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Procedia Computer Science 130 (2018) 376–382

Procedia Computer Science

www.elsevier.com/locate/procedia

The 9th International Conference on Ambient Systems, Networks and Technologies (ANT 2018)

Learning Emotions EEG-based Recognition and Brain Activity: A Survey Study on BCI for Intelligent Tutoring System

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Abstract

Learners experience emotions in a variety of valence and arousal in learning, which impacts the cognitive process and the success of learning. Learning emotions research has a wide range of benefits from improving learning outcomes and experience in Intelligent Tutoring System (ITS), as well as increasing operation and work productivity. This survey reviews techniques that have been used to measure emotions and theories for modeling emotions. It investigates EEG-based Brain-Computer Interaction (BCI) of general and learning emotion recognition. The induction methods of learning emotions and related issues are also included and discussed. The survey concludes with challenges for further learning emotion research.

Peer-review under responsibility of the Conference Program Chairs.

Keywords: BCI; Emotions; EEG; Learning; Intelligent Tutoring System

1. Introduction

Emotions or affective states elicited during learning impact learning experience, which promote or restrain the learning. For example, curiosity is expected to occur when students engage in a new topic of interest. Achieving a goal brings about pleasure or satisfaction. Confusion occurs when existing cognitive structure is inconsistent with incoming knowledge. Frustration is elicited if misconception could not be eliminated. Obviously, emotional processes intertwine with cognitive activity and there is considerable overlap in the neural circuitry that supports these two processes[1]. Either in human to human instruction class or Intelligent Tutoring System (ITS), emotions always occur when learners access in learning. In conventional class, human teacher could easily capture the cognitive and affective states of students and accordingly adjusts the speed and contents of the lecture. This adjustment refocuses students' interest and engagement and helps students overcome difficulties and solve problems, making the class efficiently. In recent years, increasing studies have employed many technologies to monitor students' cognitive and affective states and attempted to provide adaptive interfaces and contents accordingly to improve learning efficiency in Intelligent

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1877-0509 © 2018 The Authors. Published by Elsevier B.V.
Peer-review under responsibility of the Conference Program Chairs.
10.1016/j.procs.2018.04.056

Tutoring System (ITS) or online learning. In this work, we survey techniques that have been used to measure emotions and theories for modeling emotions. Among those measures used to detect emotions, Electroencephalograph based (EEG-based) emotion measures have unique potentials and benefits that are distinguished from other methods. In this work, EEG-based Brain-Computer Interaction (BCI) of emotion recognition are mainly focused and discussed. The induction methods of learning and related issues are also included. The survey concludes with challenges for further learning emotion research.

The terminology of learning emotion varies among research in different field, which is affective states in learning, affect[2], emotive states in learning, learning emotions, academic emotions[3], learning-centered affective states[4], etc. The terminology affective states/moods and emotive states are used commonly in Affective Computing. Emotions during learning, academic emotions, and learning-centered affective states are mentioned more in Pedagogy and Educational Technology. In this paper, we use learning emotions to instead other terminologies.

There are two models of general emotions that guide researchers to build emotion recognition systems, namely, the discrete model and the dimension model (as shown in Figure 1). The discrete model refers to the emotional space consisting of basic discrete emotions like joy, anger, surprise, sadness, fear and disgust. The dimensional model divides the emotional space into two main dimensions (Valence and Arousal, VA)[5] or three (Pleasure, Arousal, and Dominance, PAD)[6]. Valence refers to the positive and negative characteristics. Arousal indicates the intensity level of emotion. And Dominance reflects an individual's status, that is, in control or being controlled.

The description and terminology of general emotion models are commonly used to depict learning emotion models, while the latter ones are more specific due to learning situation. Learning emotions models vary based on a variable related to learning (as shown in Figure 1) that is, based on learning activities[3], based on learning session[7], based on learning process[8], based on instructional design[9], and based on learning environment[4]. For example, Pekrun et al.[3] have classified the learning emotions into four categories: achievement, topic, social and epistemic. This taxonomy covers a wide range of emotions that learners experience during learning activities. In this model, learners may have emotions related to 1) outcomes (achievement, like contentment, anxiety and frustration), 2) preferences for certain topics over others (topic, like empathy for the protagonist in a novel), 3) interactions with peers and teachers (social, like pride, shame and jealousy), and 4) processing new information that is encountered (epistemic, like surprise and confusion). Kort et al.[8] proposed a model of the generic learning process, which can be used as internal representations of a learner's cognitive-emotive state while engaged in learning. This emotion model of learning cycle contains the process from constructing learning to un-learning, including negative affect and positive affect. Hopefulness, awe, satisfaction, curiosity, disappointment, puzzlement, confusion, frustration, etc. are mentioned in this model.

Overall, these general emotion models and learning emotion models underlie the emotion recognition system and guide the research to induce emotions.

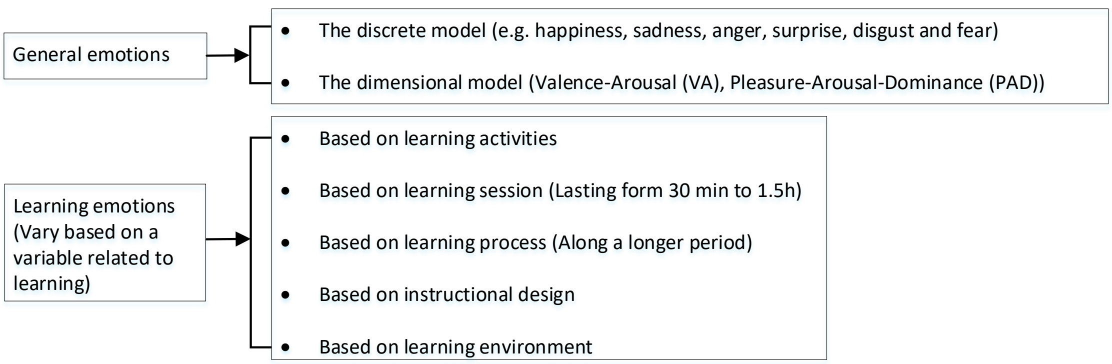

Fig. 1. The Map of Learning Models.

2. Measuring Learning Emotions

In this section, we briefly summarize and propose a taxonomy of measures used to detect learning emotions. Learning emotions have been measured through a number of methods (as shown in Figure 1), including self-report measures, observer's report, facial expression detection, gesture and posture recognition, interaction analysis, and physiological measures like EEG-based detection.

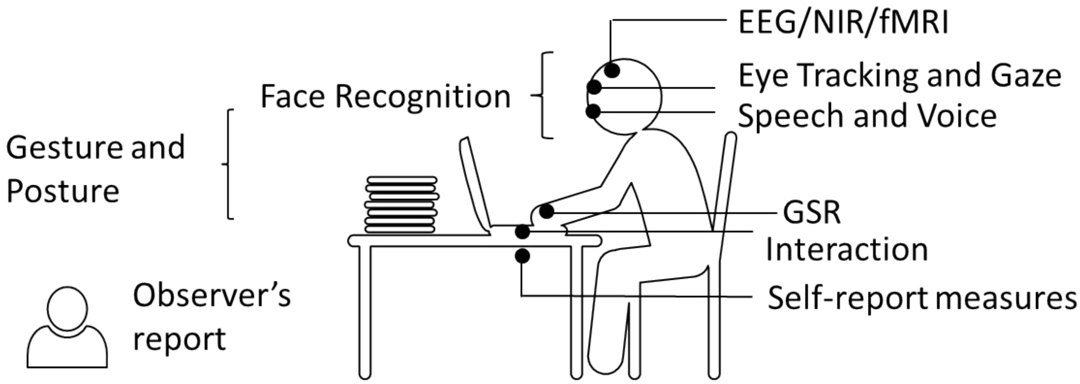

Fig. 2. Measures used to detect emotions.

These measures could be classified according to two dimensions (as shown in Table 1): objectivity (subjective and objective), and nature of features (external and internal). Objectivity refers to the way that emotion scales obtained, that is, in a subjective way or an objective way. And nature of features describes the features that represent emotions from outside or inside of the body. Self-Assessment Manikin (SAM)[10] scales are pictorial rating system, which are widely used to assess emotions on the affective valence and arousal dimensions. Bradley and Lang found that subjects selected the emotion level faster and more direct using SAM than using verbal scales. This non-verbal design assessment has been shown as an effective tool to assess emotion levels. The detection of Facial expressions is one of the most important measures to show emotions, which is based on computer vision technologies. For example, the work[11] explored approaches for automatic recognition of engagement from students' facial expressions. Physical measures of interaction like recording and analyzing typing speed and errors are investigated to detect emotions. Physiological measures like Electroencephalograph (EEG), Near Infrared (NIR), Galvanic Skin Response (GSR) have good temporal resolution and could monitor variations and trends of emotions. The fMRI has good spatial resolution, which is used with EEG simultaneously to detect and analyze affective, cognitive states and other mental states.

Table 1. Taxonomy of methods for measuring learning emotions according to objectivity and nature of features.

Objectivity	Nature of Features	
	External	Internal
Subjective	*Questionnaire* 1. Self-reported measures (e.g., arousal and valence, perceived difficulty of materials, devoted metal effort) 2. Observer's reports	N/A
Objective	*Physical measures* 1. Behavior detection (e.g., facial expression, gestures and postures, speech and voice, eye tracking and gaze) 2. Interactions (e.g., typing speed, sematic analysis of assignment) *Performance measures* (e.g., task completion time, scores)	*Physiological measures* 1. Brain activity measures (e.g., EEG, NIR, fMRI) 2. other measures like GSR

Table 2. Existing EEG-based Emotion Recognition Systems.

Emotions	Emotion Scale	Stimulus	Data Acquisition Device	Features Extracted	Classifier	Accuracy	Citation
Happiness and sadness	Binary classification	Facial pictures	62-channel electrode cap	ERD/ERS activities in gamma band	Linear LibSVM	93.5%±6.7 (trial length = 3s)	Li et al.[12] (2009)
Angry, Joy, Sadness, Pleasure	Two valance, two arousal	Music	32-channel EEG cap	Spectral powers of five bands (delta, theta, alpha, beta and gamma)	Three schemes of multi-class SVM classifier	Above 90%	Lin et al.[13] (2009)
Positive and negative	Binary classification	Movie clips	62-channel electrode cap	Spectrogram of all channels and five bands	Linear-SVM	87.53%	Nie et al.[14] (2011)
Confusion	Non-confusing, confusing	Online courses video clips	Mindset with Fp1 channel	Statistic features of raw signals, attention proprietary, meditation proprietary, and five bands	Gaussian Naive Bayes	Around 60%	Wang et al.[15] (2011)
Trajectory emotion changes	Positive and negative emotions	Movie clips	62-channel QuickCap	Power spectrum feature, wavelet feature, and nonlinear dynamical feature, using PCA, LDA and CFS to reduce dimensions	SVM	Up to 78.41%	Wang et al.[16] (2014)
Attention	Three levels: high, neutral, low	Online learning contents	24 channel of device Nexus-32	Linear features (time-domain analysis, Hjorth parameters, frequency-domain analysis) and nonlinear features	CFS and KNN (Correlation-based Feature Selection and k-Nearest Neighbors)	80.84%±3.0	Hu et al.[17] (2016)
Mild depression	Binary classification	Facial expression pictures	128 channel HydroGel Geodesic Sensor Net	Eight linear features and nine non-linear features. Using feature selection method GSW based on CFS	Five Machine learning algorithms like BayesNet	92.0% and 98.0%	Li et al.[18] (2016)
Discrete emotions	Positive, negative, and neutral	film clips	Emotiv, 14 channels	Power spectral features in five bands	SVM	Around 80%	Liu et al.[19] (2017)

3. Brain Activity and EEG-based Emotion Recognition Systems

Among those measures used to detect emotions as stated above, EEG-based emotion measures have potentials and benefits different from other methods. EEG provides a direct means for internal affective state detection, which has a good temporal resolution. Compared with physical measures like facial expression and body gestures and other physiological measures, it can expose the internal states of brain. Therefore, research on EEG-based Emotion Recognition Systems is gaining increasing focus in the field of computer science, education, biomedicine, psychology and interdisciplinary fields.

In this section, we survey existing studies on EEG-based BCI of Emotion Recognition Systems. The general emotions have been studied commonly in last two decades and the research on using EEG to detect the learning emotions is still in its infancy. In this situation, we list the studies revolving around general emotions or learning emotions are involved, as shown in Table 2. Many research works on EEG-based emotion and cognitive states recognition[20] have been based on Support Vector Machine (SVM), due to its good performance on EEG data and its suitability for small sample size. The basic idea behind SVM is to find out a maximal margin hyperplane to build the classifier. Besides binary classification, SVM could also perform multi-class classification using the kernel trick. The work[12 13 14 16 18 19] employed SVM and its related algorithms for classification of EEG signal. For example, in the work[19], Liu et al. designed and built a real-time movie-induced discrete emotion recognition system using EEG signals. Their system achieved an overall accuracy of 92.26% in recognizing high-arousal and valence emotions from neutrality and 86.63% in recognizing positive from negative emotions. And their systems classified three positive emotions (joy, amusement, tenderness) with an average of 86.43% accuracy and four negative emotions (anger, disgust, fear, sadness) with an average of 65.09% accuracy. The induction of learning emotions is more difficult than that of general emotions. And the learning emotions are mild emotions in arousal compared with general emotions. Although the recognition of general emotions had a good performance, the research on detection of learning emotions and its application has a long way to go.

4. Emotions Induction

4.1. Induction Methods

Before design and build EEG-based BCI of learning emotion recognition, one of the most important issues is to induce emotion accurately (according to emotion scale or arousal), effectively (according to emotion types or valence) and efficiently (have an affordable latency). Current Induction methods of emotions can be categorized into stimulus materials and environments. With regard to stimulus materials, pictures, sounds (or music) and video clips are used commonly. Besides International Affective Picture System (IAPS) as visual stimulus and International Affective Digitized Sound System (IADS) as audio stimulus, movie clips or other videos are used as audio-visual stimulus. Recently, standardized and non-standardized databases of movie clips to trigger general emotions have been constructed like[19], although the number is still a few. These movie clips are used to induce emotions like joy, amusement, fear, and disgust, which are more intense than learning emotions. To trigger learning emotions, tests, pedagogical contents, pictures, sounds, courses video clips have been used. For example, in the work[4], pedagogical contents are used to trigger emotions like confusion, frustration, anxiety, curiosity in one-to-one expert tutoring sessions. Additional, videos, as audio-visual stimulus, are closed to real learning in conventional classroom, gradually being taken into consideration to induce emotions. For example, Wang et al.[15 21] used online courses video clips to trigger confused and non-confused states in learning. In addition, the environment is one of available methods to trigger learning emotions. In the work[1], four computer learning environments that were well designed with AutoTutor to elicit confusion in learning have been developed. In these environments, vague hints, prompts, breakdown scenarios, contradictions, and false feedback have been used, which are highly tied to the learning process.

4.2. Induction Issues

Although researchers endeavored to induce the right emotion accurately, the gap between pre-assigned stimulus and the actual induced emotions still exists. Even though the algorithm of detection is highly improved and an amount of data is collected, this gap still would result in the inaccuracy of classification and the invalidity of measures. For example, in the work of[15], Wang et al. employed Massive Open Online Courses video clips as the confusion stimulus and a single-channel EEG headset to acquire data. They trained and tested classifiers to detect when the student is confused while watching the course material. They found weak but above-chance performance (around 60%) for using EEG to distinguish whether a student is confused. In this work, the limitation is due to the induction of confusion and lack of psychological professionalism. One the one hand, the stimulus materials were supposed to be confusing but participants found not confusing. One the other hand, the observers that gave the labels for training classifier were not formally instructed. Both of these two factors may lead to an incorrect labeling, which determines the accuracy of classification. Overall, to design and build standardized and validate database of induction materials and label these materials, which underlie the emotion recognition, is a daunting task for current research.

5. Challenges of EEG-based BCI in Education

As we stated above, researchers do many useful attempts to study BCI for intelligent tutoring system. However, there are still many challenges in this research domain. We concluded into three main categories from different aspects:

- *Challenges from the perspective of learning models and theories*
  Researchers have not clearly understood relationship and definition between learning behaviors and internal emotion induction. It is lack of corresponding theories to explain how to design an effective signal of emotion induction. If researchers cannot evaluate inducted emotion in quantity, the objective of EEG analysis is blurring. Building a learning model based on emotion induction is an urgent problem.
- *Challenges from the perspective of EEG data analysis*
  Compared with Electrocardiograph (EEG), EEG data is much weaker and easily disturbed by external factors, such as subjects' movement and environment noise. EEG data acquisition becomes the first challenge, which is related to how to improve data quality and remove artifacts. From the perspective of teaching application, EEG data should be recorded a long learning period for emotion detection. Traditional data analysis methods are used to measure brain response that is the direct result of short event. To find appropriate data analysis method for learning period is another challenge.
- *Challenges of "from the lab to the education application"*
  EEG headset is a specific and expensive device, which has only used to study and healthcare before. The simplest one usually costs several hundreds of dollars, and its testing precision cannot reach requirements of emotion recognition. If EEG headsets expect to be widely used in BCI for Intelligent Tutoring System, there are two challenges: how to reduce the cost and how to improve testing precision.

6. Conclusion

ITS or online learning systems reforms conventional learning class from teaching approaches to evaluation methods. The EEG-based emotion recognition attempts to analyze human's emotion based on brain activities, which opens a new page to study learning processing. In this paper, we reviewed the existed EEG based algorithm to measure emotions and theories for modeling emotions. We surveyed techniques that have been used to measure emotions and theories for modeling emotions, investigated EEG-based Brain-Computer Interaction (BCI) of general and learning emotion recognition, discussed the induction methods of learning and related issues, and concludes with challenges for further learning emotion research. Although researchers carry out fruitful research work, this research domain still face challenges on theories and practice. With studying further, increasing new technologies and devices will be introduced in learning emotion research field. There are full of opportunities and potentials in future.

Acknowledgements

This work was supported by the National Natural Science Foundation of China (61702417, 61703259), the Shaanxi Natural Science Foundation (2017JM6097), and the Opening Project of State Key Laboratory for Manufacturing Systems Engineering (sklm s2016001).

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