Detection of Dyslexia Using EEG Signal Decompositional technique: Variational mode decomposition and derivatives

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***Abstract*—Dyslexia is a common, specific learning disability that is influenced by neurobiological, genetic, and environmental factors, affecting individuals' ability to read and spell. Unlike its historical definition, DSM-5 classifies dyslexia as a type of neurodevelopmental disorder and emphasizes its hereditary and lifelong nature. The use of EEG signals instead of cognitive tests is explored for dyslexia assessment in this study. Processing EEG data can help identify changes in brain activity before and after treatment, providing valuable information about the effectiveness of interventions. This study compared three different Variational Mode Decomposition (VMD) algorithms to detect improvement in dyslexia using EEG data. The results showed that these algorithms could significantly contribute to determining improvement in dyslexia and that the VMD and Multivariate Variance Mode Decomposition (MVMD) algorithms worked more precisely and stable than the Successive Variance Mode Decomposition (SVMD) algorithm in diagnosing dyslexia and monitoring treatment.**

Keywords— Variational Mode Decomposition; Multivariate Variational Mode Decomposition; Successive Variational Mode Decomposition; electroencephalogram (EEG) signal processing; Dyslexia detection.

INTRODUCTION

Developmental dyslexia (DD) is a neurological condition characterized by educational difficulties in learning processes such as reading and writing, despite normal intelligence and adequate opportunities [1]. Dyslexia can significantly affect the academic achievement and quality of life of affected individuals. However, early diagnosis and individualized interventions can make a significant difference in the development of these individuals. Traditionally, the diagnosis of dyslexia was based on behavioral symptoms and aspects evaluated by psychologists. Although this diagnostic method is useful, it can be time-consuming and may not always provide a comprehensive understanding of the underlying neurological mechanisms. In recent years, researchers have explored the potential for using electroencephalogram (EEG) signal processing and analysis to facilitate dyslexia diagnosis. EEG signals can provide information about the brain's electrical activity, which can reveal patterns or abnormalities associated with dyslexia. Analysis of EEG data has been facilitated by the development of advanced signal processing techniques such as Empirical Mode Decomposition (EMD) and Variational Mode Decomposition (VMD). These methods have shown promise in extracting relevant features from EEG data that can then be used to diagnose and monitor dyslexia. In this study, researchers investigated the potential of advanced VMD algorithms such as Multivariate VMD (MVMD) and Sequential VMD (SVMD) to improve the processing of EEG signals and potentially increase the accuracy of dyslexia diagnosis. These algorithms are developed to overcome the limitations of the original VMD method such as noise sensitivity and processing speed [2-5]. In this study, we aim to investigate the potential of these advanced VMD algorithms in detecting the effectiveness of dyslexia treatment using EEG data. Specifically, we will process pre- and post-treatment EEG data of 11 children diagnosed with dyslexia using VMD, MVMD, and SVMD algorithms. By comparing the performances of these algorithms, we seek to determine whether the improved algorithms provide advantages over the original VMD method in the context of dyslexia diagnosis. This research may contribute to the development of more accurate and effective diagnostic tools for this condition, ultimately leading to better support and interventions for individuals with dyslexia.

A. Objectives

The main aims of this study are:

- To evaluate the performance of VMD, MVMD, and SVMD algorithms in processing EEG data of individuals with dyslexia.

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- To determine whether the improved MVMD and SVMD algorithms provide an advantage over the original VMD algorithm in detecting improvement in dyslexia.
- To investigate the potential of using EEG-based analysis facilitated by advanced signal processing techniques as a complementary approach to traditional behavioral assessments in detecting improvement in dyslexia.
- By addressing these objectives, the study aims to contribute to the development of more accurate and effective diagnostic tools for dyslexia, ultimately leading to better support and interventions for affected individuals.

This study is important for dyslexia research and diagnosis. It is aimed to determine whether advanced signal processing techniques such as MVMD and SVMD have the potential to contribute to the development of more accurate and effective diagnostic tools. The aim is to achieve the potential for earlier identification of dyslexia using EEG-based analysis as a complementary approach to traditional behavioral assessments. Comparative analysis of different VMD algorithms can guide research that shares this goal and provides impetus toward improving diagnostic methods.

MATERIALS AND METHOD

A. Subjects & Experimental Data

The clinical experiment that examined the beneficial effects of the Auto Train Brain yielded data from 11 children with pure dyslexia that are utilized in this study [6, 7]. Before the experiment, all participants provided their informed consent after being fully informed about the experimental technique following the guidelines set forth by the study ethics committee. Throughout the investigations, the EMOTIV EPOC-X headgear is utilized. The internal sampling rate of the headset is 2048 samples per second for each channel. The data is down-sampled to 128 samples per second per channel after significant artifacts are removed using filtering. In total, there are 14 EEG channels (AF3, F3, F7, FC5, T7, P7, O1, O2, P8, T8, FC6, F8, F4, and AF4) and 2 reference channels. The EMOTIV Headset is calibrated on the subjects' scalps using the EMOTIV APP before the investigations, and each electrode is examined to ensure that high-quality EEG data transmission is occurring. Each participant has used Auto Train for six months, had thirty minutes of visual and auditory neurofeedback, and had their brain waves measured using the EMOTIV EPOC-X across fourteen channels. Before each neurofeedback session, the 2-minute resting-state eyes-open EEG measures were obtained.

In this study, we assessed spontaneous EEG data obtained before neurofeedback sessions on Day 1 (the first day) and Day 60 (the sixtieth day) of the Auto Train Brain system used by 11 dyslexic children. To reduce power line interference and other disturbances, a Butterworth band-pass filter with a [0.5–40] Hz cutoff frequency is applied to each channel. The EEG data for each channel is additionally divided into 5-second segments. VMD technique and its variants-- MVMD and SVMD-- are then used to process the EEG data. The VMD algorithm separates input signals into modes. Its key features are sparsity characteristics, one-sided frequency spectrum, and baseband transition. VMD is useful for signal processing and adaptive mode determination [8-12]. MVMD extends VMD to multivariate datasets. Extracts multivariate modulated oscillations while minimizing bandwidth. MVMD is effective for EEG data and bivariate cardiotocographic signals [13]. SVMD decomposes signals into modes with unknown mode counts. Iterative steps update frequencies, amplitudes, and center frequencies. It is useful for separating oscillation modes in multivariate data [5].

B. Feature Extraction

Time-domain, Spectral-domain, and Non-Linear features are calculated from EEG signals processed with VMD, and derivative algorithms. We employed time domain metrics that are commonly used in the literature, including mean, skewness, kurtosis, energy, median absolute deviation (MAD), root mean square (RMS), peak-to-peak (PTP), and Hjorth (Activity (HA), Mobility (HM), Complexity (HC)) [14-17]. In addition, total power (Pow), delta, theta, alpha, beta, and gamma band powers, spectral entropy (SE), and moments (mo1, mo2, mo3) are calculated as spectral features from the frequency domain of the signal [18-19]. Due to their non-linear character, EEG signals are complex. It is occasionally possible to get insignificant results with the time-domain and spectral-domain features. The calculation of non-linear features is therefore done in our work as well, including the Hurst Exponent (HE), Lyapunov exponent (LLE), Higuchi Fractal Dimension (HFD), Katz Fractal Dimension (KFD), Correlation Dimension (CD), and Approximate Entropy (ApEn) [12-13].

C. Classification and Performance Evaluations

Following the previously mentioned feature extraction techniques, the Gun1 and Gun60 EEG segments of dyslexic patients are identified using a variety of machine learning algorithms, such as Decision Tree (DT), k-nearest Neighbor (kNN), and Bagged Tree (BT). The performance of the classifiers is assessed in this study using the following performance criteria: sensitivity (SEN), specificity (SPE), precision (PRE), and accuracy (ACC). The k-fold cross-validation (CV) approach has been used to assess the classifiers' efficacy and produce coherent classification accuracy [20].

RESULTS AND DISCUSSION

In this study, 14-channel EEG signals of 11 dyslexic children are examined using VMD, SVMD, and MVMD methods, and It was aimed to distinguish the EEG segments recorded on the first day (Day1) and the 60th day (Day60) of using the Auto Train the Brain system. Time-domain, spectral-domain, and non-linear feature sets are produced utilizing the extracted modes of the VMD, SVMD, and MVMD techniques as well as the raw EEG signal after the mod extraction process. Finally, three specific classifiers—DT, kNN, and BT—are used to detect the Day1 and Day60 EEG segments of dyslexic children.

TABLE I. PERFORMANCE EVALUATION RESULTS OF THREE DIFFERENT APPROACHES AND FEATURE SETS

		DT				KNN				BT			
		SEN	**SPE**	**PRE**	**ACC**	**SEN**	**SPE**	**PRE**	**ACC**	**SEN**	**SPE**	**PRE**	**ACC**
TimeF	**VMD**	80.48	74.47	80.29	78.82	73.65	66.31	74.70	***72.31***	88.40	78.44	85.51	85.47
	SVMD	78.80	71.13	78.37	76.20	76.06	64.18	74.23	72.06	85.72	73.60	81.78	81.56
	MVMD	82.07	76.69	82.09	***80.22***	74.86	64.33	74.61	71.71	89.43	79.52	86.76	***86.35***
	EEG	76.39	68.00	76.32	73.80	68.71	52.56	66.82	63.84	82.27	70.11	80.35	78.62
SpectF	**VMD**	82.14	75.62	81.90	80.10	74.31	65.38	74.86	72.18	89.61	77.79	85.98	85.74
	SVMD	76.76	68.42	76.21	74.02	73.75	63.81	72.97	71.06	84.07	73.71	81.52	80.78
	MVMD	82.08	76.47	82.91	80.56	74.27	66.41	75.04	***72.38***	89.35	79.75	87.10	***86.37***
	EEG	83.47	76.94	83.26	***81.28***	69.15	51.53	66.39	63.39	88.17	79.11	85.81	85.06
NonLF	**VMD**	79.06	72.27	79.29	***76.93***	74.69	65.60	75.14	72.33	89.04	74.85	84.05	***84.19***
	SVMD	74.66	64.41	73.57	71.21	73.40	58.03	70.56	68.32	82.88	65.97	77.97	77.25
	MVMD	79.31	69.62	77.69	75.89	73.69	64.75	73.94	71.29	87.35	74.77	83.74	83.33
	EEG	78.57	68.36	77.18	75.17	76.63	67.35	76.84	***73.96***	82.80	71.51	80.78	79.19

The average classification results of three signal decomposition techniques, a case of no decomposition (EEG), and three different classifiers for the time-domain, spectral-domain, and non-linear feature sets are shown in Table 1. The average classification results of the combined feature set of the extracted modes of the VMD, SVMD, and MVMD techniques are provided in the table, and results in which there is no decomposition are indicated by "EEG". It has been noted that the MVMD approach produces the highest classification performance with the BT classifier to separate two classes for time-domain (86.35% ACC, 89.43% SEN, 79.52% SPE, and 86.76% PRE), and spectral-domain (86.37% ACC, 89.35% SEN, 79.75% SPE, and 87.10% PRE) feature sets. On the other hand, the VMD technique yields the highest classification performances (84.19% ACC, 89.04% SEN, 74.85% SPE, and 84.05% PRE) for the non-linear feature set. Conversely, the SVMD method provided the lowest classification performances across all decomposition techniques. Notably, for all classifiers and approaches, the time domain and spectral feature sets yielded better classification performances.

To offer a more detailed examination, Fig.1. displays box plots of the ACC values for 11 dyslexic children for various feature sets and methods obtained using the BT classifier. Here, the classification accuracies for feature combinations that are calculated from all modes extracting using the VMD, SVMD, and MVMD algorithms are given for the pertinent techniques. It is noteworthy that for 3 feature sets and all subjects, VMD and MVMD algorithms provide higher classification accuracy than SVMD and EEG. The fact that the SVMD approach, except the spectral feature, offers nearly the same classification accuracy as EEG. Actually, for the spectral feature set, EEG offered better classification accuracy.

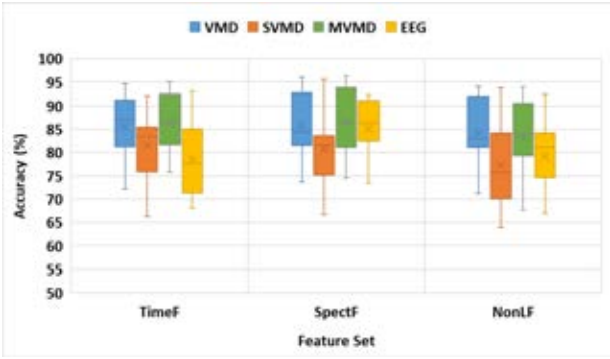


Fig. 1. Box plots showing each subject's accuracy trends for various feature sets and approaches.

To investigate the effectiveness of decomposition methods, the individual classification performances of all modes are compared with the classification performances of their combinations (given in Fig.2). Algorithms VMD and MVMD offer five modes, while SVMD offers three. For this reason, in the comparisons, classification accuracy is provided for three modes and combinations for SVMD, but classification accuracy is provided for five modes and combinations for VMD and MVMD. Modes 1, 2, 3, 4, and 5 in these figures indicate that the appropriate Mode is used to calculate the features for classifications, whereas Modes 1–5 and Modes 1–3 indicate that all Modes are used to extract the features. Although the classification performance of Modes increased for all methods after Mode 1, the highest classification performance is obtained from the combination of modes (VMD: for TimeF 72.14%~94.64%, SpectF 73.77~96.00, NonLF 71.25~94.05; SVMD: for TimeF 66.25%~92.14%, SpectF 66.62~95.60, NonLF 63.93~93.81; MVMD: for TimeF 75.71%~95.08%, SpectF 74.58~96.21, NonLF 67.68~93.88).

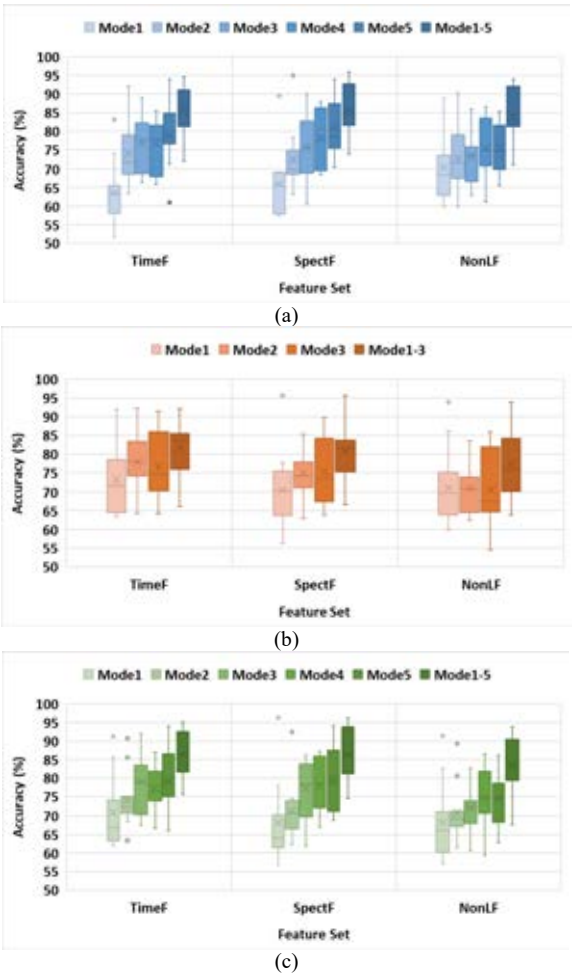


Fig. 2. Boxplots displaying the accuracy trends for each subject for the three techniques' different feature sets and extracted modes. For; (a) VMD, (b) SVMD, and (c) MVDM

CONCLUSION

In this study, to discriminate between the Day 1 and Day 60 EEG signals of dyslexic children, several strategies based on Variational mode decomposition techniques and derivatives have been developed. The extracted modes and their combinations of VMD, SVMD, and MVMD methods are used to compute the time domain (mean, skewness, kurtosis, energy, MAD, RMS, PTP, HA, HM, HC), spectral domain (total power, delta, theta, alpha, beta, and gamma band powers, SE, and mo1, mo2, mo3), and non-linear (HE, LLE, HFD, KFD, CD, and ApEn) features. Classification results showed that the VMD and MVMD method is superior to the SVMD method. On the other hand, the classification performance of the same features obtained from EEG is lower than that of VMD and MVMD methods. This shows that VMD and MVMD methods are successful in evaluating the effectiveness of the Auto Train Brain system on dyslexia.

REFERENCES

[1] R. Peterson, and B. Pennington, "Developmental dyslexia," Lancet, 379, pp. 1997–2007, 2012.

[2] E. Zerbin-Rüdin, "Kongenitale wortblindheit oder spezifische dyslexie (congenital word-blindness)," Annals of Dyslexia, vol. 17(1), pp. 47–54, 1967.

[3] J. M. Fletcher, G.R. Lyon, L.S. Fuchs, and M.A. Barnes, "Learning disabilities: From identification to intervention," Guilford Press, 2006.

[4] DyslexiaSpel., "Consultations/assessment—tests for dyslexia," 2014.

[5] M. Nazari, and S.M. Sakhaei, "Successive variational mode decomposition," Signal Processing, vol. 174, 2020.

[6] G. Eroğlu, and F. Arman, "k-Means clustering by using the calculated Z-scores from QEEG data of children with dyslexia," Applied Neuropsychology: Child, vol. 12(3), pp. 214-220, 2023.

[7] G. Eroglu, M. Köprülü, and B. Karabacak, "Dyslexia biomarker detection with QEEG data in children: Feasibility, Acceptability, Economic impact, Pilot Study and Survey Results," Qeios, pp. 1-19, 2022.

[8] MathWorks. (n.d.). Variational mode decomposition. Retrieved from https://www.mathworks.com/help/wavelet/ref/vmd.html

[9] H. Li, F. Zhou, B. Xu, B., Yan, B., and F. Zhou, "Application of Auto-Regulative Sparse Variational Mode Decomposition in Mechanical Fault Diagnosis. Electronics," vol. 12(14), 3081, 2023. https://doi.org/10.3390/electronics12143081

[10] K. Dragomiretskiy, and D. Zosso, "Variational mode decomposition. IEEE Transactions on Signal Processing," vol. 62(3), pp. 531-544, 2014. https://doi.org/10.1109/TSP.2013.2288675

[11] N. U. Rehman, and H. Aftab, "Multivariate variational mode decomposition," IEEE Transactions on Signal Processing, vol. 67(23), pp. 6039-6052, 2019. https://doi.org/10.1109/TSP.2019.2951223

[12] Y. Li, Y. Zhou, and S. Jiao, "Variable-Step Multiscale Katz Fractal Dimension: A New Nonlinear Dynamic Metric for Ship-Radiated Noise Analysis," Fractal and Fractional, vol. 8(1), 9, 2023. 10.3390/fractalfract8010009.

[13] D. O. W. Pacheco-Ortega, A. Moreno-Gomez, M. A. Perez-Lara-y-Hernandez, J. P. Amezquita-Sanchez, "Fractal dimension-based methodology for detecting and quantifying the severity of fatigue cracks in a four-story structure," In 2018 XIV International Engineering Congress (CONIIN), pp. 1-7, 2018, Queretaro, Mexico. https://doi.org/10.1109/CONIIN.2018.8489806

[14] J. Xiang, E. Maue, Y. Fan, L. Qi, F.T. Mangano, H. Greiner, and J. Tenney, Kurtosis and skewness of high-frequency brain signals are altered in pediatric epilepsy," Brain Communications, vol. 2(1), 2020. https://doi.org/10.1093/braincomms/fcaa036

[15] X. Yong, R. K. Ward, and G. E. Birch, "Robust Common Spatial Patterns for EEG signal preprocessing," Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual International Conference, pp. 2087–2090, 2008. https://doi.org/10.1109/IEMBS.2008.4649604

[16] P. Tesic, and S. Jovanovic, and M. Dick, "Analysis of vehicle/track interaction measurement data using the V/TI Monitor system," Gradjevinar, vol. 70(02), pp. 105-119, 2018.

[17] T. Cecchin, R. Ranta, L. Koessler, O. Caspary, H. Vespignani, L. Maillard, "Seizure lateralization in scalp EEG using Hjorth parameters", Clinical Neurophysiology, vol. 121, pp.290–300, 2010

[18] P. Welch, "The use of fast Fourier transform for the estimation of power spectra: A method based on time averaging over short, modified periodograms," IEEE Transactions on Audio and Electroacoustics, vol. 15(2), pp. 70-73, 1967. https://doi.org/10.1109/TAU.1967.1161901.

[19] J. S. Richman, and J. R. Moorman, "Physiological time-series analysis using approximate entropy and sample entropy," American journal of physiology. Heart and circulatory physiology, vol. 278(6), H2039–H2049, 2000. https://doi.org/10.1152/ajpheart.2000.278.6.H2039

[20] O. K. Cura, S. K. Atli, and A. Akan, "Attention deficit hyperactivity disorder recognition based on intrinsic time-scale decomposition of EEG signals," Biomedical Signal Processing and Control, vol. 81, 104512, 2023