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EEG-based ADHD Detection Using Autoregressive Model Parameters and Gaussian Mixture Models: A Speaker Verification Analogy

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Abstract

Attention Deficit Hyperactivity Disorder (ADHD) is a prevalent condition affecting a significant number of children, primarily boys. The diagnosis of ADHD relies mainly on subjective observations and interviews, necessitating the development of objective tests for accurate detection. In this study, we propose an ADHD detection method using EEG data collected from multiple channels. By employing autoregressive model parameters as features and drawing inspiration from the imposter problem in speaker verification, we employ Gaussian mixture models to define ADHD and universal background models. Subsequently, a likelihood ratio detector is designed. The effectiveness of this approach is evaluated using traditional performance measures such as the area-under-the-curve and equal-error-probability. Our results, obtained from a limited male database of approximately 6 years of age, demonstrate that the proposed approach achieves high detection probability and low equal error rate simultaneously. Notably, EEG data collected during an attention network task are utilized for analysis. Additionally, we explore the impact of contaminated data on the detection process. This research contributes to the advancement of objective ADHD detection methods and highlights the potential of EEG-based approaches in improving diagnostic accuracy.

Keywords: ADHD detection, EEG, autoregressive model parameters, Gaussian mixture models, likelihood ratio detector, traditional performance measures

I. Introduction

In the United States, Attention Deficit Hyperactivity Disorder (ADHD) affects around 9.5% of children between the ages of 4 and 17 [1]. The diagnosis of ADHD relies on the Diagnostic and Statistical Manual of Mental Disorders (DSM) published by the American Psychiatric Association (APA), which outlines specific symptoms used by behavioral scientists to determine if an individual has the disorder. While the DSM-V recognizes different subtypes of ADHD, this study focuses on distinguishing between Non-ADHD (NA) and ADHD (A) subjects only [2-4].

Given that ADHD diagnosis is based on subjective observations, researchers have been exploring quantitative techniques to aid in the diagnosis process. Successful classification of ADHD and Non-ADHD subjects has been achieved in various feature domains, indicating some degree of separability between A and NA subjects [5]. This study investigates the use of a Gaussian-Mixture-Model-based universal background model (UBM) for classifying A and NA subjects, specifically 6-year-old males. UBMs have been previously employed in speaker verification and identification, demonstrating high accuracy even in noisy conditions. Recently, GMMs and UBMs have also been studied for EEG pattern detection and classification [6-7].

The hypothesis of this study is that a UBM can address the limitations of other classification methods. Traditionally, the A/NA classification problem has involved extracting features from EEG data obtained during resting or activity tasks. However, classification accuracy tends to suffer when subjects do not perform the instructed tasks, potentially resulting in poor performance [8]. By constructing a UBM using numerous feature vectors extracted from different activities, classification robustness can be enhanced.

To the authors' knowledge, this study is the first to utilize a GMM-UBM for classifying ADHD and Non-ADHD subjects. The evaluated features are autoregressive (AR) parameters extracted from time intervals when subjects were at rest or performing an attention network task (ANT). UBMs were trained using a dataset comprising 2 A subjects and 2 NA

was conducted using Receiver Operating Characteristics (ROC) and revealed variations depending on the proportion of ANT and resting EEG data in the training and testing sets. When 100% of the feature vectors originated from ANT activity, the mean area under the ROC curve (AUC) was 0.97, with an equal error rate (EER) of 0.082. However, as resting data was added to the UBM and ADHD models, performance decreased, resulting in a mean AUC of 0.73 and a mean EER of 0.32 when 50% of the feature vectors came from ANT activity and the remaining 50% from resting EEG.

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