

Identification of ADHD Using Quantified Auditory Brainstem Responses and a Comparative Algorithm

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Abstract

Auditory Brainstem Responses have previously been reported to be aberrant in patients with neuropsychiatric diagnoses. In this study, 88 subjects from Sweden and 72 subjects from Bolivia were tested using a test battery of sound stimuli. The Gaussian Naïve Bayes AI classification model was used for analysing traits and predicting diagnosis. The test proved to have both high sensitivity and specificity. The results were consistent with previous studies where similar outcomes have been shown in other populations.

Keywords: Auditory Brainstem Response; ABR; ADHD; Gaussian Naïve Bayes

Background

The auditory brainstem response (ABR) is comprised of wave patterns following click stimulation [1]. The ABR is the averaged activity from the recorded evoked electrical potentials. The activity is recorded from surface skin electrodes which are attached to the patient's mastoid bones and vertex [2]. As ABR does not require any active subject participation it is considered to be an objective neurophysiological method.

The brainstem audiogram consists of seven characterized waves labelled I to VII, occurring within 10 milliseconds after the peak of wave I. The two waves in the beginning of the ABR, waves I and II, originate mainly from the cochlear nerve and the subsequent waves III and IV from the cochlear nucleus and the superior olivary complex (SOC). Wave V is generated from electrical activity in the lateral lemniscus and the inferior colliculus. Both waves VI and VII have their origin in the medial geniculate body of the thalamus. Analysis of the ABR typically includes identification of amplitudes and latencies of the seven peaks and their consecutive troughs. Further to this, ratios of peak amplitudes and inter-peak latencies are measured [2].

In this paper we describe how disease-specific biomarkers are found using measurements of data from ABR recordings. We also describe the predictive potential of such biomarkers for groups of patients with ADHD.

The AI classification model that was used for analysing traits and predicting diagnosis was Gaussian Naïve Bayes.

Introduction

Several audiological, neurological and psychiatric abnormalities can be detected using ABR [3]. Using quantified electrophysiological methods for detecting neuropsychiatric diseases, sensitivity and intraindividual variability are key factors for clinical usefulness [4]. In this study, we have included quantitative measures for finding norm curve similarities and differences, in line with quantification of data following qEEG measurements [4].

	Clinically diagnosed ADHD		Controls, no diagnosis	
	Male	Female	Male	Female
6-16 years	10	7	4	6
16-49 years	6	12	14	13

Table 1: Participants data.

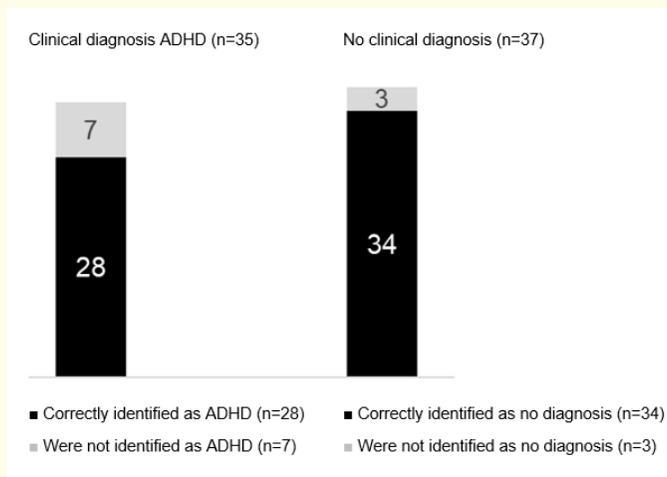


Figure 1: Number of correctly identified as ADHD and no diagnosis.

The auditory stimuli consisted of 4 different sounds (processed square wave clicks with different frequencies and amplitudes, in addition both forward and backward masking) which were presented binaurally both to healthy volunteers and patients diagnosed with ADHD (according to DSM-IV). The waveforms were digitally recorded (with 256 data points per 10 ms corresponding to 30 data points per ms) in order to be able to quantify of amplitudes (mV) with high resolution.

Firstly, well-investigated subjects were used to train the machine-learning algorithms to categorize the disease mathematically (described below). As females have shorter latencies and higher amplitudes than males, female and male subjects were separated in all analyses. Further to that, age groups were separated, below and above 16 years.

Sets of traits previously found to differentiate the ADHD group from the no-diagnosis controls in both male and female patients were used to give a percentage index where 50% was exactly in the middle of the two groups and above 50% were indicating an ADHD similarity. Consequently, below 50% pointed at greater resemblance to the no-diagnosis group. Based on these traits an index was calculated for each individual indicating percentage similarity with either of the diagnostic groups.

The SD-BERA recordings were evaluated by investigators ignorant of the clinical diagnosis of the study participants and the percentage correctly classified and not were calculated.

Gaussian Naïve Bayes Classifier is used to analyse and classify the traits of the participants: in studies with time based data it is often assumed that such values associated with each class, are distributed according to a normality, i.e. has a Gaussian distribution.

The model uses a Gaussian distribution with zero co-variance between the values and compares the classes. Finding the average and standard deviation of the interactions of classification within the data makes it possible to fit the data to a class.

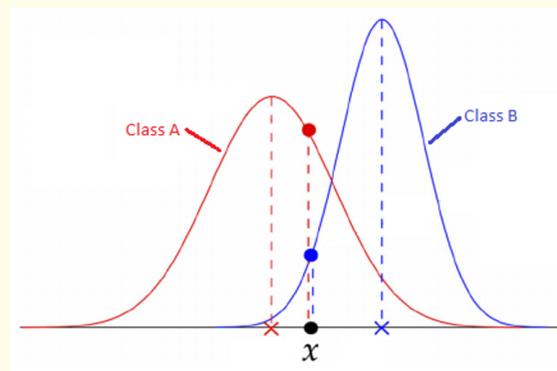


Figure 2

The illustration above is an example on a Gaussian Naive Bayes (GNB) classifier. At every time the data is compared to the distance between that point and each class-average. This is done by computing the distance from the class average divided by the standard deviation of that class.

Subjects

88 subjects were used as reference material from Lund, Sweden. 72 subjects with an average age of 18 years were then compared to the patterns of the reference groups using a machine-learning paradigm. The similarity to subjects with ADHD versus the similarity of subjects with no diagnosis was subtracted, leading to a percentage from 0 to 100%.

Results

The sensitivity of the test for ADHD vs. no-diagnosis controls was 80.0%, and the specificity vs. no-diagnosis controls was 91.9%. The present study suggests that SD-BERA provides useful markers to support the clinical diagnosis of children and adult ADHD.

Discussion and Conclusion

According to bibliography revised through this study, many audiological and neurological issues can be detected by using the auditory brainstem response. The use of disease-specific markers would provide a more integral measurement approach and would help in developing a multi-instrumental holistic treatment strategy. Characterizing instruments involving this technology may increase the accessibility to measurement, especially in those instruments with sufficient statistical evidence. In this case, for the Attention Deficit Disorder (ADD) and Attention and Hyperactivity Disorder (ADHD) results show that there is a high level of both sensitivity and specificity in the SD-BERA method. These results are consistent with other studies where similar outcomes have been shown in other populations. Further investigations are required to further explore the underlying mechanisms of this technology in the context of ADD-ADHD. Further investigations would also clarify the technology's feasibility regarding other mental disorders as well.

Conflict of Interest

Jonas Hagberg and Johan Källstrand are employed by SensoDetect AB, developing the SD-BERA technology.

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