Neural Network for Detection of Students' interest using Approximate Entropy Features of EEG data

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Abstract

Studies have found that optimizing course contents or lecture materials according to student's interest could improve learning outcomes. In this work, we advocate the use of Electroencephalogram (EEG) as a modality to qualify student's interest based on their respective brain activities. An EEG-based detection of interest in real classroom environment using Approximate Entropy (ApEn) is proposed. The method involved the use of Artificial Neural Networks (ANN) to discriminate the EEG data as relevant to either high or low situational interest. The qualitative assessment was performed by Personal Interest (PI), Situational interest (SI) questionnaires and knowledge tests which were considered as ground truth for the classifications. An accuracy of 100% and R2=0.996 was achieved in classifying 17 students as high SI or low SI. The results show that the proposed features could be used to differentiate brain activities based on student's interest.

Keywords: Situational interest, EEG, classroom, Approximate Entropy and ANN.

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1. Introduction

Researchers divided interest into personal and situational interest. while both lead to focused attention on the object of interest, situational interest is easily triggered and controlled by the situation. Therefore, many studies were carried out to explain the science of interest development and how to utilize it for the benefit of learners. For a field like mathematics "Proficiency in mathematics is a major advantage in industrialized nations" (Maloney, Schaeffer, & Beilock, 2013) where many students are scared of and not willing to do the effort, situational interest have remarkable effect. In recent study (Bernacki & Walkington, 2018), it was reported that the increase in situational interest caused by personalizing 4 units of algebra story problems to students led to greater interest in mathematics and higher score in class tests for those students compared to control group.

One way to study this interest is by studying the underlying brain activities. Electroencephalogram (EEG) is among the most effective non-invasive equipment in this case due to the advanced technology that made it available with relatively low cost. Moreover, the signals produced by EEG cannot be manipulated by participant unlike questionnaires. Therefore, its used extensively in classroom experiments to detect student's attention and engagement e.g. (Poulsen, Kamronn, Dmochowski, Parra, & Hansen, 2017), (Ko, Komarov, Hairston, Jung, & Lin, 2017) and (Sezer, Inel, Çağdaş Seçkin, & Uluçınar, 2015). These studies presented the potential of EEG to indicate attention or engagement but didn't investigate the possibility of classifying attentive and inattentive students during stimulation or in real time.

To analyze the EEG data, Approximate Entropy (ApEn) is proposed. It is an index of signal disorder and complexity which makes it proper for time series data that is changing overtime. In studying the cognitive load and brain activities ApEn is recommended (LI, JIANG, HONG, DONG, & YAO, 2016), (Cavanaugh, Mercer, & Stergiou, 2007). The features extracted by ApEn are then fed into Artificial Neural Networks (ANN) classifier to design and validate the model that can best show the differences between high and low SI students. ApEn and ANN are popular in classification process for Brain Computer Interface (BCI) systems. ApEn is widely used in analyzing physiological time series data (Alcaraz & Rieta, 2010) because of its robustness on moderate length time series data while ANN has a great ability to mimic the neural activities of the brain and achieving high accuracy in cognitive task classifications reaching 98.8% in (Zarjam, Epps, & Lovell, 2015), average of 90% in (Heger, Putze, & Schultz, 2010), (Mazher, Aziz, Malik, & Amin, 2017). Moreover, ANN is non-parametric method which eliminates possible errors resulted from parameter estimation. It also suites well non-linear data such as EEG.

The structure of this paper is as following: section 2 describes the materials and methods used in this study, section 3 presents the result of applying the proposed methods and discusses its implications. Section 4 concludes the paper.

2. Materials and Methods

2.1 Participants

The participants of this experiment were engineering students from Universiti Teknologi PETRONAS (UTP) first-year undergraduate, who have no records of mental illness and not under any medication. The experimental procedure was approved by UTP Ethical Committee. The participants were selected based on a questionnaire regarding joining mathematics club in the university. The questionnaire was run as a pre-evaluation for the level of personal/ individual interest of students and hence a balanced group with high, low and moderate interest participants were selected. Some recent studies showed no significant differences between females and males in terms of academic performance e.g. (Moldovan, Ghergulescu, & Muntean, 2017) and therefore was not considered in this study. Overall 30 students (4 females) participated in this experiment. Selected participants were notified through emails and thoroughly briefed about the experiment and each participant was compensated for their time.

Upon the arrival of participants, researchers assisted them in wearing the 8-channels Enobio EEG cap. After that, baseline data of 4 min eyes opened and 4 min eyes closed were acquired followed by about 22min of lecture. The presentation was delivered through projector to a projector screen. After the EEG recording, Situational Interest (SI) questionnaire and post-knowledge test were undertaken.

From the situational interest questionnaire result, subjects scored $\geq$ 77 out of 100 were considered high SI students while subject scored $\leq$ 63 out of 100 were considered low SI students. Subjects scored between 76 and 63 were considered to have moderate situational interest. This evaluation was selected based on trial and error to achieve proper separation between classes/ groups while maintaining proper number of subjects in each group. This procedure yielded 17 subjects, 10 high SI and 7 low SI subjects. Presentation questionnaire was used to validate the interestingness of the lecture as described in the below section.

2.2 Stimuli

A lecture on Laplace transform (duration about 22 min) that followed the curriculum for Ordinary Differential Equation (ODE) course was designed and presented in an interesting way to first-year undergraduate students. This was done by relating the materials to everyday life through a careful selection of a Laplace applications and meaningful content throughout the lecture. Using colors, fonts, shapes and pictures along with the animation to facilitate presenting the contents was helpful. A brief history of Laplace transform was added to the original lecture. The presentation slideshow was sent to experts for improvement and feedback. It was then tested with different group of students to rate the interesting points and improve the slides further. The novelty of the content i.e. being new to participants, was ensured by selecting participants who have not taken the course or the lecture before.

To test the effect of these stimuli during the experiments, a questionnaire was run at the end of each session followed by a verbal, non-formal interview. The questionnaire result showed that 83.34% agree that the lecture was interesting, and all participants agree that they look forward for similar lectures, suggesting the stimuli was interesting for majority of participants.

2.3 Methods

Entropy can extract very useful information from EEG especially when changes in time is expected to occur frequently. Entropy value is higher when signal irregularity is higher and entropy value becomes lower with regular signal (Wei et al, 2013).

High SI students are hypothesized to have high ApEn value while low SI students will have low ApEn value. Two parameters were specified to calculate the ApEn, the tolerance: r= 20% of the standard deviation and the embedding dimension: m=2 which are preferred values according to similar previous studies (Vega et al, 2013), (Hosseini et al, 2011). The ApEn was calculated as following:

$$ApEn(m,r,N) = \Phi^m(r) - \Phi^{m+1}(r) \qquad (1)$$

where $\boldsymbol{\phi}^m(r)$ is denoted to be:

$$\Phi^m(r) = \frac{1}{N-m+1}\sum_{i=1}^{N-m+1} ln\, C_i^m(r) \qquad (2)$$

N is the number of points and *ln* is the natural logarithm of the correlation integral $C_i{}^m{}_{(r)}$.

Since EEG is subjective measure and differ from one to another, the baseline data (eyes opened) were used to obtain reliable measurement for each subject and to avoid such subjectivity. The baseline condition data were processed in similar way to the lecture condition to obtain the ApEn features. The percentage of change was calculated by subtracting this baseline-ApEn from each lecture-ApEn values then divide the result by the baseline-ApEn. This procedure was performed for each of the 17 subjects (10 high SI and 7 low SI).

ANN was used to classify the features obtained by ApEn as either high or low SI. It is consisted of multiple artificial neurons that mimic the information processing and interactions of the brain. The neurons work together to form nonlinear decision boundaries which makes it suitable for the non-stationary and nonlinear EEG data. Therefore, it can recognize and create non-linear relationship between the input data and/ or outputs to yield optimum pattern recognition result.

Six networks shown in Table 1 were designed and tested to obtain the optimum classification result.

Table 1. The architecture of the designed neural networks

Layers	Net 1	Net 2	Net 3	Net 4	Net 5
Input	39	39	39	39	39
Hidden	5	10	15	20	25
Output	2	2	2	2	2

The input layers in all the networks contained 39 neurons corresponding to the 20 min of the lecture which were segmented into 30 s comprising 40 points. The first 30 s was removed because it contained some noise at the start of recording, hence, the input layer consisted of 39 neurons. The network had two classification outputs which are high and low SI. The number of neurons in the hidden layer was determined by increasing 5 neurons each time until reaching the least mean square error (MSE) and coefficient of determination (R^2).

The data were randomly divided such that 6 subjects out of 17 subjects were used for model validation and therefore were not part of the training data that used to design the model (remaining 11 subjects) which is about 35.3% of data used for validation. During designing the model (training phase), the training dataset (11 subjects) was further divided randomly into 70% for training, 15% for validation and 15% for testing the model. The training process was repeated several times with different parameters each time to obtain the best performance with the least Mean Square Error (MSE) and coefficient of determination R2. The best network model was exported and tested with the validation dataset (6 subjects) that were not part of the training set.

MATLAB 2017 toolbox was used for the implementation of ApEn and ANN.

3. Results and Discussion

This section is divided into two divisions that study the result of employing ApEn and the result of classification using ANN.

3.1 ApEn Result

The result of employing ApEn through about 20 min is shown in Figure 1. The figure shows the ApEn values for the average of randomly selected 7 high and 7 low SI subjects. The first 8 min doesn't have consistent differences between the two classes. After that, clear differences indicating high values for high SI subjects compared to low SI as expected. These high values that show the complexity of the signal due to the brain activities are also found at the 3rd and 7th minute for the high SI subjects. For the low SI subjects, the values were high only at the beginning of the lecture and decreased significantly after the 8th minute till the end of the lecture. It suggests that high SI subjects could keep their brain performance till the end of the lecture unlike the low SI ones.

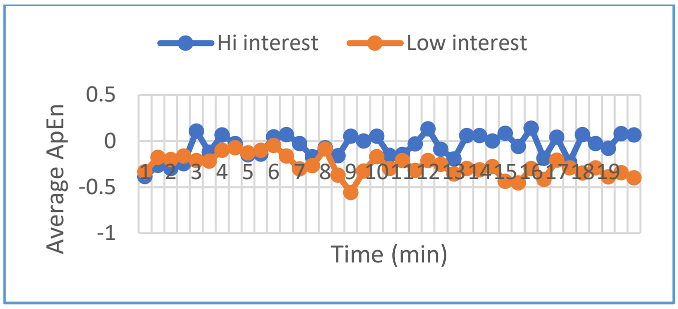

Fig 1. Averaged ApEn values between high and low SI subjects. After the 8th minute, clear difference in brain activities is observed between both groups.

3.2 Classification Result

The MSE value was decreasing by increasing the number of neurons until reaching 30 neurons where the MSE started to increase. Figure 2 shows the performance of each network described in Table 1.

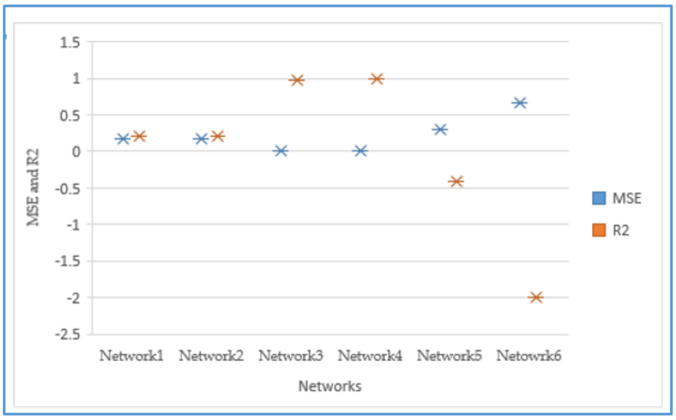

Fig 2. The performance of the designed ANN networks to classify high and low situational interested students based on ApEn features. The horizontal axis represents the 6 designed networks while the vertical axis shows the MSE and R2 values for each network.

Figure 2 shows the effect of the size of neural network on the system performance using two statistical standards the MSE and R2. Network 3 and Network4 had comparable performance while the least error was achieved with 20 neurons (Network4) MSE = 8.7E-04, $R^2 = 0.996$. Network5 and Network6 had the highest MSE because of the generalization drop effect that could be caused by overfitting. Increasing the number of neurons further increases the time required for processing. Therefore, 20 neurons network was found to give the best performance with less processing time.

The obtained model was validated using new 6 subjects (division of data into training and validation sets is described in methods section). The proposed algorithm has achieved 100% accuracy in classifying correctly the 6 subjects as high or low SI which is higher than the nearest similar study (Zhu et al, 2017) that achieved 98.99% in classifying high and low SI students. It also showed that ApEn is suitable for describing the changes of EEG signals that could be caused by cognitive functions occurring in the brains. ANN was found suitable for training the model with the acquired features using the artificial intelligence to understand the relationship between the values of ApEn and the output classes.

This study has some limitations. Even though the selected sample size was 30 subjects, only 17 of them were classified as high and low SI based on the criteria described in participants section. Therefore, future studies are encouraged to increase the number of samples to confirm and support the result obtained in this paper. It is also highly recommended to perform the experiment for different subjects/ materials, for example, science or art and compare the results to gain better understanding about interest phenomenon.

4. Conclusion

Increasing students' situational interest during learning focuses their attention and therefore maximizes their learning and knowledge gain. Assessing the performance of these students in terms of high SI and low SI, and feeding back this information to lecturers and educators assist them to improve teaching strategies in a way that triggers and maintain student's interest in the class. ApEn features obtained for the raw EEG data and fed into ANN model achieved optimum result with $R^2 = 0.996$. This result suggests the possibility of a real-time monitoring of student's situational interest in classroom.

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