EEG-enabled Affective Human-Computer Interfaces

Chapter · June 2014

DOI: 10.1007/978-3-319-07437-5_51

2 authors:

Olga Sourina
Nanyang Technological University

Yisi Liu
Nanyang Technological University

EEG-enabled Affective Human-Computer Interfaces

Olga Sourina[1], Yisi Liu[1]

[1] Fraunhofer IDM@NTU
Nanyang Technological University
Singapore
{LiuYS, eosourina}@ntu.edu.sg

Abstract. Nowadays, the human computer interfaces can be designed to be adaptive and emotion-enabled. The recognized emotions of the user can help make the user's experience more complete, more engaging, less stressful or more stressful depending on the target of the applications. Such affective human-computer interfaces are getting more attention from researchers and engineers. EEG signals are used to recognize emotions of the user in real time. We describe a real-time emotion recognition algorithm that is used to personalize different applications according to the user's current emotions. The algorithm is subject-dependent and needs a training session before running the application. Two EEG-enabled games and one adaptive advertisement based on the algorithm are designed and implemented. One game is the "Bar" game where a difficulty level of the game is adapted based on the player's score and emotions. Another game is the "Girl Twins" one where the player's emotions are monitored in real time, and an emotional companion is implemented as the girl twins avatars whose behaviour changes according to the user's emotions. An adaptive advertising movie is designed and implemented as well. Here, the real-time emotion recognition algorithm is used to adjust the scenes of the advertisement based on the current emotion recognized.

Keywords: EEG; adaptive interfaces; emotion recognition; BCI; affective computing

1 Introduction

Human-Computer interfaces can be adapted to the user's experience, knowledge, or even user's internal feelings. The recognized emotions of the user can help make the user's experience more complete, more engaging, less stressful or more stressful depending on the target of the application. It is useful to implement adaptive interfaces in many applications including games, medical applications, neuromarketing, etc.

Emotion is a mental state and an affective reaction towards an event based on subjective experience [1]. Emotions are involved in the human daily communications and are inevitable in human-computer interaction. Thus, it is important for computer "to feel" and "to understand" the user's mental state especially his/her emotions. Emotions can be recognized from the user's face expressions, speech, gestures and/or biosignals such as Electroencephalogram (EEG) or combination of biosignals (heart rate, EEG, skin temperature, electrodermal activity, etc). In games, a combination of different types of bio-signals is often used for emotion recognition [2-6]. For example, pulse, respiration and skin conductance signals were used to detect the emotional states in the game [3]. In advertisement, emotional assessment can be done from verbal self-report, visual self-report, moment-to-moment rating, facial expression recognition, and biosignals [7]. There is less work done on emotion recognition through EEG signals only and on an integration of the corresponding affective interfaces in real-time applications. Since EEG devices become more affordable, portable, wireless and easy to set up, this technology can be used in emotion assessment of the user in human-computer interfaces. It is possible to adapt applications to the user by avoiding undesired emotions and by eliciting/maintaining the targeted emotions. The true feelings of the subject towards the application could be obtained in real time and could serve as an additional input and control in human-machine interfaces, for example, to adapt graphical user interface to the user's feeling or to change the game flow. It is possible to create adaptive games and advertising movies where some parameters of the scenes, for example, the difficulty level in the games are adjusted based on the recognized emotion or, for example, shapes, sizes, and colours of visuals are changed to induce emotions targeted by the advertisement or games. In [8], we proposed a real-time subject-dependent algorithm to recognize emotions from EEG. Combination of features such as statistical, Higher Order Crossings and fractal dimensions is proposed, and SVM classifier is applied. EEG signals are used to detect the current emotional states of the user. In this paper, we describe the algorithm and show that accuracy of the algorithm is better than other algorithms. The algorithm can recognize up to 8 emotions in three-dimensional Valence (Pleasure)-Arousal-Dominance emotion model proposed by Mehrabian and Russell in [9] and [10]. In this model, arousal dimension ranges from calm to excited, pleasure (valence) dimension ranges from negative to positive, dominance dimension ranges from a feeling of being in control during an emotional experience to a feeling of being controlled by the emotion [11]. The emotion labels can be located in the dimensional model, for example, anger and fear are both high arousal and negative states, but the anger has high dominance level and the fear has low dominance level. Based on the real-time subject-dependent algorithm we design affective interfaces and implement EEG-based emotion-enabled applications such as adaptive "Bar" and "Girl Twins" games, and an advertisement movie. The number of emotions used in the games depends on the game design. In the "Bar" game, two emotions based on 1-dimensional Valence scale are used. In the "Girl Twins" game, 8 emotions based on 3-dimensional Valence-Arousal-Dominance model are recognized and interpreted as the girl twins' behaviour. One adaptive advertisement is developed, and the advertisement is adjusted based on the user's real-time emotional feedback.

The paper is organized as follows. In Section 2, the real-time subject-dependent EEG-based emotion recognition algorithm is described. In Section 3, the real-time EEG based emotion recognition training system is introduced. In Section 4, the affective adaptive applications such as adaptive games and advertisement are described. At last, Section 5 concludes the paper.

2 Real-time EEG-based Emotion Recognition

Currently, most of the existing works on EEG-based emotion recognition are offline processing. [12] and [13] did a pioneer work on real-time EEG based emotion recognition, and fractal dimension features are used to detect the emotional states. The proposed algorithms are subject-dependent which means a classifier is trained for each subject.

The algorithm proposed in [8] is used in our games and emotion-adaptive advertisement movie. Fractal dimension, Higher Order Crossings (HOC) and statistical features are used as combined features, and Support Vector Machine is used as the classifier. Up to eight emotions such as happy, surprised, satisfied, protected, angry, frightened, unconcerned, and sad can be recognized. Only 4 channels are needed in the recognition to get adequate accuracy. 6 subjects' data from DEAP database [14] are used to validate the algorithm. 5-fold cross validation was used to calculate the accuracy. An accuracy of 53.7% is obtained for 8 emotions recognition and an accuracy of 83.73% is obtained for any 2 emotions recognition (Table 1). By using 32 channels the accuracy of the algorithm can be improved from 53.7% to 69.53% for the recognition of 8 emotions, from 56.24% to 71.43% for the recognition of 7 emotions, from 59.3% to 73.73% for the recognition of 6 emotions, from 63.07% to 76.53% for the recognition of 5 emotions, from 67.9% to 80% for the recognition of 4 emotions, from 74.36% to 84.41% for the recognition of 3 emotions, and from 83.73% to 90.35% for recognition of 2 emotions.

Although emotion processing is believed to be executed in frontal lobe [15-18], different brain areas may interact with each other. For example, the parietal lobe is proved to strongly interact with frontal cortex [19], and the amygdale co-activation of parietal cortex during emotion regulation is found in [20]. Mutual Information (MI) [21] was chosen to be investigated and to be compared with the proposed algorithm as it can measure the statistical dependency between different brain areas.

The Mutual Information (MI) features are extracted using the Moddemeijer's toolbox [22], where different distributions are estimated based on histograms, and the appropriate bin size is automatically determined. Since there are 32 channels in DEAP database, the total number of the MI features is 496. The obtained accuracy is shown in Table 1. It can be seen that the proposed combined features (HOC, 6 statistical, FD) with 32 channels outperform MI features by 20.15% in the recognition of 8 emotions, by 19.16% in the recognition of 7 emotions, by 18.19% in the recognition of 6 emotions, by 17.09% in the recognition of 5 emotions, 15.64% in the recognition of 4 emotions, 13.4% in the recognition of 3 emotions, and 9.35% in the recognition of 2 emotions.

Since the EEG-based emotion recognition algorithm is a subject-dependent one, a training session is needed for each subject before the recognition. The diagram of the algorithm is shown in Fig. 1. In the training session, firstly, the raw data labelled with emotions are filtered by a 2-42 Hz bandpass filter. Secondly, a sliding window with size of 512 and 75% overlapping is used to extract the Higuchi fractal dimension (FD) feature, HOC feature and 6 statistical features. By using the combination of these features, a SVM classifier with polynomial kernel is trained and saved to be used in the real-time recognition. In the recognition phase, the EEG signals are passed to bandpass filter. Then, the FD, HOC and statistical features are extracted and fed into the SVM classifier obtained from the training session. Finally, the current emotional state of the subject is recognized.

Table 1. Comparison of classification accuracy of the proposed feature combination and Mutual Information.

Number of emotions recognized	Feature Type		
	HOC, 6 statistical, FD	HOC, 6 statistical, FD	Mutual Information
	4 channels	32 channels	32 channels
8	53.7	69.53	49.38
7	56.24	71.43	52.27
6	59.3	73.73	55.54
5	63.07	76.53	59.44
4	67.9	80	64.36
3	74.36	84.41	71.01
2	83.73	90.35	81

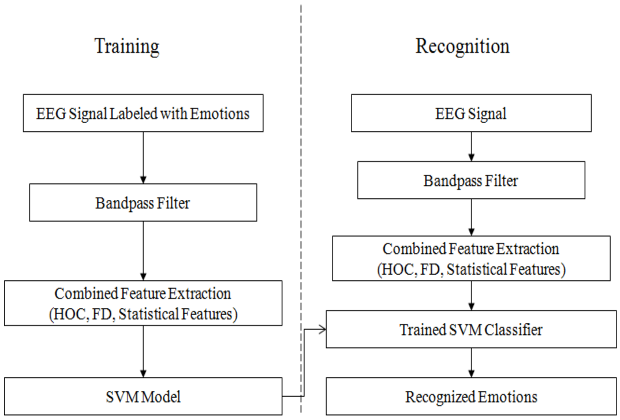

Fig. 1. Diagram of the emotion recognition algorithm with training session.

3 Emotion Recognition Training System

The time it takes to extract one new sample of HOC, statistical and FD features is less than 0.1 second as shown in Table 2 and classifying this sample by SVM takes less than 0.05 seconds. As a result, the proposed algorithm can be used in real-time emotion recognition applications such as emotion-enabled adaptive games and adaptive advertisement. As the proposed algorithm is subject-dependent, a short system training session is needed for the user.

Table 2. Comparison of features computational time per channel.

	HOC	Statistical	FD (Higuchi)
Approximate Time	0.07 seconds	0.001 seconds	0.004 second

EEG-based emotion-enabled applications require a system training session. In the training session, the user listens to sound clips labelled with emotions which are supposed to be elicited. After listening to the clips, the user is asked to assess arousal, valence and dominance levels of his/her feelings by moving the bar on a scale of 1 to 9. In Fig. 2, the screenshot of the menu of the training session is shown. The top left corner of the screen shows the number of recorded samples of EEG data and the recorded length of time for the training session. The top right corner allows the player to choose the duration of the recorded data for training. With the arousal, valence and dominance levels entered by the player to label the recorded EEG data, the SVM model is trained. The results are saved and later are used to classify new EEG data samples in the applications.

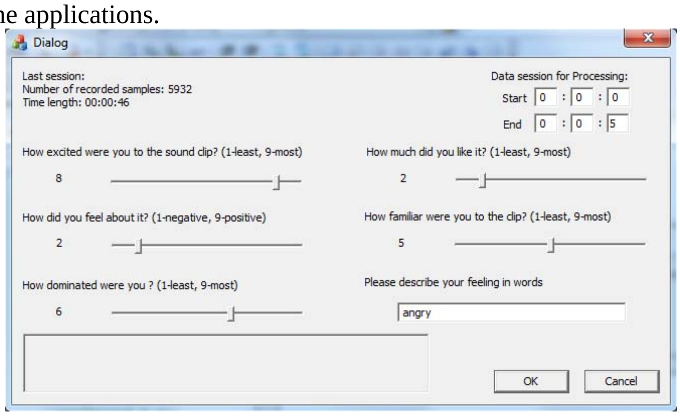

Fig. 2. Screenshot of the Training Session.

4 Adaptive Affective Applications

4.1 Data Acquisition

In the applications, we use Emotiv [23] device with 14 electrodes locating at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 standardized by the American Electroencephalographic Society [24] (plus CMS/DRL as references) to acquire EEG data. The technical parameters of the device are given as follows: bandwidth - 0.2-45Hz, digital notch filters at 50Hz and 60Hz; A/D converter with 16 bits resolution and sampling rate of 128Hz. The data are transferred via wireless receiver. Recently, the Emotiv device has become popular for research [25]. The reliability and validity of the EEG data collected by Emotiv device was done in [26] and [27].

4.2 Games

Two original EEG-based emotion-enabled games were designed and implemented based on the real-time emotion recognition algorithm: the adaptive "Bar" game and "Girl Twins" emotional companion application. Both of them were created with UDK and Maya. The player wears a wireless Emotiv device which is portable and easy to mount on the head. The diagram for the game application is shown in Fig. 3. Since our proposed algorithm uses the sliding window and shifts by 128 samples (1 second) each time, the player's emotion is recognized every 1 second and the emotional state at that time is used to update the emotion statistics. In the "Bar" game, emotion statistics are taken into account when making a decision for adjusting the difficulty level of the game. In the "Girl Twins", emotion statistics are used to update the twin girls' behaviors.

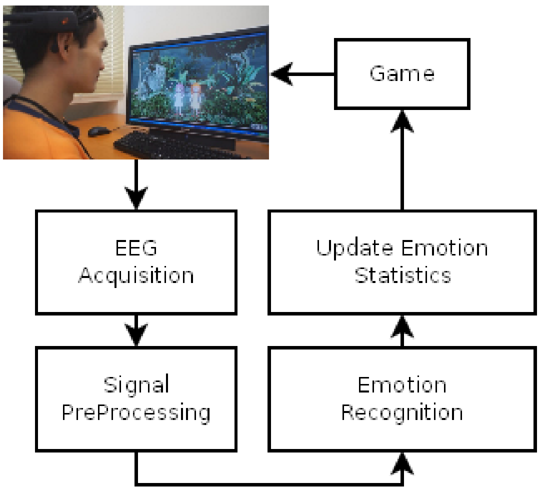

Fig. 3. Overall diagram of EEG-based emotion-enabled game.

In the “Girl Twins” emotional companion game, changes of the user’s recognized emotions are reflected on the girl twins. For each emotion, the girls’ dress style, hair color, facial expression and movement change according to the user’s recognized emotions (happy, surprised, satisfied, protected, angry, frightened, unconcerned, and sad). Based on the requirements, the girls’ behaviors change according to or opposite to the player’s emotions recognized from EEG. In Fig. 4, the screenshot of the game with girl twins with “happy” emotion is shown. Such an emotional companion could improve the player’s engagement, for example, in the case of e-learning games.

Fig. 4. Screenshot of the “Girl Twins” game representing “happy” player’s emotion.

The “Bar” game is another e-learning game. The player plays as a waiter who takes orders from customers coming to the bar. In Fig. 5, the screenshot of a customer ordering a drink is shown. The challenge of the game is that the player has to memorize the names of all customers and the drinks they ordered. Currently, the game has 3 levels of difficulty, and the difficulty level increases as follows. In level one, only first names of customers are used, in level two first names and surnames are used, and in level three names from different cultures have to be memorized. At each level, after the last order, a Customer-Drink table pops up for the player to match the names and the drinks. In this game, only negative and positive emotions defined on the valence dimension are used. The player’s emotions are being assessed continuously through the game. The decisions for changing difficulty levels in the game are shown in Table 3. An emotion is considered dominant while playing the current level if it is recognized in more than 50% of the playing time.

Table 3. Decision for changing the Difficulty levels.

Answers matching in the game	Dominant emotion while playing the current round	Difficulty of the next round
Correct	Negative	No change
Correct	Positive	More difficult
Incorrect	Negative	Less difficult
Incorrect	Positive	No change

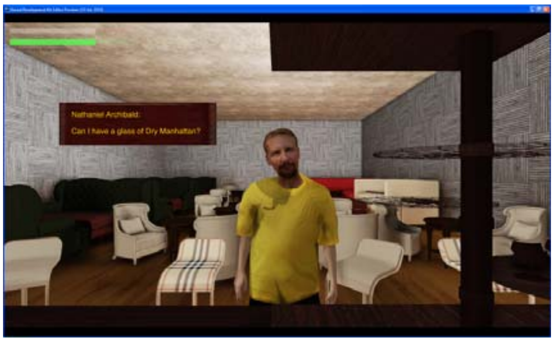

Fig. 5. Screenshot of the "Bar" game where the customer orders the drink.

4.3 Adaptive Advertising movie

To optimize the viewer's experience towards the advertisement and to maximize the advertising effect such as memorization of the products, in [28], we proposed a real-time EEG-based emotion-enabled algorithm to personalize advertising movies.

As the EEG-based emotion recognition algorithm used in the emotion-adaptive advertisement movie can recognize up to 8 discrete emotions based on the VAD model, the recognized results need to be decoded into the valence, arousal, and dominance emotional dimensions. The mapping of discrete emotions in the 3D model is illustrated in Fig. 6. "Angry" corresponds to negative high arousal high dominance; "fear" corresponds to negative high arousal low dominance; "unconcerned" corresponds to negative low arousal high dominance; "sad" corresponds to negative low arousal low dominance; "happy" corresponds to positive high arousal high dominance, "surprise" corresponds to positive high arousal low dominance; "satisfied" corresponds to positive low arousal high dominance; "protected" corresponds to positive low arousal low dominance.

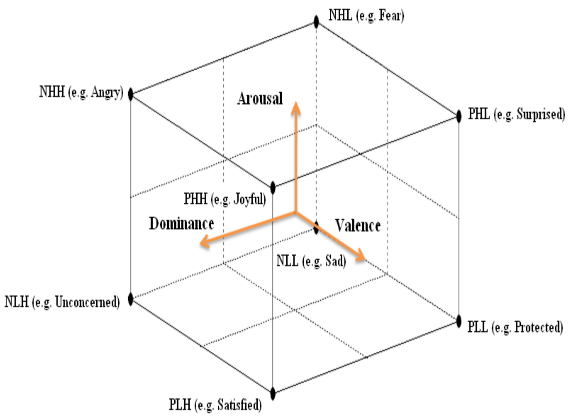

Fig. 6. 3D emotion classification model (Adopted from [9]).

The flow chart of the proposed emotion-enabled advertisement algorithm is given in Fig. 7. First, the advertising movie is shown to the user. The user's EEG signals are acquired by the EEG device. Then, the emotion recognition algorithm including bandpass filter, feature extraction and classification is applied to the EEG signals. As a result, the user's current emotional state is identified. The recognized emotion label is decoded to the corresponding arousal, valence and dominance levels as shown in Fig. 6. Then, the identified arousal, valence and dominance levels are compared with the targeted states respectively and the corresponding adjustment is made. If the recognized arousal, valence and dominance levels are compatible with the targeted levels, the default scenes of the advertising movie are shown. If at least one of them is incompatible, the movie is adjusted. For example, if the current state of the user is high arousal, but the desired state is low arousal which aims at making the audience remember the brand information, the scene colours in the advertisement are changed to cool colours to calm down the viewer.

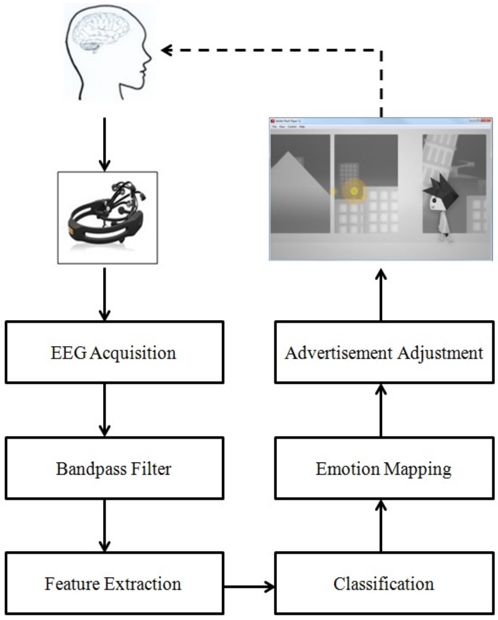

Fig. 7. Flow chart of the proposed emotion-enabled advertisement system.

We design and implement an emotion-adaptive advertisement for national library as an example of the real-time EEG-based emotion-enabled advertising system. In the designed movie, the national library is advertised as a place where a student can follow his/her creative imagination and discover the world via books. Five scenes are included as follows. In the 1st scene, a boy comes into the library. He is attracted by imaginary fireflies and chases them. In the 2nd, 3rd and 4th scene, the boy comes across several imaginary places such as a forest, a building and a path through the mountains. In the last scene, the boy catches up with the fireflies. The scene ends up by closing the book symbolizing the end of his discovery journey, and the logo of the library is shown.

A positive valence and high dominance are targeted throughout the advertisement. A high arousal is targeted at the beginning to make the subject more immersed and a low arousal is targeted when the information about the brand is shown to make the subject memorize the sign of national library.

If the viewer's recognized emotions are always compatible with the targeted emotions during the advertisement, there is no change, and the animation just follows the original basic design as shown in Fig. 8. If the current recognized arousal level is low but the targeted arousal level is high arousal level, the red colour is added to the scene to excite the viewer. If the recognized arousal level is high but the targeted arousal level of the advertisement is low arousal level, the blue colour is added to the scene to calm down the viewer. As the targeted valence level throughout the advertisement is always positive, if the recognized valence is positive, there is no change; if the recognized valence is negative, the head size of the character increases to induce positive emotion, and some curvy characters are added to make the viewer's feelings more positive.

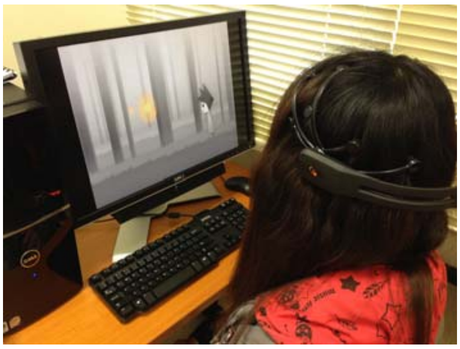

Fig. 8. The scene of the basic animation when the recognized emotion is compatible with the targeted emotion.

5 Conclusion

In this paper, we propose and implement adaptive affective applications based on the real-time EEG-based subject-dependent emotion recognition algorithm. Two adaptive games and one advertising movie are designed and implemented. The "Bar" game uses 2 recognized emotions to adapt the difficulty level of the game. In the "Girl Twins" which is the emotional companion game, 8 emotions can be recognized in real time from the player's EEG signal and interpreted as the girl twins avatars' behaviors changes according to the user's emotions. The implemented EEG-based emotion-enabled applications need short system training for the player. Real-time EEG-based emotion recognition can help to improve the user's enjoyment and effectiveness of the game and advertisement since it allows personalizing the games and advertising movie in real time. It is possible to adjust the games and advertisement in real time according to the user's emotion to make the applications more effective. Assessment of the effectiveness of the game design and proposed advertisement will be the next step in our project.

Acknowledgment

The characters of “Bar”, “Girl Twins” and “adaptive advertisement movie” are original and designed by NTU final year students Haoze Zhang, Mengying Ai, and Mohammad Rizqi Hafiyyandi respectively.

References

1. Mauss, I.B., Robinson, M.D.: Measures of emotion: A review. Cognition and Emotion 23(2), 209-237 (2009)
2. Tsai, T.W., Lo, H.Y., Chen, K.S.: An affective computing approach to develop the game-based adaptive learning material for the elementary students. In: Proceedings of the 2012 Joint International Conference on Human-Centered Computer Environments, pp. 8-13 (2012)
3. Tijs, T.J.W., Brokken, D., Ijsselsteijn, W.A.: Dynamic game balancing by recognizing affect. In: Fun and Games, vol. 5294 Lecture Notes in Computer Science, pp. 88-93. Springer Berlin Heidelberg (2008)
4. Tijs, T., Brokken, D., Ijsselsteijn, W.: Creating an emotionally adaptive game. In: Entertainment Computing - ICEC 2008, vol. 5309. Lecture Notes in Computer Science, pp. 122-133. Springer Berlin Heidelberg (2008)
5. Saari, T., Turpeinen, M., Kuikkaniemi, K., Kosunen, I., Ravaja, N.: Emotionally adapted games - An example of a first person shooter. In: Human-Computer Interaction. Interacting in Various Application Domains, vol. 5613. pp. 406-415. Springer Berlin Heidelberg (2009)
6. Gilleade, K.M., Dix, A.: Using frustration in the design of adaptive videogames. In: Proceedings of the 2004 ACM SIGCHI International Conference on Advances in computer entertainment technology, pp. 228-232 (2004)
7. Poels, K., Dewitte, S.: How to capture the heart? Reviewing 20 years of emotion measurement in advertising. Journal of Advertising Research 46(1), 18-37 (2006)
8. Liu, Y., Sourina, O.: EEG Databases for Emotion Recognition. In: Proc. 2013 Int. Conf. on Cyberworlds, pp. 302-309 (2013)
9. Mehrabian, A.: Framework for a comprehensive description and measurement of emotional states. Genetic, social, and general psychology monographs 121(3), 339-361 (1995)
10. Mehrabian, A.: Pleasure-Arousal-Dominance: A general framework for describing and measuring individual differences in temperament. Current Psychology 14(4), 261-292 (1996)
11. Bolls, P.D., Lang, A., Potter, R.F.: The effects of message valence and listener arousal on attention, memory, and facial muscular responses to radio advertisements. Communication Research 28(5), 627-651 (2001)
12. Liu, Y., Sourina, O., Nguyen, M.K.: Real-time EEG-based Human Emotion Recognition and Visualization. In: Proceedings of the 2010 International Conference on Cyberworlds, pp. 262-269 (2010)

13. Liu, Y., Sourina, O., Nguyen, M.K.: Real-Time EEG-Based Emotion Recognition and Its Applications. Transactions on Computational Science XII, Lecture Notes in Computer Science 6670, 256-277 (2011)
14. Koelstra, S., Muhl, C., Soleymani, M., Lee, J.-S., Yazdani, A., Ebrahimi, T., Pun, T., Nijholt, A., Patras, I.: DEAP: A Database for Emotion Analysis ;Using Physiological Signals. IEEE Transactions on Affective Computing 3(1), 18-31 (2012)
15. Bechara, A., Damasio, H., Damasio, A.R.: Emotion, decision making and the orbitofrontal cortex. Cerebral Cortex 10(3), 295-307 (2000)
16. Kringelbach, M.L.: The human orbitofrontal cortex: Linking reward to hedonic experience. Nature Reviews Neuroscience 6(9), 691-702 (2005)
17. Dolcos, F., Labar, K.S., Cabeza, R.: Dissociable effects of arousal and valence on prefrontal activity indexing emotional evaluation and subsequent memory: An event-related fMRI study. NeuroImage 23(1), 64-74 (2004)
18. Demaree, H.A., Everhart, D.E., Youngstrom, E.A., Harrison, D.W.: Brain lateralization of emotional processing: Historical roots and a future incorporating "dominance". Behavioral and Cognitive Neuroscience Reviews 4(1), 3-20 (2005)
19. Petrides, M., Pandya, D.N.: Projections to the frontal cortex from the posterior parietal region in the rhesus monkey. Journal of Comparative Neurology 228(1), 105-116 (1984)
20. Banks, S.J., Eddy, K.T., Angstadt, M., Nathan, P.J., Phan, K.L.: Amygdala–frontal connectivity during emotion regulation. Social cognitive and affective neuroscience 2(4), 303-312 (2007)
21. Chanel, G., Kierkels, J.J.M., Soleymani, M., Pun, T.: Short-term emotion assessment in a recall paradigm. International Journal of Human Computer Studies 67(8), 607-627 (2009)
22. . Moddemeijer, R.: On estimation of entropy and mutual information of continuous distributions. Signal Processing 16(3), 233-248 (1989)
23. Emotiv. http://www.emotiv.com
24. American electroencephalographic society guidelines for standard electrode position nomenclature. Journal of Clinical Neurophysiology 8(2), 200-202 (1991)
25. Ranky, G.N., Adamovich, S.: Analysis of a commercial EEG device for the control of a robot arm. In: Bioengineering Conference, Proceedings of the 2010 IEEE 36th Annual Northeast, pp. 1-2 (2010)
26. Stytsenko, K., Jablonskis, E., Prahm, C.: Evaluation of consumer EEG device Emotiv EPOC. In: Poster session presented at MEi:CogSci Conference 2011 (2011)
27. Duvinage, M., Castermans, T., Dutoit, T., Petieau, M., Hoellinger, T., Saedeleer, C.D., Seetharaman, K., Cheron, G.: A P300-based quantitative comparison between the emotiv epoc headset and a medical EEG device. In: Proceedings of the IASTED International Conference Biomedical Engineering, pp. 37-42 (2012)
28. Liu, Y., Sourina, O., Hafiyyandi, M.R.: EEG-Based Emotion-Adaptive Advertising. In: Affective Computing and Intelligent Interaction (ACII), 2013 Humaine Association Conference on, pp. 843-848 (2013)