Modeling the Mental Differentiation Task with EEG

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Abstract. Differentiation in human beings is the act of perceiving the difference in or between objects. In other words, it is the mental process taking place to discriminate one thing from others, a common task performed by a person on a very regular basis. Making such differentiations, small or large, easy or hard, still requires a combination of cognitive processes to occur across various parts of the human brain. In this paper, an EEG-based BCI experiment was organized to study the detection of such cognitive processes. Utilizing a machine learning tool, Artificial Neural Networks, to aid in analyzing the acquired dataset, a high correct classification rate was achieved, confirming that it is possible to computationally detect these differentiation activities from EEG signals.

Keywords: BCI, Artifical neural network, Differencitation tasks, EEG, Biosignal processing.

1 Introduction

A person given the task of differentiating two or more objects, will eventually reach a definite conclusion, or choice. However, the process of differentiation that leads to the conclusion has already completed prior to that conclusion, and finishes in a very quick, almost instantaneous manner. We normally recognize the conclusions, but rarely perceive the processes that lead to them. According to Dietrich[1], existing research efforts coming from neuroscience and psychology areas have introduced theories explaining how people differentiate objects they observe, as well as identifying the key factors that influence it. The related work from VanRullen et al.[2] and Macleod et al.[3] has demonstrated the potential in using non-invasive brain-computer interface (BCI) techniques to study mental processes. Yet the question of whether one can effectively recognize the pattern of this particular type of cognitive process was still left unanswered.

This paper describes our attempts in computationally modeling the above-mentioned cognitive process. The aim for this work is to demonstrate the effectiveness of our approach, leading us to further studies of other mental tasks

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using the same method. For this work, Electroencephalography (EEG) is used as the human brainwave capturing mechanism. A BCI experiment was carried out in which participants performed tasks that lead them into making differentiations under different circumstances. The EEG signals are captured and then processed off-line.

2 Experiment

2.1 Setup

The experiment requires test participants to sit in front of a computer display. The screen is about 72 cm away from the participant's face. The head position of the participant is located with the use of a chin rest. This is to minimize head/face movements, which could greatly affect the EEG signals. The EEG equipment we used in this experiment is the Emotive Epoch 1(a). There are 14 electrodes to record 14 channels marked and placed according to the international 10-20 system. Consequently, they are labeled as AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4. Figure 1(b) shows the locations of the electrodes with red highlighted borders.

Prior to commencing the experiment, each test participant is instructed to perform a single key-press at the *very moment* he reaches a conclusion for any screen task. The timestamps of these events will be recorded in-line with the EEG recordings, and as we recognise this key press can only happen after conscious recognition of a decision and so occurs some time after the actual brain differentiation event. Each participant took part in two sessions, one for each differentiation task. The EEG signals will be recorded throughout the sessions together with other details (timing, screen type, etc.).

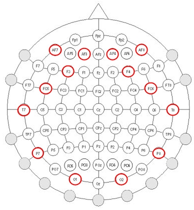
2.2 Differentiation Tasks

The BCI experiment involves test participants performing the *two* following tasks to be able to study the *differentiating processes* associated with them:

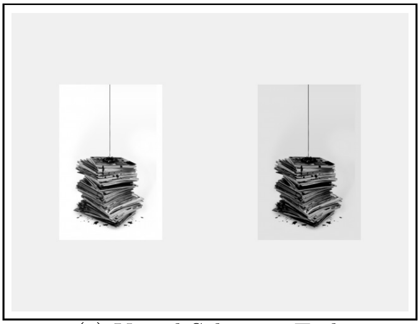
Visual Selection Task. This task requires test participants to select images (mentally) based on *visual attributes* that they are aware of. This task constrains the test participants into making quick, fast differentiation based on visual clues (Figure 1(c)). The difficulty level of this task ranges from easy to medium, depending on how *different* the two on-screen images are. The visual attributes associated with the images provided to participants are brightness, grayscale, color tone, etc.

Visual Searching Task. This task requires test participants to identify and select *specific* images (again mentally) that are placed among other images on a series of screens. The test participants are informed about the *target* image

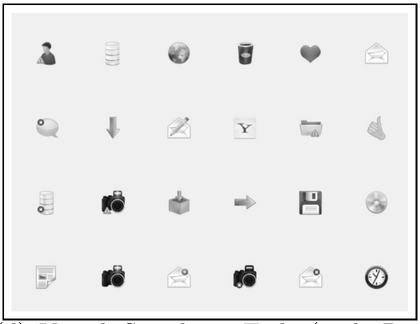
(a) Emotiv EPOC headset



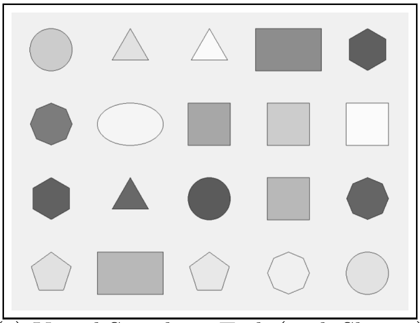
(b) Electrode locations according to the 10-20 system



(c) Visual Selection Task



(d) Visual Searching Task (with Pictures)



(e) Visual Searching Task (with Shapes)

Fig. 1. Screenshots of the mental tasks

prior to showing it on the screens (Figure 1(d)). This task *guides* the test participants into performing a combination of identifying, comparing and finally differentiating whether an image is the *target* image.

Another flavor of this task is also included, with geometric shapes in different colors in place of images (Figure 1(e)). The locations of images/shapes are random on every screen and the number of images/shapes being shown on the screen also changes over time, all in a consistent manner for all participants.

3 Preliminary Analysis

Methods. We performed time-frequency analysis on the captured EEG data in a similar manner as done by Vo et al.[4]. We used the Matlab toolbox EEGLAB[5] to perform the signal preprocessing and transformation tasks. All 14 EEG channels were bandpass filtered in the range of 3-30 Hz and were associated correctly with their 3-D Cartesian coordinates. The continuous EEG data was extracted into *two* groups of *short epochs*. One group consisted of epochs that happened *before* the event (positive epochs) while the other consisted of epochs that happened *after* the same event (negative epochs). We removed mean baseline values of data epochs (based on the differences in values created by low frequency drifts or artefacts compared to values around each epoch).
As a result, there were two groups of EEG epochs created after this task:

- **Positive epochs** contain the *differentiating process* signals. The time range offsets for each of these epochs is [-0.5 -0.01] seconds, i.e. they range from 0.5 seconds to 0.01 seconds immediately *before* the event.
- **Negative epochs** do not contain the *differentiating process* signals. The time range offsets for each of these epochs is [0.01 0.5] seconds, i.e. they range from 0.01 seconds till 0.5 seconds *after* the event.

Figure 2 describes the positions of each epoch type in relation to the event's position:

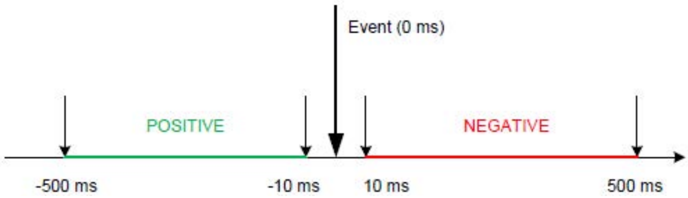


Fig. 2. Relative positions of Positive and Negative epochs

Figure 3 shows the plots of Event Related Potential activities within the *epochs* created around the *Next Screen* event. Please note that this event is raised whenever a test participant performs the key-press action to indicate he has made a differentiation.
The *event* occurs at offset 0*ms* in Figure 3. There are a few observations we can make from the figure:

- The scalp map(s) of each epoch figure consistently indicate that the majority of activations (spikes) of the EEG activities happen around the *frontal lobe* section of the brain, as depicted by Figure 4(a).
- The processed signals of these activities are depicted in Figure 4(b). From the figure, the EEG activities of the three frontal channels *AF3, AF4* and *F8* can be easily identified as the reason behind these spikes.

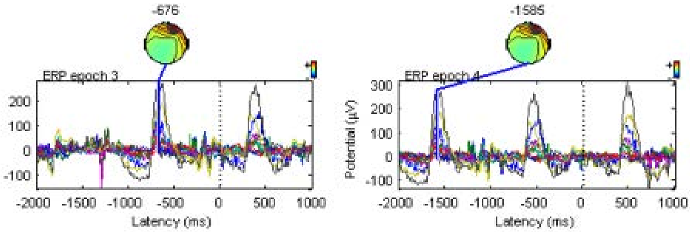
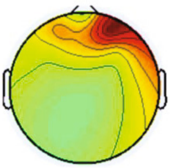
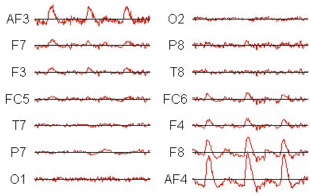


Fig. 3. Plotting of ERP data with scalp maps for Epochs



(a) EEG activations heatmap of one epoch



(b) EEG activities depicted in the scenario in Figure 3

Fig. 4. Brain activities of a differentiating task: Activations and Raw signals

- Signals spike at around latency *-500 ms*: happened in *all* epochs 3, 4, 5, 6, 7 and 8.
- Signals spike at around latency *-1500 ms*: happened in epochs 4, 5, 6, 7 and 8.
- Signals spike at around latency *500 ms*: happened in epochs 3, 4, 5, 6 and 7.

3.1 Observation

The initial analysis above has signified a few things. Firstly, there are subtle activities in EEG signals that could differentiate the epochs that contain the mental differentiation task. Secondly, whether these differences are significant enough to be the deciding factors in identifying the differentiating patterns is yet to be confirmed. To follow up this result, we used Artificial Neural Networks (ANNs) to classify these two cases (Positive vs. Negative epochs).

4 Signal Processing

With the knowledge obtained from the preliminary analysis, we used an ANN tool to verify if one can effectively classify the aforementioned two classes of epochs. For that, we reused the same EEG data epochs extracted earlier. We then labeled this dataset as follows:

- **1:** for epochs that are within the POSITIVE durations.
- **0:** for epochs that are within the NEGATIVE durations.

Then, for each epoch, the raw EEG signals from *four* EEG channels *AF3, AF4, F7* and*F8* are preprocessed identically to the process described in the previous section, up to the step where the FFT signals are placed into EEG bands. For each channel above, we compute the *mean* power values for each EEG frequency band. We only selected the values calculated from the three bands *Alpha*, *Beta* and *Theta* as part of the feature vectors. This results in 12 features for each sample (4 channels × 3 mean values).

Normalization of Vectors in Input Space: Each value of the *input-space* vectors will be *normalized.* This *normalization* process proved useful against the noisy nature of EEG signals. Assume $x \in \mathbb{R}^N$ is an input vector, the corresponding normalized vector $\widetilde{x}$ will be expressed as [6]:

$$\widetilde{x} = \frac{x}{\sqrt{\sum_i^N x_i^2}} \in \mathbb{R}^N \tag{1}$$

Features Space: To summarize, every data segment is characterized by a feature vector given by the tuple:

$$\begin{aligned} < \; & P_{af3,alpha}, P_{af3,beta}, P_{af3,theta}, \quad P_{af4,alpha}, P_{af4,beta}, P_{af4,theta}, \\ & P_{f7,alpha}, \quad P_{f7,beta}, \quad P_{f7,theta}, \quad P_{f8,alpha}, \quad P_{f8,beta}, \quad P_{f8,theta} \; > \end{aligned}$$

where each $P_{c,b}$ is the *normalized* mean power of within EEG band b from channel c.

5 Classification

5.1 Artificial Neural Network Configurations

In this section, we evaluate the performance of Levenberg-Marquardt optimization as the training function in a neural network to classify EEG data. The neural network we construct is a two-layer, feed-forward back-propagation network that has a single output node. Hence the output value regarding to a pattern T is described as [7],[8]:

$$y_1^T = g_O(b_1 + \sum_j W_{1j} \cdot g_H(b_j + \sum_k w_{jk} \cdot x_k^T)) \tag{2}$$

where

- b_1, b_j : the bias

- w_{1j} is the weight of the jth hidden neuron to the single output neuron
- w_{jk} is the weight of kth input neuron to the jth hidden neuron
- x_k^T the kth element of the input pattern T
- g_O transfer function on the output layer - linear transfer function
- g_H transfer function on the hidden layers - sigmoid transfer function

We evaluate the training performance of the network with mean squared error. The back-propagation training algorithm, using Levenberg-Marquardt optimization, will be represented by the formula [7] :

$$\delta w = (J^T J + I \cdot \mu)^{-1} J^T e \tag{3}$$

where J is the Jacobian matrix of the error function calculated in Function 3, μ is the learning rate which is updated after iteration, and *diag* being the diagonal of $J^T J$.

6 Results and Comparisons

The classification performance is measured by performing 10-fold cross-validations for every participant and task. The performance of the ANNs is categorized into three parameters: error rate, sensitivity and specificity. Table 1 summarizes the this cross-validated result.

Table 1. ANN classification results

	Participant 1	Participant 2	Participant 3	
Task 1	0.251	0.354	0.290	Error Rate
	0.718	0.536	0.625	Sensitivity
	0.780	0.755	0.795	Specificity
Task 2 (Shapes)	0.445	0.353	0.156	Error Rate
	0.385	0.651	0.853	Sensitivity
	0.725	0.642	0.835	Specificity
Task 2 (Pictures)	0.297	0.315	0.193	Error Rate
	0.707	0.598	0.764	Sensitivity
	0.699	0.772	0.849	Specificity

By observation, the correct rates range between 70 to high 80 percent. The sensitivity and specificity rates are also quite consistent across participants. There is still one exception, which is the classification result of *Participant 1* performing *Task 2 (Shapes)*, in which the error rate is significantly higher compared to the rest. A possible explanation for that could be an incorrect EEG equipment setup for that particular session.

With this result, we see that we could efficiently detect the differentiation metal task by analyzing the EEG signals using ANN. It also further strengthens our assumption that one could computationally model this type of mental task effectively. The result also suggests room for improvement, where a better EEG set up for example using more EEG channels, and more optimized ANN configuration would result in better classification accuracy.

7 Conclusions

In this paper, the trial results have demonstrated good potential in the ability to detect the cognitive process of *differentiation* from EEG signals. The use of *machine learning* tools that achieve high correct rate of 80 percent classification results, in most cases, has further strengthened the belief that we are on the right track to be able to achieve this goal. The result is far better than our original anticipation, which is encouraging to see good results obtained through the use of a stochastic signal source such as EEG.

We highly recommend that this study to be followed up by proper trials and more sizable number of test participants. In that way, we can properly *confirm* the validity of our claims, putting us one step further towards a bigger goal: computational modeling the observable architecture of the human brain.

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