Advances in the Direction Towards an Objective EEG Test for Migraine
A Data Driven Approach for Subtyping Classification of Migraine

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Bottom-Line

There is a need for safe, objective, affordable, robust, electrical biomarkers/features to diagnose and monitor all types of migraine and to better understand inter-ictal pathophysiology. Our prior EEG work in 2017 was 92.9% accurate in diagnosing migraine without aura interictally using support vector machines, an established machine learning technique. In the present preliminary study we took on the "three class problem" which is the following: **knowing only that a patient has headaches can they be accurately classified into one of the following three groups: normal control, migraine with/without aura?** While the present study is not definitive and requires more patients, results are encouraging in that they demonstrated an **80.1% accuracy for all three groups**. We used what is known as an hierarchical approach whereby we proceeded in two stages**.**

Data

HSI Database:

- 30 Participants
  - 10 MwA, 10 MA, 10 NC
- Subjects with migraine symptoms were screened using the International Headache Society criteria schedule II (ICHD-II)

Recording:

- 32 Ag/AgCl electrodes 10-20 electrode system
  - average referenced
  - digitally sampled at 1024 Hz

Results and Future Work

Results

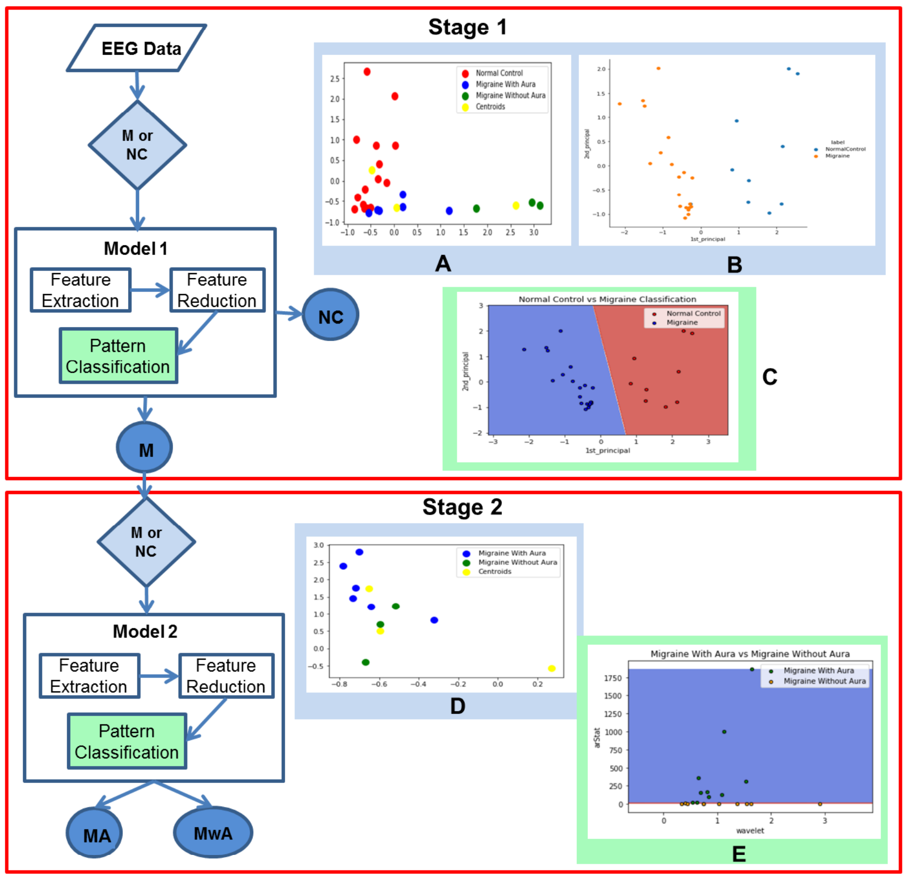
Performing direct 3 group separation using conventional machine learning techniques such as neural network, support vector machine, and decision trees, gave us a poor classification accuracy, maximizing at around 67%. We then proceeded with a hierarchical approach whereby we divided the classification into two stages (see figure). Our stage one and two classification accuracy were 97% and 83% respectively, resulting in an effective classification rate of 81%. Their respective hyperplanes can be seen in Figures C and E.

Furthermore, we identified electrical subtypes for M using unsupervised clustering learning methods (Figure A,B). Notice that there exist some patients that seem to cluster more than others. This suggests that there may exist some more subtyping within MA and MwA.

Future Work

- Expand the number of subjects
- Continue to refine the algorithm to aim for an accuracy above 90%
- Optimizing error propagation to reduce overfitting

Method



Feature Extraction and Reduction

Three electrical features were obtained to characterize the EEG patterns: synchronization, transients, and frequency statistics. Alpha phase synchronization or phase lock value were used to characterize the network patterns of the brain. Wavelet scale was used to describe the transient activity (short events). Auto-regression frequency statistics were used to obtain valuable time-frequency information. Feature selection and reduction techniques were performed on the sub-features of these 3 mutually independent features to preserve interpretability of the results.

Pattern Classification

For the pattern classification portion of the algorithm we propose a two-stage hierarchical approach. Stage one is to use a linear SVM model to differentiate M from C using a projected 2D hyperplane of the combined effective features. If the patient was found to have the electrical abnormalities of a migraineur then stage two; using another linear SVM model was applied to differentiate MA and MwA using 2 other electrical features.

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