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Sensor signal processing

FBSE-Based Approach for Discriminating Seizure and Normal EEG Signals

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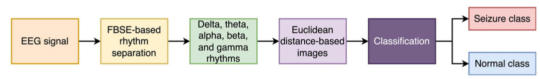

Abstract—This letter presents an innovative approach based on Fourier–Bessel series expansion (FBSE) in order to identify seizure and normal electroencephalogram (EEG) signals. The different set of FBSE coefficients are used to separate the five EEG rhythms, namely, delta, theta, alpha, beta, and gamma rhythms. Further, images are generated from the matrices obtained after applying the concept of Euclidean distance on the EEG rhythms. The generated images are employed as features for the classification using convolutional neural network. Notably, our proposed methodology achieves 100% accuracy in distinguishing between seizure and normal EEG signals on the publicly available Bonn University EEG database. This robust performance demonstrates the efficacy of our approach in handling complicated EEG signal patterns. The proposed framework for automated classification of epileptic seizure based on EEG rhythms provides information about the behavior of rhythms during epilepsy. The experimental results on the publicly available Bonn University EEG database show the effectiveness of proposed framework. The performance of the proposed framework is also compared with the other existing frameworks from the literature.

Index Terms—Sensor signal processing, classifier, electroencephalogram (EEG), EEG rhythms, epilepsy, Fourier–Bessel series expansion (FBSE).

I. INTRODUCTION

Epilepsy is one of the neurological disorders. It can be considered as a result of sudden and recurrent seizures [1]. The electroencephalogram (EEG) signals are commonly used for diagnosis of epilepsy, which are complex, nonlinear, and nonstationary in nature. The neurologists perform visual scanning of the recorded EEG signals, which may be time consuming specially for long data recording and subjective in nature. Due to these reasons, there is a need of development of computer-aided medical diagnosis systems for epilepsy. The signal processing and machine learning algorithms are useful for designing such automated systems [2], [3]. In the literature, various researchers have proposed their research methodologies in order to detect seizure EEG. Lian et al. [4] developed machine learning pipeline frameworks based on classifiers, such as support vector machine (SVM), k-nearest neighbors (KNN), and linear discriminant analysis, to classify seizure and normal EEG signals. The extracted temporal, spectral, and spatial features from raw EEG signals have been validated on classifiers (KNN, RF, and SVM) to classify seizure and normal EEG signals. Similarly, Ilias et al. [5] developed a novel multimodel deep neural network (DNN) for the robust detection of seizures using EEG signals from the Bonn dataset. Further, Aslan and Alçin [6] used Hilbert Huang transform (HHT) to extract the instantaneous amplitude and instantaneous frequency-based features, and applied extreme learning machine (ELM) to classify the EEG classes. Similarly, Zhou and Li [7] proposed the classification framework to classify the epileptic seizures using convolutional neural network (CNN) from wavelet coefficients and entropy features extracted from EEG signals. In recent work, Zhao et al. [8] explored a hybrid deep learning approach named ResBiLSTM, combining a 1-D residual neural network and bidirectional long short-term memory for epileptic seizure detection from EEG signals. The rest of this letter is organized as follows. Section II includes the proposed FBSE-based framework in order to identify seizure and normal EEG signals in automated manner, and it includes various subheadings related to different blocks shown in Fig. 1. The information regarding the classification by using CNN has been presented in Section III. Various results together with discussions are presented in Section IV. Finally, Section V concludes this letter.

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II. PROPOSED METHODOLOGY

A. Fourier–Bessel Series Expansion (FBSE)

The FBSE is a suitable technique for nonstationary signal representation, as its basis functions exhibit nonstationary characteristics [9]. The FBSE provides better spectral resolution as compared to the Fourier representation. The mathematical expression for the synthesis part of the zero-order FBSE for a signal $y(n)$ for $n = 0, 1, \ldots, (V-1)$ can be written as [10], [11]

$$y(n) = \sum_{k=1}^{V} D_k J_0\left(\lambda_k \frac{n}{V}\right) \tag{1}$$

where D_k is computed using the following analysis expression:

$$D_k = \frac{2}{V^2 (J_1(\lambda_k))^2} \sum_{n=0}^{V-1} n y(n) J_0\left(\lambda_k \frac{n}{V}\right). \tag{2}$$

In (2), the $J_1(\cdot)$ function and $J_0(\cdot)$ function represent the first- and zero-order Bessel functions, respectively. The variable λ_k, with $k = 1, 2, \ldots, V$, denotes the positive roots corresponding to zero-order Bessel function. The roots can be computed using the Newton–Raphson method [9]. The relation between the FBSE coefficient index

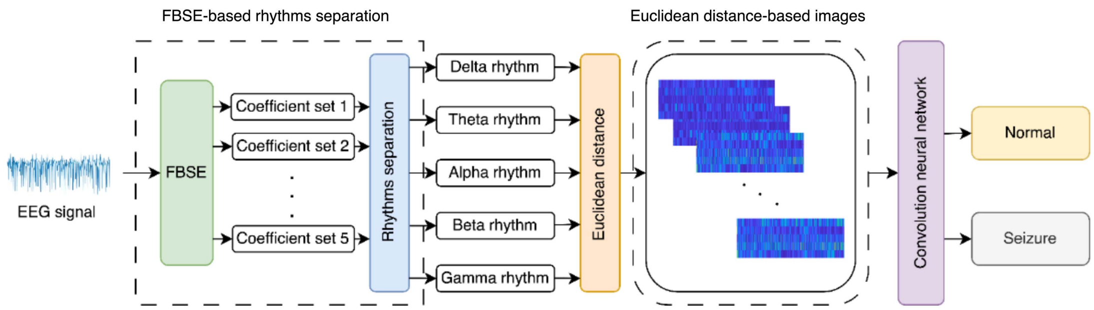

Fig. 1. Block diagram for the proposed FBSE-based approach for discrimination of normal and seizure EEG signals.

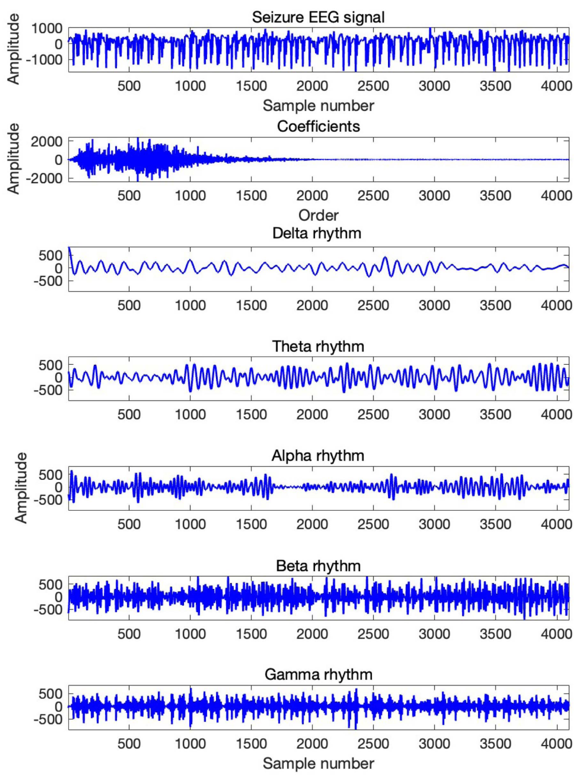

Fig. 2. Plots of seizure EEG signal, its FBSE coefficients, and corresponding separated rhythms.

k and the continuous-time frequencies f_k (in Hz) can be described by the equation, $k = \frac{2f_k V}{f_s}$ [11]. Where f_s represents the sampling rate. To cover the entire bandwidth of the signal, V should be equal to the length of the signal. In this study, the value of V for each EEG signal is 4097. For an example, the computed FBSE coefficients for a seizure EEG signal have been shown in Fig. 2.

B. Rhythms Separation

EEG signals obtained from Bonn University EEG database with sampling rate 173.61 Hz, can be represented in terms of five distinct rhythms according to their frequency bands [12]. These rhythms are termed as delta (δ), theta (θ), alpha (α), beta (β), and gamma (γ) rhythms and their frequency ranges are 0.5–4 Hz, 4–8 Hz, 8–13 Hz, 13–30 Hz, and 30–86.81 Hz, respectively. The root order ranges for $\delta, \theta, \alpha, \beta$, and γ rhythms are [24, 188], [189, 377], [378, 613], [614, 1416], and [1417, 4097], respectively, which are obtained using root order and frequency relation mentioned in Section II-A. Equation (1) for signal decomposition can be reformulated to represent these EEG rhythms as follows [12]:

$$y(n) = \sum_{k=\delta_L}^{\delta_U} D_k J_0\left(\lambda_k \frac{n}{V}\right) + \sum_{k=\theta_L}^{\theta_U} D_k J_0\left(\lambda_k \frac{n}{V}\right) + \sum_{k=\alpha_L}^{\alpha_U} D_k J_0\left(\lambda_k \frac{n}{V}\right) + \sum_{k=\beta_L}^{\beta_U} D_k J_0\left(\lambda_k \frac{n}{V}\right) + \sum_{k=\gamma_L}^{\gamma_U} D_k J_0\left(\lambda_k \frac{n}{V}\right). \quad (3)$$

In this equation, the intervals $[\delta_L, \delta_U]$, $[\theta_L, \theta_U]$, $[\alpha_L, \alpha_U]$, $[\beta_L, \beta_U]$, and $[\gamma_L, \gamma_U]$ denote the index ranges of the coefficients corresponding to the $\delta, \theta, \alpha, \beta$, and γ rhythms, respectively. These index ranges can be determined using the relation between frequency and root order of FBSE for any EEG signal with a specified sampling rate [12]. Coefficients falling outside these specified ranges can be set to zero in order to separate the EEG rhythms in time domain using the FBSE method. It should be noted that the FBSE-based rhythm separation method is a single-step process in contrast to wavelet-based method for rhythm separation, which requires multiple level of decomposition [13], which makes the FBSE-based rhythm separation easier to implement. The coefficient set (CS) corresponding to different index ranges represent the frequency bands for the various rhythms namely, delta, theta, alpha, beta, and gamma rhythms. Hence, the separation of the rhythms for any signal requires CS values (CS 1, CS 2, CS 3, CS 4, and CS 5) for above mentioned EEG rhythms. The resulting EEG rhythms of the seizure EEG signal are depicted in Fig. 2.

C. Euclidean Distance

In order to explain the Euclidean distance concept, we have considered two points A and B in the n-dimensional space, which are represented as follows: $A = (a_1, a_2, \ldots, a_n)$ and $B = (b_1, b_2, \ldots, b_n)$. The Euclidean distance between these two points is calculated with the help of the relation given as [14], Euclidean distance $= \sqrt{\sum_{i=1}^{n}(b_i - a_i)^2}$. Our proposed methodology is based on the 2-D space. Hence, the value of n would be 2 for our study, and also for simpler calculations, we have considered the point $B = (0, 0)$, which is generally termed as origin [15]. We applied this concept in each of the rhythms obtained using FBSE method. Fig. 3 represents the results after performing the concept of Euclidean distance of the separated rhythms through FBSE, and the Euclidean distance plots of rhythms of the seizure and normal EEG signals are shown below them. Fig. 4 shows the box plot representation for the Euclidean distances of various EEG rhythms corresponding to considered EEG signals for normal and seizure classes. It can be clearly seen that the Euclidean distance amplitude in the case of seizure class is much more as compared to the case of normal class from both Figs. 3 and 4. After obtaining the matrix after performing the Euclidean distance concept on the EEG

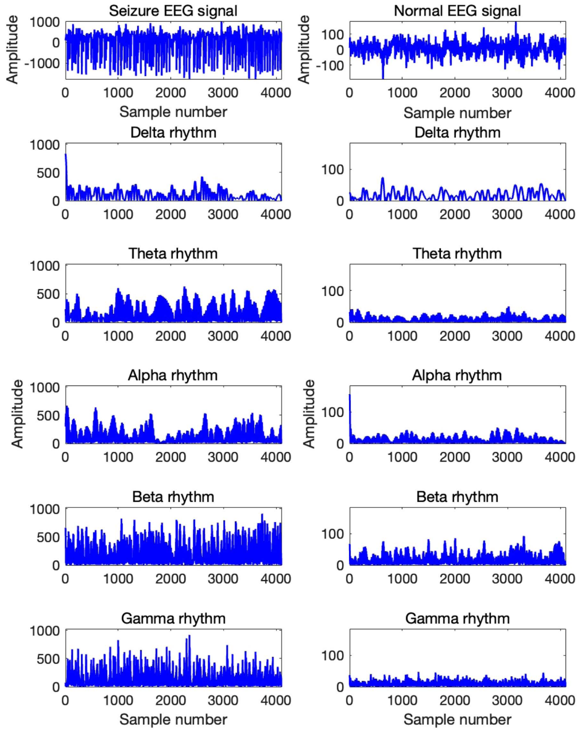

Fig. 3. Euclidean distance plots of the normal and seizure EEG signals and their rhythms.

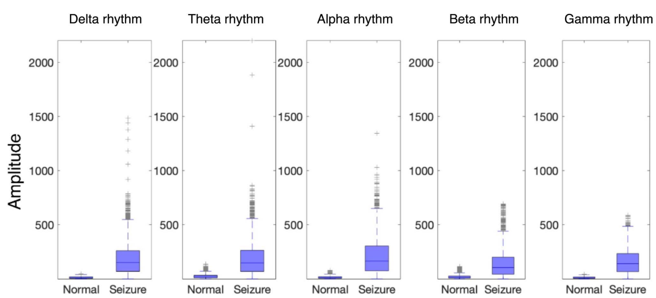

Fig. 4. Box plots of Euclidean distance of delta, theta, alpha, beta, and gamma rhythms for normal and seizure EEG signals.

rhythms for the seizure and normal classes, we converted the matrix into images, which have been represented in Fig. 5. The difference between the obtained images of both the classes can be seen clearly in Fig. 5.

III. CLASSIFICATION

We obtained a dataset consisting of 200 EEG signals evenly divided between seizure and normal classes, which were divided into two sets using an 80:20 ratio for training and validation purposes. These images were processed through a CNN [16], [17]. The CNN consists of various layers, such as convolutional layers, input layer, dense layers, a flatten layer, max-pooling layers, and an output layer [18], [19]. The architecture of the studied CNN has been shown in Fig. 6. The accuracy for the proposed classification framework for normal and seizure classes of EEG signals is computed [20]. The overall accuracy is calculated using the formula, Accuracy $= \frac{P_{\text{true}}+N_{\text{true}}}{P_{\text{true}}+P_{\text{false}}+N_{\text{true}}+N_{\text{false}}}$, where P_{true}, N_{true}, P_{false}, and N_{false} represent true positives, true negatives, false positives, and false negatives, respectively. True positives denote instances where seizure EEG signals are correctly identified as seizures, while true

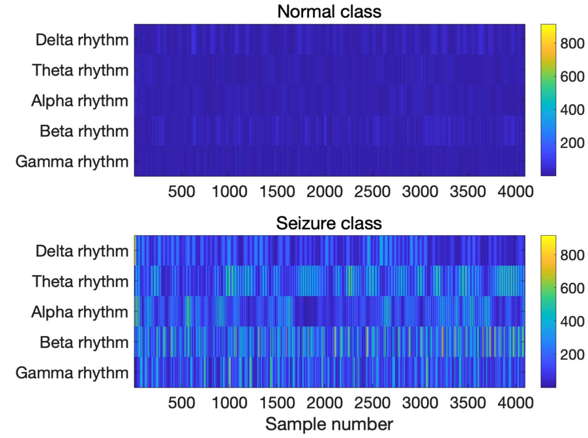

Fig. 5. Plot of Euclidean distance-based images of rhythms for normal and seizure EEG signals.

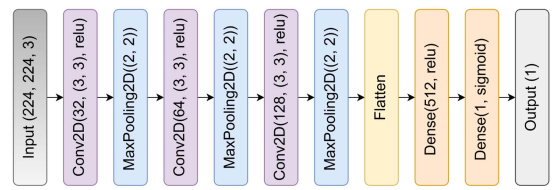

Fig. 6. Architecture of the studied CNN model.

negatives correspond to normal EEG signals correctly identified as normal. False positives occur when normal EEG signals are incorrectly classified as seizures, and false negatives arise when seizure EEG signals are mistakenly identified as normal. The CNN model was trained over ten epochs, during which it achieved a validation accuracy of 100%.

IV. RESULTS AND DISCUSSION

This section provides an analysis of the obtained results at various stages of the proposed framework in order to classify of normal and seizure EEG signals. We have used the publicly available Bonn University EEG database, which contains five subsets named as Z subset, O subset, N subset, F subset, and S subset [21]. The sampling rate of the data was 173.61 Hz. The dataset is publicly available.[1] There are 100 single-channel EEG signals present in each subset. We have considered only Z subset and S subset of the dataset. The FBSE method was then applied to normal and seizure EEG signals to obtain coefficients. The obtained FBSE coefficients represent different frequencies. Since EEG signals primarily comprise five rhythms (δ, θ, α, β, and γ rhythms), we clustered the FBSE coefficients corresponding to frequency ranges of these rhythms, and inverse FBSE is applied to obtain the respective rhythms. After obtaining the rhythms, we applied the concept of Euclidean distance to each rhythm corresponding to normal and seizure EEG signals. For an example, the normal and seizure EEG signals and their corresponding Euclidean distance plots for different EEG rhythms are demonstrated in Fig. 3. Given that the range of the Euclidean distance concept is $(0, \infty)$, it ensures nonnegative values. This nonnegativity advantage of the Euclidean distance concept allowed us to convert the obtained matrix into an image, which is demonstrated

[1] [Online]. Available: https://www.ukbonn.de/epileptologie/arbeitsgruppen/ag-lehnertz-neurophysik/downloads/

Table 1. Comparison of Accuracy Values With Previous Studies in Order to Classify Normal and Seizure Classes of EEG

Authors	Methodology	Accuracy
Zhao et al. [7]	Wave coefficient, entropy measure, CNN	95.10%
Ilias et al. [5]	Multimodel DNN	96.50%
Lian et al. [4]	Raw EEG, classifiers (KNN, RF, SVM)	99.93%
Aslan et al. [6]	HHT, ELM classifier	100%
Zhao et al. [8]	ResBiLSTM	100%
Proposed work	**FBSE-based approach**	**100%**

in Fig. 5. These generated images are then inputted into one of the studied classifiers in the domain of machine learning named CNN for the discrimination of seizure and normal categories of EEG. We have considered two cases of arrangement of Euclidean distance of EEG rhythms (increasing and decreasing order of the frequency ranges of the EEG rhythms) for image construction for classification of normal and seizure EEG signals. An accuracy of 100% has been obtained for the both the cases of arrangement for the differentiation of seizure and normal EEG signals by our proposed methodology. There are various research studies done in the past for the discrimination of seizure and normal EEG signals. Table 1 gives the comparison of our proposed methodology with the studies done in the past. From the comparison, it is found that the proposed framework is effective for epileptic seizure detection and achieves superior classification performance. In contrast, the work in [6] achieves high performance but suffers due to empirical modeling, mode-mixing issues, and computational complexity. Similarly, the work in [8] lacks comprehensive analysis and directly applies machine learning to raw EEG data. In comparison, the proposed framework utilizes FBSE-based analysis of EEG rhythms along with CNN, providing better interpretability for seizure classification. It is clear from Table 1 that our proposed methodology gives an accuracy greater than or equal to the accuracy values that the researchers have proposed in past. In future, it would be of interest to compare the proposed image representation of EEG signals with the time–frequency domain-based image representation [9] of EEG signals in the CNN framework. The proposed framework can be used to detect epileptic seizures in ruler areas where there is a shortage of doctors, which can enable them to take timely treatment. On the other hand, the proposed software framework can assist neurologist in their diagnosis process, which can improve diagnostic efficiency. The studied FBSE-based EEG rhythm separation can be studied for other applications. The higher order-based FBSE representation [9] can be studied as a part of future work. The various signal analysis techniques, feature extraction methods, and classification methods can be developed in the future for the studied problem.

V. CONCLUSION

This study has introduced a novel method for classifying epileptic seizures using EEG rhythms extracted with FBSE. The Euclidean distances computed from FBSE-based EEG rhythms have provided image representation. These images have been classified into normal and seizure classes using the CNN. The proposed framework has achieved an accuracy of 100% on the studied EEG database. The performance of the proposed framework has been compared with other existing methods studied on the same EEG database. In this study, we have considered only two cases of arrangement of Euclidean distance of EEG rhythms for image construction for classification of normal and seizure EEG signals. The other combinations of Euclidean distances for EEG rhythms can be studied as a part of future work. Future directions include the realization of the proposed framework on hardware and its study during various physical activities. The proposed method is suitable for real-time implementation of the epileptic seizure diagnosis framework. It has been studied for a relatively small dataset. It can be studied on a large dataset before applying to clinical applications. The proposed framework can be studied for other physiological signals corresponding to normal and abnormal classes.

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