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Automatic identification of ADHD children during visual attention task using variable length EEG

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Abstract – neuropsychiatric disorders affect millions of people of all ages worldwide. Attention deficit/Hyperactivity Disorder (ADHD), a typical neurodevelopmental disorder, deteriorates the performance of children in family and school settings thereby, hindering typical brain development. ADHD children, in most cases, are predominantly inattentive. In this research, automatic identification of neuronal patterns in ADHD children undergoing visual continuous performance tasks (CPT) is used to successfully differentiate between ADHD and typically developing children. The proposed methodology utilizes wavelet packet decomposition to extract relative energy from different EEG sub-bands, namely-delta (0.5-4 Hz) theta (4-8 Hz), alpha (8-13 Hz), beta1 (13-20 Hz), beta2 (20-30 Hz) and gamma (>30 Hz). The obtained feature from all bands is then passed to the Support Vector Machine (SVM) for the classification of children as normal and those with ADHD. The performance of the algorithm is assessed by following performance parameters, accuracy, sensitivity, specificity, and area under the receiver operating characteristic (AUROC) curve. While testing the classification performance keeping the relative energy of individual bands in feature space, it is observed that between groups difference in normal and ADHD is much higher in high-frequency bands i.e., beta and gamma compared to low-frequency bands. However, all other bands are interacting features that performed well along with the relevant features (beta and gamma energy bands, here). The area under the curve obtained with a subject-independent approach and combined EEG sub-band's relative energy in feature space is found to be 0.99.

Keywords – Neuropsychiatric Disorders, EEG, DWPT, ADHD, Continuous Performance Task.

I. Introduction

Electrophysiological activity, produced in the cerebral cortex of the brain, is the central basis of acquiring relevant information from the central nervous system at a functional level. The discovery of Electroencephalography (EEG) by Hans Berger in 1924 has led to the foundation of the non-invasive acquisition of neural information inside the neocortex (the uppermost part of the cerebral cortex) [1].

Extensive research has been done on EEG signal processing to explore the underpinnings of specific regions of the brain. This is consistent with the EEG's ability to characterize a variety of neurological disorders including seizures [2], Alzheimer, dementia, brain tumors and sleep disturbances. However, due to inconsistent findings when dealing with neuropsychiatric disorders including, ADHD, autism, schizophrenia, depression, etc., it is still not accepted to be used as a diagnostic tool in clinical practice [3].

Attention deficit hyperactivity disorder (ADHD) is a neurodevelopmental disorder associated with emotional imbalance, and attentional as well as behavioral dysfunction [4]. The global prevalence of ADHD, mentioned in the Diagnostic and Statistical Manual (DSM-V) is approximately 5.1%, i.e., around 380 million people worldwide [5]. This prevalence is much higher in male children compared to adults. Manifested in children within the age group between 4 and 7 years, this abnormality (persistent ADHD) may extend to adolescence in case of late diagnosis and/or improper treatment. However, a few studies suggest that ADHD symptoms persist in only 15% of people with childhood onset. This implies that the onset of disease in adults (symptomatic ADHD) is independent of the childhood history for most (85%) cases [6]. Several genetic and environmental factors are responsible for the onset of disease and the complex etiology suggest that the identification of neuro marker for ADHD diagnosis should be done separately in children and adults.

The current diagnostic procedure followed by clinicians is still based on a questionnaire approach which includes various rating scales like Conner's rating scale, DIVA, BRIEF-P, ASRS, etc. [4], [7]. This procedure is long and tedious, requiring multiple settings with the trained specialist to observe the symptoms and meet the criteria mentioned in DSM-V. An alternative method for automatic detection of attention state by engaging subjects in cognitive tasks like continuous performance task (CPT), sustained attention to response test (SART) etc., while recording EEG is believed to accelerate the process of diagnosis, thereby, filling the gap of the scarcity of trained specialist in low- and middle-income countries [8]

The use of quantitative EEG (QEEG) to extract different EEG sub-bands and Increase theta-beta power ratio (TBR) in ADHD compared to normal controls, has been the main focus of ADHD detection and validated in numerous publications [9]. A commercial diagnostic tool based on TBR using a single electrode (Cz) was also approved by Food and Drug Administration (FDA) in 2013, known as the Neuropsychiatric EEG-based assessment Aid (NEBA) system [10]. Nevertheless, there is a gradual decrease in low-frequency (delta and theta) waves in the transition from childhood to adolescence in the normal population [11]. This results in different EEG spectra for children, adolescents and adults That is why, inconsistent findings were reported by various researchers against TBR as a biomarker, especially for adult ADHD diagnosis [11][12].

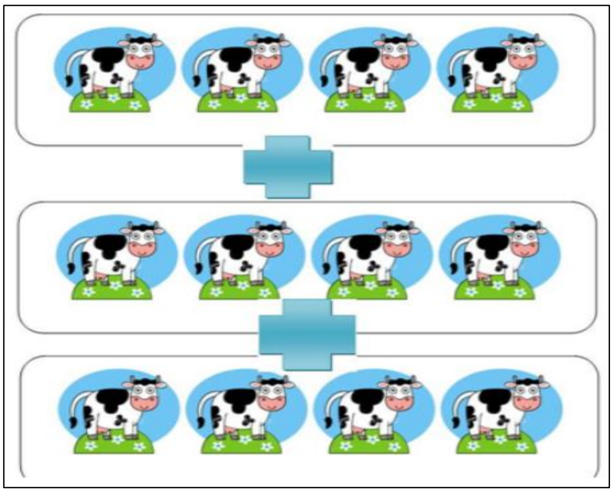

Fig. 1: A sample image displayed during visual CPT [14].

Another important aspect of research in ADHD is the study of the difference in functional connectivity between ADHD and normal controls using EEG and/or fMRI modalities to find the neural correlates of ADHD [13]– [15]. This approach is based on the application of graph theory and various connectivity measures are investigated to be used as neural markers such as phase lag index (PLI), directed phase transfer entropy, etc. [15]– [18].

In this research, the most dominant EEG sub-band involved in ADHD detection is investigated by extracting the relative energy concentration within each band. This requires EEG signal transformation from time to frequency domain which is obtained by discrete wavelet packet decomposition. The details of the dataset and proposed methodology are given in Section II. Subsequently, classification results, obtained using the SVM classifier are presented in Section III.

II. Materials and Methods

The present research work has used the standard EEG Dataset of a total of 121 subjects 61 ADHD and 60 normal controls, publicly available at: ieee-dataport.org. The description of data and the task in which the participants are engaged during EEG recording is covered in this section.

A. *Data description*

All subjects are primary school children within the age group between 7 and 12 years. Children in the ADHD group were carefully selected to exclude subjects with other comorbidities. The EEG recording is performed with 19 channels placed on the scalp using the standard 10-20 electrode placement system with a sampling frequency of 128Hz and a 16-bit quantizer [18].

B. *Task conditions in EEG recording*

Visual CPT consists of 20 images, displayed one after the other. These images, having 5-16 characters, are shown randomly and the participants are asked to count these characters. The next image is displayed after the response to the previous image. Therefore, the length of the EEG record is different for each subject, based on the amount of time taken by each of them to complete the counting task. A sample image with 12 cartoon characters is shown in Fig. 1 [14].

C. *Proposed Methodology*

The proposed algorithm for the automatic classification of children as normal controls and ADHD is shown in the block diagram in Fig 2.

The proposed method includes EEG signal decomposition using a 4-level discrete wavelet packet transform (DWPT). The relative energy obtained from each sub-band is used in the feature space to train the SVM classifier. The dimensionality (D) of feature space with combined EEG sub-bands is:

$$D = [\mathrm{s} \times (\mathrm{f} * \mathrm{c} * \mathrm{b})] \qquad (1)$$

where, s is the number of instances, f is the feature, c is the number of channels and b is the number of energy bands extracted from DWPT. This corresponds to 171 features. The combined feature space with all 171 features is then fed to variates of the SVM classifier. The highest accuracy and AUROC are obtained with cubic SVM

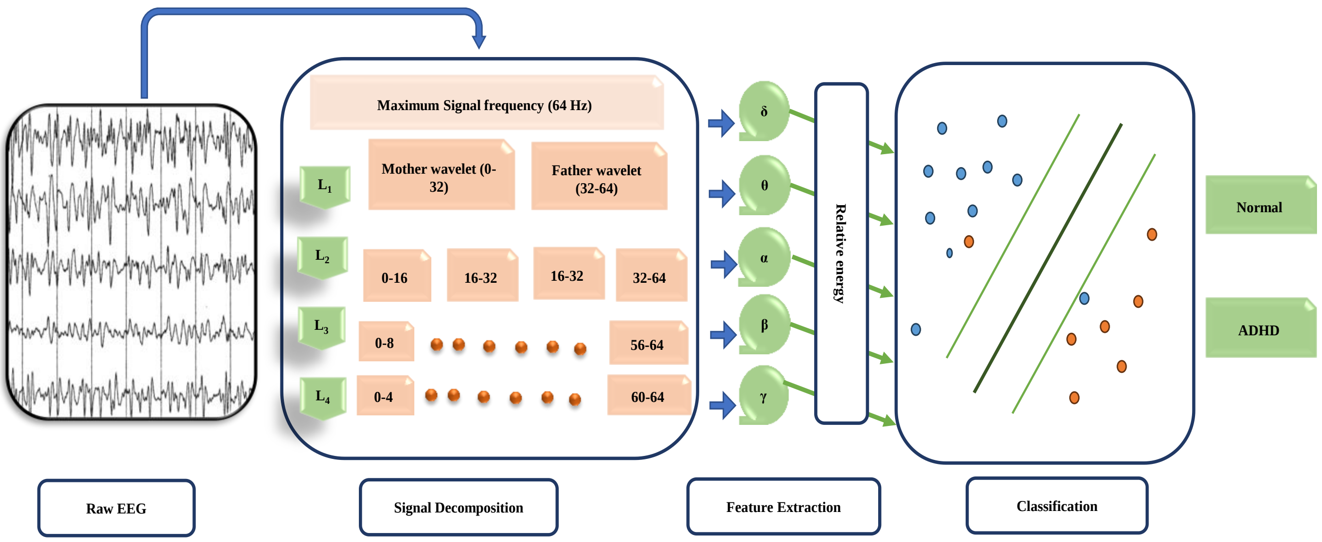

Fig. 2 Block diagram representing proposed classification method for automatic ADHD detection.

D. *Discrete wavelet packet transform*

Wavelet packet transform is an alternative to wavelet decomposition with the advantage of higher frequency resolution. It allows the decomposition of both the approximate and detailed coefficients of mother and father wavelets in parallel. This results in finer intervals obtained with DWPT, unlike wavelet transform which decomposes only approximate coefficients. The frequency axis [0,1/2] is split into 2^j sub-bands at each level, j. Each sub-band is obtained as follows:

$$\left[\frac{n * f_s}{2^{j+1}}, \frac{(n+1) f_s}{2^{j+1}}\right]$$

where, $n = 0, 1, 2, \ldots \ldots \ldots . 2^j - 1$ and f_s is the sampling frequency [2],[19]. The signal decomposition block in Fig. 2 illustrates different EEG sub-bands obtained with 4 level DWPT method of signal transformation from time to frequency domain.

E. *Performance parameters*

True Positive Rate (TPR), TNR and area under the curve is used to evaluate the performance of classification. Accuracy is not a good measure here due to the high-class imbalance of normal and ADHD training instances.

True positive rate (TPR) reflects the ability of the classifier to successfully identify the ADHD children, which is assigned a positive class (represented by 1). It measures the overall sensitivity of the model, using the predicted labels from classifier output as given below:

$$Sensitivity\ (TPR) = \frac{TP}{TP + FN} \qquad (2)$$

Similarly, True negative rate (TNR) or specificity measures the efficacy of the model in terms of its ability to correctly identify the children in the normal control group. It is evaluated as follows:

$$Specificity\ (TNR) = \frac{TN}{TN + FP} \qquad (3)$$

where, TN: True Negative, FP: False Positive and TP: True Positive.

Area under receiver operating characteristics curve (AUROC): The receiver operating characteristics curve is the standard method of estimating the classification efficiency on the imbalanced dataset. It avoids skew-sensitivity (due to imbalance) by summarizing the classifier over a range of FPRs and TPRs.

The area under the ROC is another important metric to represent imbalanced data. This curve can be understood as the likelihood that a random positive example will be ranked higher than a random negative example in the model [20].

III. Results

Automatic detection of ADHD using EEG signal is a widely explored area of research in lieu of cheap and simple acquisition of high-resolution data compared to other modalities like, functional magnetic resonance imaging (fMRI), computed tomography (CT), etc.

EEG recordings of 60 normal children and 60 ADHD under task conditions are utilized in this research to access the attention state of the subjects. The response time for each participant to complete the task is indicated by the variable length of EEG recording, as the appearance of the next image depends on the child's response to the current image. The average response time of normal and ADHD differ only by 0.5 min (30 sec). this can be seen in Fig.3 as the same region shared by both blue and red dots corresponding to the response time of normal controls and ADHD children, respectively.

Once the EEG signal is decomposed by DWPT and the relative energy of each sub-band is extracted. An SVM classifier is trained with features of each sub-band alone to find the dominance of a

Table 1. Performance of SVM with individual energy bands in feature space

Energy Bands	**Accuracy (%)**	**TPR (%)**	**TNR (%)**
Delta (δ)	76.0	78.1	57.3
theta (θ)	75.6	75.0	62.0
Alpha (α)	73.0	77.6	54.2
Beta (β1)	77.1	79.6	74.2
Beta (β2)	76.0	77.9	73.7
Gamma (γ)	88.7	90.5	86.3

Fig. 4 Area under the receiver operating characteristic curve

specific band in the classification task. The results obtained are tabulated using TPR and TNR along with the accuracy in Table. 1.

Subsequently, the classification performance is tested by combining all the features in the feature space and fed to the SVM classifier. This model outperformed the previous results obtained with individual energy bands in feature space. Fig. 4 shows the classifier output, achieved with combined features in feature space. Interestingly, the area under the curve is 0.99.

IV. Discussion

Automatic detection of ADHD in children is a challenging task due to the complex etiology of the disease itself. Moreover, a child's brain is not fully developed even in the case of normal controls. Therefore, a subtle difference in the electrical activity of the brain between the groups cannot be easily detected unless a well-defined protocol is set to capture the attention state. Additionally, a suitable set of features applied to the classifier play a major role to get accurate results.

In this work, the response time for every child to finish the visual CPT task, shown in Fig. 3, is evaluated. It is clear from Fig. 3 that the response time is not a good measure for discriminating the ADHD children and normal controls because there exists a considerable overlap in response time between the two groups. Very few among the ADHD children consumed more than average time to complete the task of counting the cartoon characters.

Classification results obtained in Table 1 indicate the contribution of each band to differentiate ADHD children from normal controls. The highest TPR corresponding to the gamma band energy feature show that 90% of ADHD children are correctly identified by the classifier. For instance, the relative energy in the high-frequency band i.e., beta1, beta2 and gamma effectively improves the classification performance. This is in line with the activation of high-frequency waves during mental tasks which represents the focused and attention state of the brain [21]. However, these features alone, are not sufficient to get the best efficiency. This means, that low-frequency bands also contribute to the classification of children as ADHD and normal. Although, these features alone are not effective when interacting with the relevant features, performed well.

The results of comparison of the present work with recent study is shown in Table 2.

Table 2. Comparison of the proposed model with a recent study on the same dataset.

Study	Dataset/Subjects	Most relevant Features	Window Size	Accuracy
Anika et. al [22]	120 subjects 48 ADHD 50 Normal	Complex PCA derived features (F*C*B =11*19*4)	2 sec	~94%
Proposed Model	Same 60 ADHD 60 Normal controls	Relative sub-band energy F*C*B=1*19*9	1 sec	95%

F: Features, C:channels, B: energy bands

V. Conclusion

The main aim of this research is to investigate a specific frequency band responsible for the accurate prediction of ADHD children using EEG during attentional tasks. Relative energy for each EEG sub-band is extracted by discrete wavelet packet decomposition to acquire finer resolution in individual bands. It is found that the group's differences are dominant in high-frequency bands, specifically, beta1, beta2, and gamma bands. These findings contradict the state-of-the-art results which report the alteration in alpha activity. Therefore, an emerging automatic feature extraction strategy (Deep learning) will be employed in the future in an attempt to achieve better classification and avoid the tedious job of feature engineering.

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