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Primary Color Decoding Using Deep Learning on Source Reconstructed EEG Signal Responses

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***Abstract* - The exploration of utilizing the brain's response to varied colors for controlling one's surroundings via a brain-computer interface (BCI) presents a promising avenue. Enabling users to interact with their environment by focusing on specific colors could offer an intuitive interface, allowing for tasks like adjusting lighting or opening doors. In this study, the focus lies on developing an intra-subject classifier for red, green, and blue (RGB) visual evoked potentials (VEPs) recorded through electroencephalogram (EEG). By employing three distinct deep neural networks (DNNs), previous research propositions were tested, assessing information in both source and cathode space. Notably, analyses conducted in electrode space consistently outflanked those in source space. The best classifier accomplished a normal precision of 78% across subjects, with a singular subject arriving at an amazing 97% exactness. In terms of clinical significance, this research underscores the potential of leveraging deep learning techniques to effectively distinguish between VEPs corresponding to different colors within EEG recordings, offering insights into potential applications in assistive technologies and neurological research.**

I. INTRODUCTION

A system called brain-computer intervention (BCI) allows users to operate devices using only the brain. Those with physical limitations will benefit from these systems as an alternative to traditional methods that often require a direct connection to the device. Before using the brain-computer interface, brain activity needs to be measured in some way. Electroencephalography (EEG) is a commonly used method. EEG is an important component of BCI because it is invariant and can be performed in real time [1].

The brain needs to be recorded and then the brain-computer interface analyses the data. This often requires grouping them into clusters, each representing a BCI function. One of the primary elements of BCI is to make this arrangement. If BCI performance is unsatisfactory in the absence of a reliable classification system, most controls will find it undesirable. Each signal can be used to build an individual robust, first determining what factors influence the task at hand and then classifying the data based on those characteristics. Knowing which features are necessary for a given activity can necessitate subject matter expertise and can pose considerable challenges, especially for novel tasks. Since deep learning learns both features and classification from data, it's an intriguing alternative to traditional machine learning [2]. This makes it easier to discover unique characteristics for any work and reduces the requirement for subject-matter expertise.

A BCI paradigm must provide the information that users need to perform, with one task being sufficiently different from another. Users will have difficulty and struggle to remove these instructions [1]. Also, according to Allison et al. we would like to point out that different users will receive different signals even when trying to perform the same brain task. [1] Humans have developed reactions to colors we can tell whether something is red or blue without even thinking. Considering the importance of color vision in human life and how quickly people can see different colors, it makes sense that color stimulation affects the brain differently. Check if it will be useful for example, recognizing different color codes could allow users to control their environment by opening and shutting entryways and turning lights on and off. Past examinations have researched the conveyance of brain action in people presented to red, green, and blue (RGB) colors. In one review, the Naive Bayes RGB classifier accomplished an exactness of 59% [3]. Similar information utilized in this examination was utilized in [4] to test and prepare AI classes. The best outcomes were gotten with the base distance geodesic separating (Fg-MDM) Riemannian classifier, with a typical precision of 74.49% for one subject. The review utilized dee[learning and recreation, a cycle that decides the sum and area of brain movement in the mind in light of electroencephalogram signals, to give better variety coding.

The introduction, data and methods, results, and discussion make up the four main components of this paper's organization. The section on materials and methods includes descriptions of the classification techniques, source reconstruction, and dataset utilized in this work. There is a conclusion given in the end. Online [5] is a report on this subject that is more detailed.

II. DATA AND METHODS

A. DATASET

The dataset utilized for preparing and testing the classifiers made in this work presented members to essential tones (RGB). The subject saw the varieties on a screen at timespans seconds, with 140 redundancies of each variety displayed in an irregular request. A dim screen with a cross in the middle was displayed for 1.3-1.6 seconds aimlessly in the middle of between every cycle.

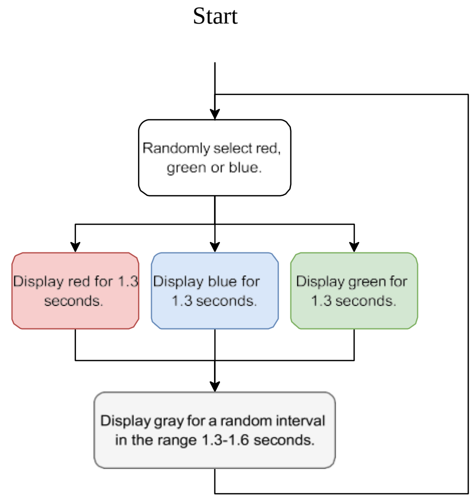

Fig: 1. The EEG recording stimulus protocol.

The above Fig: 1. shows an illustration of this approach. The data includes structural MRI and 60-channel EEG recordings made during color presentation from 31 individuals (10 females), whose ages ranged from 28.8 to 29.8 years. All members had typical or remedied to-typical visual perception without variety anomalies. Preceding cooperation, each subject gave their educated assent, and the review was directed in consistence with the Helsinki Statement. The Information Insurance Authority allowed endorsement for the review (NSD, reference number 968653). The dataset was caught at Aalto College's Aalto Neuroimaging research center.

B. PREPROCESSING

Training and testing neural network classifiers using preprocessed raw EEG recordings. A 50Hz notch filter is used to prevent interference from power lines. A band pass channel with a recurrence scope of 0.1-45 Hz was utilized to wipe out pointless frequencies. After filtering, the data is down sampled to 200Hz. To account for the effect of each stimulus, the data were divided into several time periods. It was decided to set a short duration

In order to apply baseline correction, the means of the 0.2 seconds of data from each channel were calculated, and the means were then subtracted from the corresponding channels over the duration of the epoch. A peak-finding method was used to identify blinking artifacts. If a blink artifact was detectedwithin 200ms of the stimulus's start, the corresponding epochs were eliminated. SSP, or signal-space projection, was used to lessen the blink artifacts that remained. A threshold of 150 µV was established for the highest allowable peak-to-peak amplitude in each period. As a result, any epoch where there was a more than 150 µV disparity between at least one EEG channel's peak and lowest values was eliminated. Using MNE- Python, all pre processing was completed [6].

C. SOURCE RECONSTRUCTION

Magnetic resonance imaging (MRI) data of all subjects were used to develop a forward model. Correlation of the book was done to enable digitized electrode positions to be translated into MRI frames for good forward modelling. Brain volume conduction was defined using a boundary element model (BEM). On the outer layer of the white matter, the sources were scattered. The DSPM approach was then used to resolve the backwards issue [7]. Utilizing the programmed parcellation of the mind volume recommended by [8], the source space information were amassed into locales of interest (returns for money invested), creating 150 dipoles (75 in every side of the equator). Two activities were finished to join every one of the sources in a return on initial capital investment into a solitary worth: Decide the worth's sign for each source first, then, at that point, pick the sign that is all the more habitually shown as the prevailing sign. All source values without the predominant sign ought to be flipped. Decide the return for capital invested esteem by taking the mean of all the acquired source values. The sufficiency of the dipoles is more pivotal data for most applications than their direction [9]. A typical worth of the amplitudes in the return for money invested is gotten by flipping the signs, forestalling the cancelation of restricting signs during the averaging system. MNE-Python was utilized for the source remaking and dividing [6].

D. CLASSIFICATION METHODS

The review's primary objective was to explore source space portrayal in EEG classification. By changing the info layer of the organization, similar brain network designs can be utilized for the two sorts of information in light of the fact that the information is comparable in both source-and anode space (nchannels × ntimes, with nchannels is the quantity of dipoles or terminals for source-and cathode space, separately). In this work, three neural networks were used with Keras [10]:

- Graph Convolutional Neural Network - **Shallow EEG-GCNN,** [11]
- Convolutional Neural Network **(EEGNet)**, [12]
- Convolutional neural network **(Deep ConvNet)**,[13]

With the exception of a few small adjustments required for integration, all three networks were developed using the exact hyperparameters as described in the publications in which they were first suggested. An adjacency matrix is used by the neural network with graph convolution (GCNN) to use a graph to show the data structure. Every dipole is regarded as a node, and the feature vector of each is its time series. The adjacency matrix's element aij value represents the edges between nodes I and J. For the sake of this work, aij was set to 1 if nodes i and j do not share a border and to 0 otherwise.

In this work, only intra-subject classifiers have been investigated. As a result, data from a single person required to be used for training and testing each classifier. In order to investigate various configurations and hyperparameters prior to testing, the subsequent routine was created: Two groups test subjects and validation subjects are randomly selected from among the subjects. Each training set and validation set in the validation subject's dataset is randomly divided. Each test subject's dataset is divided into a test set and a training set at random. Cross validation was actually used to segment each participant within the group. The goal of dividing the sample into test and validation individuals is to investigate various DNN architectures and hyperparameter setups. It is possible to train several configurations on the validation subject and then assess them using the validation set. You can find multiple configurations by repeating this technique. However, because of potential overfitting, It is necessary to consider the accuracy found for the validation topic to be overly optimistic. The final configuration is tested on the subject being tested to determine how well it generalizes.

Using a smaller subset of ROIs/electrodes couldbe beneficial for categorization. Because some brain regions may be more descriptive than others for the given task, focusing primarily on those regions may improve categorization and lessen the absolute sign to-commotion proportion in the information. Since the point is to recognize between visual evoked possibilities (VEPs), the cerebrum's occipital curve, which processes visual information, might be one such region [14]. The ongoing endeavor since the point is to recognize visual evoked possibilities (VEPs), the mind's occipital curve, which processes visual data, may be one such district [14]. This study investigated two distinct arrangements: utilizing all returns for capital invested and terminals and utilizing a particular subset of returns for capital invested and cathodes. To pick a particular arrangement of returns on initial capital investment or terminals, no ideal determination system was utilized. Every one of the 24 returns on initial capital investment in the occipital curve of source space were remembered for the chose set. The occipital curve was in nearness to the eight anodes chose for cathode space.

III. RESULTS

The classifiers for EEGNet and profound ConvNet (DCN) were prepared and assessed in both source-and cathode space. For both channel setups all channels and picked channels these classifiers were made. Just source space utilizing all returns for capital invested was the GCNN's development. The intra-subject classifiers' exactness and standard deviations, which were evaluated through a 5-crease cross-approval process. Knowing two examples from the information: DCN beats EEGNet, and anode space classifiers for the most part outflank source space classifiers is conceivable. There is a perceptible distinction between the top and base performing subjects for all classifiers, particularly those that are getting along admirably. Some subjects improper behaviour during the EEG recording may help to partially explain this. Throughout the recording, the subjects were watched, and notes were made about which subjects were drowsy or moved too much. The findings demonstrate that these individuals typically perform below average. Furthermore, two EEG channels near the occipital lobe in one patient did notwork properly and did not provide any signal. In every test, this

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subject performed among the lowest. A subset of participants was excluded from a prior study that used the same dataset [4]. A number of prerequisites, including the subjects' proper behaviour and the absence of flat channels on the visual cortex, were the reason for excluding these subjects from the study. Using deep learning method with all electrodes, the best results in this research offer an average precision of 84% for the same portion of participants used in the prior study. The study's findings are contrasted with those published in [4].

IV. DISCUSSION

The average performances of DCN and EEGNet were all higher in electrode space than in source space, regardless of the electrode and ROI choices. This was not the expected result, as different scenarios should be simpler to differentiate under the source space representation, which has a theoretically superior spatial resolution [9]. This unexpected outcome could be explained, in part, by the fact that both networks were developed for electrode space categorization. While there are similarities between the two representations, a DNN architecture's suitability for source- and electrode space is not always the same. A significant portion of the spatial resolution may be lost while averaging the sources. It essentially down samples the source space spatially. As a result, some of the benefits of employing source reconstruction to increase spatial resolution can be lost. As previously indicated, one way to improve categorization would be to employ a limited set of specified ROIs. The advantage of this strategy is that it lowers the data dimensionality. Alternatively, the data could be divided into smaller sections by summing the data, or by selecting a subset of the entire collection of sources (about 8000). By focusing on particular regions that have been demonstrated or are anticipated to be significant for decoding color stimuli, one may preserve a high spatial resolution in those areas while concurrently reducing the volume of information. The study's architectures were employed using their initial hyperparameters, and the findings demonstrate how some DNNs can be used for a variety of applications. The usually arbitrary parameter selection in DNNs is one of the problems with deep learning highlighted in [2], as it can be difficult to completely rule out the potential that some tuning based on the test set has occurred. The fact that EEGNet and DCN, with their original hyperparameters, categorize more accurately than previous research on RGB stimuli provides additional evidence that these structures are suitable for EEG decoding and that their parameters are not overfit to the test sets of the original publications. There are a number of reasons to think that future efforts will be able to surpass the performance this experiment reported. It should be noted that while EEGNet and DCN both functioned rather well, their designs and hyperparameters remained unchanged. It makes sense to believe that these structures could be better suited to the task of RGB stimulus classification by being more specifically designed for it. For example, testing various count and breadth of layers in the model could be part of this customization. The findings demonstrate that selecting a portion of channels near the occipital region does improve performance. Given this, it becomes sense that there would be a preferred subset of channels to utilize. To investigate this, a systematic search for the ideal channel subset should be used. In addition to potentially improving the classifier's performance, selecting a selection of channels would need fewer electrodes and less data. This would increase the classifier's suitability for a BCI, where minimal electrode requirements and cheap computing power are crucial considerations.

This study did not account for variations in color tones and lighting. The variability of these characteristics should be considered in the direction of a BCI implementation, and more research should elucidate the color classification in more realistic settings. The utility of a color-based BCI may be limited by color vision impairment; more testing on individuals who are color blind may help define the limitations of this strategy.

V CONCLUSIONS

Overall, the results of this study suggest that deep learning may be a useful technique for classifying RGB input. Every architectural project is made with the minimum amount of changes necessary to achieve the goals at hand. Therefore, the accuracy of DCN and EEGNet suggests that some DNNs may be suitable for many tasks. Changing this model to disperse the RGB response can also lead to better results.

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