A Dynamic Mode Decomposition Based Approach for Epileptic EEG Classification

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***Abstract*—Epilepsy is a neurological disorder that affects many people all around the world, and its early detection is a topic of research widely studied in signal processing community. In this paper, a new technique that was introduced to solve problems of fluid dynamics called Dynamic Mode Decomposition (DMD), is used to classify seizure and non-seizure epileptic EEG signals. The DMD decomposes a given signal into the intrinsic oscillations called modes which are used to define a DMD spectrum. In the proposed approach, the DMD spectrum is obtained by applying either multi-channel or single-channel based DMD technique. Then, subband and total power features extracted from the DMD spectrum and various classifiers are utilized to classify seizure and non-seizure epileptic EEG segments. Outstanding classification results are achieved by both the single-channel based (96.7%), and the multi-channel based (96%) DMD approaches.**

***Index Terms*—Dynamic mode decomposition (DMD), epileptic EEG classification, DMD spectrum**

I. Introduction

Epilepsy is defined as the excessive and instant electrical discharges of the neurons, and it influences at least 50 million people all around the world as reported by the World Health Organization (WHO) in 2005 [1]. Considering the fact that imaging is an expensive and time consuming procedure, electroencephalography (EEG) is one of the mostly used techniques to detect epilepsy. EEG captures the electrical activity of the brain via electrodes [2]. In 1958, the International Federation in Electroencephalography and Clinical Neurophysiology accepted 10-20 electrode placement system as a standard. Electrode names are given in accordance with the brain regions as (F) frontal, (C) central, (O) occipital, (T) temporal and (P) posterior. Since functions of the brain are related to different areas, electrodes are placed near them [3].

Features extracted from EEG signal may be used for the diagnosis of neurological and physiological disorders. There are many approaches for feature extraction which can affect the detection accuracy [4]. Fourier Transform (FT) is widely used as the feature extraction algorithm, however, FT assumes that the analyzed signal is stationary, but EEG signals are not. Since FT only reveals frequency information [5], time-frequency based methods were introduced such as Short-Time Fourier Transform (STFT), and Wavelet Transform (WT). While STFT provides local analysis using a single window, WT uses several filters to introduce a multi-resolution analysis [6], [7]. Empirical Mode Decomposition (EMD) was introduced as a data-driven technique that decomposes the signal into Intrinsic Mode Functions (IMFs) which are zero-mean oscillations [4], [8].

There exist several studies on the detection and classification of epilepsy using EEG signals in the literature. One of the most essential steps in this problem is the extraction of useful features from the data to achieve high classification accuracy. In accordance with this purpose, several methods have been proposed, and performances of the approaches were compared. Yamaguchi indicated that the success of WT over FT to obtain local low frequency characteristics from Power Spectral Density (PSD) of epileptic EEG signals [9] is similar to the performance of WT over STFT using subband activities mentioned in a paper published by Kıymık et al [6]. Alickovic et al. compared Wavelet Packed Decomposition (WPD), Discrete WT (DWT) and EMD for epileptic EEG signal classification using spectral features and concluded that WPD yields better results than EMD [10]. As a new technique Kutz et al. used the Dynamic Mode Decomposition (DMD) on neural recordings by performing Hankelisation process to Electrocortiogram (ECoG) signals in order to detect sleep spindle networks [11]. In another study, DMD algorithm is applied on EEG signals, using DMD powers and curve lengths to distinguish seizure and seizure free EEG signals [12].

In this paper, a new approach that utilizes DMD algorithm is proposed to differentiate seizure and non-seizure epileptic

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EEG signals. A new pre-processing technique utilizing single channel EEG recordings with Hankelisation process is introduced for constructing the data matrix for DMD algorithm. DMD Spectrum is calculated and used to extract novel features for classification.

II. Materials and Methods

In the proposed study, classification of pre-seizure and seizure EEG segments is performed using a Dynamic Mode Decomposition based approach. Epileptic EEG signals of 16 epilepsy patients, recorded from 18 channels (Fp1-F7, F7-T1, T1-T3, T3-T5, T5-O1, Fp1-F3, F3-C3, C3-P3, P3-O1, Fp2-F8, F8-T2, T2-T4, T4-T6, T6-O2, Fp2-F4 F4-C4, C4-P4, P4-O2) with 10ms sampling rate that were labeled as pre-seizure and seizure segments by expert neurologists of İzmir Katip Çelebi University, were used. Ethical approval was obtained to use these EEG signals in various signal processing studies. Using the dynamic modes of the signals obtained by the DMD algorithm, DMD spectral subbands powers of pre-seizure and seizure EEG segments were calculated as features. Decision Tree (DT), Logistic Regression (LR), Naive Bayes (NB), K-Nearest Neighbor (KNN), and Support Vector Machine (SVM) are utilized to classify the features.

A. Proposed DMD Based Approach

The dynamic mode decomposition (DMD) algorithm which was proposed for the solution of problems encountered in fluid flow analysis by Schmidt, is a matrix decomposition method [13], [14]. By using the DMD algorithm, the state of a non-linear and dynamic system at a future instant in time may be predicted [15]. Fundamental approach is to linearize the system using a Least Squares (LS) approximation. Then the eigenvalues and eigenvectors of the system are obtained to decompose the given signal into dynamic modes. In addition to flow studies, the DMD algorithm has recently been implemented to analyze biological signals with encouraging results [11], [12], [15].

Using multichannel recordings, $N \times M$ EEG data matrices, are used to analyze biological signals by the DMD method. Here M denotes the number of time samples called 'snapshot', N is the number of channels [12]. However, EEG signals recorded from different channels will provide different classification performance according to the epileptic focus centers. Therefore, in our proposed study, we introduce a method to obtain $N \times M$ EEG data matrices from a single EEG channel (single-channel DMD approach). The performance of the proposed single-channel DMD approach is also compared with that of the multi-channel DMD approach used in the literature, using the EEG signals recorded from the channels in the right-, left-hemisphere, and both hemispheres.

B. Dynamic Mode Decomposition

The following two approaches are introduced in our study to obtain the EEG data matrices for the DMD algorithm.

$i)$ **Single-channel based approach:** Let $Y = [y_1, y_2, \ldots, y_{T-1}]$ is the $T = 700$ samples long EEG signal recorded from a single channel. $M = 140$ samples long (1.4 sec) EEG segments with no overlap were obtained using this single-channel EEG signal. $N \times M = 5 \times 140$ size EEG data matrices were generated using these EEG segments.

$ii)$ **Multi-channel based approach:** Using $L = 5$ EEG channels together, $L \times M = 5 \times 140$ size EEG data matrices with no overlap were generated. This procedure is repeated by using 5 channel EEG signals recorded from the left hemisphere (Fp1-F7, F7-T1, T1-T3, T3-T5, Fp1-F3), and 5 channel EEG signals recorded from the right hemisphere (Fp2-F8, F8-T2, T2-T4, T4-T6, Fp2-F4). In addition, using 10 channel EEG signals recorded from both hemispheres, 10×120 size data matrices were obtained.

To get sufficient number of modes to fully capture the dynamics of neurological activity, data augmentation method based on the Hankelization principle described in [11], [14] was applied. Then, augmented EEG data matrices X_a with $K \times L = 200 \times 100$ dimension were obtained. The steps of the proposed DMD approaches are given in the following.

$$X_a = \begin{bmatrix} \vdots & \vdots & \ldots & \vdots \\ x_1 & x_2 & \ldots & x_{L-1} \\ \vdots & \vdots & \ldots & \vdots \end{bmatrix} X'_a = \begin{bmatrix} \vdots & \vdots & \ldots & \vdots \\ x_2 & x_3 & \ldots & x_L \\ \vdots & \vdots & \ldots & \vdots \end{bmatrix}$$

A linear relationship shown in (1) can be written between X_a and X'_a which is a shifted version of X_a in time.

$$X'_a = AX_a \tag{1}$$

where A is a transition matrix. The singular value decomposition (SVD) of the augmented EEG data matrix $X_a = U\Sigma V^*$ is calculated, and (1) may be rewritten as,

$$X'_a = AU\Sigma V^*. \tag{2}$$

By using the left singular vectors U, the inverse of the singular values Σ^{-1}, and the Right singular vectors V, the approximate value $\tilde{A}$ of the transition matrix A may be defined as,

$$\begin{aligned} A = X'_{aug}X_a^+ = X'_a V\Sigma^{-1}U^* \\ \tilde{A} = U^*AU \\ \tilde{A} = U^*X'_a V\Sigma^{-1}U^*U \\ \tilde{A} = U^*X'_a V\Sigma^{-1} \end{aligned} \tag{3}$$

The eigendecomposition of $\tilde{A}$ is obtained using the matrix of eigenvectors (W), and the diagonal matrix (Ω) of DMD modes eigenvalues (λ_m).

$$\tilde{A}W = W\Omega \tag{4}$$

Finally, the matrix of DMD modes, Φ is calculated. Each column of Φ contains the DMD mode ϕ_m, corresponding to eigenvalue λ_m [11], [12], [15],

$$\Phi = X_a' V \Sigma^{-1} W. \tag{5}$$

C. The DMD Spectrum

To obtain the **DMD Spectrum**, oscillation frequencies and mode power of the dynamic modes are used. The oscillation frequencies f_m of the dynamic modes are calculated using the imaginary part of complex eigenvalues λ_m as shown in (6). Note here that, multiple modes may be obtained having the same oscillation frequency f_m. We define "the oscillation frequency set" which contains the frequency information of all modes as $F_{DMD} = \{f_m\}$. Each mode frequency value is used once to obtain the set. Mode powers P_m are calculated as the norm-square of the modes as shown in eq. (6) [11], [12], [15].

$$\begin{aligned} f_m &= |imag(\frac{\omega_m}{2\pi})| \\ P_m &= ||\phi_m||^2 \end{aligned} \tag{6}$$

Here, f_m denotes the oscillation frequency (Hz) of the m^{th} DMD mode, $\omega_m = \frac{log(\lambda_m)}{\Delta t}$, $\Delta t = 0.01$ is the time difference between sequential snapshots, $imag(.)$ denotes the imaginary part of a complex number, and $||.||^2$ is the Euclidian norm.

In the DMD method, it is not necessary to obtain one mode at each frequency value. There may be more than one mode, as well as no mode at some frequencies. In other words, oscillation frequencies do not have a uniform distribution as in the case of traditional Fourier spectrum [15]. Therefore, in order to obtain a single power value for each frequency, DMD powers at the same frequency are added as,

$$P_{DMD}(f_m) = \sum_{i=1}^{L_k} P_m^i(f_m) \qquad \forall \{f_m\} \in F_{DMD}. \tag{7}$$

where $P_m^i(f_m)$ is the i^{th} element of DMD power vector $P_m(f_m)$ at the frequency f_m, $L_f m$ is the length of DMD power vector $P_m(f_m)$, and $P_{DMD}(f_m)$ is the sum of DMD powers at the frequency f_m.

The DMD Spectrum is obtained by plotting the $P_{DMD}(f_m)$ vector which contains a single power value for each frequency with respect to the oscillation frequency vector F_{DMD}. Example of DMD spectra obtained for the pre-seizure and seizure epileptic EEG data matrices are shown in Fig. 1.

D. Feature Extraction

Using the DMD spectrum, Subband Powers (Delta (P_δ), Theta(P_θ), Alpha (P_α), Beta(P_β), and Gama (P_γ)) and Total Power (P_T) were calculated as features.

$$\begin{aligned} P_\delta &= \sum_{f_m=0}^{4} P_{DMD}(f_m); \qquad P_\theta = \sum_{f_m=4}^{8} P_{DMD}(f_m) \\ P_\alpha &= \sum_{f_m=8}^{13} P_{DMD}(f_m); \qquad P_\beta = \sum_{f_m=13}^{30} P_{DMD}(f_m) \\ P_\gamma &= \sum_{f_m=30}^{50} P_{DMD}(f_m); \qquad P_T = \sum_{f_m=0}^{50} P_{DMD}(f_m) \end{aligned} \tag{8}$$

where, $P_{DMD}(f_m)$ indicates the value of the DMD Spectrum at frequency value f_m (in Hz), $\forall f_m \in F_{DMD}$.

Also, to compare the success of our proposed DMD approaches, Subband Powers and total power were calculated using the Power Spectral Density (PSD) obtained by the Welch method. Welch method applied using a Hamming window and an overlap of 50% [16]–[19].

III. Classification and Performance Evaluation

In the proposed DMD approaches, various classifiers; Support Vector Machine (SVM), K-Nearest Neighbours (K-NN), Naïve Bayes (NB), and Logistic Regression (LR) were used to classify the features obtained from pre-seizure and seizure epileptic EEG segments.

The SVM, which is the supervised learning method, works according to the decision boundaries determination principle called 'hyperplanes' which can distinguish classes optimally from each other [20], [21]. In the KNN classification algorithm, the distance between the sample to be classified and k neighbor is calculated. Then, this sample is assigned as an element of the class which includes more neighbors with a short distance. In the proposed experiment, k=10 neighbor was chosen and Euclidean distance used for calculation of distance [22]. Naive Bayes classifier, on the other hand, performs classification processes based on a probabilistic basis according to Bayes theorem. The probability of membership of the sample wanted to be classified is calculated separately for all classes. The sample is assigned as a member of the class with a high probability of membership [22].Logistic regression (LR) is one of the most commonly used statistical classification methods that produce two outputs such as yes/no, on / off, or 1/0 [23].

In addition, Accuracy (ACC) and 5-fold Cross-Validation (CV) methods were used to evaluate the performance of our approaches [10], [20], [21].

IV. Results and Discussion

In this study, DMD-based approaches were proposed to classify pre-seizure and seizure epileptic EEG data. Dynamic modes of epileptic EEG segments were obtained using the DMD method and DMD Spectra were established utilizing these DMD modes. Subband powers and total power were calculated from DMD spectra as features. In order to evaluate the performance of the proposed DMD approaches, Power Spectral Density (PSD) was obtained using a classical PSD estimation method, the Welch method. Then, the same features

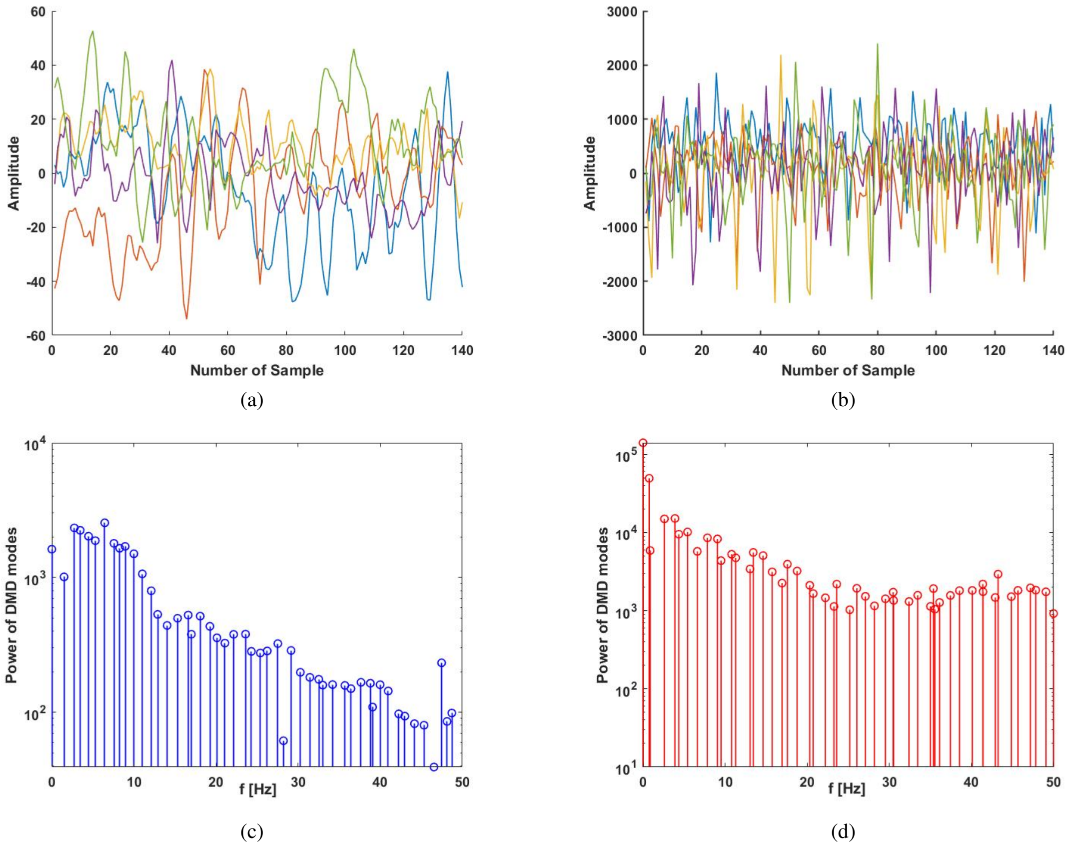

Fig. 1: An example mode decomposition using; (a) 5 Pre-Seizure EEG segments, (b) 5 Seizure EEG segments together, (c) DMD Spectrum of Pre-Seizure EEG segments, (d) DMD Spectrum of Seizure EEG segments.

were calculated from the PSD estimation. In the last part of the study, extracted features were classified using several classifiers. Performance evaluation results of DMD-based and PSD-based pre-seizure and seizure epileptic EEG classification are given in Table I.

In Table I, the rows are shown as Fp1-F7, F7-T1, T1-T3, T3-T5, Fp1-F3, Fp2-F8, F8-T2, T2-T4, T4-T6, Fp2-F4 indicate that the features used in the classification process were obtained from the EEG segments recorded from the respective channels. In single-channel based DMD and PSD approaches, ”Right Hems.” and ”Left Hems.” denote that the feature sets used by classifiers were generated by combining the features obtained from the channels in the respective hemisphere (Right Hemisphere: Fp2-F8, F8-T2, T2-T4, T4-T6, Fp2-F4; Left Hemisphere: Fp1-F7, F7-T1, T1-T3, T3-T5, Fp1-F3). Additionally, ”Two Hems.” indicates that the feature sets are obtained by combining the features obtained from the channels in both hemispheres. On the other hand, in multi-channel based DMD approach, ”Right Hems.” and ”Left Hems.” denote that the EEG data matrices analyzed by the DMD algorithm were obtained using the EEG segments recorded from the channels of corresponding Hemisphere. ”Two Hems.” shows that these EEG data matrices were obtained using the EEG segments recorded from the channels of both hemispheres.

The highest accuracy values for both Single-channel based DMD approach (96.7%) and PSD-based approach (96%) are achieved from the T3-T5 channel with the SVM and NB classifiers. The 94.1% accuracy is achieved for the Single-channel based DMD approach from the left hemisphere (”Left Hems.”) with the SVM and LR classifiers, while 92.2% accuracy was obtained for the PSD-based approach from the left hemisphere (”Left Hems.”) with LR classifier. In addition, the classification accuracy of the feature-set obtained using the Single-channel based DMD approach is higher than that of the PSD approach for all classifiers except for SVM in the Fp1-F7 channel. On the other hand, the single-channel based DMD approach provided maximum classification accuracy of 94.4% for the left hemisphere (”Left Hems.”), while multi-channel based DMD approach provided the maximum classification accuracy of 93.9% for the same hemisphere.

V. Conclusion

EEG signals are frequently used in the diagnosis, follow-up, and treatment of epilepsy, one of the most common neurological diseases due to ease of recording and low cost [19]. Many epileptic seizure detections and classification algorithms have been developed to facilitate the analysis of long-term recordings of epileptic EEG signals. The dynamic mode

TABLE I: Performance Evaluation results (ACC %) of Single- and Multi-Channel based DMD and PSD based Approaches

Approach	Components	SVM	KNN	NB	LR
	Fp1-F7	91.2	91.2	89.5	89.5
	F7-T1	91.7	93.4	93.4	93.4
	T1-T3	96.1	95.6	93.4	95
	T3-T5	**96.7**	96.1	96.7	96.1
	Fp1-F3	91.7	93.4	92.8	92.3
	Fp2-F8	90.1	89.5	89	87.8
Single-channel DMD	**F8-T2**	90.1	92.3	92.8	91.7
	T2-T4	91.2	89.5	90.1	89
	T4-T6	90.6	90.1	89	89
	Fp2-F4	87.3	84.5	85.6	89.5
	Right Hems.	90.2	89.4	90.3	**90.8**
	Left Hems.	**94.1**	93.4	93.7	94.1
	Two Hems.	91.5	91.3	91.7	**92.3**
	Fp1-F7	76.7	91.2	88.5	90.2
	F7-T1	94	93	92.4	94.6
	T1-T3	95.6	95.1	92.4	95.8
	T3-T5	**96**	95	94.3	94.2
	Fp1-F3	89	88.5	88.9	88.9
	Fp2-F8	87.9	89.1	87.4	88
PSD	**F8-T2**	77.7	89.4	89.6	90.8
	T2-T4	87.6	88.5	86.2	88.3
	T4-T6	71.3	88.4	87.3	87.6
	Fp2-F4	81.2	84.1	80.4	83.7
	Right Hems.	85.8	86.7	86.1	**87.2**
	Left Hems.	92	91.3	92.1	**92.2**
	Two Hems.	88.5	88.3	89.1	**89.5**
	Right Hems.	90.7	89.5	**90.6**	89.3
Multi-channel DMD	**Left Hems.**	93.5	92.7	92.9	**93.9**
	Two Hems.	94.6	93.5	**94.7**	94.5

decomposition (DMD) method that provides a decomposition of a non-stationary signal into dynamical modes has recently been applied to neuro signals and successful results have been obtained [11]–[15].

In this study, we present new methods based on DMD approach to distinguish Pre-seizure and Seizure EEG signals. Multi-channel EEG signals may be decomposed into their oscillations by using DMD. However, channel dependent analysis of EEG signals are necessary in many applications. In our proposed study, single-, and multi-channel based DMD approaches are introduced, and features for classification are extracted from the resulting DMD spectrum. In addition, the Power Spectral Density-based approach is also implemented to evaluate the performance of our method. DMD based approaches provided higher classification accuracies than PSD based approach. Moreover, single-channel based DMD approach resulted higher classification performance than the multi-channel based DMD approach except "Two Hems." It is shown that the presented single-channel based DMD approach may be effectively used in EEG studies.

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