

QEEG-BASED CLASSIFICATION WITH WAVELET PACKET AND MICROSTATE FEATURES FOR TRIAGE APPLICATIONS IN THE ER

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Introduction

Despite increasing use in clinical neuropsychiatry, quantitative assessment of patients based on EEG recordings has yet to find widespread use in acute care settings, particularly the **Emergency Department (ED)**. One significant reason for this is the fact that the usual clinical EEG is based on electrodes placed over the entire scalp, a procedure that is lengthy, invasive, and requires the participation of a consulting specialist.

Our goal is to design a portable device called the **Brain Stethoscope** to be used in such settings for triage purposes by non-specialist ED professionals (Fig. 1). The device will rely on Quantitative EEG measurements (QEEG), based only on a recording from five frontal electrodes referenced to linked ears. It should include three levels of binary classifications: 1) "Within Normal Limits" ("Normal") vs. "Outside Normal Limits" ("Abnormal,") (N/A), 2) "Organic" vs. "Functional," (O/F) and 3) "Lateral" vs. "Global" (L/G), according to the classification tree depicted in Fig. 2. The "Functional" group includes some psychiatric disorders.

In this work, we address the N/A and the O/F problems and provide strong evidence for the potential clinical utility of such a device. The device's analyzing software is based on classical quantitative EEG methods supplemented by more recent ideas, some of which exploit the time-domain information which the classical approach ignores.

Classical QEEG methods

- Neurometric QEEG methods originally reported and extensively studied by E. Roy John *et al.* [1-4]. Methods are based upon extracting quantitative measures (features) from Electroencephalogram (EEG) signals recorded from electrodes placed at standard locations on the human scalp.
- Classical QEEG variables:
 - Absolute and relative power,
 - Mean Frequency,
 - Inter/intra hemispheric Symmetry and Coherence
- Classical QEEG frequency bands:
 - Delta (1.5-3.5 Hz), Theta (3.5-7.5 Hz), Alpha (7.5-12.5 Hz), Beta (12.5-25 Hz), Gamma (35-50 Hz), S (1.5-25 Hz)
- Binary classification problems addressed by means of Fisher Linear Discriminant functions constructed using a subset of QEEG features.

Additional features: LDB

- The Local Discriminant Basis Algorithm (LDB) algorithm finds an optimal coordinate system for distinguishing among multiple classes of signals [5]. It is a variant of the *best basis method* for selecting an optimum set of wavelet packet features with a measure of dissimilarity as cost function.
- Input: Power spectrum of data set.
- Output: Basis of wavelet packet features ranked by the cost function. (LDB features no longer adhere to the standard QEEG frequency bands.)

Additional features: Microstates

- Capture the temporal dynamical structure of the EEG. The EEG is segmented into a sequence of stable spatial configurations called *microstates*.
- Use four leads F7, Fp1, Fp2, F8 and consider the behavior of the vector: $E(t) = [F7(t), Fp1(t), Fp2(t), F8(t)]$. Map each vector $E(t)$ to the closest Haar-Walsh wavelet packet w_i .

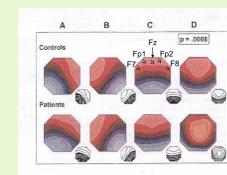


Fig. 3. Taken from [6]. Microstate classes of schizophrenic patients and controls for 10-20 System. Mean normalized equipotential maps of four microstate classes (A-D). Map areas of opposite polarities are arbitrarily coded in blue and red.

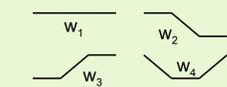


Fig. 4. Haar-Walsh wavelet packets W_1, W_2, W_3, W_4 .

QEEG-based Classification

- For each binary classification problem, N/A and O/F:
- Five linear discriminants (output: value between 0 and 1).
 - Select *critical value* T to make the output binary.
 - Use majority voting strategy.

Results

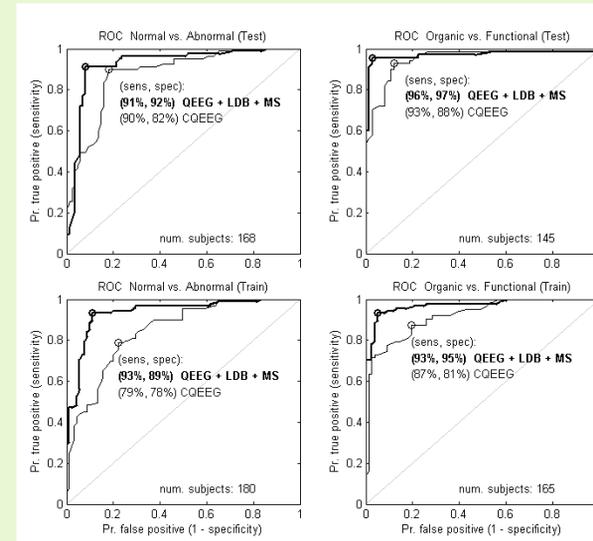


Fig. 5. Improved ROC curves using LDB and microstate features in addition to CQEEG features for "Normal" vs. "Abnormal" classification (Left) and for "Organic" vs. "Functional" classification (Right).

Training and testing data sets

Data sets used for training and testing linear discriminants were provided by the research database of the Brain Research Laboratories (NYU School of Medicine). Each data set consisted of 1-2 minutes of artifact-free EEG epochs (2.56 seconds each), recorded on a resting subject with eyes closed. These epochs were identified by expert technicians who made sure they did not contain artifacts such as those produced by muscle (EMG) or eye movements.

Table 1: Size of training and testing data sets.

Classification	Training	Testing
A/N	180	168
O/F	165	145

Sensitivity and specificity

The classification algorithm performs binary classification of the form: "positive test result" (referred to as "disease") vs. "negative test result" ("no disease"). Convention: "Abnormal" and "Organic" both correspond to "positive" test results.

Sensitivity is the ratio of "true positives" over the number of subjects for whom disease is truly present. *Specificity* is the ratio of "true negatives" over the number of subjects for whom disease is truly absent.

Conclusions

This work demonstrates the feasibility of a portable device for quantitative EEG diagnostic in the ER, using a greatly reduced set of easily accessed (frontal) electrodes. Initial results show that similar performance can be obtained on "raw" EEG data with artifacts (muscle, eye movements, etc.) removed from an automatic artifact identification algorithm.

The addition of new EEG features to the set of classical QEEG features improves classification performance by up to 10% in sensitivity and/or specificity.

Literature cited

- [1] E. R. John, *Functional Neuroscience, Vol II: Neurometrics, Clinical Applications of Qualitative Electrophysiology*, Lawrence Erlbaum Associates, New Jersey, 1977.
- [2] E. R. John, L. S. Prichep, J. Friedman and P. Easton, "Neurometrics: Computer-assisted differential diagnosis of brain dysfunctions," *Science* 293, pp. 192-169, 1988.
- [3] E. R. John, L. S. Prichep, and P. Easton, "Normative data banks and neurometrics. Basic concepts, methods and results of norm construction," in *Methods of Analysis of Brain Electrical and Magnetic Signals: EEG Handbook*, A. Gevins and A. Remond, Eds., pp. 449-495. Elsevier, 1987.
- [4] E. R. John and L. S. Prichep, "Principles of Neurometric Analysis of EEG and Evoked Potentials," in *Electroencephalography: Basic Principles, Clinical Applications and Related Fields*, E. Niedermeyer and F. Lopes Da Silva, Eds., pp. 989-1003. Williams & Wilkins, 1993.
- [5] N. Saito and R. R. Coifman, "Improved discriminant bases using empirical probability density estimation," in *Proceedings of the Statistical Computing Section of the Amer. Stat. Assoc.*, 1997, pp. 312-321.
- [6] D. Lehmann, et. al., "EEG microstate duration and syntax in acute, medication-naive, first-episode schizophrenia: a multi-center study," *Psychiatry Research: Neuroimaging*, vol. 138, pp. 141-156, 2005.

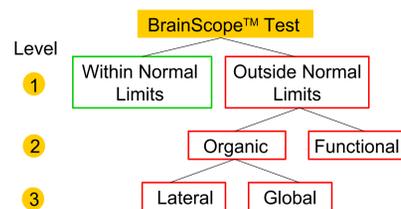


Fig. 2. Three-level, tree-structured classification algorithm for Brain Stethoscope™ device.



Fig. 1. Prototype of portable Brain Stethoscope (BrainScope™) device for use in Emergency Departments (ED). The result of the three-level classification is indicated graphically on horizontal color bars. In addition, the device indicates the result of three alert conditions (BrainStem Dysfunction, Active Seizure, Burst Suppression).

For further information

Please contact elvir@everest-co.com. Information on Everest Biomedical Instruments Company can be found at <http://www.everest-co.com>. For information on ongoing research at the Brain Research Laboratories, Department of Psychiatry, NYU Medical school, visit: <http://www.med.nyu.edu/brl>

