기계학습 기반 알츠하이머성 치매의 다중 분류에서 EEG-fNIRS 혼성화 기법

호티키우칸[O], 김인기[*], 전영훈[**], 송종인[**], 곽정환(교신저자)[*]
[O]한국교통대학교 소프트웨어학과,
[*]한국교통대학교 소프트웨어학과,
[**]광주과학기술원 전기전자컴퓨터공학과
e-mail: htkkhanh94@gmail.com[O], jgwak@ut.ac.kr

An EEG-fNIRS Hybridization Technique in the Multi-class Classification of Alzheimer's Disease Facilitated by Machine Learning

Thi Kieu Khanh Ho[O], Inki Kim[*], Younghoon Jeon[**], Jong-In Song[**], Jeonghwan Gwak(Corresponding Author)[*]
[O]Department of Software, Korea National University of Transportation,
[*]Department of Software, Korea National University of Transportation,
[**]School of Electrical Engineering and Computer Science, Gwangju Institute of Science and Technology

● 요 약 ●

Alzheimer's Disease (AD) is a cognitive disorder characterized by memory impairment that can be assessed at early stages based on administering clinical tests. However, the AD pathophysiological mechanism is still poorly understood due to the difficulty of distinguishing different levels of AD severity, even using a variety of brain modalities. Therefore, in this study, we present a hybrid EEG-fNIRS modalities to compensate for each other's weaknesses with the help of Machine Learning (ML) techniques for classifying four subject groups, including healthy controls (HC) and three distinguishable groups of AD levels. A concurrent EEF-fNIRS setup was used to record the data from 41 subjects during Oddball and 1-back tasks. We employed both a traditional neural network (NN) and a CNN-LSTM hybrid model for fNIRS and EEG, respectively. The final prediction was then obtained by using majority voting of those models. Classification results indicated that the hybrid EEG-fNIRS feature set achieved a higher accuracy (71.4%) by combining their complementary properties, compared to using EEG (67.9%) or fNIRS alone (68.9%). These findings demonstrate the potential of an EEG-fNIRS hybridization technique coupled with ML-based approaches for further AD studies.

키워드: 뇌파(EEG), 근적외선분광법(fNIRS), 알츠하이머성 치매(Alzheimer's disease), 기계학습(machine learning), 다중 분류(multi-class classification)

I. Introduction

Along with the older population tendency, AD is considered as the most prevalent dementia defined as the decline of brain function that interferes the daily activities of the elderly and leads to extensively increasing in the proportion of deaths every year [1]. Thus, early and accurate diagnosis of AD is a proceeding necessary issue along with a sharp upward trend in the incidence rate. While the common tools for timely AD interpretation are brain imaging techniques, such as functional magnetic resonance imaging (fMRI) and computed tomography (CT) which heavily depend on exhaustive testing sessions and experienced

radiologists. Hence, the integrated approach of electroencephalography (EEG) and functional near-infrared spectroscopy (fNIRS) has arisen great interest [2], especially in medical treatments due to its aptitude of investigating the correlation between oscillatory electromagnetic brain activity and the concentration change of oxy- and deoxy-generated hemoglobin and eliminating the shortcomings of previous methods. However, the possibilities of using hybrid EEG-fNIRS to differentiate different AD levels have not yet investigated comprehensively.

To efficiently access the capability of the hybrid EEG-fNIRS structure across various applications, ML algorithms, which are widely utilized in the brain signal domain, have been adopted to analyze patterns obtained from both EEG and fNIRS data to compensate the high variability in EEG-fNIRS analysis [3, 4]. However, most of existing researches focused on simple ML classifiers to tackle the multi-class classification problems and normally achieved accuracies below 80%. Hence, novel learning approaches to deal with dynamic brain signals for classification purposes of both fNIRS and EEG are essentially needed. Therefore, it is great of interest and importance to adopt both traditional neural networks and deep learning architectures to avoid the time-consuming process and feature engineering steps; and to capture representative high-level features as well. These models would be applied on fNIRS and EEG simultaneously, and the final prediction would be voted by majority voting techniques to boost the accuracy in our AD multi-class classification study.

II. Related Works

An extensive number of studies exploited different modalities to access and diagnose various neurological disorders, including AD. In particular, combining multiple monitoring technologies furnishes a new approach to synthesize the advantages and overcomes the limitations of each other. 765 papers were included in the initial search and 128 papers were chosen through the PRISMA protocol to demonstrate the feasibility of enhancing the performance of the hybrid EEG-fNIRS based on optimizing the feature extraction techniques [4]. Perpetuini et al. [3] showed the ability of multimodal EEG-fNIRS to measure brain activity along with neurovascular coupling and detect their modifications with respect to AD during the working memory task. They used the general linear model to classify AD and HC with an AUC up to 0.88. Cicalese et al. [5] built the EEG-fNIRS system to collect data from 29 subjects during a random digit encoding-retrieval task. A linear discriminant analysis was then applied to classify four groups: HC, MCI and two AD patient groups with the higher accuracy (79.31%) obtained by the integrated EEG-fNIRS feature set, compared to either EEG or fNIRS alone.

However, simple ML classifiers could not overcome the challenge of the imbalanced class distribution, which is as similar to our available dataset. Thus, a novel learning approach including complex neural networks and deep learning-based models should be involved to directly capture useful information from features obtained from EEG and fNIRS signals and then easily to discriminate HC from three levels of AD patients.

III. The Proposed Scheme

1. Subjects and Data Preprocessing

In this study, we recruited the elderly participants living in Gwangju city and the adjacent cities, South Korea. Each subject's status was labelled based on a set of medical examinations, such as MMSE, MRI, PET and personal interview. For both fNIRS and EEG dataset, we included all features (fNIRS features and ERSP features, which denoted the average dynamic change in amplitude of three EEG frequency bands) extracted from two experimental stages (Oddball – a cognitive ability test, 1-back – a memory ability test). The final EEG-fNIRS feature set was then used for our classification task. Table 1 summarizes the subject demographics in our study.

Table 1. Subject Information

Label	Disease Severity	No.of Patients
0	Healthy Control (HC)	19
1	Presymptomatic AD (aAD)	9
2	Prodromal AD (pAD)	11
3	AD Dementia (ADD)	3
Divided	Training: 80% (Leave One Out Cross-Validation is applied) Testing: 20% (Majority Voting)	

2. Proposed ML Models

On one hand, since only important fNIRS features were extracted, we obtained a relatively fewer number of features. A traditional neural network was perfectly chosen to classify four subject groups to avoid the over-fitting problem, which could be observed from a more complex model applied on a simple data. On the other hand, a complex hybrid CNN-LSTM model was applied on ERSP features extracted from EEG signals during Oddball and 1-back tasks. This is because we could take synergetic advantage of adopting both a 1D-CNN layer to capture spatial features and followed by three LSTM layers

to capture temporal features. At the final stage, ach model (NN and CNN-LSTM) could generate predicted classes. We thus voted those predicted classes based on the majority voting method to obtain the highest classification accuracy.

3. Classification Results

Table 2 summarizes the classification metrics using NN for fNIRS features, CNN-LSTM for ERSP features from EEG, and the majority voting method for EEG(Oddball)-fNIRS and EEG(1-back)-fNIRS feature sets. In general, the EEG-fNIRS set was able to earn a higher accuracy (71.4%) in comparison with using EEG (67.9%) or fNIRS (68.9%) alone.

Table 2. Classification Results

Task	Classification metrics	fNIRS	EEG(ERSP)
Oddball	Accuracy	0.689	0.679
	Precision	0.725	0.684
	Recall	0.689	0.679
	F1 Score	0.683	0.676
1-back	Accuracy	0.654	0.621
	Precision	0.671	0.620
	Recall	0.654	0.621
	F1 Score	0.633	0.602
Voting	Accuracy	0.714	
	Precision	0.775	
	Recall	0.714	
	F1 Score	0.693	

IV. Conclusions

In this paper, the capability of multimodal EEG-fNIRS together with the ML models to distinguish three AD stages from HC was investigated. To gain insight on the significant differences between four classes, fNIRS features and ERSP features extracted from EEG signals during Oddball and 1-back tasks were both used. The classification results showed that although we used an imbalanced dataset, both proposed models (NN and CNN-LSTM) yielded promising accuracies. More importantly, the combination of both feature sets provided a higher accuracy compared to solely using either one of them. These findings suggest that the integrated EEG-fNIRS system hold a significant and promising role to ameliorate the assessment process and AD diagnosis.

ACKNOWLEDGEMENT

This work was supported by the Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (Grant No. NRF-2020R1I1A3074141), the Brain Research Program through the NRF funded by the Ministry of Science, ICT and Future Planning (Grant No. NRF-2019M3C7A1020406), and “Regional Innovation Strategy (RIS)” through the NRF funded by the Ministry of Education.

REFERENCES

[1] Z. Li, H.-I. Suk, D. Shen, and L. Li, "Sparse multi-response tensor regression for Alzheimer's disease study with multivariate clinical assessments," IEEE transactions on medical imaging, vol. 35, no. 8, pp. 1927-1936, 2016.

[2] N. Sengupta, C. B. McNabb, N. Kasabov, and B. R. Russell, "Integrating space, time, and orientation in spiking neural networks: A case study on multimodal brain data modeling," IEEE Transactions on neural Networks and Learning systems, vol. 29, no. 11, pp. 5249-5263, 2018.

[3] D. Perpetuini et al., "Working Memory Decline in Alzheimer’s Disease Is Detected by Complexity Analysis of Multimodal EEG-fNIRS," Entropy, vol. 22, no. 12, p. 1380, 2020.

[4] Z. Liu, J. Shore, M. Wang, F. Yuan, A. Buss, and X. Zhao, "A systematic review on hybrid EEG/fNIRS in brain-computer interface," Biomedical Signal Processing and Control, vol. 68, p. 102595, 2021.

[5] P. A. Cicalese et al., "An EEG-fNIRS hybridization technique in the four-class classification of alzheimer’s disease," Journal of neuroscience methods, vol. 336, p. 108618, 2020.