

Classification of attention deficit/hyperactivity disorder (ADHD) by extracting non-linear features of children's EEG

Ahmadreza Heidarpour^{1,a}, Mousa Shamsi^{1,a}, Faramarz Alsharif^{2,b}, Bruno Senzio-Savino^{2,c}, and Mohammad Reza Alsharif^{3,d}

¹Faculty of Electrical Engineering, Sahand University of Technology, Tabriz, Iran

³Graduate School of Engineering and Science, University of the Ryukyus, Okinawa, Japan

²Department of Information Engineering, Faculty of Engineering, University of the Ryukyus, Okinawa, Japan

E-mail: ^a{a_heydarpour, shamsi}@sut.ac.ir, ^bfaramarz_asharif@yahoo.com

^cb.senzio@gmail.com, ^dasharif@ie.u-ryukyu.ac.jp

Abstract: ADHD is the most frequent disorder in children. According to researchers, it is the most common disorder of childhood and detection of that is very important. In this study, database includes totally 30 subjects, of which 12 are the ADHD and the other 18 are healthy subjects. Using non-linear features, that selected by Wilcoxon test, we address the classification of both groups (healthy and hyperactive). In this paper, the support vector machine (SVM) classifier with 4 kernel function (Polynomial kernel_3, Multilayer perceptron(mlp), Radial basis function(rbf), and quadratic) is used.

Keywords: Attention deficit/hyperactivity disorder (ADHD), Entropy, Empirical mode decomposition (EMD), Wilcoxon test, Support vector machine(SVM).

1. Introduction

Typically, 3-5% of children in the school ages have ADHD [1], and man-woman ratio of it is 9:1[2]. There are various tests for evaluating both cognitive abilities and motor-mental functions of child, including Wender Utah Rating measurement [3,4], parent Karnes' questionnaire [3], and teacher Karnes'. Because of the variety of ADHD criteria, in which behavior reports are required from parents and teachers, patients will refer to a physician and she/he recognize this disorder. Using analysis of EEG signal to obtain those features being helpful scientifically and medically is a way to reach ADHD recognition.

In this study, using both non-linear features (EMD, entropy) and Wilcoxon test, significant relationships between two groups will be investigated. Then given features will be applied for classification task.

2. Methodology

In this paper, database includes totally 28 subjects, of which 12 are the ADHD and the other 18 are healthy subjects[5-8]. Our aim is classifying ADHD subjects from healthy by extracting non-linear features of EEG signals. For this purpose, we use support vector machine, SVM classifier with kernel functions as follows: Polynomial, mlp, rbf, and quadratic. Also, feature selection is based on Wilcoxon test. Four category of nonlinear features are extracted from EEG signals: signal entropy[9-14], EMD-IMF4[15] (entropy of intrinsic mode function in 4 level of empirical Mode Decomposition), EMD-IMF5, EMD-IMF6. Figure 1 demonstrates our proposed algorithm. As shown in Table 1, based on our proposed algorithm, the best achieved accuracy with polynomial-3 kernel for signal entropy, EMD-IMF4, EMD-IMF5 and EMD-IMF6 is 81%, 80.5%, 91% and 90.5%, respectively.

3. Results

The obtained results show that accuracy of the algorithm increases from signal entropy to EMD-IMF6. Due to the nature of EMD, IMFs would be ordered from highest frequency to lowest one. We could find some differences in entropy of two groups (healthy and ADHD) at low frequencies. Thus, the extracted features from low frequency components of signal will be so effective. Also, from Wilcoxon test, we could find that the significant differences between two groups is more high based on Shannon entropy at Channel T5 as well as sample entropy at Channel F4 (Table 2). Therefore, the disorder will affect more on this brain's area.

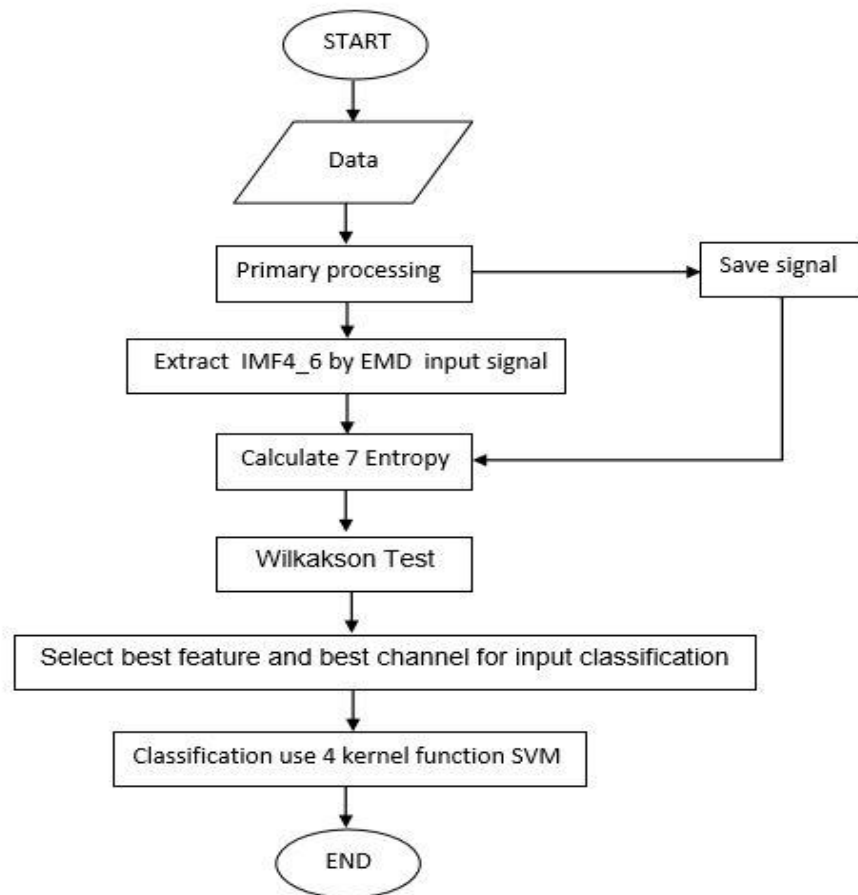


Figure 1: The Proposed algorithm.

Table 1: SVM classifier results based on 4 different categories of features and kernel functions.

Kernel Function	Signal Entropy	Entropy EMD-IMF4	Entropy EMD-IMF5	Entropy EMD-IMF6
Polynomial-3	81	80.5	91	90.5
RBF	76.7	81.2	90	93.2
MLP	75.45	81.6	83.5	91
Quadratic	77.6	80.01	85.7	90.3

Table 2: The best selected channels based on Wilcoxon test with threshold equals 0.02 (p_value).

		Channel
Entropy EMD-IMF5	Shannon Entropy	T5, F8
	Sample Entropy	F4,O1,Fz,C3,T3
Entropy EMD-IMF4	Shannon Entropy	Cz,T4,T5,F4,O1,F7,Fz,Fp2
	Sample Entropy	C3,T3,F4,P3,Fp2,Cz,F3,T5,T6,F7

4. Discussion

With due attention to various articles, we could find the correctness of our results about significant

area for both groups. The common property of these area are their role to cause impairment in the brain, and appearing other significant is itself as a reason for the way of signal record (at rest time)

and performance of both sample and Shannon entropy. For example, in [16], Swartwood et al. Through studying 46 healthy and ADHD subjects with evaluation test of attention (To Vo) calculated that in subjects with ADHD at area O2, T 6, T 5 in open eyes mode, much more alpha will be observed. Also, alpha production encoding condition at T5 is different from two groups.

In this study, Sohen et al. [17] imposed EEG signal approximate entropy of healthy and ADHD subjects, and found that average approximate entropy in patients with ADHD at FP2 and FP8 is much less than that of healthy ones; thus, we could conclude that there is a highest significant relationship between these entropy and these area.

5. Conclusion

Using non-linear features obtained from EEG signals of both healthy and ADHD children's brain, classification was done, and average hundred bar of training and random experiment for rbf kernel function (92.2%) was obtained, that with due attention to the classification results, we found the most differences between two groups at low frequencies.

6. References

- [1] W. Pelham, E. Gnagy, K. Greenslade and R. Milich, "Teacher ratings of DSM-III- R symptoms for the disruptive behaviour disorders", *J Am Acad Child Adolesc Psychiatry*, Vol. 31, pp. 210–218, 1992.
- [2] A. James, E. Taylor, "Sex differences in the hyperactive syndrome of child-hood", *J Child Psychol Psychiatry*, Vol. 31, pp. 43–446, 1990
- [3] R. A. Barkley, "hyperactive children: A handbook for diagnosis and treatment ", 2nd ed, New York: Guilford Press, 1982
- [4] M. F. Ward, P. H. Wender and F. W. Reimherr, "The Wender Utah Rating Scale: an aid in retrospective diagnosis of childhood attention deficit hyperactivity disorder", *Am J Psychiatry*, Vol. 150, pp. 885- 90, 1993.
- [5] M. Ahmadlou and H. Adeli, "Fuzzy Synchronization Likelihood with Application to Attention-Deficit/Hyperactivity Disorder", *Clinical EEG and Neuroscience*, vol. 42, pp. 6-13, 2011.
- [6] M. Ahmadlou and H. Adeli, "Wavelet-Synchronization Methodology: A New Approach for EEG-Based Diagnosis of ADHD", *Clinical EEG and Neuroscience*, vol. 41, pp. 1-10, 2010.
- [7] M. Ahmadlou and H. Adeli, "Functional community analysis of brain: A new approach for EEG-based investigation of the brain pathology", *NeuroImage*, vol. 58, pp. 401–408, 2011.
- [8] M. Ahmadlou, R. Rostami and V. Sadeghi, "Which attention-deficit/hyperactivity disorder children will be improved through neurofeedback therapy? A graph theoretical approach to neocortex neuronal network of ADHD", *Neuroscience Letters*, vol. 516, pp. 156–160, 2012.
- [9] V. A. Unakafova and K. Keller, "Efficiently measuring complexity on the basis of real-world data," *Entropy*, vol. 15, pp. 4392-4415, 2013.
- [10] Y. Zhang and L. Wu, "Optimal multi-level thresholding based on maximum Tsallis entropy via an artificial bee colony approach," *Entropy*, vol. 13, pp. 841-859, 2011.
- [11] X. Liu, A. Jiang, N. Xu, and J. Xue, "Increment entropy as a measure of complexity for time series," *Entropy*, vol. 18, p. 22, 2016.
- [12] A. H. Darooneh, G. Naeimi, A. Mehri, and P. Sadeghi, "Tsallis entropy, escort probability and the incomplete information theory," *Entropy*, vol. 12, pp. 2497-2503, 2010.
- [13] R. Sharma, R. B. Pachori, and U. R. Acharya, "Application of entropy measures on intrinsic mode functions for the automated identification of focal electroencephalogram signals," *Entropy*, vol. 17, pp. 669-691, 2015.
- [14] S.-D. Wu, C.-W. Wu, S.-G. Lin, C.-C. Wang, and K.-Y. Lee, "Time series analysis using composite multiscale entropy," *Entropy*, vol. 15, pp. 1069-1084, 2013.
- [15] N. E. Huang and Z. Wu, "A review on Hilbert-Huang transform: Method and its applications to geophysical studies," *Reviews of Geophysics*, vol. 46, 2008.
- [16] J.N. Swartwood, M. O. Swartwood, J. F. Lubar and D. L. Timmermann, "EEG Differences in ADHD-Combined Type during Baseline and Cognitive Tasks", *Pediatric Neurology*, Vol. 28 No. 3, pp. 199-204, 2002.
- [17] H. Sohn, L. Kim, W. Lee, B. S. Peterson, J. H. Chae, S. Hong, S," Linear and non-linear EEG analysis of adolescents with attentiondeficit/hyperactivity disorder during a cognitive task", *Clinical Neurophysiology*, Vol. 121, pp. 1863-1870, 2010.