An EEG-fNIRS Hybridization Technique in the Four-Class Classification of Alzheimer’s Disease

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Introduction
Alzheimer's disease (AD) is projected to become one of the most expensive diseases in modern history, and yet diagnostic uncertainties exist that can only be confirmed by postmortem brain examination. Machine Learning (ML) techniques have been proposed as a feasible alternative to the diagnosis of several neurological diseases and disorders, such as AD. An ideal ML-derived diagnosis should be inexpensive and noninvasive while retaining the accuracy and versatility that make ML techniques desirable for medical applications. Electroencephalography (EEG), and functional Near-Infrared Spectroscopy (fNIRS) have been widely employed in constructing hybrid classification models to compensate for each other's weaknesses. In this study, we present a hybrid EEG-fNIRS model for classifying four classes of subjects including one healthy control (HC) group, one mild cognitive impairment (MCI) group, and two AD patient groups.

Hypothesis
The primary objective of this study is to evaluate the feasibility of utilizing hybrid EEG-fNIRS data to classify subjects at different stages of cognitive decline (as defined by the attending physician).

Methods
A concurrent EEG-fNIRS setup was used to record data from 29 subjects (eight healthy controls, eight MCI patients, six mild AD patients, and seven moderate/severe AD patients) during a random digit encoding-retrieval task. The mental state of each subject was examined using the Mini-Mental State Examination (MMSE), and all rating scores were recorded. EEG-derived and fNIRS-derived features were sorted using a Pearson correlation coefficient-based feature selection (PCCFS) strategy and then fed into a linear discriminant analysis (LDA) classifier to evaluate the performance of single-modal features and hybrid features.

Results
The result showed that the hybrid EEG-fNIRS feature set was able to achieve a higher accuracy (79.31%) by integrating their complementary properties in a Leave one out cross validation (LOOCV) test, compared to using EEG (65.52%) or fNIRS alone (58.62%), as shown in Figure 1. Moreover, by mapping the channels that consisted of the optimal features to a 3D rendering of the brain, our results indicated that the right prefrontal and right parietal regions are potentially associated with the progression of AD (Figure 2).
Fig. 2. Cortical activation mapping derived from the EEG (yellow) and fNIRS channels (blue) that contributed to the optimal hybrid feature set. The larger the size of the circle, the more features the corresponding channel contributes.
Fig. 1. Performance evaluation of EEG features (A), fNIRS features (B) and hybrid features (C) using PCCFS. In each sub-figure, the black solid line denotes average accuracy while shaded area denotes the standard error.
Conclusion
The result suggests that the hybrid model is a superior and effective way to accurately classify and assess AD patients, with accuracy approaching 79.31% in the four-class hybrid model. It is important to note that chance in our model is defined as the ratio of the largest group over the total sample size (~27.6%), which we exceed by a significant margin. Future studies should consider combining these imaging modalities with other popular imaging techniques (such as PET) to further validate the value of hybrid EEG-fNIRS model in the diagnosis of AD in clinic.

Statement of Impact
The findings in the present study suggest that the proposed hybrid EEG-fNIRS model holds great promise to provide physicians with a more definitive and preemptive diagnosis of AD. We also believe that the improved confidence in the diagnosis would thus permit physicians to treat AD more effectively, therefore improving patient outcomes and reducing the cost associated with AD management.

Keywords
Electroencephalography (EEG); functional near-infrared spectroscopy (fNIRS); Alzheimer's disease; machine learning; classification