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

Leslie S. Prichep[1,2] *Elvir Causevic*[3,4] *Ronald R. Coifman*[4] *Robert Isenhart*[1]
Arnaud Jacquin[3,*] *E. Roy John*[1,2] *Mauro Maggioni*[4] *Frederick J. Warner*[5]

[1]Department of Psychiatry, New York University Medical School, New York, NY
[2]Nathan S. Kline Institute for Psychiatric Research, Orangeburg, NY
[3]Everest Biomedical Instruments, Chesterfield, MO
[4]Department of Mathematics, Yale University, New Haven, CT
[5]Plain Sight Systems, Hamden, CT

ABSTRACT

We describe methods for the classification of brain state using quantitative analysis of the EEG (QEEG). Neurometric analysis of EEG collected from the 19 standard locations of the International 10-20 System already provides such a tool. In this work we demonstrate the effectiveness of this approach when the available inputs are reduced to a set of five frontal electrodes. This system has applications in certain critical clinical care situations, such as emergency room triage, when a full EEG might be unavailable, inconvenient, or time-consuming. Additionally, we augment the standard neurometric QEEG analysis with local discriminant basis features of the power spectrum and microstate-like features which exploit the rich temporal structure of the EEG. These enhancements provide clear gains in sensitivity and specificity on a representative database.

1. 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. 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. 1.

In this note, 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.

2. WHAT IS QEEG?

Neurometric QEEG methods have been extensively studied since they were originally reported by E. Roy John [1-2]. The Neurometric method [1-4] is based upon extracting quantitative measures (also called *features*) from Electroencephalogram (EEG) signals, recorded from electrodes placed at standard locations on the human scalp. These features are log-transformed for Gaussianity, then age-regressed and z-transformed with respect to expected normal values, thereby expressing them as (dimensionless) standard scores, or *z-scores*. Multivariate composite features are also constructed as Mahalanobis distances across a set of features, with the intercorrelation removed.

Classical QEEG frequency bands are listed in Table I. Classical QEEG (CQEEG) variables are Absolute and Relative Power, Mean Frequency, Inter- and Intra-hemispheric Symmetry and Coherence for monopolar and bipolar regions. The binary classification problems are addressed by means of Linear Discriminant (LD) functions which are constructed using a subset of QEEG features (usually fewer than 12 per discriminant). The discriminant weights are obtained using a statistical pattern recognition toolbox which includes Fisher Linear Discriminants [5].

[*] Corresponding author, email: arnaudj@everest-co.com

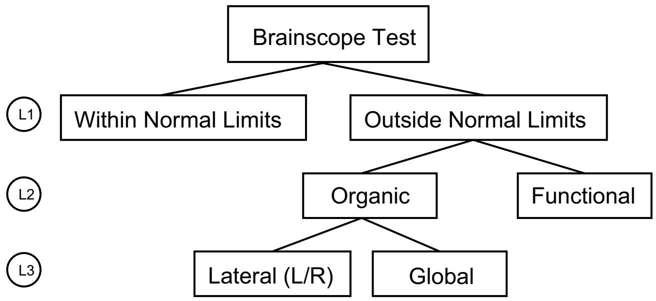

Fig 1. Three-level, tree-structured classification algorithm for Brain Stethoscope device.

Numerous research studies have shown that QEEG methods are effective and reliable for the detection and classification of different types of neuropathologies [6,7].

3. LDB METHODS

The local discriminant basis (LDB) algorithm is a method for finding optimal coordinates for distinguishing among multiple classes of signals [8]. It is a variant of the best basis method for selecting an optimized set of wavelet packet features in which a measure of dissimilarity is chosen as the cost function. This is a supervised learning approach in which training data from two or more classes of data are used to select best discriminating features, which are then used as inputs to statistical classifiers.

We describe the application of this method to the N/A classification problem considered here. The training data consisted of EEG recordings for 180 subjects, 91 of which were classified as "Normals" and 89 as "Abnormals." For any given channel, we compute a power spectrum for each subject using the multitaper spectrum analysis method [9]. This provides us with registered signals from two different classes which serve as appropriate input to the LDB procedure. In particular, we use a variant of the usual LDB approach in which a more comprehensive search procedure is applied in the Haar-Walsh packet case, giving access to a much richer collection of coordinate systems [10]. The algorithm outputs a basis of wavelet packet features, ranked by the cost function, and the best few of these are reserved for further evaluation.

These LDB features may be viewed as surrogates for the classical QEEG features in that they are found by "filtering" the power spectrum of the EEG in some fashion. They differ from conventional QEEG features in that there is no strict adherence to the use of standard EEG frequency bands. As in the case of QEEG, the final LDB features used were age-regressed and z-transformed for easy comparison with existing features. This process was carried out for each of the five channels used and for each of the ten pair-wise channel power spectrum ratios.

4. EEG MICROSTATES

The temporal dynamical structure of the EEG is encoded as a sequence of stable spatial configurations, called *microstates*, separated by brief transitional periods. The nature of these microstates and their relationship to various psychiatric disorders are topics of significant current interest [11]. The features we exploit in this application, while not derived from true EEG microstates, provide a crude and easily calculated substitute in the absence of the full set of EEG electrodes.

Four of the five electrodes used in the application are the electrodes F7, Fp1, Fp2, and F8 from the standard 10-20 System. These four form a linear spatial array on the forehead and we consider the temporal behavior of the vector $E(t) = [F7(t), Fp1(t), Fp2(t), F8(t)]$. We compute the inner product $v_i = \langle E(t), w_i \rangle$ for each of the four Haar-Walsh wavelet packets $w_1 = [1, 1, 1, 1]$, $w_2 = [1, 1, -1, -1]$, $w_3 = [-1, -1, 1, 1]$, and $w_4 = [1, -1, -1, 1]$, and at each point in time we determine which of these inner products is largest. This converts the sequence of spatial EEGs into an integer sequence of labels (e.g. 111223344400111…) which is then "pruned" – all constant subsequences whose length is less than some value (3, say) are removed (in fact, they are set to a 5th value of "0"). For example, this means that sequence 111223344432111 becomes 111000044400111. The resulting sequence is interpreted as being a sequence of "states" (the non-zero pieces) separated by regions of either noise or transition between states (the "0" pieces).

From this sequence, we compute a 4 x 4 matrix of transition probabilities, the eigenvalues of that transition matrix, and the relative dwell times for each of the states. This gives us a set of 24 features for each patient. These features are then age-regressed and z-transformed before being further evaluated.

5. RESULTS

5.1. Training and testing sets

The data sets used for training and testing the linear discriminants were provided by the research database of the Brain Research Laboratory (Dept. of Psychiatry, NYU School of Medicine). Each data set consisted of 1-2 minutes of artifact-free EEG epochs (2.56 seconds each), recorded on a subject at rest with eyes closed. These epochs were identified by expert EEG technicians who made sure they did not contain segments of EEG corrupted by artifacts such as those produced by muscle (EMG) or eye movements (EOG). The sampling rate for the data was 100 Hz. The "true" classification information ("diagnosis") for each data set was known a priori.

For N/A classification, we used a training set of 180 data sets and a testing set of 168 samples (with 89 "Normals"). For O/F classification, we used a training set of

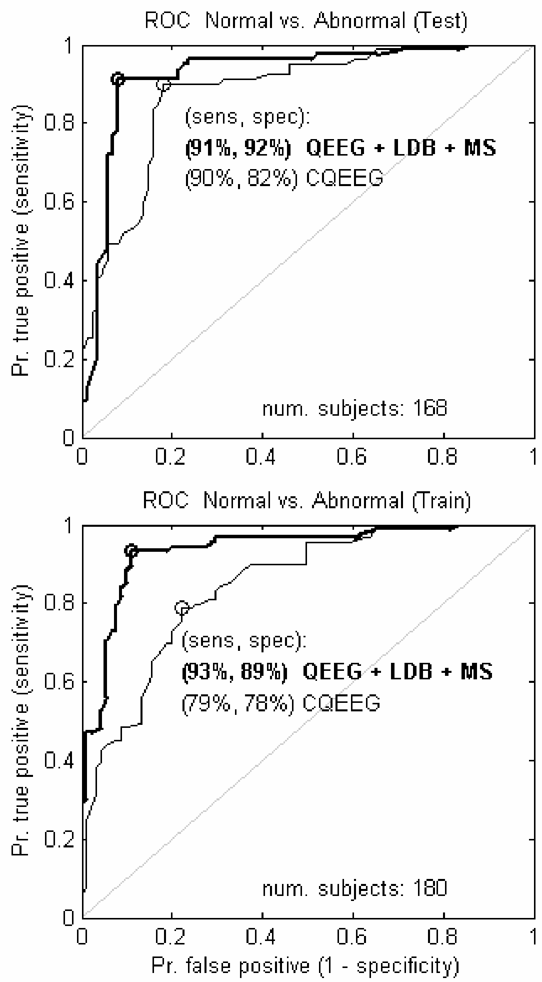

Fig 2. Improved ROC curves using LDB and microstate features in addition to CQEEG features for "Normal" vs. "Abnormal" classification.

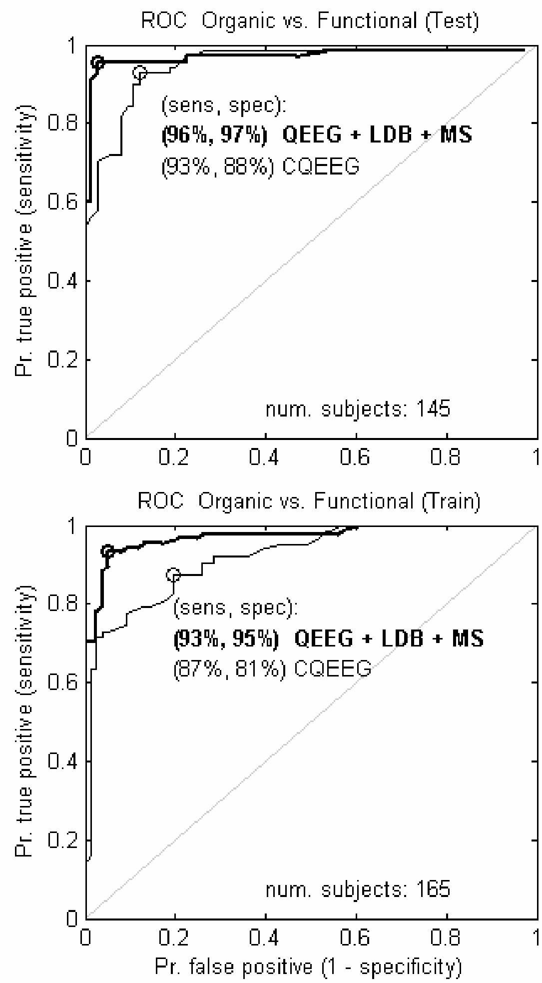

Fig 3. Improved ROC curves using LDB and microstate features in addition to CQEEG features for "Organic' vs. "Functional" classification

165 data sets (samples) and a testing set of 145 samples (with 75 "Functionals").

5.2. Definitions of sensitivity and specificity

The classification algorithm performs binary classification of the form: "positive test result" (which we refer to as "disease" for convenience) vs. "negative test result" ("no disease"). We adopted the convention that "Abnormal" and "Organic" both correspond to "positive" test results. The *sensitivity* of a classifier is the ratio of "true positives" over the number of subjects for whom "disease" is truly present. The *specificity* of the test is the ratio of true negatives over the number of subjects for whom disease is truly absent. These ratios are usually expressed as percentages. A test is all the better as sensitivity and specificity are closer to 100%.

5.3. ROC curves for QEEG-based classification

For the two classification tasks considered, a collection of linear classifiers was developed. The final results presented here were obtained, in each case, from a majority voting among five such classifiers. In each of the individual classifiers, a collection of five features chosen from among the LDB and microstate-like features was added to the base group of about ten CQEEG features that had been chosen for the binary classification problem in question. A few of the classifiers omitted from two to four of the original QEEG features after adding the five newer features.

The output of a binary discriminant is a number which can take any value between 0 and 1. Once a critical value (or threshold) T is selected, the output of the test becomes binary and sensitivity and specificity for this particular threshold can be computed. The ROC curves of Figs 2-3 were obtained by varying the threshold between 0 and 1 in increments of 0.01. Optimal threshold values were obtained by maximizing the quantity: (1.25×sensitivity(T) + specificity(T)). The sensitivity and specificity indicated in the graphs of Figs 2-3 were those corresponding to these optimal threshold values.

Fig. 2 shows the improved sensitivity and specificity of the voting classifier for the "Normal" vs "Abnormal" classification task when LDB and Microstate features are added to the set of classical QEEG features. We can see that while sensitivity numbers are not much changed, the test specificity increases by 10% for the test group. Fig.3 shows results for the voting classifier in the "Organic" vs. "Functional" classification task. Again, sensitivity gains are modest but specificity is significantly increased.

TABLE I
CLASSICAL QEEG FREQUENCY BANDS

Frequency Band Name	Band limits (Hz)
Delta1	0.5 – 1.5 Hz
Delta (δ)	1.5 – 3.5 Hz
Theta (θ)	3.5 – 7.5 Hz
Alpha (α)	7.5 – 12.5 Hz
Beta (β)	12.5 – 25 Hz
Delta + Theta + Alpha + Beta (S)	1.5 – 25 Hz
Beta1	25 – 35 Hz
Gamma (γ)	35 – 50 Hz
Alpha1	7.5 – 10 Hz
Alpha2	10 – 12.5 Hz

6. CONCLUSIONS

This work demonstrates feasibility of an approach to quantitative EEG diagnostics using a greatly reduced set of easily accessed (frontal) electrodes. The exact numerical results presented are likely to change slightly under the use of the currently specified system when a much larger set of data is collected and processed by the Brain Stethoscope. However, the LDB algorithm allows for continued redefinition of features adapted to such a growing database. Clearly, the addition of new EEG dimensions to the set of classical QEEG features improves classification performance as measured by ROC curves.

7. REFERENCES

[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 neurometics. Basic concepts, nethods 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] M. I. Schlesinger, V. Hlavac, V. Frank, Statistical pattern recognition toolbox for Matlab, http://cmp.felk.cvut.cz/~xfrancv/stprtool/index.html

[6] L. S. Prichep and E. R. John, "QEEG profiles of psychiatric disorders," *Brain Topography*, vol. 4, no. 4, pp. 249–257, 1992.

[7] L. S. Prichep, E. R. John, S. H. Ferris, B. Reisberg, M. Almas, K. Alper, and R. Cancro, "Quantitative EEG correlates of cognitive deterioration in the elderly," *Neurobiology of Aging*, vol. 15, no. 1, pp. 85–90, 1994.

[8] N. Saito and R. R. Coifman, "Improved discriminant bases using empirical probability density estimation," in *Proceedings of the Statitical Computing Section of the Amer. Stat. Assoc.*, 1997, pp. 312–321.

[9] D. J. Thomson, "Spectrum estimation and harmonic analysis," *Proceedings of the IEEE*, vol. 70, no. 3, pp. 1055–1096, 1982.

[10] C. Thiele and L. Villemoes, "A fast algorithm for adapted time-frequency tilings," *Applied and Computational Harmonic Analysis*, vol. 3, pp. 91–99, 1996.

[11] 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.