A Tensor-based Machine Learning Approach to EEG Feature Detection: Examination of Working Memory Network Dysfunction in Schizophrenia

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Background

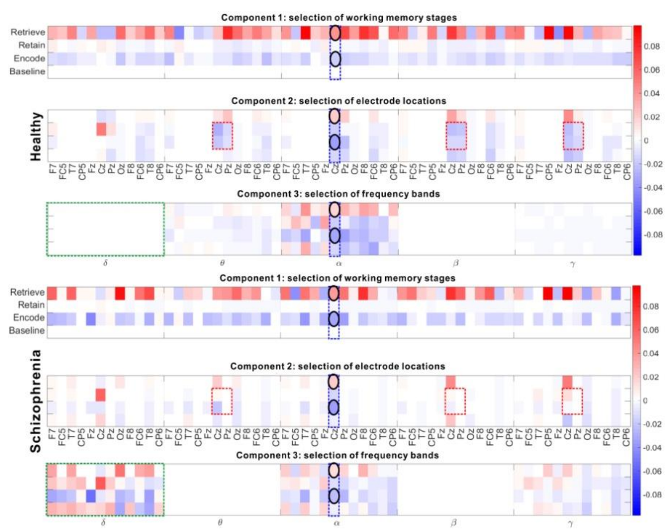
Human memory function can be assayed in real-time by electroencephalographic (EEG) recording; however, the clinical utility of this method is dependent on the reliable determination of functionally and diagnostically relevant features. Data-driven machine learning approaches capable of modeling non-stationary signal have been explored as a way to synthesize large arrays of EEG data. Although standard machine learning approaches reduce the data to a 1D vector before classification, the EEG record could be more precisely characterized by a tensor (e.g., a 3D matrix) representing processing stages, spatial locations, and frequency bands as individual dimensions. We derive a novel tensor-based classification method and test it on EEG data collected during memory task performance in healthy normal and clinical (schizophrenia) samples.

Methods

Schizophrenia (SZ, n=40) and healthy control (HC, n=20) subjects completed an EEG Sternberg task. EEG was analyzed to extract 5 frequency components (delta, theta, alpha, beta, gamma) at 4 processing stages (baseline, encoding, retention, retrieval) and 12 scalp sites representing central midline, and bi-lateral frontal and temporal regions. A tensor-based learning algorithm was applied to the resulting 240 features (forming a 5×4×12 tensor) to classify correct (-1) vs. incorrect (+1) responses on a trial-by-trial basis. In this approach, a linear model is directly constructed from the tensor, and hence the model coefficients comprise another tensor. The algorithm decomposes the coefficient tensor into a summation of three components and identifies the sparse patterns of these components from data. Thus, coefficients in each component guide the respective selection of spectral frequency, temporal (processing stages), and spatial (electrode sites) dimensions most related to trial performance. Using this approach, the selection of features along any dimension takes into account weightings represented on the other two dimensions. Separate models were constructed for SZ and HC samples for comparison of common and disparate feature patterns across the dimensions.

Results

Task accuracy was significantly lower in SZ ($p < .001$). In both groups, task performance was most dependent on encoding and retrieval stage activity, with higher encoding uniformly and lower retrieval activity generally associated with better task performance across electrode sites. This pattern appears most prominently in central alpha activity (Figure; blue border). Groups differed in two main ways: (1) centroparietal theta, beta, and gamma during encoding and retention predicted higher accuracy in HC (Figure; red border), and (2) delta activity across stages and electrodes (Figure; green border) predicted lower accuracy in SZ. The new tensor-based model outperformed GEE and SVM solutions according to AUC values (HC: 55.2%; SZ: 58.6% versus the best AUC 53% from GEE and SVM).



Discussion

Tensor-based classification enabled interpretation and summary across all dimensions, which was not possible for classifiers based on single vectors.

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