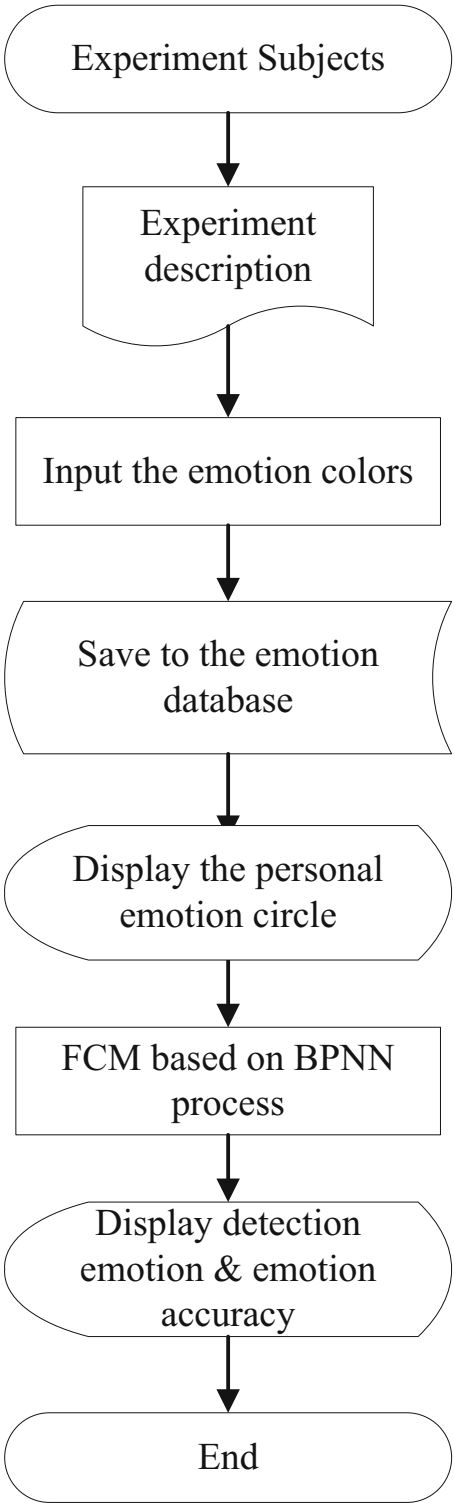


Fig. 3 Backpropagation neural network

Fig. 4 Experiment flow



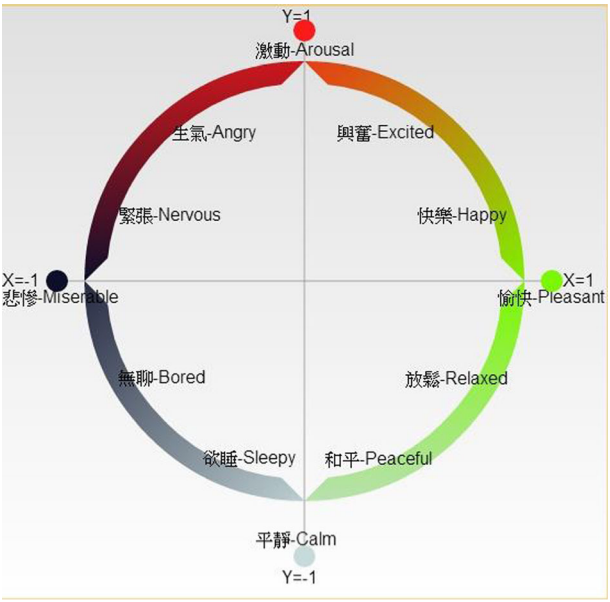


Fig. 5 Personal emotion circle

3.1 Experiment flow

The experiment flow in the beginning step, experiment subjects input their basic data (name, age, gender, etc.…), second step input the four colors about the emotion (arousal, pleasant, miserable and sleepy), third step save the data to the database, fifth step display the personal emotion circle, sixth step using FCM based on BPNN model to process the input data and seventh step display the emotion detection and emotion accuracy shown in Fig. 4. This experiment system imports the subject's data to emotion database and calculates the color record to draw the personal emotion circle shown in Fig. 5. The personal emotion circle presents the every unique individual's emotion color in Thayer's model. There 12 emotions in

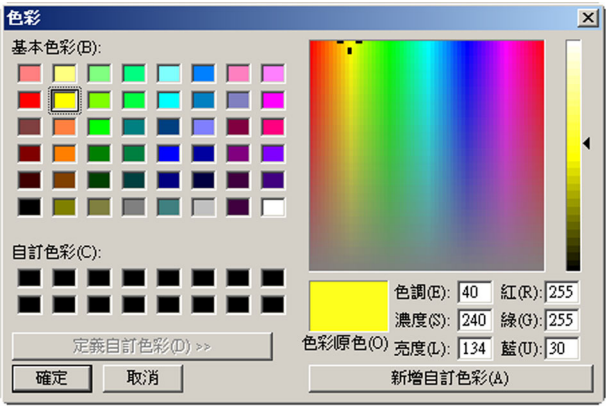


Fig. 6 Color picker in system

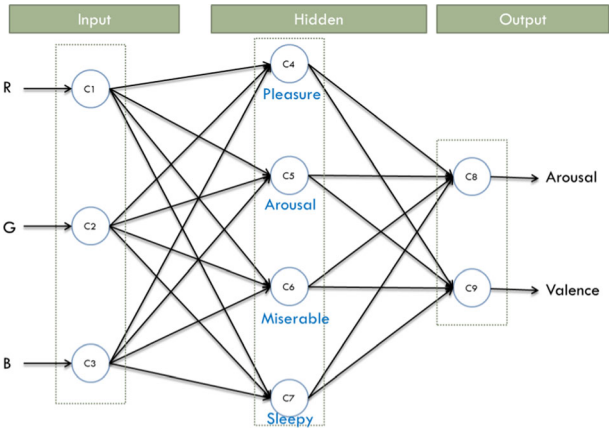


Fig. 7 Emotion colors detects with BPNN model

the personal emotion circle, each emotion joins a color which was calculated by input four emotion colors. The color picker that combines the simple mode 48 colors and complex mode including 16777216 possible colors was shown in Fig. 6. The simple mode provide 48 basic colors for user to choose emotion color easily and the complex mode provide the user to choose emotion color by RGB parameter that are $256 \times 256 \times 256$ possible colors.

3.2 BPNN process

This experiment uses the subject's emotion colors (input layer: RGB color), each emotion colors include pleasant, arousal, miserable and sleepy, four emotion status (Hidden layer). Gathering the every set emotion colors importing to the BPNN to

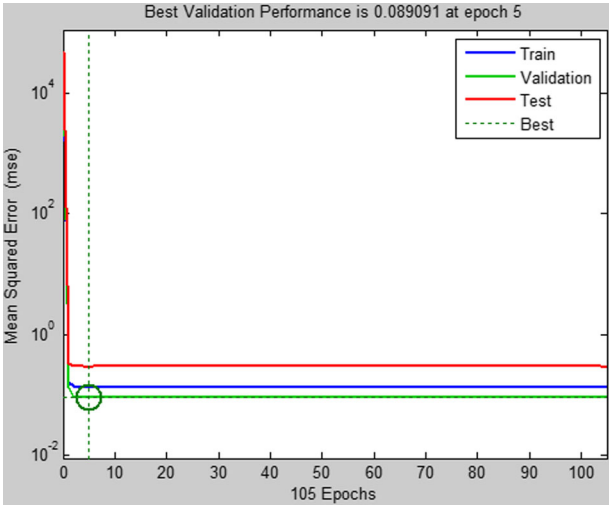


Fig. 8 MSE during the training, validation, test and simulation process

train and simulate showed in Fig. 7. The nodes in input layer were represented the RGB (Red, Green and Blue) color, and the value was from 0 to 255. The nodes in hidden layer were represented the emotion classification which are pleasure, arousal, miserable, and sleepy. The node in output layer were represented the detecting emotion color which are involving arousal and valence.

4 Result

The result of emotion color detecting shows a splendid solution. The result lists below:

Input: 240 samples from 60 users' RGB color
Output: 120 values with two vectors: arousal and valence
Simulation Best Validation MSE = 0.089091
Simulation MSE = 0.1057, Simulation MAE = 0.1574
Correction zone rate = 78 % (less than 30°)

In the result shows use the model in this research can gradually converge into the stable small value the best validation value is 0.089891 and shown as Fig. 8. The BPNN process can provide the appropriate induce solution for data mining in color detecting emotion. In the Fig. 9 shows the RGB color data in four emotion classifications present different trend. The R (Red) color in the arousal emotion is the highest value the mean is 240.03, the second is pleasure emotion the value is 177.61, the third is sleepy emotion the value is 147.26 and the fourth is miserable emotion the value is 63.68. The G color in the pleasure emotion is the highest value the mean is 221.84, the second is sleepy emotion the value is 155.21, the third is

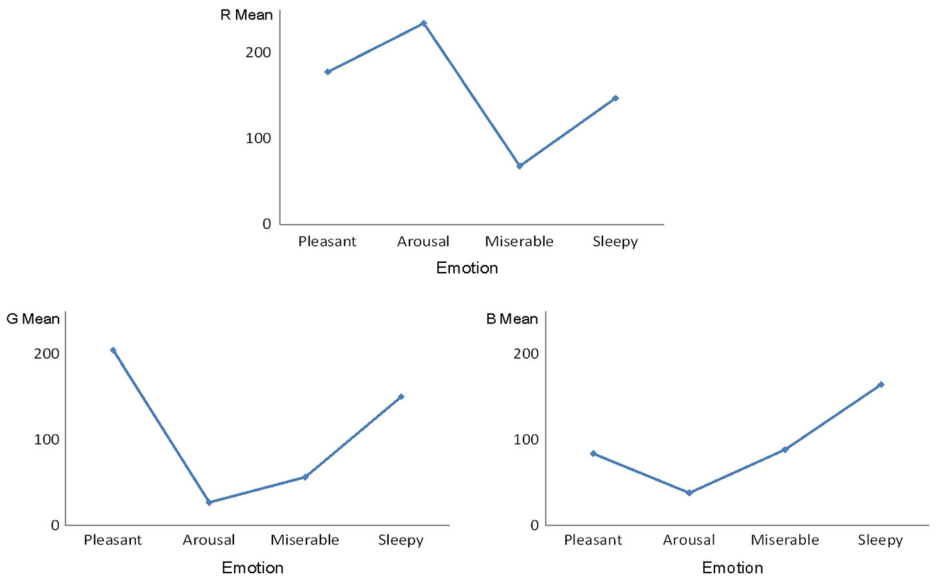


Fig. 9 RGB color mean figure

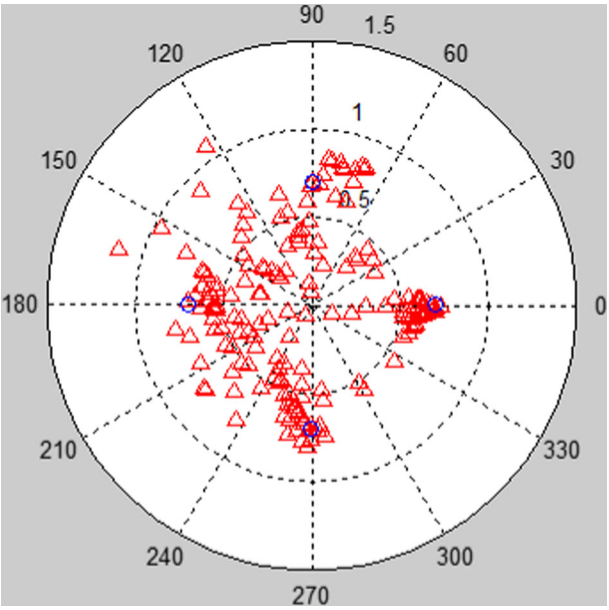


Fig. 10 outputs (*red triangle*) & targets (*blue circle*) shows in the polar coordinate

miserable emotion the value is 54.40 and the fourth is arousal the value is 23.08. The B color in the sleepy emotion is the highest value the mean is 172.79, the second is miserable emotion the value is 83.13, the third is pleasure the value is 59.06 and the fourth is arousal the value is 28.99. In the Fig. 10 shows the outputs data (triangle mark) and target data (circle mark) in the polar coordinate. The red triangle mark is the forecast emotion; the blue circle mark is the target emotion. The correction zone rate that was calculated by output data and target data is 78 %. The correction rate is target data degree subtracts output data degree less than 30°.

5 Conclusion

In this detecting emotion framework found the relations between the color and emotion while uses the FCM model. The emotion responsive color was affected by a lot of factors, because every single individual has the unique emotion color pattern. This research has the significant result in training and simulation convergence. And the emotion forecast accuracy is during in a well Interval. Some of emotion word in different culture will present entirely different. In this paper, miserable is an obvious case.

How to intuitively input the emotion color in the emotion detection interface is an import issue, simple color picker or complicated one are different. From this model, emotion data of examinee's response can be expanded in 2 directions: (1) tracing emotion process in diverse situations, (2) transform emotional fluctuating data to emotion map for calculating personalize emotion map. The emotion map is not only collecting the examinee's emotion but also analyzing the individual positive psychological area for constructing a fitting affective path.

References

1. Aarts R, Abate A, AbdelBaky M, Abraham A, Acampora G, Adami A, Agarwal A, Ahtinen A, Alam S, Alesanco A (2010) "2010 Index IEEE Transactions on Information Technology in Biomedicine Vol. 14." IEEE Trans Inf Technol Biomed 14:1483
2. Acampora G, Loia V, Vitiello A (2011) Distributing emotional services in ambient intelligence through cognitive agents. SOCA 5:17–35
3. Castellano G, Villalba SD, Camurri A (2007) "Recognising human emotions from body movement and gesture dynamics." In: Affective computing and intelligent interaction, ed. Springer, pp 71–82
4. Cheng BHC, De Lemos R, Giese H, Inverardi P, Magee J (2009) "Software engineering for self-adaptive systems," ed. Springer, pp. 48–70
5. Choi Y, Choo M, Chin S (2005) Prototyping a student model for educational games. JIPS 1:107–111
6. D'Mello S, Chipman P, Graesser A (2007) "Posture as a predictor of learner's affective engagement." In: Proceedings of the 29th Annual Cognitive Science Society. pp 905–910
7. Damasio A (2008) Descartes' error: emotion, reason and the human brain. Random House
8. Ekman P (2000) "Handbook of cognition and emotion." Dalgleish T, Power M (eds) Wiley, pp 45–60
9. Ekman P (2000) "Handbook of cognition and emotion." Dalgleish T, Power M (eds) Wiley, pp 51–53
10. Fayyad U, Piatetsky-Shapiro G, Smyth P (1996) From data mining to knowledge discovery in databases. AI Mag 17:37
11. Goleman D (2006) Emotional intelligence: why it can matter more than IQ. Random House Digital, Inc
12. Grimm M, Kroschel K, Harris H, Nass C, Schuller B, Rigoll G, Moosmayr T (2007) "On the necessity and feasibility of detecting a driver's emotional state while driving." In: Affective Computing and Intelligent Interaction, ed. Springer, pp 126–138
13. Han J, Kamber M, Pei J (2006) Data mining, second edition: concepts and techniques. Elsevier Science
14. Hofmann M, Beaumont LR (2005) "Content networking: architecture, protocols, and practice," ed. Elsevier, pp 179–216
15. Holden R, Rubery J (2013) "Emotion." In: Pearsall J (ed) Oxford dictionaries. Oxford University Press
16. Izard CE (1984) "Emotion-cognition relationships and human development." Emotions, cognition, and behavior. pp 17–37
17. Jaques PA, Vicari RM (2007) A BDI approach to infer student's emotions in an intelligent learning environment. Comput Educ 49:360–384
18. Kapoor A, Burleson W, Picard RW (2007) Automatic prediction of frustration. Int J Hum Comput Stud 65: 724–736
19. Komatsu T, Ueda K, Komeda T (2007) "Comprehension of users' subjective interaction states during their interaction with an artificial agent by means of heart rate variability index." In: Affective Computing and Intelligent Interaction, ed. Springer, pp 266–277
20. Kosko B (1986) Fuzzy cognitive maps. Int J Man-Mach Stud 24:65–75
21. Levine D (2007) Neural network modeling of emotion. Phys Life Rev 4:37–63
22. Liu C, Conn K, Sarkar N, Stone W (2008) Physiology-based affect recognition for computer-assisted intervention of children with Autism Spectrum Disorder. Int J Hum Comput Stud 66:662–677
23. Liu Q-F, Kim S-H, Lee S (2009) Prediction of microfiltration membrane fouling using artificial neural network models. Sep Purif Technol 70:96–102
24. Loia V, Senatore S (2013) "A fuzzy-oriented sentic analysis to capture the human emotion in Web-based content." Knowledge-Based Systems
25. Malkawi M, Murad O (2013) Artificial neuro fuzzy logic system for detecting human emotions. Hum-Centric Comput Inf Sci 3:1–13
26. Mandryk RL, Atkins MS (2007) A fuzzy physiological approach for continuously modeling emotion during interaction with play technologies. Int J Hum Comput Stud 65:329–347
27. Martin MMW, Weng M, Timothy TKS, Shih K, Jason JCH, Hung C (2013) "A personal tutoring mechanism based on the cloud environment." 4:37–44
28. Pantic M, Rothkrantz LJ (2003) Toward an affect-sensitive multimodal human-computer interaction. Proc IEEE 91:1370–1390
29. Peña-Ayala A (2014) Educational data mining: a survey and a data mining-based analysis of recent works. Expert Syst Appl 41:1432–1462
30. PhridviRaj MSB, GuruRao CV (2014) Data mining–past, present and future—a typical survey on data streams. Procedia Technol 12:255–263
31. Picard RW (2000) Affective computing. MIT Press, Cambridge
32. Picard RW, Vyzas E, Healey J (2001) Toward machine emotional intelligence: analysis of affective physiological state. IEEE Trans Pattern Anal Mach Intell 23:1175–1191
33. Pittman RE. Taxonomy of learning. Pedia Press

34. Rezazadeh IM, Wang X, Firoozabadi M, Hashemi Golpayegani MR (2011) Using affective human–machine interface to increase the operation performance in virtual construction crane training system: a novel approach. Autom Constr 20:289–298
35. Sexton RS, Gupta JN (2000) Comparative evaluation of genetic algorithm and backpropagation for training neural networks. Inf Sci 129:45–59
36. Sexton RS, Dorsey RE, Johnson JD (1998) Toward global optimization of neural networks: a comparison of the genetic algorithm and backpropagation. Decis Support Syst 22:171–185
37. Shetty GR, Chellam S (2003) Predicting membrane fouling during municipal drinking water nanofiltration using artificial neural networks. J Membr Sci 217:69–86
38. Stach W, Kurgan L, Pedrycz W (2010) A divide and conquer method for learning large Fuzzy Cognitive Maps. Fuzzy Sets Syst 161:2515–2532
39. Tan M, He G, Li X, Liu Y, Dong C, Feng J (2012) Prediction of the effects of preparation conditions on pervaporation performances of polydimethylsiloxane(PDMS)/ceramic composite membranes by backpropagation neural network and genetic algorithm. Sep Purif Technol 89:142–146
40. Tan M, He G, Nie F, Zhang L, Hu L (2014) Optimization of ultrafiltration membrane fabrication using backpropagation neural network and genetic algorithm. J Taiwan Inst Chem Eng 45:68–75
41. Tao J, Tan T (2005) "Affective computing: a review," In: Affective computing and intelligent interaction, ed. Springer, pp 981–995
42. Thayer RE (1989) The biopsychology of mood and arousal. Oxford University Press, New York
43. Vlahos GE, Ferratt TW, Knoepfle G (2004) The use of computer-based information systems by German managers to support decision making. Inf Manag 41:763–779
44. Wagner J, Vogt T, André E (2007) "A systematic comparison of different HMM designs for emotion recognition from acted and spontaneous speech." In: Affective Computing and Intelligent Interaction, ed. Springer, pp 114–125
45. Yang Y-H, Lin Y-C, Su Y-F, Chen HH (2007) "Music emotion classification: a regression approach." In: Multimedia and Expo, 2007 I.E. International Conference on. pp 208–211
46. Zhou F, Qu X, Helander MG, Jiao J (2011) Affect prediction from physiological measures via visual stimuli. Int J Hum Comput Stud 69:801–819

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