EEG-based Neglect Detection for Stroke Patients

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***Abstract*— Spatial neglect (SN) is a neurological syndrome in stroke patients, commonly due to unilateral brain injury. It results in inattention to stimuli in the contralesional visual field. The current gold standard for SN assessment is the behavioral inattention test (BIT). BIT includes a series of pen-and-paper tests. These tests can be unreliable due to high variablility in subtest performances; they are limited in their ability to measure the extent of neglect, and they do not assess the patients in a realistic and dynamic environment. In this paper, we present an electroencephalography (EEG)-based brain-computer interface (BCI) that utilizes the Starry Night Test to overcome the limitations of the traditional SN assessment tests. Our overall goal with the implementation of this EEG-based Starry Night neglect detection system is to provide a more detailed assessment of SN. Specifically, to detect the presence of SN and its severity. To achieve this goal, as an initial step, we utilize a convolutional neural network (CNN) based model to analyze EEG data and accordingly propose a neglect detection method to distinguish between stroke patients without neglect and stroke patients with neglect.**

***Clinical relevance*—The proposed EEG-based BCI can be used to detect neglect in stroke patients with high accuracy, specificity and sensitivity. Further research will additionally allow for an estimation of a patient's field of view (FOV) for more detailed assessment of neglect.**

I. INTRODUCTION

Spatial neglect (SN) is a common disorder that arises after stroke and has been observed in 28.6% of stroke patients [1]. SN is a perceptual disorder characterized by inattention to stimuli in the contralesional visual field. People with SN usually display inattention to one side of themselves, such as inability to shave one side of the face or dress one side of their body. Lesions to the attentional networks [2], ventral frontal lobe, right inferior parietal lobe or superior temporal lobe can cause SN [3]. Left-side neglect is more common and often more severe compared to right-side neglect [4]. SN is a strong predictor of disability and it could possibly develop safety concerns; a diagnosis of SN is often accompanied by extended hospitalization [5], an increased risk of falling [6], and poor stroke recovery outcomes [7].

Existing clinical assessments of SN have several shortcomings. The current gold standard method is the Behavioral Inattention Test which consists of 6 subtests in the conventional test: line crossing, letter cancellation, star cancellation, figure and shape copying, line bisection, and representational drawing [8]. It is difficult to determine SN using only one subtest and the drawing tests can be subjectively scored. Additionally, these tests to do not assess the patient in a realistic, dynamic environment; they are not sensitive to changes in neglect severity, and they are affected by compensatory strategies. Therefore, performance between subtests can also be highly variable [9]. Furthermore, BIT gives an overall score, which is compared to the established cutoff score to return a "yes-or-no" diagnosis of SN; it does not give the extent to which the patient has SN. These issues present a clinical need for an objective measurement of SN that will identify its presence as well as the severity.

To overcome these limitations of the BIT, our goal is to develop an electroencephalography (EEG)-based brain-computer interface (BCI) that can not only detect neglect but enable thorough assessment of neglect severity through the estimation of neglected field of view. As a first to step to achieve these goals, we built an EEG-based BCI and showed that it can detect neglect with high accuracy. EEG is used as the measurement modality in the proposed BCI system because it is portable and more cost-effective than other brain imaging techniques. Moreover, it has very high temporal resolution. Furthermore, certain EEG features were shown to be associated with neglect: (i) on average there is an increase in N100 and P200 responses in the EEG of perceived targets compared to neglected targets in stroke patients and (ii) the N100a EEG component which is expected around 130-160ms after a stimulus, does not exist in the EEGs of neglect patients in response to contralesional stimuli [10]. Finally, to develop a classification algorithm based on the recorded EEG that will distinguish between stroke patients with and without neglect, we utilize a deep learning methodology based on convolutional neural network (CNN) structures. Such deep learning structures have been used to develop classification and object recognition algorithms for various applications [11]. For example, they are used to analyze time-series data [12] for speech recognition [13], time-series classification [14] and stock price prediction [15]. Recently, there have been attempts to analyze EEG data using

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TABLE I

	Age	Sex	Stroke Hemisphere	Days Since Stroke	BIT Total	BIT subtests below cutoff (/6)
SN01	76	M	Right	115	44	6
SN02	51	M	Right	9	25	5
SN03	67	M	Right	3	127	5
SN04	72	F	Right	-	130	2
SN05	57	F	Left	7	134	2
WSN01	68	F	Right	17	139	1
WSN02	80	M	Left	21	140	0
WSN03	66	F	Left	10	142	1
WSN04	69	M	Left	5	143	0
WSN05	57	M	Left	8	145	0
WSN06	69	F	Bilateral	10	146	0

deep CNN structures [16] both in time [17] and frequency domains [18]. In this paper, we consider EEG data as a multi-channel time-series and develop a classifier to detect neglect. Our experimental results with stroke patients show that our method can detect neglect with high accuracy, specificity and sensitivity.

II. METHODS

A. Participants

11 stroke patients: 5 patients with SN and 6 patients without SN (WSN) participated in the experiments. Experimental procedures were approved by the Institutional Review Board (IRB) of the University of Pittsburgh (IRB number PRO15020115). Participants must score at least 8/10 on a visual acuity test to be eligible. Once the eligibility was confirmed, BIT was administered to determine the presence or absence of neglect. A diagnosis of neglect was established by either a total BIT score lower than the established cutoff (<129), or a score lower than the cutoff score on more than one subtest [8]. Patients with recent seizures were excluded from this study. Patient characteristics are detailed in Table I. Note that SN04 is missing time since stroke information.

B. Data Collection

The participants are seated 114cm away from the screen, which corresponds to a viewing area of 17.23° by 9.74°. A modified version of the Starry Night Test [19] is used for the experiments, see Figure 1. In this test, the screen is divided into an 8x8 grid and targets are shown in 64 random locations on this grid. A target appears 3 times in every location for a total of 192 targets. These targets are red dots which cover 0.22° of a person's visual field. They are shown for 66ms on the screen and the time between each target is randomized from 700ms to 2200ms. There are also distractors, which are smaller green dots that are shown randomly every 50-250ms. The reason for the randomized appearance of targets and distractors is to reduce the risk of seizure [20]. The experiment begins with a calibration session, where the targets stay on the screen until the participant presses a key on keyboard or for 3 seconds. The response times corresponding to all targets are recorded. EEG is not collected during the calibration session in which we learn the ground truth for the neglected visual field. The same test is then repeated while the EEG data are collected, but during EEG collection targets are shown just for 66ms. This paradigm is designed for quantitative SN evaluation and to detect both the presence and severity of SN.

EEG was collected through 16 electrodes located at Fp1, Fp2, F3, F4, Fz, Fc1, Fc2, Cz, P1, P2, C1, C2, Cp3, Cp4, P5 and P6 according to 10-20 system with sampling frequency of 256Hz.

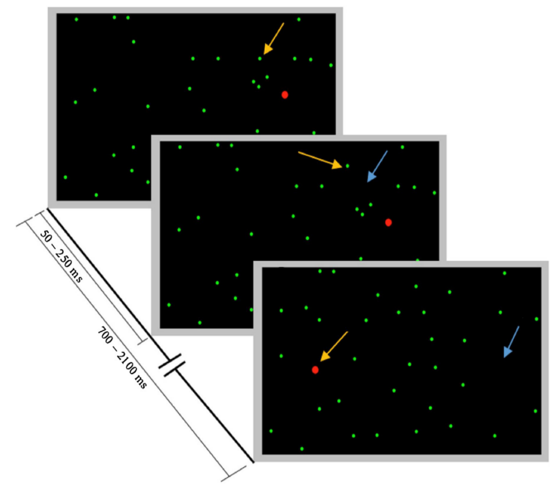

Fig. 1. Starry Night Test Paradigm

C. Preprocessing

After the calibration session, the target locations corresponding to slow-time and fast-time response targets are identified. Specifically, to achieve this separation, a time threshold for every patient is calculated using Otsu's method [21]: if a target's corresponding response time is greater than the threshold value, it is considered as a 'slow-response target' or a neglected target; if it is smaller than the threshold value then it is a 'fast-response target' or an observed target. This procedure provides information about the perceived or potentially not perceived/neglected locations on the observed visual field of the computer screen and it is used as a ground-truth for the following EEG analysis. Accordingly, EEG data are first processed through an 8^{th} order Butterworth band-pass filter with corner frequencies of 2 and 62 Hz, and then through a 4^{th} order notch filter with corner frequencies of 58 and 62 Hz, and EEG corresponding to slow-response and fast-response targets are separated from each other to be used in the following classification approach.

More specifically, after filtering, as there is a minimum of 700ms between each target presentation during EEG collection based on the designed paradigm, see Fig. 1; 192 EEG segments, each 700ms long and time-locked to the presented targets, are extracted from each patient's recorded EEG data. As EEG is very person-specific, and we are aiming at a classification across individuals, first 500ms of the EEG segments are considered to include the desired response, and a baseline correction was applied to each segment using the last 200ms of their data. Baseline correction is achieved in the spectral domain such that the spectrum of the desired responses is corrected by the baseline spectrum of the baseline. These spectrum are computed through Fourier transforms with a Hamming window. After baseline correction, every channel is normalized using min-max normalization to generate a common scale for all data.

D. Classification

We developed a classification algorithm to distinguish between the preprocessed and segmented EEG data corresponding to the slow-response targets for stroke patients with and without neglect. More specifically, we utilized EEGNet [22] to build this classifier. EEGNet includes a CNN model that can be applied to recorded multi-channel EEG. EEGNet is paradigm agnostic and can be trained with limited EEG data. As our results below demonstrate, we identified that the CNN structures in EEGNet are more robust to overfitting to training data and outliers in the recorded EEG with high generalization.

The classification approach/structure is depicted in Fig 2. In this classification method, a 2D convolutional layer (a temporal filter) with a size of $(30, 1)$ is followed by a batch normalization and a depthwise convolution [23] layer of size $(1, 16)$ (a spatial filter). Depthwise convolution is used to reduce the number of trainable parameters and most importantly, in EEG applications, such a filtering approach allows us to train spatial filters (based on electrode location) for each temporal filter output. A batch normalization [24] layer is then applied along the extracted spatiotemporal features. These features are then processed through an exponential linear unit [25] and an average pooling layer of size $(4, 1)$ to reduce computational complexity. After these layers, a dropout [26] with a rate of 0.25 is applied. Note that throughout this process in each convolutional layer, we regularize each filter with a maximum norm constraint of 1 on its weights and use L2 kernel regularization to further avoid overfitting [27].

The model continues with a separable convolution layer [23] with the same size as the depthwise layer, $(1, 16)$. Separable convolution layers are depthwise convolution layers followed by pointwise convolutions. Such an approach reduces the number of parameters while the pointwise convolution optimally combines the extracted spatiotemporal features. Before the final step an average pooling layer of size $(8, 1)$ is used for further dimension reduction.

The model concludes with the classification layer. Specifically, the output of the last average pooling layer is flattened to a vector, then fed to a fully connected layer with 4 units, followed by a final layer with 2 units to classify. To get classification probabilities, the model ends with softmax activation layer.

III. RESULTS AND DISCUSSION

We present here the results for classification between recorded EEG responses corresponding to the slow-time responses for stroke patients with and without neglect to demonstrate the performance of the proposed approach for neglect detection. In our approach, the proposed CNN-based deep learning model was implemented using Tensorflow [28].Here the classification/ neglect detection results are obtained through 10-fold cross validation. For each training set, the model was trained from the start for 100 epochs and each network was trained with a mini-batch size of 16. We chose categorical cross-entropy as the loss function and Adam [29] as the optimizer, with parameters $\alpha = 10^{-3}$, $\beta_1 = 0.9$ and $\beta_2 = 0.999$. We did not explicitly set any weight decays. The model had approximately 1400 trainable parameters and each optimization of epoch lasted for approximately 3 seconds on CPU. We observed for the training data that in average neglect detection accuracy, specificity, sensitivity, and F1 score are 90.65%, 90.32%, 87.13%, and 0.9223 respectively.

TABLE II
SUMMARY OF PERFORMANCE MEASURES.

Cross Validation	Accuracy	Specificity	Sensitivity	F1 Score
Set 1	89.21%	88.43%	87.32%	0.8842
Set 2	88.41%	88.89%	87.26%	0.8889
Set 3	90.29%	90.62%	87.56%	0.9062
Set 4	88.49%	88.31%	86.48%	0.8831
Set 5	91.37%	90.51%	86.45%	0.9051
Set 6	88.40%	88.89%	87.38%	0.8889
Set 7	92.03%	91.31%	86.83%	0.9131
Set 8	89.50%	86.80%	87.21%	0.8680
Set 9	89.85%	90.28%	86.21%	0.9028
Set 10	90.22%	89.58%	86.60%	0.8958
Average	89.73%	89.34%	86.97%	0.8934

The results obtained from the test data are listed on Table II. On this table, in each row average values demonstrate the results for each test data of the 10-fold cross validation. Even though the training set results are better than the test set results, we observe from Table II that overall accuracy, specificity and sensitivity were calculated on average to be 89.73%, 89.34%,and 86.97%, respectively, with an F1 score of 0.8934. Specificity is the accuracy of detecting the neglected targets while sensitivity is the accuracy of detecting non-neglected targets. These results demonstrate that the proposed approach generalizes to test data with high performance. Moreover, through an in depth analysis of our results, we observe that to detect neglect Cz, P1 and F3 as the most informative channels.

IV. CONCLUSION

In this paper, we have developed and tested an EEG-based BCI for spatial neglect detection. For neglect detection and EEG analysis, we utilized a CNN-based deep learning model to identify EEG features not only in time domain, but also in the spatial domain to improve the detection of neglect across stroke patients with and without neglect. We also showed that our approach can detect neglect with high accuracy, specificity and sensitivity generalizing from training to test data.

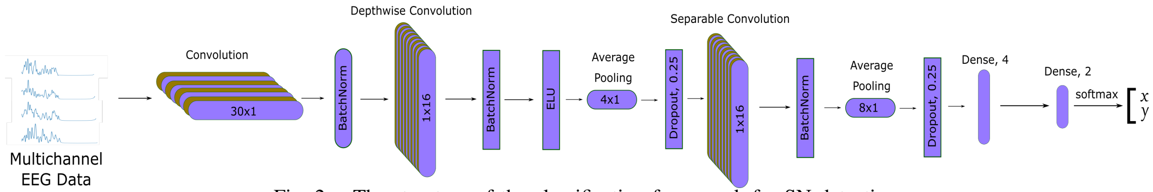

Fig. 2. The structure of the classification framework for SN detection.

Future investigations will use the proposed BCI to estimate a patient's neglected field of view (FOV). The area of neglected FOV could be an objective measurement of SN severity. Additionally, the system can be used to track the progression and rehabilitation of SN in a patient based on the changes in the neglected FOV. Accordingly, the development of this EEG-based BCI system could improve the assessment of SN and offer a more versatile and detailed alternative to the BIT.

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