A Fast and Accurate Approach for Real-Time Seizure Detection in the IoMT

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***Abstract*—We propose an EEG-based seizure detection method which uses the discrete wavelet transform (DWT), Hjorth parameters and a k-NN classifier. Seizure detection is performed in three stages. In the first stage, EEG signals are decomposed by the DWT into sub-bands and Hjorth parameters are extracted from each of these sub-bands. In the second stage, a k-NN classifier is used to classify the EEG data. The results demonstrate a significant difference in Hjorth parameters between interictal and ictal EEG with ictal EEG being less complex than interictal EEG. We report an accuracy of 100% for a classification of normal vs. ictal EEG and 97.9% for normal and interictal vs. ictal EEG. We propose an Internet of Medical Things (IoMT) platform for performing seizure detection. The proposed framework accommodates the proposed scheme for seizure detection and allows communication of detection results. The IoMT framework also allows the adjustment of seizure detection parameters in response to updated performance evaluations, and possible changes in seizure and signal characteristics as well as the incorporation of other sensor signals to provide an adaptive, multi-modal framework for detecting seizures.**

***Index Terms*—IoT, Electroencephalogram (EEG), Epilepsy, Seizure Detection, Feature Extraction, Hjorth Parameters**

I. Introduction

Epilepsy is a neurological disorder characterized by recurrent spontaneous seizures. A seizure is a sudden and transient interruption of brain function which may also be marked by convulsions and a loss of consciousness [1]. Antiepileptic drugs (AEDs) can be used to control seizures, though seizures in more than 30% of patients remain intractable to AEDs [2]. Epilepsy has a considerable negative impact on the quality of life of patients. There is also a high rate of sudden unexplained death in epilepsy (SUDEP) in comparison to the general population [3]. Brain implantable devices for the control of seizures hold promise as a newly emerging modality for the control of seizures. The prediction and detection of seizures are both of considerable importance, as warning and early detection can result in timely treatment [4]–[9].

The scalp electroencephalogram (EEG) and intracranial EEG (icEEG) contain information on the physiological states of the brain and are thus useful signals for understanding and monitoring brain function and dysfunction. In epilepsy we are primarily interested in two states: ictal (seizure) and interictal (between seizure). Seizures can be identified by visual inspection of the EEG, though this takes considerable time and effort [10]. Computer assisted detection of seizures can be valuable if it can overcome these drawbacks. EEG signals can be well characterized from extracted features which serve to capture distinctive information and can be central to the accuracy of classification [11], [12]. In this paper we propose an EEG-based seizure detection method which uses the discrete wavelet transform (DWT), Hjorth parameters and a k-NN classifier and a framework built around the proposed scheme for seizure detection which allows communication of detection results through the Internet-of-Medical-Things (IoMT).

The remainder of this paper is organized as follows: Section II discusses the novel contributions of this paper. Section III describes research on seizure detection. Section IV presents a design and architecture overview of the proposed solution. Section V discusses the implementation of the proposed design. Experimental results and validation procedures are discussed in Section VI. Section VII presents conclusions and future directions for the research.

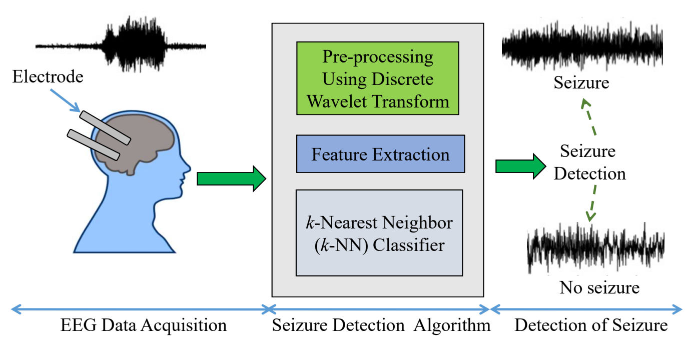

Fig. 1: Block diagram of the proposed seizure detection paradigm.

II. Novel Contributions of This Study

We envision an IoMT device called "Neuro-Thing" which performs fast and accurate seizure detection at the patient end, and sends EEG data and information on the occurrence of seizure to the IoMT cloud where this information can be accessed by stakeholders.

We propose a seizure detection method using the discrete wavelet transform (DWT), Hjorth parameters (HP) and a k-nearest neighbor (k-NN) classifier. A block diagram of the proposed system is shown in Fig. 1. We use the DWT to decompose the EEG signal into five sub-bands, and provide a time frequency representation of the EEG. We used a Daubechies wavelet of order 4 to determine the sub-bands (detail coefficients D1-D4 and approximation coefficient A4). HPs (activity, signal complexity and signal mobility) are derived from these detail and approximation coefficients. The extracted features were then employed within a k-NN classifier for classification.

III. Related previous research

Several methods have been proposed for epileptic seizure detection. The approximate entropy (ApEn) based seizure classification approach [13] found that ApEn drops significantly within the epileptogenic zone during seizure activity. Artificial neural network (ANN) based classifiers have been proposed in seizure detection schemes [14], [15]. In [16], a deep neural-network based method for seizure detection has been presented. Wavelet transform based features have been extracted and applied to ANN for the classification of seizure and non-seizure activity [11]. In the short term Fourier transform (STFT) based approach [17], features have been extracted from the short term Fourier transform using the smoothed-pseudo Wigner-Ville distribution and classification is performed using an ANN classifier. The decomposition of the EEG using wavelet transform and classification using radial basis function network (RBF) and multilayer perception network (MLP) has been investigated in [18]. Most of these approaches use different combinations of features to improve classification accuracy. In this paper, we investigate classification accuracy using HPs of the DWT decomposed EEG signals. A comparison of the proposed approach with existing methods is shown in Table I.

IV. The Proposed Seizure Detection Approach

A. The Proposed Architecture of Neuro-Thing

The overall architecture and flowchart of the proposed "Neuro-Thing are shown in Fig. 2 and Fig. 3, respectively. The EEG is acquired and decomposed into several sub-bands using DWT. HP values are extracted from the different sub-bands to form a feature vector. The feature vectors are submitted to the k-NN classier. The memory unit stores the patients data, and is connected to a low power wireless module. The wireless module enables data to be transferred to clinical care staff through the Internet. The k-NN classifier is trained using training datasets.

B. Discrete Wavelet Transform based Preprocessing Unit

The wavelet transform provides a TF decomposition of a signal by capturing low frequency information using long duration windows and high frequency information using short duration windows. The decomposition step is achieved by low pass and high pass filters as described by the following equations [22]:

$$HPF(S) = A_{1m} = \sum_{n} S(k)h(2m-n), \tag{1}$$

$$LPF(S) = D_{1m} = \sum_{n} S(k)g(2m-n), \tag{2}$$

where $S(k)$ is the input sampled signal and g and h are the impulse responses of low-pass and high-pass filters, respectively. The output of the low pass filter is called the approximation coefficient (A_1). The output of the high pass filter is called the detail coefficient (D_1). This decomposition step is repeated for the approximation coefficient at every level. The subsequent detail coefficients are denoted as D_2, D_3, and D_4. The last approximation coefficient is denoted as A_4. The filtering employed at each decomposition stage doubles the frequency resolution and down-sampling halves the time resolution. The Daubechies wavelet function of order 4 (db4), and the four level DWT, allowed an analysis of signals in the range 0 to 86.8 Hz with the breakdown of sub-band frequencies as shown in Table II.

C. Hjorth Parameter (HP) Extraction Unit

Hjorth parameters (activity, signal complexity, and signal mobility) have been shown to be highly effective for capturing the complex dynamics of brain signals [23]. Signal complexity and signal mobility quantify the level of variations along the signal. First order variations of the signal are addressed using signal mobility whereas second order variations are addressed using signal complexity. The HP unit calculates the parameters from the EEG signal and passes them to the k-NN classifier.

D. k-Nearest Neighbor Classifier

The k-nearest neighbor classifier [24] is both simple and nonparametric. The k-NN algorithm has of two phases: the training phase and the classification phase. The training set consists of feature vectors with a class label. The class labels and feature vector of the training sample are stored. In the classification phase, the test or query points are assigned to a label. The k-NN algorithm compares a library of reference vectors with an input feature vector or query point and the query point is assigned to a class based on the nearest reference feature vectors. The nearness of the datasets was calculated using the Euclidean distance metric. The algorithm classifies data based on a majority vote from the k nearest neighbors as opposed to the single nearest neighbor.

The training of the Neuro-Thing is critical for accurate detection of seizures. There are several options for training in a connected system. These include: (1) Slow updates: The update is delivered from the cloud on a monthly or quarterly basis. This training uses a large amount of data, and can be

TABLE I: Comparison to Existing Seizure Detection Methods.

Works	Methods	Cases	CA (%)
Kumar, et al. 2014 [19]	Discrete wavelet transform and neural network classifier	A-E	100
		A, D-E	95
Tawfik, et al. 2016 [20]	Weighted permutation entropy (WPE) and support vector machine (SVM)	A-E	98.5
		A, D-E	96.5
Yavuz, et al. 2018 [21]	Cepstral analysis and generalized regression neural network	A-E	99
		A, D-E	97.25
Current Paper 2018	DWT based Hjorth parameter and k-NN classifier	A-E	100
		A, D - E	97.85

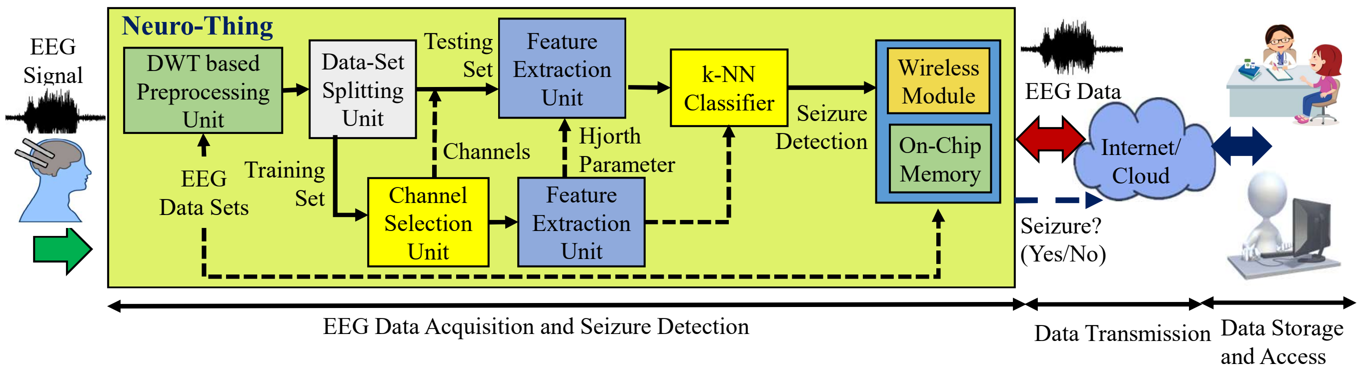

Fig. 2: Block diagram of the proposed novel IoMT-enabled seizure detector architecture.

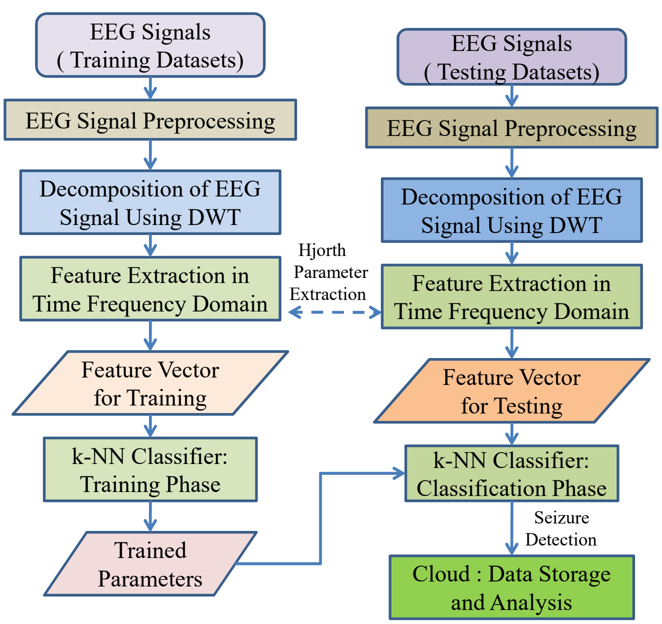

Fig. 3: Flowchart of the proposed novel fast and accurate seizure detection algorithm.

TABLE II: Frequency characterization of the proposed system

Parameters	Value
Detectable seizure frequency	0-87 Hz
D_1	43.4-86.8 Hz
D_2	21.7- 43.4 Hz
D_3	10.85-21.7 Hz
D_4	5.43-10.85 Hz
A_4	0-5.43 Hz

accurate as historic data are fully used. (2) Faster updates: The update is delivered from the cloud on a more frequent basis, for example, weekly. The training uses less than a comprehensive amount of data. The solution can be moderately accurate as historic data are used. (3) Real-time or near-real time training: Updates are provided at a frequent rate, daily or even hourly. The data is from on-chip memory. This is fast, but may be less accurate.

V. Implementation of The Proposed System

A system-level simulation of the proposed system was implemented in Simulink® Version 9.2 R2017A. The prototype of the proposed system for a individual statistical feature, signal mobility, is shown in Fig. 4. In the first level of decomposition the signal is passed through high pass and low pass filters. The same decomposition step is repeated up to the 4th level. As indicated above, each decomposition halves the time resolution and doubles the frequency resolution. A Simulink® user defined function was used to construct the DWT algorithm. Subsequently, Hjorth parameters were extracted from the decomposed signals. The HP values were used as a feature for the k-NN classifier. Another Simulink® user defined function was created to build the k-NN classifier. The classifier stores the feature vectors and class labels of the different EEG datasets during the training phase. When a new test point is applied to the system for classification, the algorithm calculates its k nearest neighbors and a class is assigned based on voting amongst those neighbors. The IoMT implementation was carried out using ThingSpeak, an open data platform for IoT applications, which was utilized to gather and analyze data in the cloud. In the Simulink® environment, the information related to seizure detection was sent to the cloud using the ThingSpeak Input block from the Simulink® Desktop Real-time library.

VI. Experimental Results

The EEG datasets were from the widely used open source database available from the University of Bonn [25]. This database contains five datasets, denoted as A, B, C, D and E. Each dataset contains 100 EEG segments and each data segment (of 23.6s duration) consists of 4097 data points. In this study we used datasets A, D and E. Dataset A consists of scalp EEG recorded from five healthy subject when their eyes were open. Datasets D and E consists of intracranial EEG (icEEG) recorded from the epileptogenic zone of patients during interictal and ictal states, respectively. That is, D consists of seizure free intervals, whereas E contains seizure activity. The EEG and icEEG were recorded using a 128-channel amplifier system with an average shared reference. The spectral bandwidth of the acquisition system was 0.53 to 40 Hz. Data was sampled at 173.61 Hz followed by 12 bit analog to digital conversion.

Example EEG epochs from dataset A (scalp EEG from normal subjects), D (interictal icEEG from the epileptogenic zone) and E (ictal icEEG from the epileptogenic zone) are shown in Fig. 5. The DWT was used to decompose the EEG into five sub-bands. The Hjorth parameters activity (AC), signal complexity (SC), and signal mobility (SM) were calculated for all sub-bands of the 300 EEG epochs.

TABLE III: Extracted feature coefficients for dataset A

Coefficient	Activity	Signal Complexity	Signal Mobility
D_1	18.44	0.9371	1.4586
D_2	362.5	0.4688	1.8296
D_3	3.88e+03	0.7145	1.7259
D_4	7.33e+03	1.2315	1.1894
A_4	1.91e+04	1.4909	0.7691

Table III shows the value of the approximation and detail coefficient of the different sub-bands for dataset A. The average signal complexity for datasets A, D, and E was 0.71, 0.65, and 0.48 . It is evident that signal complexity is higher in normal EEG compared to ictal EEG, which corresponds to the findings reported in [26]. On the other-hand, activity and signal mobility is higher for data set E recorded during seizure. Dataset D, which consists of seizure free icEEG, is almost identical to dataset A (normal scalp EEG). Hjorth parameters from different sub-bands were applied to a k-NN classifier. In this study, the following cases were tested: (1) Case 1: Set A versus Set E, and (2) Case 2: Set A and D versus Set E.

Table IV summarizes the results showing the classification accuracy, sensitivity, and specificity with individual and combined features. Fig. 6 illustrates a comparison with existing competitive methods and demonstrates the superiority of the proposed system.

VII. Conclusions

We have described an automated seizure detection method which uses DWT based Hjorth parameter extraction and k-NN based classification. A system level simulation of the proposed system was performed in Simulink®. The experimental results show that DWT based Hjorth parameters are highly effective in distinguishing EEG signals, leading to an improved classification accuracy in comparison to existing methods. We have also proposed an IoMT framework for continuous monitoring of neurological symptoms. In addition to the EEG which was explored here, this framework can be expanded to include wireless icEEG sensors, biosensors, or other body worn sensors such as limb worn accelerometers to detect patient activity including seizures [27]–[29].

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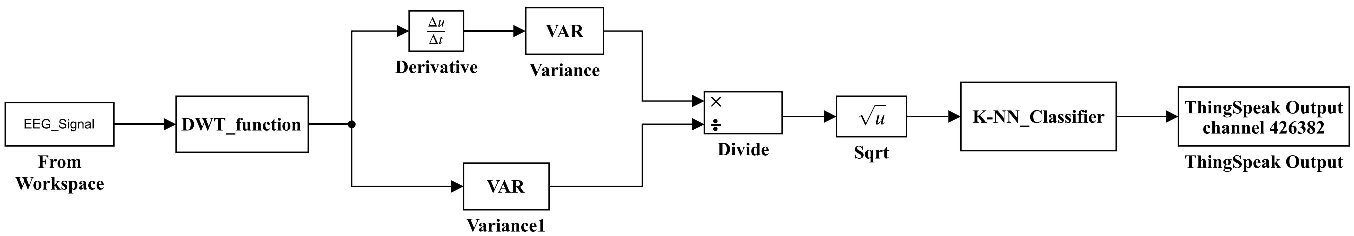

Fig. 4: Simulink® model of the proposed system.

TABLE IV: Performance of k-NN classifier for different features.

Case No.	Dataset	Performance	AC+SC+SM	AC+SC	AC+SM	SC+SM	AC	SC	SM
Case 1	A-E	Accuracy (%)	100	100	100	100	100	100	100
		Sensitivity (%)	100	100	100	100	100	100	100
		Specificity (%)	100	100	100	100	100	100	100
Case 2	A, D-E	Accuracy (%)	96.21	96.63	96.21	96.21	97.85	96.8	96.21
		Sensitivity (%)	93.84	93.71	93.84	93.84	94.7	94.6	93.84
		Specificity (%)	97.41	98.14	97.41	97.41	98.77	97.91	97.41

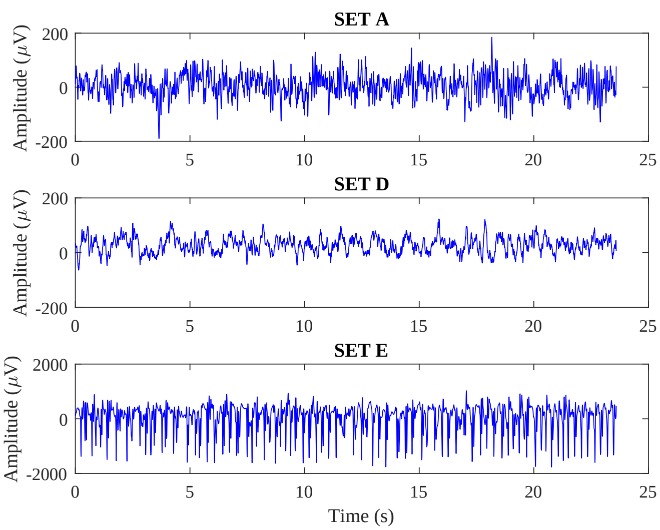

Fig. 5: Example scalp EEG and icEEG from datasets A, D, and E.

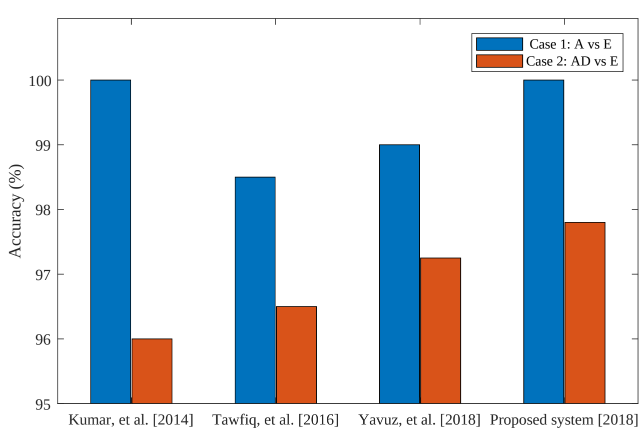

Fig. 6: Comparison of accuracy with existing methods.

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