Affective Computing in Education:

Unpacking Possibilities and Challenges

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Abstract: The main purposes of this study are to analyze the affective computing platforms and to examine the possibility of educational use of affective computing technology. In the early 2000s, affective computing, which is an artificial intelligence-based system capable of analyzing and interpreting human emotions, was on the rise, and the research on these technologies has become explosive. There have been many studies on the development of technology itself, but only few studies have classified affective computing from an integrated point of view. In this paper, we analyzed affective computing platforms that are developed over the last 10 years to identify its possibilities and challenges in education, based on the following criteria for the classification: (a) facial expression-based platforms, (b) biometric-based platforms, and (c) text/verbal tone-based platforms. The platforms were analyzed by the following criteria: (a) the category of affective computing, (b) the technical characteristic (e.g., input method, input data, output data and Internet access), and (c) the fields of application. We found that some of the platforms offer free software (SDK/API) to encourage various future applications of their platforms, but that analysis methods and fields of application are limited to commercial and marketing contexts. In conclusion, this study suggests various scopes of application to future researchers and proposes possibilities of educational use of affective computing in particular.

Keywords: Affective computing, Affective computing platform

INTRODUCTION

Recently, since smart devices and wearable devices are more accessible to the public, the interaction between individuals and digital devices has become more frequent and continuous than in the past. Generally, the interactions that occur during the process of using smart devices have a one-way pattern in which the user employs the given technology as it is. (Bunt, Conati, & McGrenere, 2010). In addition, there is a lack of flexibility and adaptability to provide the user with the necessary information and feedback in a timely manner. Recently, artificial intelligence technology has been rapidly developed, and it is becoming possible to provide a user-customized service that automatically grasps a person's intention. Furthermore, attempts have been made to recognize emotional information such as facial expressions and gestures in the interaction between a person and a smart device, and the computing technology utilizing such emotional data is called “Affective Computing".

Affective computing is the computing that relates to, arises from, or influences emotions (Picard, 1995). In general, affective computing refers to an artificial intelligence-based system that can study, analyze and interpret human emotions in intelligent ways. In other words, artificial intelligence systems recognize psychological reactions from physical or sensory stimulation and utilize them in the interaction between human and computer. An IT research company called Gartner in the US announces 10 promising technology strategies every year. From 2016 to 2018, Gartner paid attention to innovative technology detecting human emotion and the high potential as it keeps expanding to a highly wide range of fields of application (Panetta, 2017). Such attention on affective computing is quite reasonable since it could improve the satisfaction of users by responding appropriately to human’s subconscious or subtle emotional flow with its vast scope of application in not only for commercials but also for educational fields.

The need to study sentiment and emotion occurring during the learning process has been emphasized for a long time. However, the current use of affective computing technology is quite limited as it has been used mainly for consumer behavior analysis, commercial marketing, and advertisement. There are many of affective computing platforms being actively developed; however, the platforms are also focused on such commercial use. Therefore, we explored the various cases of the developed affective computing platform and analyzed the characteristics and the context of its application in order to draw the possibility of affective computing in education.

RELATED TECHNOLOGY TREND ANALYSIS

Technology Overview

In this paper, a service platform refers to an operating system (OS) and software platform. It can be collectively referred to as the software platform. In order to preempt the emotional computing platform market, the providers of affective computing platform often offer developers and users API (Application Programming Interface) or source codes of their software and free program development tools to encourage them to develop applications based on the providers' service platform.

Affective computing software platforms include middleware and applications that can provide a variety of services to users based on a general-purpose operating system. Affective computing software platforms can be broadly divided into two types; one is open to the public that provides APIs to developers and the other one is open source that exposes its source code.

The service channel in affective computing platforms is various. It can be the web, mobile application, or hybrid which combining both web and mobiles. The hybrid channel is emerging as it keeps elaborating the way of combination of various channels and overcoming disadvantages.

The user environment based on commands or techniques for operating a digital device, typically known as UI is basically used together with API, which is a language, or a message format used for communication between an operating system and an application program for platform service. Developers utilize UI and API depending on their intention or purpose whether they tend to develop by themselves or use open sources. The types of utilization for platform service can be defined as the followings: 1) providing UI development and API for each platform; 2) providing an open UI by the web and API for each platform; 3) providing UI for each platform and open API for each platform; and 4) providing open UI and API (see Table 1). The affective computing platform that is developed and operated in these ways can measure emotional data in various directions (Kim, Ryu, Lee, & Kim 2010).

Table 1. Platform service type

	Open API Use	**API Development for Each Platform**
Open UI Use	4	2
UI Development for Each Platform	3	1

Biological Signal Detection and Emotion Information Discovery Technology

The technologies that can recognize human emotional information through the detection of various biological signals are classified into 1) biological signal detection technology related to emotion, 2) data collection and pattern recognition technology, and 3) emotional state recognition technology (Yoon & Chung, 2010).

In order to recognize human emotions, research studies have been conducted with video, voice, and biological signals. Bartlett, Littlewort, Fasel, & Movellan (2003) distinguished seven kinds of emotions such as neutral, anger, disgust, fear, joy, sadness, and surprise by using SVM (Support Vector Machine) for a short period of time. In addition, Nwe, Foo, & Silva (2003) proposed an emotion recognition method using Hidden Markov Model which is one of the statistical models for predicting direct causes. They classified anger, disgust, fear, joy, sadness and surprise by using their emotion recognition method and analyzed emotion data from voice additionally. They refined the accuracy of the analysis up to 78%. Based on these previous research studies, Metallinou, Lee, & Narayanan (2008) proposed a multiple sensor emotion recognition method that analyzes more than two sources of information from facial expression and voice, and they proved that the multiple sensory method has a higher accuracy of the affective information output than a single sensory method. However, although emotion recognition technology through facial expressions and voices has been developed enough to be applied to emotional robots, facial expressions and voices have limitations that it can be vulnerable to misunderstanding by the context due to the indirect representations of emotions (Bos, 2006).

On the other hand, the emotion recognition method using biological signals can compensate the misunderstanding by indirect representations because it is based on objectively expressed signals. Typically measured signals include electroencephalogram (EEG), blood volume pulse (BVP), respiration, skin conductance (SC), electrocardiogram (ECG), electromyogram (EMG), and skin temperature (SKT). The method extracts emotion-related characteristics from such bio-signals and measures them through corresponding to emotions. The characteristics of each bio-signal are shown in the Table 1.

The emotion measurement using biological signals is as follows. Picard, Vyzas, & Healey (2001) proposed a method to distinguish eight emotions: anger, hate, grief, platonic love, romantic love, joy, and reverence by using EMG, BVP, SC and respiration. They obtained 81% of the reliability by repeatedly measuring data from one experimenter and continuously correcting the data. Kulic & Croft (2005) used ECG, SC, and EMG to grasp the interaction between human and robot in terms of anxiety. Fuzzy inference was used to normalize the values. This study is based on the claim that human emotion should be considered when designing robots. Research using various types of biological signals has been steadily increased since the 2000s with the emergence of affective computing. Affective computing technology has already reached a very fine level and continues gradually refining the technology. The platforms presented in this study use affective technologies intensively and emotion data are derived by collecting biological signals or performing emotion recognition analysis according to the characteristics and direction of each platform.

Table 2. The characteristics of biological signal for emotion recognition

(source: Yoon & Chung, 2010)

Biometrics	Features
Electroencephalogram (EEG)	● Measuring electrical activities of the brain neurologically or physiologically, and measure the brain by attaching electrodes to the brain or cerebral cortex ● Distinguishing by frequency band
Electrocardiogram (ECG)	● Measuring electrical behaviors by cardiac activity marks ● Measuring by attaching metal electrodes to human body's chest, arms and legs to amplify electrical signals generated during heartbeat ● Mainly used to diagnose heart-related diseases by analyzing measured ECG waveforms
Electromyogram (EMG)	● Indicating the degree of muscle activity or tension of a particular muscle ● Measuring the electrical activity of muscles by attaching an electrode to the skin surface of the human body or inserting a needle electrode into the muscle. ● Generally used as an adjunctive method of diagnosis related to nerve or muscle
Blood volume pulse (BVP)	● Measuring the amount of blood flowing through the blood vessel ● Measuring by the amount of reflected light with photoplethysmograph (PPG) consisting of a light emitting part and a photo sensor attached to the skin
Skin temperature (SKT)	● Capillaries contract when tensed while reducing skin temperatures ● Dependent on external factors like skin electrical conductivity ● Slow response
Skin conductance (SC)	● Measuring the change in electrical conductivity of skin by stress or other stimuli ● Able to distinguish between angry and panic

METHODS

Research Methods and Questions

This study analyzed affective computing platforms that have been actively used in various contexts for the last 5 years until June 2018. Overall, while a substantial number of research studies regarding the technological advancement of affective computing have been done, there are few studies on technology usage cases and applications. Affective computing is an emerging technology and has a relatively short history. Therefore, we conducted a primary research using the online search method on Google to locate relevant platforms that utilize affective computing technology. The search process surfaced a total of 31 affective computing platforms. The second round search was conducted through collecting a wide range of literature published on the web, regarding case studies on the actual use of the platforms selected from the primary research.

Based on the above search process, we were able to identify and classify the affective computing platforms that are currently being used by the emotion detecting method, whether the platform perceives the emotion through facial, biometric, or text/verbal expression. The representative platforms were re-selected with the affective computing classification criteria derived from the second-round search. In total, seven platforms were selected according to its history a) whether it has the potential to use or has been already used in education, b) whether it is used for the research purpose rather than the commercial, and c) whether it offers free software (SDK/API) considering its easy application to educational fields in the future. Therefore, this study aims to analyze the seven platforms by the category of affective computing, the technical characteristic (i.e., input method, input data, and output data); and Internet access required, and fields of application, as shown in Table 2 below.

We used some of the available platforms and recorded the results of the experience. Also, we collected the relevant literature by analyzing the research conducted using the identified platforms.

Data analysis was conducted based on the direct observation and the analysis of literature. The concepts and features of affective computing were extracted from the previous case studies with actual participation to analyze its characteristic and propose ways of viable applications to the educational context.

The research problems derived from above procedure, therefore, are as follows:

RQ 1: What characteristics are relevant to categorize affective computing platforms?

RQ 2: How are the use of affective computing platform feasible in education?

RESULTS

Category of Affective Computing Platforms

The nature of affective computing is usually classified according to the emotion detecting methods. In the current technology, it can infer emotions through facial expressions, which reveals emotion in the most intuitive way. Secondly, it can recognize emotion through biometric information, and lastly it can be done through text/verbal tones expressed by a person. We also reviewed platforms that use mixed methods.

Facial Expression-Based Platforms

Facial expression is a primal source to infer human emotion. According to the position and the movement of eyebrows, lips, nose, mouth, and muscles of a face, it allows affective computing to detect what emotion is being expressed.

Table 3. Selected affective computing platforms

Platform	Detecting Category	Fields of Application	Feasibility in Education	Input Method	Input Data	Output Data	Free Software	Online/ Offline
Affectiva	Facial	Business, Education, Gaming, Healthcare, Media & Advertising, Retail, Robotics, SNS	Y	Webcam, Video	Facial expression	Demographic data/ Chart and graph outlining the types and depth of emotion/ Emoji relevant to users' emotion	Y (Limited)	Both
Face Reader	Facial	Academic Research, Business, Customer service, Education, Market research,	Y	Webcam	Facial expression, gaze direction, head orientation Action	Demographic data/ Chart and graph outlining the types and depth of emotion	Y (Limited)	Both
Air Class	Facial	Education	Y	Webcam	Facial expression	Chart and graph outlining Engagement score	N	Online
Empatica	Biometric	Academic Research, Healthcare, Human Behavior	Y	Wristband	Electrical changes across the surface of the skin, parasympathetic nervous system activation or vagal tone detected by heart rate variability	Chart and graph outlining users' biometric data including emotional state	Y (Limited)	Online/ Offline (Limited)
IBM Watson Tone Analyzer	Text/ Verbal	Business, Customer service, SNS	Y	Speaking/ Writing	Text, words, phrase, sentence	Chart and graph outlining the types of emotion, the depth of emotion, users' social degree, and types of writing	Y	Both

Vokaturi	Text/ Verbal	Business, Customer service, Education	Y	Speaking	Live or recorded voice and speech	Five types of emotion	Y (Limited)	Both
iMotions	Mixed	Academic Research, Business, Customer Service, Education, Marketing, Training	Y	Webcam, Eye-tracking glasses, EEG headsets, GSR/ EMG/ECG devices Video	Facial expression, eye-tracking EEG, ECG, GSR, EMG,	Chart and graph outlining users' biometric data including emotional state, types of emotions including confusion &frustration	N	Both

Case 1. Affectiva

Affectiva is one of the best-known platforms in affective computing, which is first developed at MIT Media Lab in 2009. As this platform has a longer history, it has been successfully applied to various fields such as business, education, gaming, healthcare, media, advertising, retail, robotics, and Social Network Service (SNS). Affectiva can analyze the users' demographic data (e.g., gender, ethnicity, age), types of emotions (e.g., joy, sadness, disgust, contempt, anger, fear, and surprise), and depth of emotions by the facial information via a webcam and recorded video. Once Affectiva classifies and analyze the facial expression by Paul Ekman's Facial Action Coding System (FACS) (Ekman & Friesesn, 1978), it presents the result chart and graph of users' emotion. In the SNS context, relevant emojis (e.g., emoticons) are appeared as an output of the analysis. Their SDKs are free for non-commercial open source projects, and adaptable to both online and offline environments. Affectiva has been already used for educational purpose, and thanks to its easy and free access to the SDKs, it can expand its possibility even further for experiments in education fields.

Figure 1. Affectiva

(Source: youtu.be/mFrSFMnskI4)

Case 2. Face Reader by Noldus

Face Reader is a software program developed by a Dutch company, Noldus, which provides a variety of services based on the human behavior research. According to the website statement, this software can be used potentially in business, customer service, research in general, market research, and even education. It analyzes facial expression data accumulated via a webcam and provides information regarding users' emotional state (i.e., happy, sad, scared, disgusted, surprised, and angry, contempt, and neutral) and the depth of emotion. Face Reader is partially open to the public, as it costs for the SDKs but offers the API for free. Face Reader can also work in both online and offline environments.

Figure 2. Face Reader

(Source: noldus.com/human-behavior-research/products/facereader)

Case 3. Air Class

Compared to other affective computing platforms and software, Air Class is a virtual training software program made only for the educational purpose in 2016. As Air Class is an education-specialized software program, the measured emotion is used to see learners' attention and engagement in the learning process. The information, which shows the degree of learners' attention and engagement (engagement score) is detected through the faces captured via a webcam. Air Class instantly analyzes and reflects the engagement score on the instructors' screen, which enables the instructors to monitor learners' engagement and distraction, and flexibly deploy their teaching strategy in a context. Air Class needs an Internet connection and does not offer free SDK/API.

Figure 3. Air Class

(source: airclass.com)

Biometric-Based Platforms

Emotions can be detected by biometric information left on a human body. Biometric-based platforms are ideal to detect both the type and depth of emotion. Biometric platforms have been mainly designed for healthcare. The most notable platform is Empatica, explained below.

Case 1. Empatica

Empatica is an affective computing company that developed the first device in the world detecting users' physiological data sensed from the wrist in 2011. Their device comes in two types with different purposes. One named Embrace is optimized to manage convulsive seizures, and the other one, named E4 is for research requiring physiological signals in real-time. While both can be used for research purposes, E4 would be more appropriate to encompass all research areas that require biometric data.

Empatica is equipped with the additional technological features such as the PPG sensor, EDA sensor (GSR sensor), infrared thermopile, Gyroscope, 3-Axis Accelerometer, and peripheral temperature sensor. Among these features, EDA sensor is the one measuring emotions such as fear, anxiety, and positive excitement through the electrical changes across the surface of the skin. Although the devices (Embrace and E4) also indicate emotions, they are more suited for healthcare and human behavior analysis settings, due to the focus on users' physiology in daily life. Once the devices detect and analyze users' physical conditions, immediately the biometric data are displayed in chart and graph formats within the applications via APIs. Empatica has a high potential in education for utilizing the device and the application with APIs to understand the emotional state of learners.

Their APIs is accessible for people who purchased E4 to develop own application. Since the affiliation between the app and the device requires an Internet connection, it functions best in online environments. However, E4 can record and store the data up to 60 hours in the flash memory. Once it has an internet connection, it uploads data to the E4 connect server.

Figure 4. Empatica

(source: empatica.com/research/e4)

Text/Verbal Tone-Based Platforms

Emotions can be detected by tones of a speech or a writing based on what word is selected and how strong it is expressed. The platforms using such emotion detecting methods are presented below.

Case 1. IBM Watson Tone Analyzer

The Tone Analyzer is one of the services enabled by Watson which is the artificial intelligent by IBM. It can detect tones, degree of sociality, and types of emotion including fear, anger, joy, sadness, analytical, confident, and tentative by either analyzing text, word, phrase, and sentence in documents or converting speech to text for analyzing the tone of the dialogue. While output data is reveled differently with the type of developers, it mostly shows charts and graphs outlining emotional data. The disadvantage of text analysis is that there is always a possibility to be spelled wrongly and to be written in incorrect grammars. However, Tone Analyzer provides the spell and grammar check function, which increases the accuracy of the detection.

IBM website states that Tone Analyzer is ideal to predict people's emotion on SNS, or to enhance customer services responding to individual customers adaptively and at scale. However, it can also effective in educational settings by analyzing learners' personal feedback in writing to see if the learner is frustrated or satisfied, and to treat in a right manner. API/SDKs are available for developers and can work both online and offline according to how it is built.

Figure 5. IBM Watson Tone Analyzer

(source: youtu.be/wUb--6FPBik)

Case 2. Vokaturi

Next, Vokaturi is a platform found in 2016, Netherlands, that infers emotions by analyzing human voice and speech. Because Vokaturi detects emotions by the tone of a voice or speech, it is free from the language barriers, and can be used globally. Currently, Vokaturi offers a free software library that can recognize five types of emotions such as happiness, neutrality sadness, anger, and fear with limited technical support and 66.5% of accuracy rate,. Vokaturi can work both online/offline settings according to where the SDK is integrated.

Vokaturi has been used for research regarding emotion in MOOCs environments (Hillaire, Iniesto, & Rienties, 2017), but resulted in a weak accuracy of predicting emotional content of speech. Vokaturi still implies its possibility of future usage in education by highlighting the importance of emotion.

Figure 6. Vokaturi

(source: vokaturi.com)

Mixed Emotion Detecting Platforms

There are also platforms which see emotions through more than two technologies combined, although the platforms are quite rare to find. The example is stated below.

Case 1. iMotions

iMotion, founded in 2005, is the only platform in the list integrating more than two affective computing technics. It enables scalable biometric and human behavior research in the areas of psychology, neuroscience, human factors engineering, health, business and human computer interaction as well as the following fields, business, customer service, marketing, and education/training. iMotion perceives affective data through webcam, eye-tracking device, EEG headset, and GSR/EMG/ECG devices, and even a recorded video to combining all biometric information resulting in concrete and accurate data.

Their technical partnership with other affective computing platforms such as Affectiva, Emotient, and Empatica made it even stronger to detect human behaviors and emotions. With this strong capability, it measures the users' emotional state, types of seven basic emotions including joy, anger, surprise, fear, contempt, sadness, disgust, as well as two advanced emotions such as confusion and frustration illustrated in charts and graphs. It is possible to request a free demo; however, it does not offer free software to the public. iMotion can be used in both online and offline situations, if it is not necessary to use the immediate facial expressions from a webcam and is fine with a recorded video instead.

Figure 7. iMotions

(source: imotions.com/products/)

DISCUSSION

Educational Possibilities of Affective Computing platforms

The affective computing platforms reviewed in this study hold high possibilities to be used for educational applications that support personalized learning experiences. Personalized emotional data in affective computing platforms are used based on machine learning. If artificial intelligence recognizes and studies various learning patterns of individuals according to the emotional state, it can provide customized education to learners. When a learner participates through affective computing platforms, it provides personalized results based on emotions. AC platform can identify when emotional valence and arousal happen in the process of learning and the effect of such sentiments on individuals' learning outcomes and engagement. Ultimately, affective computing can be used to analyze the learner's characteristics, strengths, and weaknesses based on these identified data enabling the learners to determine their learning direction and recognize additional interests that even the learners have not been aware of. In addition, AC platforms can identify the interests and weaknesses of individual learners and automatically recommend customized content such as supplementary and deepening to learning disposition. In addition, it can help determine whether a student reached the learning goal in an affective domain which is difficult to see.

Challenges of Affective Computing in Education

The need to study the role of various types and states of emotions in human learning processes has long been emphasized. Recently, affect which role remained only secondary in human cognitive process, has gained the renowned interest with the importance of socio-emotional learning. Now, the process of learning is considered not as a mere act of motivation or cognition alone, but a collective process in which various emotional responses are intertwined.

While affective computing has several potentials discussed in the above section, some challenges of integrating affective computing in education exist. Firstly, data sources to analyze emotional states available in the common platforms are mainly from commercial activities such as emotional reaction while watching an advertisement. Thus, such platforms are likely to have limited applications to learning contexts, which tend to have more subtle states of emotions.

Second, intuitiveness of affective data is another challenging area. As affective computing platforms are still limited in presenting or visualizing emotional data, learners tend to have difficulties intuitively understanding and interpreting data output. How to visualize affective data for users' intuitive interpretation is the promising area for future research.

The last challenge is associated with detecting and analyzing the flow of emotional changes and co-occurring multiple emotional status. The current platforms and research studies appear to rather simplify emotional states that can be detected with sufficient discriminant powers. However, human emotions are highly vulnerable to the surrounding situations, including the place, time, other people, content, and tools. So far, many research studies on affective computing have been conducted in lab settings, hence limiting their applications in real situations with diverse factors involved. Further, human emotion is seldom a single state, but rather a complex composite of multiple emotional states (e.g., surprise and sad) (Harley, Bouchet, & Azevedo, 2012). Such a complexity of co-occurring multiple emotional states should be considered in the education use of affective computing, since learning processes are not linear, but complex, iterative with several states of emotion emerging, evolving and disappearing.

CONCLUSION

With the rapid development of artificial intelligence and analytics technology, it is now possible to provide intelligent customizable services that detect and analyze invisible subtle emotions such as facial expressions and gestures in human and machine interactions. This study reviewed various affective computing platforms that can analyze and understand students' psychological state through emotional data analysis on biometric data, expression, action, and written/verbal tone expression. In conclusion, this study found that the research on affective computing in education is in its infancy, while the field holds many potentials that can support socio-emotional learning processes. We suggest that affective computing particularly holds a great potential in online learning environments such as MOOCs where low completion rates have been the consistent problem. For instance, affective customize feedback mechanisms can be developed to detect early signs of drop-outs and to provide emotional support for learners to sustain their learning processes and interest.

Future empirical research is needed to better understand the role of affective feedback with intelligent and customizable functions.

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