Identifying User Engagement Patterns for Online Videos Using EEG Signals

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Abstract

The study on user engagement for online videos is interesting as the number of online videos is growing exponentially. There are multiple videos available for a single topic with varying presentation and thus have different levels of user engagement. This paper primarily focuses on the study to identify patterns in user engagement while watching some videos gathered from online resources. The aim is to identify the segments of recorded video that cause a change in engagement of the user watching the video using a passive brain computer interface. This study allows us to get insights on where the dip or rise in user engagement occurs while watching a video. The insights gathered may further help the creators/producers of the media to better assess the content and modify them accordingly to make them more engaging.

Author Keywords

E-Learning; Brain Computer Interface; Electroencephalography; Task Engagement

CCS Concepts

•**Human-centered computing** $\rightarrow$ *User studies; Laboratory experiments;*

Introduction

The accessibility to high speed internet and electronic devices has made online media consumption very feasible. This has made e-learning a very popular mode of learning as it can be done one's own pace and comfort. With the widespread adoption of e-learning technologies, delivering educational content via recorded lectures is gaining momentum. In a traditional classroom setting the speaker can estimate the attention level and user engagement through facial expressions, body posture and eye contact. This type of non-verbal feedback allows the speaker to modulate their voice, incorporate gestures or revisit a certain topic when they observe a dip in attention level. These gestures and voice modulation ensures sustained users attention level. However, in an online setting the lack of such feedback might prevent the speaker from using such gestures at appropriate times which might reduce the overall effectiveness of the online lecture.

Online videos are used to deliver educational content in areas where good quality traditional classroom learning is not available. Improving content would result in spreading education in a more efficient manner and this impacts a large demographic of people who are dependent on e-learning as their source of knowledge.
The goal is to improve the quality of content delivered through online lectures. In order to achieve this, we used passive BCI to determine parts of the recorded online videos (sourced from TED series: Small Thing Big Idea) where the user engagement dips. The insights gained can be used by the video creator to modify the content of the video where there is a significant dip in engagement, in order to increase the user engagement during that particular section of video.

Passive BCI refers to measuring the brain activity while the user is performing a particular task.The recorded brain activity can be used to perform further analysis before giving the feedback.In this study we will be using the brain activity recorded using passive BCI to calculate the engagement.

Related Work

Some research has already been done in the area of adaptive learning with EEG signals. Passive BCI has widely been used to measure attention. Liu et. al., developed a system to measure degree of human attention with the help of EEG signals from mobile sensors. They used SVM classifier to analyze whether students are attentive or not. The classification accuracy of the system was 76.82% [2].
Relevant work done by Wang et al., also used single channel EEG headsets to detect mental states of students while they watched Massive Open Online Courses (MOOC). They achieved comparable performance to human observers in detecting confusion in students [7].
Another study conducted by Liu et. al., inferred the cognitive state of students while they participated in face-to-face and online instructions. EEG recordings were used to analyze their concentration and comprehension levels using three types of classification models local, global and multitask learning wherein the local model achieved the highest accuracy [3].This gives us an insight that interactions that are present in face-to-face instruction play a vital role in user concentration.
With respect to user engagement, Andujar et. al., developed a prototype application which could measure user's engagement level while he/she was reading. It aimed to enhance user's reading engagement physiologically. A BCI device measured user's engagement and if it dropped below the baseline then a video related to reading was showed to increase the engagement level. [1].This work helps in understanding that the engagement levels can be sustained by using some sort of a cue when there in a decrease in engagement. Furthermore, Tambe et. al., pro-

posed a smart E-Learning system which used emotions to predict videos. They used Neurosky Brainwave detector to record the EEG signals and Random Forest classifier to predict different emotions. The classification accuracy of the system was 97.03% [5].
The above mentioned work are novel and creative but almost all of them focus on improving engagement level of users with the help of giving feedback directly to the user. However, the goal of this study was different, i.e. it tried to identify the engagement levels of users for different segments of videos and which may further be used to provide the feedback to the video creator in order to improve the video content.

Figure 1: User watching video while EEG data was collected

Methodology
The following methodology has been used to calculate the user engagement.The main steps involved are mounting the headset, survey, watching the video, calculation of user engagement. The above steps have been briefly described below:

1. The EEG device was first mounted on the user's scalp. In order to perform the alpha calibration, the user was asked to close their eyes and relax for 3 minutes.The EEG data recorded for these 3 minutes acts like the baseline reading.

2. Before the users starts watching the online video, they were asked to fill a survey which included the PANAS survey too .

3. The users then watched the video one after the other (see Figure 1) with a 3 minute break between each video to relax .During this break they were asked to fill out a small survey related to the video. The order of the videos were changed for each user to eliminate any potential bias.

4. The brain data was recorded using the EEG device when the user started watching the video and was synced using the timestamps, taken at the start and end of the video, for each video.

5. The user was again asked to fill the PANAS survey at the end of watching all the videos.

6. The user engagement was calculated for the duration of the video and compared with the baseline alpha reading.The same was calculated for multiple users and compared to check similarities in engagement patterns.

Figure 2: Emotiv Insight headset

Apparatus
A non-invasive BCI device, Emotiv Insight (see Figure 2) was used to acquire the EEG data. The device has five channels to record and collect the EEG signals. The five channels that are based on the 10-20 international system are AF3, AF4, T7, T8, Pz. Yaomanee et. al., proved that electrodes placed on the frontal lobe perform better in obtaining cognitive data [8]. Therefore, for the study, the brain data was acquired through AF3 and AF4 channels .It is a highly portable headset which connects to the computer wirelessly via Bluetooth.

User Engagement Measurements
After the user study, engagement values with respect to time for each video and for each participant were calculated. Engagement can be effectively calculated using three affective states - theta, alpha and beta, as described by the formula below [4]:

$$E = \frac{\beta}{\alpha + \theta}$$

Here, E represents engagement, θ (theta) represents state of drowsiness or creativity, α (alpha) refers to state of relaxation and β (beta) represents the state of being focused and alert [1].

For the study, data from AF3 and AF4 channel was isolated and then averaged for each second. Next, exponential weighted moving average was calculated to filter the engagement values [6].Exponential moving average helps to make a smoother graph by taking average over a period of data and places more importance on the more recent data as compared to older data. It reacts more significantly to recent changes in engagement values. For the study, a sliding window of 5 seconds was used to calculate exponential moving average.

Study Results and Analysis

User Demographics

The participants' age ranged between 18 to 34 years, where fifty percent of them had a Master's degree as their highest level of education while the other half had a Bachelor's degree. There were 4 male and 2 female participants. According to the survey the participants rated that they were more interested towards Science Technology, Mathematics, Music, Arts and Sports as compared to Literature, Geography, History, Finance and Fashion. All of the participants were comfortable watching videos in English and spent anywhere between 5 – 20 hours watching online videos. They were well rested before the survey with an average of 7-8 hours of sleep. The participants also self-reported that they were highly engaged while watching the videos. Furthermore, they found the videos to be interesting and were easily able to follow the video without any subtitles. The participants also reported that they were not distracted by any external factors during the course of the study.

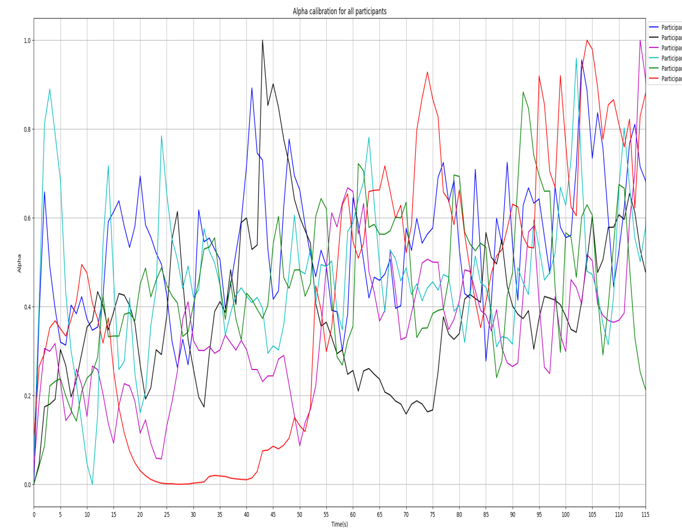

Figure 3: Plot of engagement values of participants during alpha calibration

Study Results

Figure 3 shows the baseline engagement of the participants during alpha calibration. Participant 1 and 2 showed sudden spikes in engagement between seconds 40 and 45. A similar spike was observed for participant 6 around 70th second. Then for video 1 (see Figure 4), participants 2 to 6 show the dip in engagement around 53 to 55 seconds mark. Then around 73 second mark, participant 2,3,4 and 6 show a rise in engagement. Similar behaviour was seen in 2nd video (see Figure 5), participant 2,3,5,6 show a rise in engagement between 52 to 55 seconds. Further, every participant except participant 6 show a drop in engagement around the 60-second mark. For video 3(see Figure 6), every participant shows a dip between seconds 30 and 35 and then a rise again between seconds 35 and 40. These

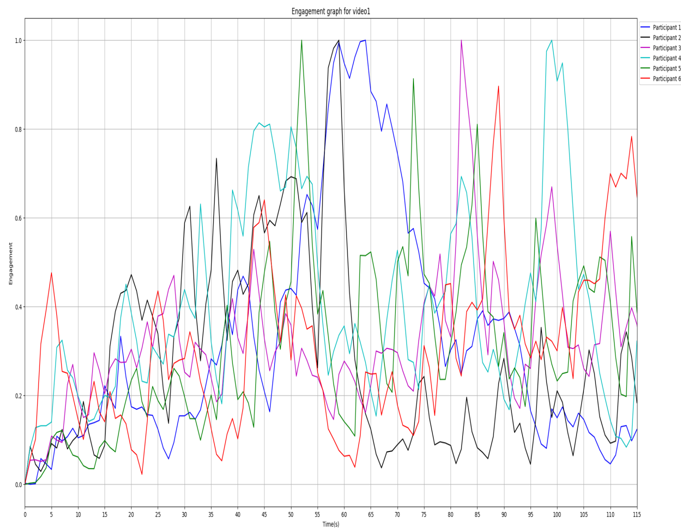

Figure 4: Plot of engagement values of participants while watching video 1

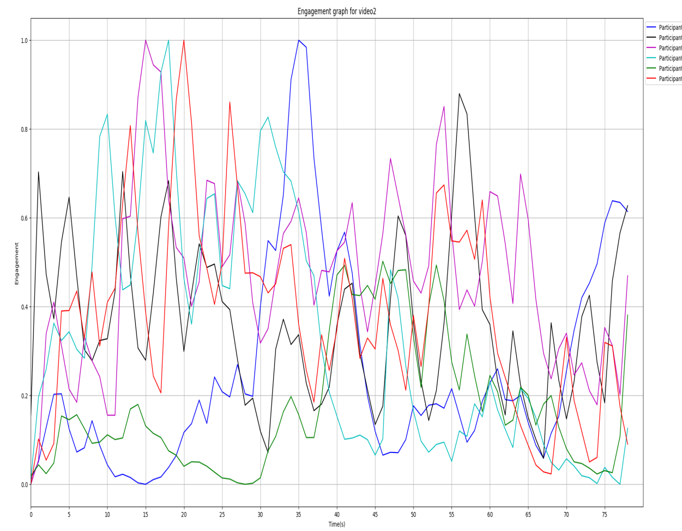

Figure 5: Plot of engagement values of participants while watching video 2

patterns of changing engagement in a time multiple participants segment for were seen throughout the duration of the videos. The engagement plots for videos are more widely spread as compared to alpha calibration plot as expected. This is because while watching a video the participant's engagement will change based on whether they find the portion of the video that's playing interesting or uninteresting.

Conclusion

We were able to identify common patterns in user engagement, while watching a video, for different participants. There were clear, easily identifiable dips or rises within a given time segment.

Future Work

For future work, the study can be expanded to include more number of videos and a larger participant pool. Furthermore, to automate the process, the data obtained can be fed to a machine learning algorithm which can then efficiently identify the dips and rises in user engagement.

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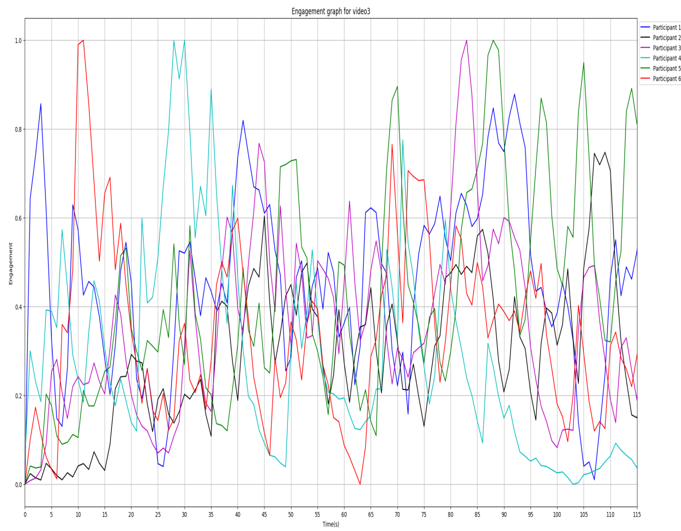

Figure 6: Plot of engagement values of participants while watching video 3

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