Classification of Traumatic Brain Injury Using Support Vector Machine Analysis of Event-Related Tsallis Entropy

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Abstract—An estimated 1.4 million Americans suffer from traumatic brain injury (TBI) each year [1]. Current methods of detecting TBI, such as computerized tomography (CT), magnetic resonance imaging (MRI), and Positron Emission Tomography (PET) scanning are time-consuming and expensive [2].

Here, the viability of a potentially more cost-effective means of detecting TBI is presented. Support vector machine (SVM) analyses are employed to classify 15 TBI and 15 normal individuals’ EEG recordings taken during a working memory test. The features used by the SVM analyses include different sets of event-related Tsallis entropy functionals. The analyses demonstrate a strong correlation between the event-related functionals (ERFs) and the presence of TBI, attaining classification accuracies as high as 90%.

I. INTRODUCTION

While early intervention can mitigate the severity of symptoms resulting from secondary pathology, mild TBI is often not diagnosed early due to a lack of obvious symptoms soon after the incident or injury (Shaw, 2002). Currently, the most common methods of diagnosing TBI are CT, MRI, and PET scanning. These methods are often undesirable due to expense and time-consuming testing, and therefore are usually not employed for every injury that may pose the risk of TBI. Delayed diagnosis and medical intervention to prevent further development of brain damage from secondary pathological symptoms, including edema and hemorrhaging of the brain, leads to unnecessarily worse prognoses for patients [2].

Here a potentially more cost-effective means of screening for TBI from EEG recordings will be demonstrated, which could allow for earlier medical intervention and therefore better prognoses for TBI patients. This method utilizes EEG data recorded during a short visual “old-new recognition” test in order to determine the differential brain activity of subjects with traumatic brain injuries from those who are age-matched normal subjects. The current method involves the use of event-related Tsallis entropy functionals and support vector machine analyses.

II. METHODS

A. Participants

The data used in this study were provided by the University of Kentucky (UK) and Oak Ridge National Laboratory (ORNL). The data were originally collected by Dr. Victoria Vagnini et al. [3] in the laboratory of Dr. Yang Jiang of the Behavioral Science Department in the College of Medicine at UK. Normal volunteers were recruited using fliers posted at the UK Introductory Psychology subject pool classes. The normal participants were required to have no medical history of TBI. TBI participants were recruited through fliers at a local private practice neurologist’s office and through local newspaper advertisements. Records obtained indicated that the TBI participants had sustained their injuries an average of 13 years (SD 7.2 years) prior to the data collection, had an average Glasgow Coma Score of 8.7 (SD 2.9) and an average loss of consciousness of 7.2 days (SD 12 hours). CT and MRI scans indicated moderate to severe injury in a variety of regions in the brain, including brain stem, frontal, temporal, parietal, and occipital lobes in both the right and left hemispheres. All participants were compensated $10/hour; TBI participants were compensated an extra $20 dollars for travel expenses as they were recruited from outside the greater Lexington area [3].

B. Data Collection

Participants were connected to 32-channel EEG caps using a Neuroscan™ system. Recordings were taken during a visual working memory (old-new) task [3]. For the task, stimulus pictures were presented to the participants via a computer display at an angle of 7 degrees approximately 65 cm from the participants. The size of the objects presented in the stimulus images were approximately 8 cm by 6 cm, and consisted of line drawings displayed in front of a black background. Participants were initially shown 100 images for 5 seconds each and asked to memorize the images. The images were shown for a second time after a short break, with the participants again asked to memorize the images.
The participants were then shown 140 images, 70 of which were from the then “familiar” set of 100 images, and 70 of which were previously unseen “unfamiliar” images. EEG recordings were taken while these 140 images were shown and the participants were tasked with determining whether the images were familiar or unfamiliar and to click corresponding keys on a keyboard. Stimulus onset was delayed randomly at 100ms, 300ms, or 500ms, in order to avoid expectation effects. Each picture was presented for one second with inter-stimulus intervals of 1100ms-1500ms. Fixation markers were presented for 1500ms, and participants were tasked with staring at the display without blinking until a fixation cross (+) appeared. The task of 140 images took approximately 9.5 minutes [3].

C. Tsallis Entropy

The challenge presented in analyzing EEG data lies in the process of estimating the information contained in the signal without knowledge of the method of encoding. A plausible assumption, however, is that the ability of individuals who have suffered traumatic brain injuries to process information is less than that of individuals who have not suffered brain damage. Such disparity in information processing by the brain could theoretically be evident in the amount of information present in EEG data recorded from normal and brain-damaged individuals during cognitively taxing activities [4].

Fortunately, a formula for estimating the entropy of an intensive system, first proposed by Tsallis, is applicable for analyzing the entropy, and therefore the amount of information contained within EEG signals and other natural signals [4]. The general formula for Tsallis entropy is presented as Equation (1),

$$S_T = 1 - \sum p^2(x_i) = 1 - \frac{1}{k} \sum p^2(y_i),$$ (1)

where $y_i$ is the physical instantiate (EEG voltage pattern) of the information event $x_i$, and $p(x_i)$ and $p(y_i)$ are the probabilities of $x_i$ and $y_i$, respectively.

Given the relationship presented in Equation (1), the amount of information contained within an EEG signal, or the entropy of the signal, can be estimated if the probability of occurrence of the physical instantiates of information events within the signal is known.

Observations of known physical instantiates of information in nature provide examples that can be used to estimate the probability of the physical instantiates in EEG recordings. Specifically, critical points (local maxima, local minima, and discontinuities) appear to delineate physical instantiates in nature [4]. In the case of neuronal coding, the information contained in action potentials (APs) spreading across neuronal membranes is coded by the frequency of occurrence of action potentials [4]. The individual APs, and therefore the information they code for, are delineated by periods of static electric potential across the neuronal membranes [5]. The points marking the beginning and ending of APs, therefore, are points of discontinuity in the time-varying voltage across neuronal membranes. Thus, local critical points appear to delineate the physical instantiates of the information events in neuronal signals.

D. Event-Related Tsallis Entropy Functionals

For each of 15 normal and 15 TBI participants, recordings from 25 of the 32 channels were used in analyses, due to failure of some of the leads to correctly adhere to the participants’ scalps during the recordings. The arrangement of the leads on the participants’ scalps was divided into six regions corresponding to six major regions of the cerebral cortex. The regions included the “central lobe” region (anterior parietal lobe), “frontal lobe” region (frontal lobe), “left temporal lobe” region (left temporal lobe), “occipital lobe” region (occipital lobe), “parietal lobe” region (posterior parietal lobe), and “right temporal lobe” region (right temporal lobe). The 25 channels used in analyses were randomly selected such that the same number of channels was selected from the same regions for each patient. Specifically, we selected three channels in the central lobe region, six in the frontal lobe region, three in the left temporal lobe region (left temporal lobe), three in the right temporal lobe region, seven in the parietal lobe region, and three in the right temporal region; see Fig. 1 for a diagram of the regional boundaries used.

Within each of the signal recordings were time intervals corresponding to the 140 images shown, each having the condition of either being “familiar” or “unfamiliar” images. Windows of 400 ms for 100 of these 140 images, 50 familiar and 50 unfamiliar, were extracted for analyses. These event-related windows included 100 ms of data prior to the showing of the images and 300 ms during which the images were shown. The Tsallis entropy for each of these 100 windows was then calculated, for a total of 100 event-related Tsallis entropy functionals, 50 corresponding to familiar images and 50 corresponding to unfamiliar images. The average of the familiar and unfamiliar event-related functionals (ERFs) for all of the channels in each region was also determined. Thus, 12 regional average ERFs were calculated for each participant, 6 familiar and 6 unfamiliar. These familiar and unfamiliar regional average ERFs were later used as features for support vector machine analyses.
E. Support Vector Machines

Support vector machines are a collection of techniques for pattern classification and nonlinear regression. Support vector machines have been widely applied in machine learning, optimization, statistics, neural networks, functional analysis, etc. The main idea is to construct a hyperplane as the decision surface to separate data from two different categories. For later convenience, we denote the two categories by +1 and -1, respectively. The goal is to maximize the margin between positive and negative examples.

In this work, we used regional average ERFs as feature inputs to classify normal and TBI responses. We conducted SVM analysis using the SVM functions in Matlab™ [6].

III. RESULTS

Initially, SVM analyses were performed on the familiar and unfamiliar regional averages separately in order to test the ability of the regional averages for use as an accurate means of classifying normal and TBI participants. For these analyses, all participants’ data were used for training and for prediction. Thus, the results of these analyses are self-prediction classification measures.

Classification analyses were performed using all possible combinations of the six regional averages for both the familiar and unfamiliar sets separately. The accuracy of the SVM classification varied greatly depending on which combination of regional averages were used during training and prediction. Individual regional averages attained accuracies ranging from 43.3% to 66.7%, with occipital regional averages performing best in both familiar and unfamiliar sets. On average, the familiar regional averages performed better than the unfamiliar regional averages. The results of individual regional averages and combinations of two regional averages for familiar and unfamiliar sets are presented in Fig. 2. The diagonal squares of the matrices presented in Fig. 2 contain the results of individual regional averages. The off-diagonal squares contain the results of combinations of two regional averages. The upper and lower triangles of the matrices presented are symmetrical. Using two regional averages can improve the accuracy to 73.7% for familiar images and 76.7% for unfamiliar images.

The results attained using combinations of three regional averages are presented in Fig. 3. On average, combinations of three regional averages performed with greater accuracy than individual regional averages or combinations of two regional averages. The highest accuracies for both familiar and unfamiliar sets were attained using combinations including the frontal and occipital lobe regions. The best classification using familiar images is improved to 83.3% while the best classification using unfamiliar images remains at 76.7%.

Results from combinations of four and five regional averages are presented in Fig. 4. The diagonal squares of the matrices presented in Fig. 4 contain the results from combinations of five regional averages, in which one of the six regional averages was excluded. The off-diagonal squares contain the results of combinations of four regional averages in which two of the six regional averages were excluded. As in Fig. 2, the upper and lower triangles of the matrices presented in Fig. 4 are symmetrical. On average, the familiar combinations performed better than the unfamiliar regional averages for combinations of four and five regional averages. Combinations of four and five regional averages also performed better, on average, than combinations of fewer regional averages. The best accuracy using four familiar images was 90%, obtained using signals in the frontal, occipital, left temporal, and right temporal lobe regions. The best accuracy using four unfamiliar images was 86.7% obtained using signals from several different combinations of regions.

The familiar and unfamiliar classification results attained using all six regional averages were identical, with a classification accuracy of 83.3%.

Two general trends can be observed from the results of the combination analyses. First, the average classification results of all combinations increased as the number of regional averages included in the combinations increased. Second, familiar combinations also performed better, on average,
than unfamiliar combinations as the number of regional averages used increased.

Overall, the most accurate classification was obtained using a combination of four familiar regional averages. The regions included the frontal, left temporal, parietal, and right temporal lobe regions. Using these familiar regional averages, the SVM achieved a classification accuracy of 90%.

### IV. CONCLUSION

One of the earliest studies performed on classification of pathological neurological conditions using Tsallis entropy analysis of EEG data (quantified EEG, qEEG) was conducted by Sneddon et al. [7]. Specifically, Sneddon et al. examined the accuracy of a qEEG-based early detection method for Alzheimer’s disease and related disorders (ADRD). The method involved analysis of scalp EEG data gathered from the dorsolateral prefrontal sites and the posterior parietal sites of 48 (32 normal, 16 impaired) subjects while they performed a delayed match-to-sample working memory task [7]. The criteria for diagnosing ADRD from the scalp EEG data developed by Sneddon et al. proved to have a high accuracy of 92%, with sensitivity and specificity of 88% and 94%, respectively [7].

In the current study, SVM analyses of Tsallis entropy functionals, not qEEG values, achieved a classification accuracy of 90% using familiar average regional ERFs of the frontal lobe, occipital lobe, and right and left temporal lobes. The sensitivity and specificity using these features were 87% and 93%, respectively. These results suggest a strong correlation between average regional ERFs and the presence of moderate to severe TBI. With further research, it may be possible to design a diagnostic screening system for mild TBI utilizing ERFs to determine whether more costly and definitive testing procedures, such as CT, MRI, and PET, may be necessary.

### REFERENCES


