Detecting Interest in Video Advertisements Using EEG Data Analysis

Hadrian Jules Y. Ang
Ateneo De Manila University
Katipunan Ave, Quezon City 1108
(02) 426 6001
hadrianang@outlook.com

Gabriel Alberto Sanchez
Ateneo De Manila University
Katipunan Ave, Quezon City 1108
(02) 426 6001
influx571@gmail.com

Jose Antonio Pascual
Ateneo De Manila University
Katipunan Ave, Quezon City 1108
(02) 426 6001
joaoiep@gmail.com

ABSTRACT

For a commercial or advertisement to be considered good, it must capture the viewer's attention and hold the viewer's interest. The curiosity, flow, wonder, and excitement that interest then cues can be beneficial to advertisers and the product that they are selling. The goal of this study is to build a model that predicts levels of viewer interest in advertisements based on EEG, EOG and EMG signals. Participants of the experiment were Ateneo college students majoring in different courses and coming from different year levels. The resulting linear regression models per advertisement, with 10-fold cross-validation, had r-values ranging from -0.0332 to 0.4089 Additional features were engineered, creating another set of models with r-values ranging from -0.0021 to 0.4213. An additional linear regression with 5-fold student-level cross-validation was performed with an r-value of 0.129627. SVM classification with 10-fold cross validation was also used, with classifier accuracy reaching 66.6667% for the original set of features and 67.1111% with the additional features.

General Terms

Measurement, Experimentation, Human Factors,

Keywords

EEG, EMG, EOG, Brainfingers, Nerual Impulse Actuator, SVM, Linear Regression

1. BACKGROUND OR CONTEXT

For a commercial or advertisement ("ad") to be considered good, "something must be inherent in the commercial that allows it to live on in the mind of the consumer way after its thirty seconds on screen" [1]. For an ad to properly stay with a viewer, one has to inspire interest in a product, issue or cause. Interest, proposed to be a commonly felt emotion, arises in contexts that offer novelty, change, possibility, mystery or challenge [2]. Emotions tend to cause other related emotions that amplify the original experience and in the case of interest, these are curiosity, flow, wonder and excitement [2] [3]. All of these are potentially beneficial to an advertiser selling a product, pushing for a cause or drawing attention to an issue or event.

The first formal advertising framework was AIDA made by E. St. Elmo Lewis in 1898: an acronym that stands for attention, interest, desire and action [4]. Despite being established over one hundred years ago, this framework already included interest as one of the desirable characteristics in an ad. One of the categories of models used in advertising would be the Pure Affect Models, which states that consumers form preferences "on the basis of elements such as liking, feelings and emotions induced by the advertisement. . . ." [4]. Because of this, being able to detect interest in advertising may help create models towards better advertisements that not only help advertisers, but also viewers, as they are able to view more interesting and stimulating commercials.

Brain-computer interfaces (BCI) are defined as "communication systems that do not depend on the brain's normal output pathways of peripheral nerves and muscles" [5]. BCIs have applications in medicine and gaming; Brainfingers (specifically the Neural Impulse Actuator model), a BCI created by Dr. Andrew Junker, was originally marketed as a gaming peripheral.

One of the uses of BCI data is emotion detection, such as in a study done by Plotnikov et al. entitled "Measuring Enjoyment in Games Through Electroencephalogram (EEG) Signal Analysis". In the study, a set-up involving four commercial electrodes was used (two temporal, two frontal). The study's 8 participants then played an open-source version of Tetris with different speeds. A computer then recorded scores and answers to a questionnaire. To detect flow, a Gaussian Kernel SVM was trained for each user with 67% of samples for training and the other 33% for testing, achieving an average accuracy of 81% while an SVM trained for all users achieved an accuracy of 73% (alpha, beta, theta, delta and gamma waves from each electrode were used as features) [6].

One of the emerging fields that uses BCIs today is called "neuromarketing" which seeks to combine disciplines such as economics, neuroscience and psychology to study decision making situations [7]. This field is promising because it allows researchers to gather objective data from viewers' brain responses and use this to derive information that can help investigate things such as brand loyalty and decision making [7].

In the study entitled "Use of EEG as a Neuroscientific Approach to Marketing," 20 participants viewed a set of advertising videos with a 64 channel Tin/ Silver electrode cap placed on their heads for data recording [7]. After watching the videos, the participants answered a questionnaire based on a Likert scale (1 – hate it, 2 – didn't like, 3 – indifferent, 4 – like it, 5 – love it). There were 30 videos in all, shown in different blocks 6 at a time. Numerous techniques were then used for cleaning and data analysis. One of them is the creation of brain mappings for the ad with the highest and lowest ratings where frequency band activity was mapped to parts of the brain they originated from (coloring the parts of a brain image with greater activity in a certain frequency range). The mappings were then compared and contrasted with each other to see differences in certain areas of the brain to find correlations between brain activity and the ratings. The researchers found that parts of the brain that are related to interest actually did exhibit more activity in the relevant bands when the participants were watching the videos they rated the highest [7].

Choromonska et al. performed a marketing survey to find out the better of two very similar advertisements [8]. The difference between the two ads was only the addition of a manual gesture and a change in camera angle for four seconds. Based on their post-test examinations, most participants did not consciously see a difference; however, the version with the manual gesture had significantly better scores than the one without it. The researchers then used EEG (in a 10-20 placement system) to search for statistically significant differences in frontal cortex activity and EMG to search for differences in facial muscle activity to find out if this difference in perceived ad quality registers itself through brain waves or facial muscle activity. In the second by second analysis of the data, significant but weak correlations were found between the EEG data of the two ads (based on alpha activity) and a strong difference in the activity of a certain facial muscle was found. Though they declared their results to be observational, the researchers concluded that the brain indeed registers differences between ads and that it can be captured to some extent with EEG and EMG [8].

As seen in the few studies above, BCI technology is filled with inherent possibilities; thus, it may be interesting to find what kinds of models or classification algorithms work well with BCI data so that one may derive more information from raw data recordings.

Reviews of classification algorithms with BCIs have been done before; however, Brainfingers is different from usual laboratory EEGs because it has a fewer electrodes (only 3). This is opposed to the studies mentioned above that used laboratory EEGs that may have many more electrodes to capture signals from specific areas of the brain. Though there is no straightforward way of accurately mapping EEG data from Brainfingers to specific areas of the brain (since it only has three electrodes), it is at least able to split the signals into Alpha, Beta and Theta bands and includes electrooculogram (EOG) and electromyogram (EMG) data [9] [10]. An additional advantage would be Brainfingers' portability and ease of set-up compared to lab EEGs.

2. GOAL AND RESEARCH QUESTIONS

The goal of this paper is to create a machine-learned model of viewer interest in advertisements using EEG, EOG, and EMG data. The specific research questions of the paper are:

1. What is the relationship between the various brain signals and viewers' reported interest?
2. Which set of ad features correlate with levels of interest?
3. How can we build a model of viewer interest using data from a device such as Brainfingers? How good are the models?

3. METHODS

3.1 Participant Profile

The participants of the study were 25 Ateneo college students from different year levels majoring in various fields.

Participants averaged 3.54 hours of television a week and 9.2 hours of watching YouTube. Out of 25 participants, 11 were female, 14 were male and their ages ranged from 17 to 21 years old.

3.2 Instruments

The group used the Brainfingers Neural Impulse Actuator (NIA) to gather data, as it is one of the consumer-oriented EEG devices that also features EOG and EMG. With the help of the SDK, the group created a C# program that synchronizes the videos to be shown, the Brainfingers' recording and question pop-ups. The program was set to query data from Brainfingers every 100 milliseconds.

The group compiled ads of different genres such as action, comedy, romance, musical, drama and educational. The order with which the videos appeared was not randomized, so it was uniform across all participants. The advertisements chosen were for products used daily, mostly consisting of food and hygiene products

Table 1 below lists videos that were chosen, written in the order they were shown. All of these were made and aired in the Philippines. The group tried to choose a good balance of supposedly interesting and uninteresting ads, in hopes of creating a more even class distribution in the final data set.

A questionnaire popped up after each advertisement, asking the participants to rate how interested they were with what they had just watched (a text box was provided for comments). An even number scale of 1-4 was used to force a certain choice, rather than leaving an undecided / neutral option. These assessments were then used as classes for data analysis.

3.3 Data Gathering

For the data gathering phase, the participants were tested individually, the procedure taking around 15 minutes per person. Testing started with a briefing on the procedure and the participants were urged to answer as honestly as possible throughout the process. A pre-test questionnaire was given to collect data such as age, gender, course and average amount of time spent watching television and YouTube each week. Brainfingers was then calibrated for each participant. A second briefing was then given before the video, explaining the video compilation and the question prompts between ads. Brainfingers was then calibrated; the group made sure that each participant was in the balanced state before playing the advertisements (shown in Figure 1 below).

The participants watched a video compilation composed of advertisements of different genres, while staying grounded with the Brainfingers control box (by touching the box), as past research has shown that this improves results [9]. The participants were also advised not to touch the Brainfingers headband. The testing was done one participant at a time either in ALLS or an adjacent room.

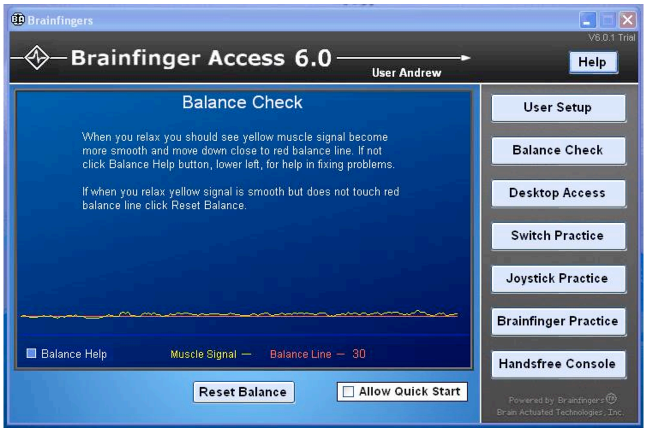


Figure 1. Yellow Line Matching Red, Balanced State

By compiling videos together, the group was able to collect a lot more data (more recordings on different ads) and it also helped simulate a long commercial break. The Brainfingers Access Suite's calibration tool was used again to ensure that participants returned to the baseline, the brain's default state, after each advertisement to ensure brain activity recorded is caused by the ad being viewed [7].

Brainfingers was used as an EEG device to measure the activity of the participants' brainwaves, specifically the alpha, beta and theta waves. Data from the Brainfingers' EOG and EMG functionality was also recorded. The study also involved the answers to the question previously stated. The questionnaire popped up after each advertisement and had to be answered before the next one would play. The C# program was used to synchronize video viewing and the querying of data that the Brainfingers Access Suite records program also included a GUI for asking the necessary questions and recording their results to generated text files.

After each test, there was a debriefing where the member of the group giving the test asks what the participant thought about the ads or what they felt while viewing the ads (shown below).

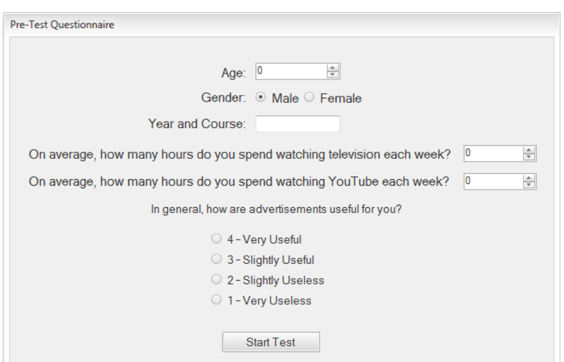
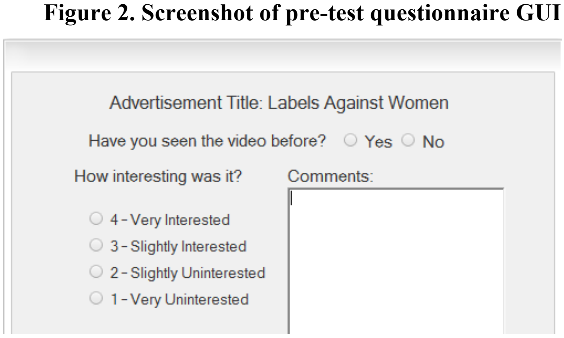


Figure 2. Screenshot of pre-test questionnaire GUI



F igur e 3. Screenshot of Post-Ad questionnaire

3.3.1 Debriefing Questions

Did you enjoy watching the advertisements?
What is your general feeling as of the moment?
Do you have any further reactions with some of the advertisements? What about the study itself?

3.4 Results and Data Analysis

Feature vectors extracted were divided per person, per advertisement, resulting in nine feature vectors per person. Division of EEG data into bands (Alpha, Beta, Theta) was automatically done by the Brainfingers Access Suite and was only queried by the group's program.

3.4.1 Data cleaning

Data gathered consisted of multiple feature vectors per advertisement (as the C# program made one query / reading every 100 milliseconds). Because of this data had to be cleaned then compressed into a single feature vector per ad. Feature vectors that had dimensions two standard deviations away from the mean (computed within the individual ad data sets only) were removed using a simple Java program. This cleaning was done to remove data noise often caused by movements of the NIA headband, especially since some participants may brush the headband with their hands or move their head around as part of their reactions to the advertisements. The mean of each dimension was then computed in order to collapse all data from a certain person's ad viewing experience it into a single feature vector (per person, per ad), resulting in 225 vectors (25 participants, 9 advertisements each). Each vector was then labeled based on the ratings participants gave them during the data gathering phase.

3.4.2 Additional Features

Additional features based on previous studies were added to aid in model building later on. Theta waves are associated with working memory and emotional processes, while alpha waves are related to a decrease in information processing (sometimes called "idling rhythms") [7]. The ratio of these two waves, which may help describe amount of information processing, was then computed with the equation below. A smaller value for this ratio would mean a more active mind, while a larger one would mean idleness.

$$\frac{\alpha}{\theta} = \frac{Alpha1 + Alpha2 + Alpha3}{Theta1 + Theta2 + Theta3} \qquad (1)$$

The study by Plotnikov et al. aimed at measuring enjoyment in video games found that certain trends were apparent in the EEG "attention ratio," or the Theta/Low-Beta wave ratio, namely, there is usually a negative correlation between this ratio and a person's attention level [6]. The attention ratio was then computed for each vector using the equation below.

$$Attention = \frac{Theta1 + Theta2 + Theta3}{3 * Beta1} \qquad (2)$$

According to other studies, there are interrelations between Alpha and Beta waves; thus, their ratio can be used to assess levels of mental attentiveness [11]. This feature was then computed using the following equation.

$$\frac{\alpha}{\beta} = \frac{Alpha1 + Alpha2 + Alpha3}{Beta1 + Beta2 + Beta3} \quad (3)$$

After computing these additional features, they were appended to each feature vector, creating a total of 14 dimensions.

3.4.3 Exploratory Data Analysis

Before data models are built, it would be interesting to see which features correlate with interest. Correlations between features and self-reported levels of interest were computed using Microsoft Excel's data tools. Table 3 below shows features with a noticeable level of correlation (at least compared to the other features), as they had absolute values greater than 0.1.

Table 1. Descriptions of Advertisements

Number	Title	Genre	Company/ Product	Language	Description	Source	Length
1	Labels Against Women	Educational / Critical	Pantene	English	Men and women are shown in various daily situations. Labels are then flashed while the scenes of men and women are juxtaposed together. This emphasizes the difference in labels such as boss – bossy, persuasive – pushy, showing that women are labeled wrongly for things men are praised for.	http://www.youtube.com/watch?v=kOjNcZvwjxI	61s
2	Click Tayo!	Musical	Cherry Mobile	Taglish	Sarah Geronimo sings and dances while walking through a presentation of mobile phones. Features of the phones, such as Wi-Fi connectivity and QWERTY keyboards, are then shown in big flashy text together with simulated phone UIs.	http://www.youtube.com/watch?v=qakLtm8JV5Y	62s
3	Bouncer	Comedy	Selecta Cornetto	Filipino	The ad starts with the line “Hanggang saan aabot ang 20 pesos mo?” A young man then uses a single twenty peso bill to pay the bouncer to a club, but this isn’t enough money, so the bouncer just brings out a flashlight, moves it around, simulating club lights, while asking the teenager to dance. The ad then suggests that the viewer spend the money on ice cream instead.	https://www.youtube.com/watch?v=AKZGSG3Gy5c	32s
4	Palmolive Naturals Intensive Moisture Janella’s MTV	Musical	Palmolive	Taglish	A woman, played by Janella Salvador, goes to what seems like a Palmolive convention called “Great Hair Day” and sees her crush. She suddenly becomes conscious of her hair, but she sings that she is prepared for the chance encounter because she used Palmolive shampoo. She then breaks into a song and dance number ending with her crush approaching her with a gift.	http://www.youtube.com/watch?v=Moo0QqAdfXQ	62s
5	Coke Ko ‘To	Comedy	Coca-Cola	Taglish	A woman who has just purchased a bottle of coke when her friend arrives. The two friends then play a game where they clap their hands together faster and faster. The first one who makes a mistake loses and the winner gets the bottle of coke.	http://www.youtube.com/watch?v=ET8vRoXWhGI	29s
6	Noel	Drama	Jollibee	Filipino	An OFW comes home to the Philippines from Qatar after 2 years of not spending Christmas with his family. He is driven to his family by an old taxi driver whose son has been abroad for 5 years. They both talk about how wonderful Christmas is with the family; however, the OFW senses the sadness of the taxi driver (since unlike him, his family is not in the country). When they arrive at Jollibee, the OFW is greeted by his family, as he surprises his kids with his arrival for Christmas. He then invites the old taxi driver to join them for Christmas and they then enjoy a dinner together in Jollibee.	https://www.youtube.com/watch?v=2DmID9cTums	51s
7	Everybody	Musical	Rexona	English	In a shower room, men wearing towels break into a song and dance number of the Backstreet Boys’ “Everybody.” They then proceed to use their deodorant sticks as microphones. The ad ends with a zoom in of the Rexona product.	http://www.youtube.com/watch?v=fHj3a-JAMTQ	31s

8	Ramon Bautista vs. Parokya ni Edgar	Musical / Comedy	Nescafe	Taglish	The band Parokya ni Edgar is singing in front of a sari-sari store when a woman suddenly appears warning them that their planet is in danger. A giant robot, controlled by the villain Rebolto, crashes into the city from space. The band then uses their own giant robot, called Edgar, conveniently hidden underneath the sari-sari store. Despite their own giant robot, the band starts to lose the battle. They then bring out Nescafe 3 in 1 Coffee to power up their robot, but instead of fighting they offer Rebolto coffee. The ad ends with the band and Rebolto drinking coffee together.	http://www.youtube.com/watch?v=2WnafG7er8w	189s
9	First Love	Drama / Romance	McDonalds	Taglish	A man narrates how every time he goes to McDonalds, he remembers meeting his first love when they were still kids. He talks about how they liked the same things like dipping fries in ice cream sundaes. Years later he meets his first love again, but she is now married to someone else, but he is still happy despite not ending up together.	http://www.youtube.com/watch?v=8VdG8eCxors	62s

Table 2. Additional Data

Advertisement	Average Rating Given by Participants (out of 4)	Number of Participants Who have Seen It Before
1. Labels Against Women	2.72	17
2. Click Tayo!	1.96	12
3. Bouncer	3.56	23
4. Palmolive Natural Intensive Moisture Janella's MTV	1.72	12
5. Coke Ko 'To	3.20	17
6. Noel	3.24	16
7. Everybody	2.48	4
8. Ramon Bautista vs. Parokya ni Edgar	3.36	6
9. First Love	3.24	20

Table 3. Notable Correlation Levels

Data Set	Attributes	R	R^2
Ad#1	Alpha1	-0.1111	0.0123
	Beta1	0.1342	0.0180
	Beta2	0.1689	0.0285
	Beta3	0.2089	0.0436
	Theta1	-0.1251	0.0157
	Theta3	-0.1154	0.0133
	Glance	-0.1657	0.0275
	Muscle	-0.2794	0.0781
	Attention	-0.1888	0.0356
	Alpha/Beta	-0.2882	0.0831
Ad#2	Beta1	0.1195	0.0143
	Beta3	0.1308	0.0171
	Muscle	-0.1501	0.0225
Ad#3	Alpha1	0.1195	0.0143
	Alpha2	0.1401	0.0196
	Alpha3	0.1509	0.0228
	Beta1	0.2256	0.0509
	Beta2	0.2764	0.0764
	Beta3	0.2469	0.0610
	Theta1	0.2065	0.0426
	Theta2	0.1537	0.0236
	Theta3	0.2080	0.0433
	Glance	0.1462	0.0214
	Muscle	0.2061	0.0425
	Alpha/Theta	-0.5596	0.3132
	Attention	0.2023	0.0409
	Alpha/Beta	-0.2139	0.0458
Ad#4	Alpha1	-0.1821	0.0332
	Alpha2	-0.1919	0.0368
	Alpha3	-0.2050	0.0420
	Beta1	-0.2219	0.0492
	Beta2	-0.2146	0.0461
	Beta3	-0.2051	0.0421
	Theta1	-0.1855	0.0344
	Theta2	-0.1776	0.0315
	Theta3	-0.1913	0.0366
	Glance	-0.1809	0.0327
	Muscle	-0.2659	0.0707
	Alpha/Theta	-0.1553	0.0241
	Attention	0.1070	0.0114
Ad#5	Beta1	-0.2571	0.0661
	Beta2	-0.3704	0.1372
	Beta3	-0.4466	0.1995
	Theta1	0.1129	0.0127
	Muscle	-0.3342	0.1117
	Attention	0.1761	0.0310
	Alpha/Beta	0.1284	0.0165
Ad#6	Beta2	0.1510	0.0228
	Beta3	0.1035	0.0107
	Muscle	0.1213	0.0147
Ad#7	Alpha/Theta	-0.1560	0.0243
	Attention	0.1151	0.0132
	Alpha/Beta	-0.3202	0.1025
Ad#8	Alpha2	-0.1049	0.0110
	Alpha3	-0.1455	0.0212
	Beta1	-0.3384	0.1145
	Beta2	-0.4558	0.2078
	Beta3	-0.5531	0.3059
	Muscle	-0.5211	0.2715
	Attention	0.2847	0.0811
	Alpha/Beta	0.4521	0.2044
Ad#9	Alpha1	-0.1714	0.0294
	Alpha2	-0.1503	0.0226
	Alpha3	-0.1927	0.0371
	Beta1	-0.1656	0.0274
	Beta2	-0.1828	0.0334
	Beta3	-0.2067	0.0427
	Theta1	-0.1806	0.0326
	Theta2	-0.2277	0.0518
	Theta3	-0.1699	0.0289
	Glance	-0.2540	0.0645
	Muscle	-0.5889	0.3468
	Attention	-0.0903	0.0082
	Alpha/Beta	-0.1216	0.0148
Data Set	Beta1	-0.1315	0.0173
	Beta2	-0.1388	0.0193
	Beta3	-0.1550	0.0240
	Muscle	-0.2011	0.0404

Based on the correlation results across each advertisement, two signals were most notable; beta waves varied between positive and negative correlation with interest labels depending on the advertisement, but muscle signals were almost always negative. The negative muscle signal makes sense as minimal facial muscle movement may mean the person is really paying attention to the ad. Beta waves are usually associated with focused concentration and may increase when doing a mathematically related task or suppressing an action [12]. The correlations of beta waves with the interest label were sometimes negative and sometimes positive. One possible explanation would be that some ads may have needed focus to appreciate (such as Ad#1), while others may have needed loosening up (such as Ad#8).

3.4.4 Linear Regression With Original Features

University of Waikato's Weka library was then used for data analysis [13]. The group ran Linear Regressions with 10 fold cross-validation on the entire data set (all 225 vectors), then on data sets divided according to advertisements being watched (25 vectors each). The group first ran the algorithm using only features that came from recorded data; thus, each vector had 11 dimensions.

Table 4. Linear Regression Results

Data Set	Model	R	R^2
Ad#1	-0.7619 * Alpha1 + 1.3841 * Beta1 + -1.1026 * Beta2 + 0.4141 * Beta3 + 0.2446 * Theta1 + -1.5445 * Muscle + 2.8998	-0.1957	0.0383
Ad#5	-0.4333 * Beta2 + 0.2737 * Theta1 + -0.6447 * Theta3 + 3.5416	0.4064	0.1652
Ad#8	-0.407 * Beta3 + 0.0695 * Theta1 + 3.8276	0.4089	0.1672
Ad#9	1.2385 * Beta2 + -1.2889 * Beta3 + -0.9078 * Theta2 + 1.713 * Theta3 + -0.8216 * Muscle + 3.4488	-0.0332	0.0011
Whole Data Set	-0.777 * Alpha2 + 0.3033 * Alpha3 + 0.3837 * Beta2 + -0.3193 * Beta3 + -0.1001 * Theta1 + 1.5825 * Glance + -0.3096 * Muscle + 3.443	0.1302	0.0170

3.4.5 Additional Feature Engineering Results

Linear regression was ran again to evaluate whether or not additional features can contribute to model building. The same process as the original set of features was followed, running linear regression on data sets per advertisement then the data set as a whole. Since there are three new attributes (Alpha/Theta, Attention, Alpha/Beta) each feature vector now has14 dimensions.

Table 5. Linear Regression Results with new features

Data Set	Model	R	R^2
Ad#1	-1.8252 * Muscle + -0.7139 * Alpha/Theta + -1.1193 * Attention +5.1099	-0.0947	0.0090
Ad#3	0.8281 * Theta3 + -1.5673 * Glance + -0.5359 * Alpha/Theta + 4.1957	0.2031	0.0412
Ad#5	-0.5556 * Alpha3 + 1.1648 * Beta1 + -0.7991 * Beta2 + -0.6172 * Beta3 + 0.8641 * Glance + -0.5387 * Alpha/Beta + 4.8217	0.2825	0.0798
Ad#8	0.6654 * Beta2 + -0.8963 * Beta3 + 3.7815	0.4213	0.1775
Ad#9	-0.4891 * Beta2 + -0.6124 * Theta2 + 1.4297 * Theta3 + -0.8923 * Muscle + -0.2784 * Alpha/Beta +4.289	-0.0021	0.0000
Whole Data Set	0.1454 * Alpha1 + -0.6587 * Alpha2 + 0.2544 * Beta1 + 0.3033 * Beta2 + -0.3593 * Beta3 + -0.2055 * Theta1 + -0.1317 * Theta2 + 1.8509 * Glance + -0.348 * Muscle + 0.3853 * Attention + -0.1878 * Alpha/Beta + 3.4192	0.1259	0.0159

Though the addition of new features allowed the creation of one additional model (for Ad # 3), its effect on r-values was inconsistent. While it did improve the r-values of the model in some advertisements, a few of them also dropped, most notably the r-value for whole data set's model. Looking at results for the entire data set (instead of per ad), the new features did not correlate very well with interest ratings (thus, they are not included in Table 3) with the values -0.0769, 0.0441 and -0.0693 for Alpha/Theta, Attention and Alpha/Beta respectively.

Previous studies have found that the Theta/Low-Beta or "Attention" ratio seems to be negatively correlated with attention levels (which serves as a factor in interest) [6]. The group's analysis of data had different results though, as the correlation values were positive for six of the nine advertisements (including the r-value for the entire data set which had a value of 0.0225). Positive values in the six ads ranged from 0.0442 in Ad #6 to 0.2847 in Ad #8. Negative values in the three other advertisements ranged from -0.0227 to -0.1888. This inconsistency may be due to the difference in equipment and methods used, as the cited study used the Elemaya Visual Energy Tester combined with 2 frontal and 2 temporal electrodes (as opposed to the Brainfingers' 3 frontal electrodes). Since positioning of electrodes, and number of electrodes are key factors when it comes to EEG, data in the relevant frequency range may not have been too accurate [6].

The correlation of Alpha/Theta ratios with the interest levels were negative for 6 of the 9 ads, having values ranging from -0.0166 to -0.5596, while it had a value of -0.0873 for the whole data set. Alpha waves are associated with relaxation and usually rise when one's eyes are closed, while Theta waves are associated with daydreaming, stress or frustration and the line between being awake or asleep [12]. Since high Alpha/Theta ratios are associated with decreases in information processing, a negative correlation with interest would make sense (though it would still depend on the actual advertisement, as not all may need this information processing).

In the study conducted by Liu et al. on measuring degrees of human attention, the Alpha/Beta ratio was one of the features that contributed greatly to the accuracy of their SVM classifier [11]. It was not as significant in linear regression models though, as it was of significance only in three of the ten models constructed. The ratio did correlate reasonably well with interest ratings; however, it was inconsistent across advertisements. For ads where the correlation reached reasonable levels, the value was often negative, implying increased interest with either lower alpha waves or higher beta waves.

Overall, the additional features did not contribute significantly to the results and in some cases, models with the original features correlated better with interest.

3.4.6 Student-Level Cross-Validation

To create a possibly better, more general model, linear regression with student-level cross-validation was executed using data with the engineered features. The process was done by first creating the five-folds, each containing data from five participants; they were then labelled Test Set A, B, C, D, E. Training Set A was then created, which contains all the data in Test Set B, C, D, E (all the data except Test Set A). This process was repeated to create Training Set B, C, D, E. Running linear regression with each of the training sets mentioned produced the models below.

Table 6. Student-Level Cross-Validation Results

Training Set	**Model**
Set A	0.1976 * Alpha1 + -0.6922 * Alpha2 + 0.4083 * Beta1 + -0.1776 * Beta3 + -0.2394 * Theta1 + 0.2928 * Theta2 + -0.7435 * Theta3 + 1.7747 * Glance + -0.3389 * Muscle + 0.561 * Attention +-0.1904 * Alpha/Beta +3.2489
Set B	0.5818 * Alpha1 + -0.8528 * Alpha2 + 0.3552 * Alpha3 + -0.7499 * Beta1 + 0.9754 * Beta2 + -0.5712 * Beta3 + -0.1064 * Theta1 + 0.1754 * Theta2 + -0.2989 * Muscle + -0.2124 * Alpha/Theta + -0.1676 * Alpha/Beta + 3.7934
Set C	-0.145 * Alpha1 + -0.2297 * Alpha2 + 0.4772 * Alpha3 + -0.1953 * Beta1 + 0.4958 * Beta2 + -0.2837 * Beta3 + -0.2743 * Theta1 + 1.2752 * Glance + -0.2924 * Muscle + 0.3585 * Attention + -0.1435 * Alpha/Beta + 3.0679
Set D	-0.6202 * Alpha2 + -0.2426 * Alpha3 + 0.6322 * Beta1 + -0.4232 * Beta3 + -0.0773 * Theta1 + 0.2277 * Theta3 + 1.3639 * Glance + -0.3927 * Muscle +-0.3042 * Alpha/Beta + 4.0856
Set E	0.3301 * Alpha1 + -0.8486 * Alpha2 + 0.1716 * Alpha3 + 0.18 * Beta1 + -0.1692 * Beta2 + 0.0467 * Theta1 + -0.142 * Theta2 + -0.3984 * Theta3 + 1.3907 * Glance + -0.3593 * Muscle + -0.1813 * Alpha/Theta + -0.112 * Alpha/Beta + 3.7796

The models were then used to test their corresponding test sets resulting in predicted ad ratings. The correlation between predicted ad ratings and the actual ratings was 0.129627 or an r^2-value of 0.016803. While there is still a correlation, it is very weak and is only slightly better than the results with 10-fold cross-validation performed with the engineered features (though that model was created without dividing the data set based on participants). The correlation is also still weaker than the linear regression with 10-fold cross-validation done without the engineered features.

3.4.7 SVM Classification

One of the algorithms that has been used for classification of brain-computer interface data before would be Support Vector Machines (SVM) [12]. This is because SVM is said to be flexible enough to handle the dimensionality of the data very well [10]. The group ran the algorithm on each data set with 10-fold cross validation using RBF, Linear and Polynomial kernels, all using Weka in conjunction with libsvm [15]. All other settings aside from the kernel were left as their default values. To divide the data set into two classes, ratings of 3 or 4 were classified as "interested" and ratings of 1 or 2 were classified as "uninterested". The class distribution was not very balance, as 148 vectors were labeled as "interested" and only 77 were labeled as "uninterested". Table 7 below shows the accuracy of the classifier.

Table 7. SVM Results with Original Features

Data Set	**Linear**	**Polynomial**	**RBF**
Ad#1	56%	52%	56%
Ad#2	68%	68%	68%
Ad#3	96%	96%	96%
Ad#4	84%	80%	84%
Ad#5	84%	92%	80%
Ad#6	80%	76%	80%
Ad#7	44%	40%	56%
Ad#8	92%	92%	88%
Ad#9	84%	88%	88%
Whole Data Set	66.6667%	66.2222%	63.5556%

Table 8. Kappa and ROC Results

Data	**Linear**		**Polynomial**		**RBF**	
	Kappa	ROC	Kappa	ROC	Kappa	ROC
Ad#1	-0.078	0.467	-0.154	0.433	-0.078	0.467
Ad#2	-0.075	0.472	-0.075	0.472	-0.075	0.472
Ad#3	0	0.5	0	0.5	0	0.5
Ad#4	0	0.5	-0.068	0.476	0	0.5
Ad#5	0.254	0.601	0.702	0.851	-0.068	0.476
Ad#6	0	0.5	-0.071	0.475	0	0.5
Ad#7	-0.136	0.433	-0.222	0.391	0.116	0.558
Ad#8	0.468	0.667	0.468	0.667	0	0.5
Ad#9	-0.064	0.477	0	0.5	0	0.5
Whole Data Set	0.049	0.519	0.063	0.525	-0.011	0.496

Based on the results above, when it came to the whole data set, the linear classifier performed the best with a 66.6667% success rate. Though results within individual advertisements seem quite high, one cannot conclude that the classifier worked, as class distributions within these small 25 vector data sets are often skewed towards one side; thus, simply labelling everything as "interested" may still give a high success rate. Based on the Kappa statistic values in Table 8, the models were not very good classifiers, despite high accuracy rates reported (probably due to skewed class distributions); thus, correct classifications are probably due to chance.

SVM was run again with the additional features that were engineered, namely Alpha/Theta, Attention and Alpha/Beta (totalling 14 dimensions).

Table 9. SVM Results with Additional Features

Data Set	**Linear**	**Polynomial**	**RBF**
Ad#1	60%	56%	60%

Ad#2	64%	60%	68%
Ad#3	96%	96%	96%
Ad#4	84%	84%	84%
Ad#5	88%	88%	80%
Ad#6	76%	76%	80%
Ad#7	40%	44%	48%
Ad#8	92%	88%	88%
Ad#9	80%	76%	88%
Whole Data Set	67.1111%	62.2222%	61.7778%

Table 10. Kappa and ROC Results w/ Additional Features

Data	Linear		Polynomial		RBF	
	Kappa	ROC	Kappa	ROC	Kappa	ROC
Ad#1	0.074	0.533	0	0.5	0	0.5
Ad#2	-0.142	0.444	-0.202	0.417	-0.075	0.472
Ad#3	0	0.5	0	0.5	0	0.5
Ad#4	0	0.5	0	0.5	0	0.5
Ad#5	0.503	0.726	0.503	0.726	-0.068	0.476
Ad#6	-0.071	0.475	-0.071	0.475	0	0.5
Ad#7	-0.222	0.391	-0.129	0.436	-0.045	0.478
Ad#8	0.468	0.667	0.336	0.644	0	0.5
Ad#9	-0.106	0.455	-0.136	0.432	0	0.5
Whole Data Set	0.088	0.535	-0.020	0.492	-0.044	0.482

Based on the results above, the additional features did not contribute much to the model, as Kappa values remain close to 0 (or 0 in some cases) for most classifiers. In some cases, it actually reduced the model's classification accuracy. Though these additional features were cited in other studies as significant contributors to SVM classifiers, using them in conjunction with each other may have harmed results. In the study by Liu et al. the researchers tried multiple subsets of features in order to find the one that would create the best classifier [11]. This method is computationally expensive for vectors with 14 dimensions and so has not been included in this study, but doing this in future studies may contribute to the accuracy of classifiers and models produced.

3.4.8 For Further Study

Since Brainfingers only has three electrodes, it may have lacked the sensitivity and resolution of better sensors, as it even lacks the ability to measure delta and gamma waves. The use of devices with more electrodes may help gather better data that can lead to better results. Despite the Brainfingers' easy set-up, the different fits of the adjustable headband may have also influenced results, as wearing it too tight, too loose or even moving it slightly when worn, affected the data gathered. Different ways of presenting the videos may also produce different results (such as presenting them in a different order or in blocks).

Different data cleaning techniques may help get better results, as removing data points two standard deviations away and taking means as a response to headband issues may have also caused a loss of information.

Pre-processing techniques such as separating data according to fixed window lengths together with taking additional interest ratings during ad viewing may provide more data and take better note of EEG, EOG or EMG changes. This also means all the data from a single ad does not get compressed into a single feature vector leading to a larger and better data set (which can help a lot in classification). Another way to improve the results would be to look for a different way of labeling data with their respective classes. Though participants were asked to answer honestly, numerous other factors may have affected self-assessments.

Research can still be done on other features that can be engineered to help produce better models. The use of other algorithms may also lead to a better model and more conclusions, as there may still be a non-linear relationship between the attributes. Other popular classifiers such as different neural networks or Bayesian classifiers may come up with better results. In addition to these, testing different feature subsets in model creation may improve classifiers, especially with SVM classification.

Reducing the skewedness of the data set towards a certain class may also improve the classifier (there were too many "interested" cases in this study). To help the results even more, more participants are needed to increase the size of the data sets per advertisement. This may help lead to more information about certain ad characteristics and form better, more conclusive classifiers within each ad data set. In addition to this, more advertisements may also help to balance the distribution of reported interested and uninterested classes.

4. CONCLUSION

Attempts to find relationships with EEG data and self-reported interest levels had mixed results. The study found that there are indeed relationships between EEG (and also EMG) data and interest. Muscle signals and beta waves usually had reasonable levels of correlation with interest. The idling rhythms, or Alpha/Theta ratio, showed the expected inverse relationship with interest; however, the study had different findings from literature, as it usually found a positive correlation between the attention ratio and interest.

No linear model could be made out of almost half of the data sets (per advertisement). Models that were actually made with 10-fold cross validation had reasonable r-values and adding new features such as the attention ratio and idling rhythms helped construct an additional model; however, most r-values were negatively affected by this.

Though the SVM classifiers seemed to perform reasonably with classification rates above 60% the data set had a lot more data points classified as "interested" rather than "uninterested". The very low Kappa values show that correct classifications are most likely due to chance.

Overall, the models are not very good and may not serve as very good predictors of interest in future applications. Based on the results of the study, it is very difficult to conclude that a viable model may be constructed out of data from a consumer device, such as Brainfingers.

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