USER IDENTIFICATION FROM FNIRS DATA USING DEEP LEARNING

ABSTRACT: This paper discusses the potential of functional near-infrared spectroscopy (fNIRS) brain-computer interfaces (BCIs) to identify an individual using only her brain data. fNIRS is a lightweight, portable, non-invasive functional neuroimaging tool that uses light to capture hemodynamic responses in the brain. We show that among 30 subjects, it is possible to determine the subject from whom a segment of the fNIRS data originated with 63% accuracy. Random chance is 3.3% for 30 subjects. Additionally, we explore the effect of the fNIRS brain data window size used during feature construction, on the classification accuracy.

INTRODUCTION: FNIRS has become more prevalent as a brain measurement tool, resilient to noise and artifacts [1,2]. Deep learning has been used to classify data obtained using fNIRS [3,4]. fNIRS has also been used for user identification (picking a specific individual out of a group) [5] and authentication (a binary, “yes” or “no” classification) [6] with SVM and Naive Bayes classifiers. This study uses fNIRS brain data obtained during resting state from a larger group than previously investigated [5] to perform user identification via deep learning.

MATERIALS AND METHODS: The data was obtained from 30 subjects during a study investigating mental workload during long supervisory control tasks [7]. The first 30 minutes (22200 measurements) were used, while the subjects were in a resting state. An ISS, Inc., Imagent device with wavelengths of 690 and 830 nm was used. Each of its two probes, had four linearly spaced light sources, and one detector, with source-detector distances between 2.5 and 3.5 cm. The raw data was processed using Homer 2 [8]. Only data obtained through the two longest channels was used, as it is less noisy. A high-pass filter was applied at 0.5 Hz. Features were constructed over a set time window. The average, maximum, minimum, slope, and standard deviation were calculated for each window, for each channel, for each of the measures oxy-hemoglobin (HbO), deoxy-hemoglobin (HbR), their sum, and their difference---resulting in a total of 40 features. The dataset was classified using a Multilayer Perceptron with 10 hidden layers, each with 200 nodes. The model was trained over the collection of the first 70% of the data for each subject, and tested on the last 29% of the data, removing the middle 1%. Each feature was z-score normalized before classification. This procedure was repeated for varied time windows, to explore the accuracy during each condition. As all the measurements were performed over the same time period, the number of instances per class depends upon the window size for each condition. To minimize the impact of fewer training instances, we modulated the epoch count (training iterations) to keep the total number of training instances constant over all tests (so, conditions with more windows were trained with more iterations of the same samples). Accuracy is calculated as the mean of accuracies of the last 25% training epochs for each condition.

RESULTS: Table 1 shows testing accuracies for each window size. The maximum accuracy achieved under this configuration was 63%, for window size of 1 second, closely followed by 61% accuracy with window size of 3 seconds. As random chance is 3.3%, this is a significant result.

DISCUSSION: These results suggest that there may be a specific brain signature unique to each individual even during a resting state, which could have implications regarding our understanding of the brain, and the systems that can be built using this information. One limitation of the study is that both testing and training data were collected during one sitting for each subject, with sensor placement potentially affecting the classification, despite z-score standardization. Further studies should be done to support and extend these results, examining the aforementioned limitation.

CONCLUSION: We have shown that fNIRS has the potential to identify an individual, suggesting its potential for use in biometrics and active authentication. However, it is important to investigate the privacy threats of mining brain data, and to develop policies to prevent their misuse.

Table 1: Accuracy of classification for each feature calculated over the specified time window, the number of instances per class before splitting into testing and training sets, the number of epochs used, and the standard deviation of the averaged accuracies.

	1 sec	**3 sec**	**9 sec**	**15 sec**	**24 sec**	**30 sec**	**60 sec**	**90 sec**
Unique Instances / Class	1800	600	200	120	75	60	30	20
Epochs	67	200	600	1000	1600	2000	4000	6000
Accuracy	63%	61%	57%	55%	47%	51%	45%	47%
Std. Dev	0.011	0.027	0.013	0.009	0.006	0.003	0.004	0.001

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