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Classification of ADHD and non-ADHD subjects using a universal background model

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ABSTRACT

ADHD affects a major portion of our children, predominantly boys. Upon diagnosis treatment can be offered that is usually quite effective. Diagnosis is generally based on subjective observation and interview. As a result, an objective test for the detection or presence of ADHD is considered very desirable.

Based on EEG, across multiple channels, using autoregressive model parameters as features, ADHD detection is approached here in analogy with the imposter problem known from speaker verification. Gaussian mixture models are used to define ADHD and universal background models so that a likelihood ratio detector can be designed. The efficacy of this approach is reflected in the traditional detector performance measures of the area-under-the-curve and equal-error-probability. The results – based on a limited database of males, approximately 6 years of age – indicate that high probability of detection and low equal error rate can be achieved simultaneously with the proposed approach, when using EEG collected during an attention network task. The effect of using contaminated data is investigated as well.

1. Introduction

In the US, ADHD is a condition that affects approximately 9.5% of children ages 4–17 [1]. Diagnosis of ADHD is done by using the Diagnostic and Statistical Manual of Mental Disorders (DSM), published by the American Psychiatric Association (APA) [2], which provides a list of symptoms that behavioral scientists use to determine whether or not a subject has a mental disorder. While DSM-V (2013) recognizes three different subtypes or presentations of ADHD, the data available for this effort provided the binary labels of Non-ADHD (NA) and ADHD (A) only.

Since diagnosis is done through subjective observations made by teachers, parents, and behavioral scientists, finding quantitative techniques to aid the diagnosis of ADHD has gained attention. In fact, classification of ADHD (A) and Non-ADHD (NA) has been done relatively successfully [3–8], which implies that A and NA subjects are separable to some extent in several feature domains.

This study concerns the use of a Gaussian-Mixture-Model-based universal background model (UBM) for the classification of A and NA subjects, consisting of 6-year old males. UBMs have been used in the past for speaker verification and identification, and have achieved high levels of accuracy under different noise conditions [9,10]. Moreover, GMMs and UBMs have recently been studied for the detection and classification of EEG patterns [11,12].

The hypothesis addressed here is that a UBM can potentially address the shortcomings of other classification schemes. Over the last 30 years, the A/NA classification problem has been tackled by extracting features from EEG data when the subjects are resting with their eyes closed or performing some activity. However, when test subjects do not perform the activity they are instructed to perform, classification accuracy is more likely to be poor (perhaps even resembling guessing). Therefore, a UBM built using a large number of feature vectors, extracted from several activities, may make classification more robust.

To the best of the authors' knowledge, this is the first time a GMM-UBM is used for the classification of ADHD (A) and Non-ADHD (NA) subjects. In this study, the features evaluated are AR parameters, which were extracted from time intervals where A subjects and NA subjects were resting or performing an attention network task (ANT). UBMs were trained using a training dataset associated with 2 A subjects and 2 NA subjects, and then tested with a dataset associated with 1 NA subject and 2 A subjects that were not part of the training dataset. Performance was analyzed in terms of Receiver Operating Characteristics (ROC) and shown to vary depending on how much of the training and testing dataset came from ANT. When all the training and testing feature vectors

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originate from ANT activity (100% ANT, 0% resting EEG), a mean AUC (area under curve, for ROC) of 0.97 was obtained, with an EER (equal error rate, P{A/NA} = P{NA/A}) of 0.082. As resting data is added to the UBM and ADHD models, performance decreases, resulting in a mean AUC of 0.73 and a mean EER of 0.32 when 50% of the training and testing feature vectors come from ANT activity and the other 50% come from resting EEG.

The structure of this paper is as follows: Section 2 provides an overview of how EEG has been used for the discrimination between ADHD and Non-ADHD subjects. In Section 3, the methods used are described. Section 4 covers the experiments done as well as the corresponding results. Lastly, Section 5 provides the conclusions.

2. Related work

Since 1999, advances have been made towards quantitatively finding differences between ADHD subjects and Non-ADHD subjects during baseline eyes closed activity. In 1999, a study reported that the θ/β power ratio of ADHD subjects tends to be higher than that of Non-ADHD subjects [7]. In that study, the power ratio was obtained by computing the PSD estimates from the FFT. For classification, the θ/β power ratio of Non-ADHD subjects was averaged, and power ratios that were more than 1.5 standard deviations above the average θ/β power ratio of control subjects (the threshold) were classified as associated with ADHD subjects, whereas those that fell below the threshold were classified as Non-ADHD. This simple decision rule was reported to yield 98% of sensitivity. However, another study replicating the methodology of the latter study, reported 84% accuracy (sensitivity + specificity divided by 2).

Although a method that achieves 84% accuracy may not be accurate enough for diagnosis, it could be used for pre-screening. A study found that parents and teachers can detect ADHD with an accuracy ranging from 54% to 63%, which is equivalent to guessing, whereas the θ/β power ratio has been claimed to achieve 84% to 97% accuracy of classification [13]. The latter claim has been seriously called into question recently [14].

Another study [3] used power in frequency bands along with semi-supervised learning during eyes closed activity in order to diagnose ADHD subjects. In this study, the power and power ratios in the α, β, θ, and γ frequency bands were computed and the mutual information criterion was used to choose the least redundant features for training of a Gaussian support vector machine (SVM). The accuracy of classification was 97%.

In our earlier publication [4], AR parameters, extracted from attention activity, and supervised learning were used for the classification of ADHD and Non-ADHD subjects. AR(7) models were computed from windows of 2 s, and a KNN classification accuracy between 85% and 95% was obtained. In addition, a confidence metric was derived from the vote count of the KNN classifier, which ranged from 91% to 99%.

The effectiveness of event-related potentials (ERPs) has also been studied [5]; 74 control and 74 ADHD subjects performed a visual two-stimulus GO/NOGO task while their EEG data was recorded. Independent component analysis (ICA) was performed on the ERPs, and these features were used to train a SVM classifier, which achieved 92% accuracy of classification (90% sensitivity and 94% specificity).

UBMs have been studied for the purpose of classification and person verification. In a recent study, UBMs based on a multi-sphere support vector data description (MSSVDD) and based on GMMs were used to classify control subjects and alcoholic subjects [11]. The features extracted in this study were 12 power components in the 8–30 Hz frequency band and AR(21) coefficients. The EER of the GMM-UBM was found to be 0.221 and that of the MSSVDD was found to be approximately 0.1.

For EEG task classification, popular algorithms and frameworks involve Hidden Markov Models (HMM), since a task can be modeled as a sequence of mental states [15]. In fact, a study used HMM for mental task classification and modeled EEG as a chaotic signal. The models were tested using multiple datasets, and accuracy reported of approximately 72% for the worst case.

With the rise in popularity of deep learning, deep neural networks have been developed to detect patterns in EEG. With a training dataset of 50,900 feature vectors and a testing dataset of 500,000 feature vectors, a deep belief network (DBN) was developed for EEG anomaly detection [16]. The DBN was compared to SVM for the same task, and according to the F1 scores, DBNs slightly outperformed SVMs (0.475 vs 0.439).

Although some deep learning networks, such as recurrent neural networks (RNN), DBN, or long-short-term memories (LSTM) hold promise for the classification of A and NA, the dataset used for this paper is not large enough to be used for deep learning. To the best of our knowledge, there are large EEG datasets available online, such as [17], but not for ADHD.

3. Methods

An overview is provided in Section 3A of how the data were collected, in Section 3B of channel reduction, in Section 3C of details for AR modeling, and in Section 3D of GMM-UBMs.

A Data collection

Children between the ages of 6 and 8 years visited the research lab as part of an ongoing longitudinal study focused on frontal lobe development from infancy through childhood. Information regarding diagnosis of ADHD was obtained via maternal report. EEG was recorded using a stretch cap (Electro-Cap, Inc Eaton, OH: E1-series cap) in the extended 10/20 system pattern. Recordings were made from 26 electrodes located equidistant across the scalp.

Electrode impedances were kept under 20k ohms. The electrical activity from each lead was amplified using separate bioamps (James Long Company, Caroga Lake, NY). During data collection, the high-pass filter was a single pole RC filter with a 0.1 Hz cut-off (3 dB or half-power point) and 6 dB/octave roll-off. The low-pass filter was a two-pole Butterworth type with a 100-Hz cut-off (3 dB or half-power point) and 12 dB/octave roll-off. The EEG signal was digitized at 512 samples per second for each channel so that data were not affected by aliasing. The acquisition software was Snapshot-Snapstream (HEM Data Corp, Southfield MI). Prior to the recording of each subject, a 10 Hz, 50 μV peak-to-peak sine wave was input through each amplifier and digitized for 30 s. This signal was analyzed and the resulting power values used to calibrate the EEGs.

After the EEG electrodes were applied, children participated in eyes open, eyes closed, and quiet VIDEO baseline events to collect resting EEG data. Then the children completed a battery of cognitive tasks designed to assess various aspects of attention [18] using the child version [19] of the Attention Network Task (ANT) and various aspects of cognition associated with executive functions (e.g., number Stroop, Dimensional Change Card Sort Task, Digit Span Task). Data from the ANT were used in the analyses that are the focus of this report.

The ANT was designed to assess Posner's brain-based attention networks [18] and yields measures of conflict, alerting, and orienting. The test requires the child to respond to a central target (a yellow fish on a light blue background) displayed on a computer screen and indicate whether the fish is facing left or right. The child is instructed to look at the fixation point, above or below which the target will appear. The target may appear with or without flankers (other fish), which may or may not be congruent with respect to