2021 43rd Annual International Conference of the
IEEE Engineering in Medicine & Biology Society (EMBC)
Oct 31 - Nov 4, 2021. Virtual Conference

Classification of Epileptic Seizure From EEG Signal Based on Hilbert Vibration Decomposition and Deep Learning

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***Abstract*— a convolution neural network (CNN) architecture has been designed to classify epileptic seizures based on two-dimensional (2D) images constructed from decomposed mono-components of electroencephalogram (EEG) signals. For the decomposition of EEG, Hilbert vibration decomposition (HVD) has been employed. In this work, four brain rhythms – delta, theta, alpha, and beta have been utilized to obtain the mono-components. Certainly, the data-driven CNN model is most efficient for 2D image processing and recognition. Therefore, 2D images have been generated from one-dimensional (1D) decomposed mono-components by employing continuous wavelet transform (CWT). Next, simultaneous multiple input images in parallel have been directly fed into the CNN pipeline for feature extraction and classification. For evaluation, the EEG dataset provided by the Bonn University has been taken into consideration. Further, a 5-fold cross-validation technique has been applied to obtain generalized and robust classification performance. The average classification accuracy, sensitivity, and specificity reached up to 98.6%, 97.2%, and 100% respectively. The results show that the proposed idea is very much efficient in seizure classification. The proposed idea resourcefully combines the advantages of HVD and CNN to classify epileptic seizures from EEG signal.**

***Clinical relevance*— Hilbert vibration decomposition, brain rhythms, continuous wavelet transform, scalogram, epileptic seizure, convolution neural network.**

I. INTRODUCTION

The frequent occurring of epileptic seizures leads to disarray in the state of being active neurons, loss of awareness, and sensations [1–4]. Certainly, EEG based epileptic seizure detection is simple, low cost, reliable, and easy to use compared to other acquisition tools [3]. Generally, medical professionals inspect epileptic seizures by visual observation of long-recorded EEG signals, which is time-consuming and error-prone [1–2]. Therefore, an automated classification of epileptic seizures using EEG signals can improve the diagnosis and treatment process [3–4]. In recent years, machine learning techniques have been extensively employed to classify epileptic seizures which usually depend on pre-defined hand-crafted features extracted from different domains such as time, frequency, frequency-time of EEG signal [1–6]. However, the EEG signal is non-stationary and non-linear. Hence, non-linear decomposition techniques, such as empirical mode decomposition (EMD) and Hilbert vibration decomposition (HVD) have been efficiently and successfully applied in epileptic seizures classification [5–6]. In recent times, the HVD extensively and successfully adopted in the classification of epileptic seizures as it is simple and efficient technique for the decomposition of non-stationary and non-linear signals [5–6]. The HVD decomposes signal into a certain number of mono-components (MC) with slowly varying instantaneous amplitude and frequency. Besides, it preserves the phase information in decomposed mono-components and also helps in seizure localization [5–7]. Additionally, the decomposed MC are extensively used to obtain insightful information, which has efficiently improved classification of epileptic seizures [5–6]. For example, in [5] work, seven MC have been decomposed by HVD from EEG of different brain rhythms to extract features. Then, least square-support vector machine (LS-SVM) classifier has been employed to classify epileptic seizures with an accuracy of 97.66%. Certainly, epileptic seizures detection can be improved further by investigating multiple mono-components of the EEG.

Nowadays, CNN has been widely used in the field of biomedical signal and image processing [8–13]. The CNN architecture is the most emblematic approach for 2D image recognition [3]. Typically, data-driven CNN automatically and adaptability learns and derives relevant features from inputs [1–3]. In this view, various techniques have been adopted to construct 2D images from 1D signals [2–4]. Indeed, 2D images generation techniques and CNN have been frequently used to successfully classify complex biomedical signals [4]. The recent contributions of the CNN models for epileptic seizures classification are remarkable [2–6] [8–13]. For example, in [4], the CWT has been used to generate 2D images from EEG segment. Thereafter, a CNN model has been employed to detect epileptic seizures. In [2], a trained CNN model has used 2D images captured from EEG recordings to predict epileptic seizures with an accuracy of 94.8%. In [7], frequency-based features have been extracted from brain rhythms and directly fed into a deep neural network (DNN) to detect seizures. In [9], raw EEG signals were directly fed into a 13 layered CNN model and achieved accuracy of 88.7%.

Motivated from the aforementioned works, HVD and CNN have been adopted to classify epileptic seizures using EEG recording of different brain rhythms. The contribution of this work are as follow;

- The relevance of brain rhythms in epileptic seizure classification has been addressed.
- Decomposition of EEG has been explored by HVD which provides better frequency resolution and preserve the phase information.

- Generation of 2D images from EEG signals has been conducted by CWT, which preserves the temporal information.
- A CNN pipeline has been designed to accept simultaneous multiple image in parallel as inputs.

This paper has been structured as follows: section II consists of introduction of proposed method followed by experimental setup in Section III. Next, section IV discusses the experimental performance. Finally, the conclusion of proposed idea discuss in section V.

II. Proposed Method

The outline of the proposed idea has been displayed in Fig. 1. First, different brain rhythms (BR) have been obtained from EEG. Thereafter, the HVD has been utilized to decompose EEG into multiple MCs. Next, a 2D image from each MC has been generated by CWT. Finally, simultaneously 2D images of multiple MC in parallel have been directly fed into the CNN pipeline to discriminate the epileptic seizures. The description of the proposed method in the below:

A. Processing and Brian Rhythms

Four BR — δ (0.5 to 4 Hz), θ (4 to 8 Hz), α (8 to 12 Hz), and β (12 to 30 Hz) have been chosen for analysis of epileptic seizures [5]. For this purpose, a band pass filter with appropriate cut-off frequencies has been used [10]. Certainly, it is convenient to design a seizure classification method by considering EEG segments, which could minimize the computational burden. Therefore, EEG recordings have been segmented with a predefined duration [3–6]. Now, HVD has been used to decompose mono-components from each of the EEG segments.

B. Hilbert Vibration Decomposition (HVD)

The HVD technique decomposes the non-stationary and nonlinear signal into multiple MC [5–7]. The decomposition process mainly works in three steps — first measuring the instantaneous frequency of signal followed by detection of the synchronous envelope and finally, MC with the highest energy is separated from the main signal [7]. The HVD works iteratively and in each iteration, the largest components having slowly varying frequency component is decomposed from initial signal. The Hilbert transform is employed to obtain analytical signal (1) of multicomponent signal ($x(t) = x_1, x_2, x_3, \ldots x_n$).

$$A_s(t) = x(t) + j\tilde{x}(t) = A(t)e^{j\phi(t)} \tag{1}$$

where, $A_s(t)$ represents the analytical signal of $x(t)$. The $A(t)$ and $\phi(t)$ denotes instantaneous amplitude and phase of $x(t)$ respectively. The $\tilde{x}(t)$ (2) is Hilbert transform of signal $x(t)$.

$$\tilde{x}(t) = \frac{1}{\pi} P.V. \int_{-\infty}^{\infty} \frac{x(\tau)}{x(t-\tau)} d\tau \tag{2}$$

where, P.V. is Cauchy principal value. Now, the instantaneous frequency, $\omega(t) = (d\phi(t))/d(t)$ has been calculated. The main signal can be represented by (3), where $A_l(t)$ and $\omega_l(t)$ refer instantaneous amplitude and frequency of the l^{th} component respectively.

$$x(t) = \sum_l x_l(t) = \sum_l A_l(t) \cos\left(\int \omega_l(t) dt\right) \tag{3}$$

Next, synchronous envelope and separation of MC have been evaluated. Eventually, the largest energy component ($x_{l-1}(t) = x_l(t) - x_1(t)$) has been detracted from main signal, where, x_{l-1} is residue that hold the lowest energy and can be disintegrated during succeeding iteration. Now, 2D images have been generated from each decomposed MC of EEG segment for considered BR.

C. 2D Image Construction

The CWT has been employed to construct 2D images from decomposed MC of EEG. The CWT depicts signal activities that vary across time within a range of time scales [4]. The absolute value of the CWT has been used to represent the 2D scalogram texture [5]. Meanwhile, CWT provides long and short time windowing for low and high frequency signals respectively. Hence, low and high-frequency signals can be better analyzed. The CWT of a signal can be obtained by (4);

$$WC_x(m,n) = \frac{1}{\sqrt{m}} \int_{-\infty}^{\infty} x(t)\, \psi^*\left(\frac{t-n}{m}\right) dt \tag{4}$$

where, $WC_x(m, n)$, m, and n depict wavelet coefficients, scaled, and position parameters respectively. The ψ^* and $x(t)$ is the conjugate of wavelet function and time series respectively. The Morlet wavelet function which is appropriate for spectral analysis of complex signal has been used in this work. Further, for each MC a scalogram image has been generated which has been used as input to the CNN model.

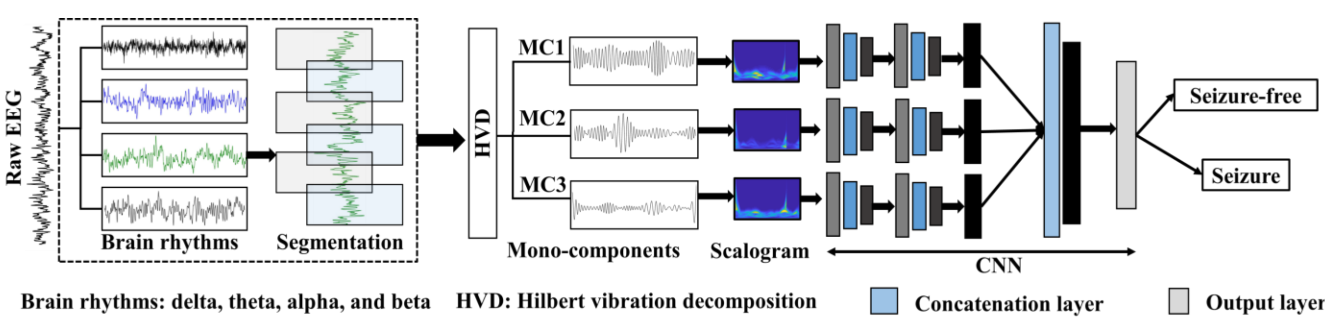

Fig.1. The framework of the proposed method for classification of epileptic seizure from EEG, where MC1, MC2, and MC2 depicts decomposed mono-components of an EEG segment.

D. Convolution Neural Network Architecture

The CNN has been extensively and successfully employed in epileptic seizure classification [1–3]. The CNN architecture and its layers of hierarchies have been shown in Fig. 2. As shown, there are convolution, batch normalization, max-pooling, fully-connected, and output layers [2–4]. The convolution layer is the core block of CNN that have learnable kernels, which perform convolution operation with input to extract insightful information. Next, the outcome of the convolution layer is passed through the ReLU function, which reduces the complexity as well as allow the model to learn quickly and perform much better. Further, the batch normalization (BN) layer has been used to improve stability, convergence speed, and performance. Besides, a Max-pooling layer is used to learn the sharp and smooth features. In addition, the dropout layer has been employed which reduces the over-fitting issue and prevents to optimize the weights of all neurons in a layer synchronously. Finally, the output layer having a sigmoid function computes the probability of appropriate classes based on the outcome of the fully connected layer. Certainly, the CNN can extract the abundant number of features from simultaneous multiple inputs images in parallel [3–4].

III. EXPERIEMNTAL METHODOLOGY

A. Data

For experimental validation, the Bonn University EEG dataset has been taken into account [14]. The dataset consists of five sets of recorded EEG signals— A, B, C, D, and E. Each set contains 100 channel files of EEG with a duration of 23.6s. The sampling rate has been tuned to 173.61Hz with a 12-bit resolution. Healthy volunteers were mediated to record EEG signals of sets A and B. Besides, sets C, D, and E consist of EEG recordings of the patients having epileptic seizures activities. However, EEG signals of sets C and D have been recorded between occurrences of seizure events, which behave like seizure-free signals. The set E encloses only epileptic seizures recordings. The EEG dataset has been clustered into three classes —normal (A, B), interictal (C, D), and ictal class (E). Empirically, one set from each class has been selected to evaluate the proposed idea. The selected sets are — normal (A), interictal (D), and ictal (E).

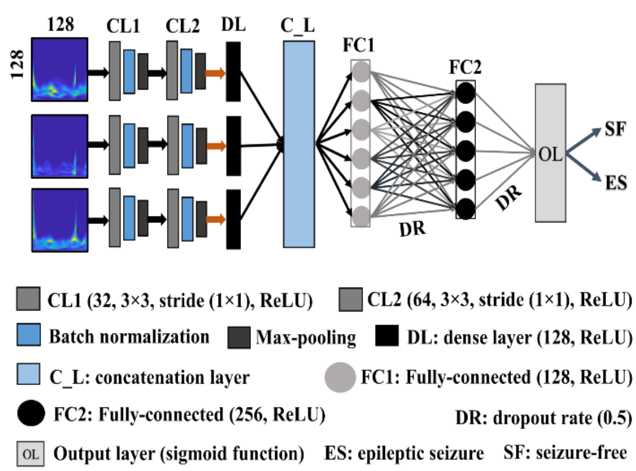

Fig. 2. The CNN pipeline for classification of epileptic seizures using 2D images constructed from decomposed mono-components of EEG.

B. Experiment

The band pass filter with cut-off frequencies has been employed to obtain different BR. Further, the EEG signals have been segmented based on a duration of 5.9s with 20% overlap. Empirically, first three MCs (MC1, MC2, and MC3) from each EEG segment have been decomposed by HVD. After that, 2D images from each MC have been constructed by CWT. In Fig. 3, MC of normal, interictal, and ictal with their respective scalogram image has been displayed. In total, 1500 scalogram images have been constructed from each set. As for the CNN pipeline, the elementary need is a fixed size of inputs images, therefore all images before feeding into CNN have been resized to 128x128 resolution.

The CNN pipeline has been trained with Adam optimizer, while other parameters learning rate, batch size, and the number of epochs have been tuned for all classification tasks to 0.00001, 64, and 20 respectively. Finally, classification tasks have been performed on the group– A vs. E, D vs. E, and A vs. D. In addition, a 5-fold cross-validation technique has been used which reduces the overfitting problem, as well as minimizing bias and variance in the dataset. The samples have been arbitrarily split into five subsets (K1, K2, K3, K4, and K5) and each subset keeps the proportionate distribution of categories in the dataset. Indeed, four subsets have been used to train the CNN model and the rest subset holds out for testing. Additionally, four subsets that are used to train the model have been divided in the ratio of 80:20 for training and validation set.

IV. RESULTS AND DISCUSSION

In this work, binary classification task has been performed on above discussed groups for each BR. Herein, the accuracy (η) (5), sensitivity, S_e (6), and specificity, S_p (7) have been evaluated to observe the classification performance.

$$\eta = \frac{TN + TP}{TN + TP + FN + FP} 100\% \tag{5}$$

$$S_e = \frac{TP}{TP + FN} 100\% \tag{6}$$

$$S_p = \frac{TN}{TN + FP} 100\% \tag{7}$$

where, TN, TP, FN, and FP represents true negative, true positive, false negative and false positive respectively.

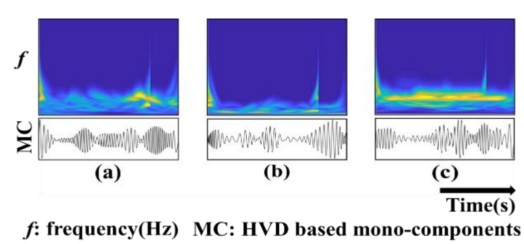

Fig. 3. The 2D scalogram images of a decomposed MC from (a) normal (b) interictal, and (c) ictal EEG segment of β respectively.

The η achieved up to 98.6%, 96.1%, 96.2%, and 92.6% to discriminate normal and ictal for δ, θ, α, and β respectively. The δ band has achieved maximum classification η, S_e, and S_p in comparison to other BR. In case of interictal and ictal for δ, θ, α, and β band, η has been recorded up to 100%, 96.2%, 98.0%, and 99.1% respectively. In Fig. 4, the average η, S_e, and S_p obtained for the aforementioned groups of BR has been displayed. In addition, Table I summarized the η, S_e, and S_p achieved for classification of A-E (δ), D-E (α), and A-D (β) when different subsets have been used for testing, in which the first column depicts the subset used for the test. The experimental results show that the proposed method is efficient and suitable for the classification of epileptic seizures. Further, a comparative study has been conducted in concerned with recent machine learning algorithms and the results have been summarized in Table II. Therein, observed that the proposed method performance is remarkable, efficient, and better than other works.

V. Conclusions

The EEG recording of four brain rhythms — delta, theta, alpha, and beta has been utilized for the analysis of epileptic seizures. The efficient and simple HVD has been employed to decompose the EEG into three mono-components. Certainly, HVD is suitable for the analysis of narrow as well as wideband signals with better frequency resolution. Next, CWT has been applied to construct 2D images from each mono-component. Finally, 2D images have been fed to the CNN pipeline to perform both feature extraction and classification. The proposed idea shows the ability to classify epileptic seizures of different brain rhythms with favourable performance.

Acknowledgment

The authors acknowledge Eureka/Sunrise/Early career Project with Ref: NECBH/2019-20/118] under North East Centre for Biological Sciences and Healthcare Engineering (NECBH) Twinning Outreach Programme hosted by Indian Institute of Technology Guwahati (IITG), Guwahati, Assam funded by Department of Biotechnology (DBT), Ministry of Science and Technology, Govt. of India with number BT/COE/34/SP28408/2018 for providing necessary financial support.

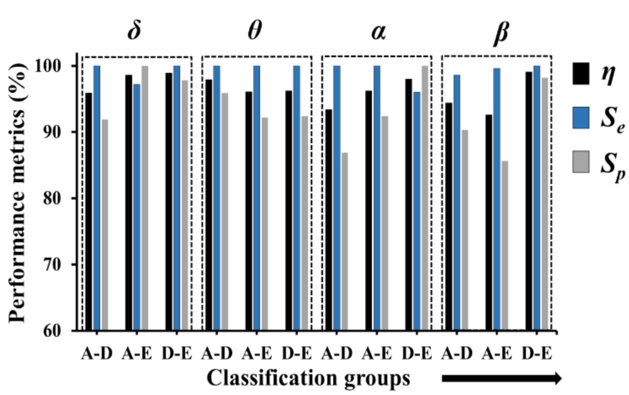

Fig. 4. The average η, S_e, and S_p obtained by the CNN pipeline after employing 5-fold cross-validation technique on different classification groups of brain rhythms.

TABLE I: TESTING OF MODEL WITH DIFFERENT SUBSETS

BR	δ			α			β		
ST	A – E			D – E			A – D		
	η	S_e	S_p	η	S_e	S_p	η	S_e	S_p
K1	100	100	100	90.0	80.0	100	95.5	92.0	99.0
K2	100	100	100	100	100	100	100	100	100
K3	93.0	86.0	100	100	100	100	78.0	99.0	57.0
K4	100	100	100	100	100	100	99.5	99.0	100
K5	100	100	100	100	100	100	99.5	99.0	100

Note: ST: subset holdout for testing.

TABLE II: A COMPARATIVE STUDY

Works	Methods	Performance (%)		
		η	S_e,	S_p
George *et al.* [2]	EEG CNN	94.8	-	-
Mutlu *et al.* [5]	HVD, LS-SVM	97.6	97.0	96.5
Mutlu *et al.* [6]	HVD, E_n, CNN	96.3	-	-
Gao *et al.* [8]	EEG, RQA, CNN	92.2	91.8	92.0
Acharya *et al.* [9]	EEG, CNN	88.7	90.0	95.0
David *et al.*[11]	EEG, RNN	91.3	91.8	90.5
Daoud *et al.*[12]	EMD, CNN	98.6	-	-
Akyol *et al.*, [13]	SEA based DNN	97.2	93.1	98.2
This work	**BR, HVD, CNN**	**98.6**	**97.2**	**100**

Note: E_n: entropy, RNN: recurrent neural network, RQA: recurrence quantification analysis, SEA: stacking ensemble approach.

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