Learner's Positive and Negative Emotion Prediction using i-Emotion

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Highlights: Bio Sensor in emotion includes the use of a sensor known as Brain Computer Interface (BCI) in recognizing the emotion signals that occur in the human brain (electroencephalograph signals). The researcher used a BCI tool to collect the required data of attention and meditation value scale through a qualitative sampling. The respondent for this research are school kids' age between 7 to 12 years old. In order to classify their positive and negative emotions, these EEG signals involves a lot of data and need to be mined in order to make it valuable and meaningful. By using rule-based (PART) classifier, the decision lists represent the regularities of the attention and meditation levels among kids. The data were generated and converted into several rule sets named rule-based prediction set and have been implemented in the i-Emotion using MATLAB environment. A baseline set which is adapted from an established eSense meter values was also coded into the prototype. The reliable relationship between EEG signals of attention and meditation and their impact towards the positive and negative emotion among kids while learning illustrate the potential in

detecting mental states which relevant to tutoring such as comprehension , engagement and learning impact.

Key words: *Brain Computer Interface, rule-based prediction set, baseline set, attention, meditation.*

Introduction

The brain is a fascinating organ for the humans and the part of the body that regulates almost all of the human activity. Scientists agree on the fact that the human brain is the main source of emotion. EEG had been selected to be the input signal for emotion detection as EEG is one of the useful bio signals from the brain to detect the human emotion (Murugappan et al., 2007). However, technologists have largely ignored emotion and created an often frustrating experience for people because the affective factor of human brain signals (electroencephalogram signals) has been found to be always misunderstood and hard to measure (MediaLab ,2013). Emotion is an important aspect of the psychological changes of a human being. Emotion also adjusts the state of the human brain and directly or indirectly influences several processes. Emotion is omnipresent and an important factor in human life (Horlings, 2008). People's emotion heavily influences their way of communicating, but also their acting and producing. A lot of research is already done after recognizing emotion. For example, research has been done to make computers recognize emotion from speech (Bhatti, Wang, & Guan, 2004; Dellaert, Polzin, & Waibel, 1996) , facial expressions or a fusion of both methods (Fasel & Luettin, 2003; Pantic & Rothkrantz, 2000).

In order to capture these human brain signals, a BCI headset is used. BCI tools are becoming more available on the public market, which enables more diverse research in a currently narrow field. EEG studies led to the research and development of Brain-Computer Interface (BCI) of many areas nowadays. For example, paralyzed or disabled patients will be helped to interact with the external world by mapping brain signals to human cognitive or sensory-motor functions (Bos et al., 2010)). Lots of BCI applications had been developed for education and gaming purposes. Some of the developers made use BCIs to developed game-based learning to enhance the learning experience through the gameplay. In this study, the EEG data of the attention and meditation level of the kids while learning will be captured using a BCI headset tool. This data will be stored in comma separated value (CSV) format. These attention and meditation value will be analyzed and interpreted accordingly in order to determine the positive and negative emotion of the kids while learning. A prototype of the emotion prediction system named i-Emotion was developed to summarize the entire process involved starting from preprocessing to the end using MATLAB environment.

Management Design of i-Emotion

The management design for the automation process of the prediction of positive and negative emotion in i-Emotion is depicted in the following Figure 1.

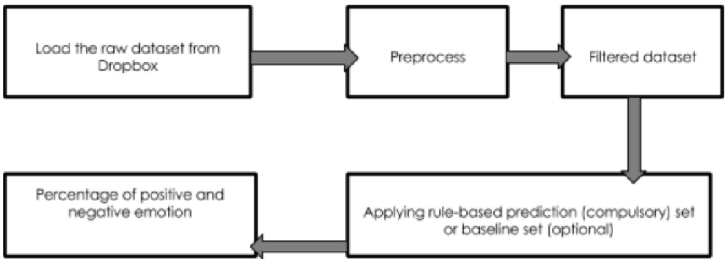

Figure 1: Management Design of i-Emotion

Implementation Context of i-Emotion

An emotion prediction prototype (i-Emotion) was developed based on the rule-based classifier. i-Emotion is an automation of the whole processes involved in this research using MATLAB environment. It is able to classify the emotion of the kid into two categories or classes of positive and negative emotion, depending on the readings of their attention and meditation value scale captured from their brain signals. According to Keller's ARCS model, both low and high levels of attention could be detected and the reaction feedback could be provided so that the learner could improve or sustain their attention (Rebolledo & Freitas, 2008). From the literature study, it was found that meditation level is correlated to attention state of a human brain (Chan & Woollacott, 2007). Short-term meditation training was found to improve attention and self-regulation (Tang et al., 2007), enhance attention stability (Lutz, Slagter, & Rawlings, 2009), reduce stress and increase mental focus (Chan & Woollacott, 2007). Lutz et al. (2009) also stated that the attention state is cultivated by meditation state at the first place. Crowley et al. (2011) reported that meditation state represents the user's state of arousal or the state where a person is active or attentive to a certain situation. As meditation and attention

interrelated to each other, this research considered both attention and meditation readings from the headset and the mean value of both readings will be calculated at every second (where each row of the CSV data represent one-second interval). The meditation and attention are summed up together and divided by 2 . The mean value indicates the value of the emotion either in positive or negative that occur in every second. This formula was coded into the prototype.

There are two testing sets that can be applied in order to determine the kids' positive and negative emotion: rule-based prediction set or baseline set. The baseline set is a set of baseline readings highlighted by the previous key researchers while the rule-based prediction set is the set developed for this research. Rule-based prediction set or baseline set or both are applied in i-Emotion for the comparison and validation purposes. Baseline set of the positive and negative emotion is adapted from eSense attention and meditation meter returned by the headset. For a better understanding of this research, the eSense meter was altered into a baseline set to differentiate between the positive and negative emotion as illustrated in the following Table 1. In this baseline set, the positive and negative emotion will meet at a red dotted baseline of 40. The attention and meditation readings between 41 to 100 represent the neutral, slightly elevated and elevated levels while negative emotion with the values of 1 up to 40 represents the reduced and strongly lowered levels of attention and meditation. The baseline set is applied in order to validate and to compare the results of the applied rule-based prediction set.

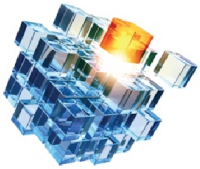

Table 1:Baseline set

Value	Levels	Emotion
1-20	Strongly lowered	Negative (below than 40)
21-40	Reduced	
41-60	Neutral	Positive (more than 40)
61-80	Slightly elevated	
81-100	Elevated	

The implementation of the classification algorithms helps in acquiring new knowledge from the data collected from the human brain wave. Previously, the prediction of positive and negative emotion was possible through the baseline set highlighted by the former researchers. This research intended to reveal the potential application behind the readings of the attention and meditation and to extract how far the data can help in predicting positive and negative emotion of the kids while learning. In this case, the regularities of the attention and meditation readings of the respondents were taken into account and rule-based classifier was identified as the best classification algorithm which can help in the prediction of the positive and negative emotion. WEKA provides a list of decision for the dataset that has been classified using rule-based classifier and the entire decision list was converted into the rule sets (named as rule-based prediction set)and coded into MATLAB. The rule sets generated by the classifier summarize the regularities in the readings and help in the realization of prediction system of the emotion. In order to generate the results, i-Emotion needs the information that the user need to prompt such as:

a. Enter the respondent's number (1 to 9)
b. Enter the number of session (1 or 2)
c. Enter the desired technique/set.

Note: 1=baseline set, 2=rule based set, 3=both sets

d. Enter the type of the graph to be displayed.

Note: 0=off, 1=based on average over time, 2=based on attention over meditation

The following Figure 2 shows the sample output displayed by i-Emotion using baseline and rule-based prediction sets. The percentage of positive and negative emotion display on top of the graph indicate the percentage of a respondent who experiences a positive and negative emotion while learning. The obvious difference between the output of both sets is the points of negative emotion (in red dots) of rule-based prediction set are also scattered in the positive emotion area (in blue dots).This is due to the set of rules which are no longer depending on the baseline of 40 to differentiate between the positive and negative emotion.

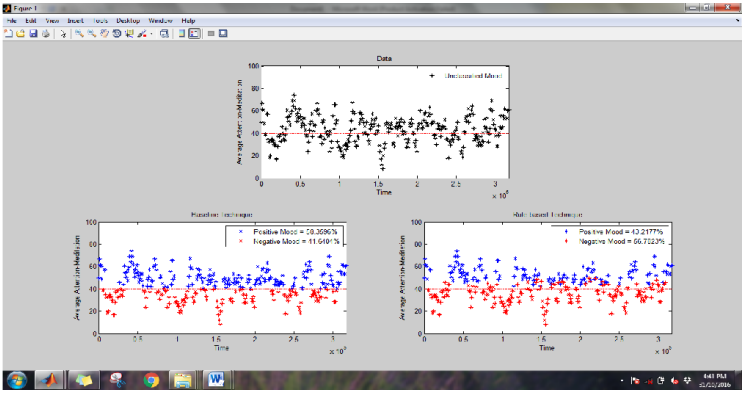

Figure 2: The output of i-Emotion

Advantages and Commercial Values of i-Emotion

i-Emotion presents the finding that it is possible to predict the class variable of the positive and negative emotion using the explanatory variables of the attention and meditation levels. The outcome of this research shows that different kid will have different adaptation towards learning session. The results are encouraging and show that the headset tool has the potential not only to record brainwave activity but also to differentiate between mental states or emotion. The reliable relationship between EEG signals of attention and meditation and their impact towards the positive and negative emotion of the kids while learning illustrates the potential to detect mental states which relevant to tutorings such as comprehension , engagement, and learning.

i-Emotion demonstrates the potential of exploiting the attention and meditation readings from the human brain using a BCI tool. It also shows that the positive and negative emotion or emotion can be easily predicted by inding the regularities of the trends in the attention and meditation readings. i-Emotion highlights the solution upon the challenges faced by the academic practitioners in dealing with the students nowadays. By using the predictive system of i-Emotion, teachers, parents and other academic practitioners will be able to monitor and observe the current emotion of the student after involving in a learning session. This may be applicable to a student who needs high supervision from the teachers or any student with academic problems. These students may have a lack of confidence and having a low ability to stay focus and calm themselves in class whenever they feel hard and stress. Therefore, teachers might be able to monitor their progress in the class and can deal with their positive and negative

emotion during the learning session. In summary, this research will give hope and awareness that i-Emotion is another important learning aid in school which can be implemented by the Ministry of Education that will help teachers to capture and provide much relevant information to enhance the learning impacts among the students.

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