Deep Recurrent Neural Network for Seizure Detection

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Abstract*— EEG is one the most effective tools used in the diagnosis of epilepsy. However, proper diagnosis of epilepsy requires the detection and analysis of epileptic seizures for a long period of time. Manual monitoring of long term EEG is tedious and costly. Therefore, a reliable automated seizure detection system is desirable. Most current state-of-the-art methods use hand crafted feature extraction and simple classification techniques, which often leads to sub-par performance due to lack of generalizability across patient dataset. Consequently, this work introduces novel deep recurrent neural network (DRNN) architecture to perform automated patient specific seizure detection using scalp EEG. We further propose a unique mapping of seizure EEG signal for efficient processing with the DRNN. This mapping allows the proposed deep architecture to simultaneously learn both temporal and spatial features of raw seizure EEG respectively. The proposed DRNN architecture is tested with long term patient specific scalp EEG data of 5 subjects with approximately 34 hours of EEG extracted from a publically available dataset. Overall, the proposed network successfully detects 100% of total seizure events with an average detection delay of ~7.0 sec. The results demonstrate superior performance to that of the current state-of-art seizure detection methods. The proposed DRNN architecture also obtains a runtime of approximately 30ms for 1 sec segment of 18 channel EEG. The low processing time with sparse use of computing resources and superior performance make the proposed architecture appropriate for real-time use.

Keywords—Deep Neural Network; Bidirectional Recurrent Neural Network; Seizure detection; DRNN; EEG

I. INTRODUCTION

Epilepsy is a common and serious neurological disorder typically characterized by frequent unprovoked seizures. These seizures occur due to abnormal synchronous firing of cortical neurons. Potential risk of mortality makes early diagnosis and timely treatment of epilepsy a critical task. The most common tool utilized in clinical diagnosis of epilepsy is the electroencephalography (EEG). The EEG directly measures and records the electrical activity of the brain. This allows for identification of the abnormal neural oscillations recorded due to epileptic seizures. However, proper diagnosis of the disease requires long term monitoring of the EEG [1], which, if manually performed, could be a tedious task. Therefore, an automated seizure detection method may be quite helpful in the diagnosis of epilepsy. Furthermore, timely intervention at an onset of a seizure may also be important in the evaluation process and subsequent treatment for the disease. Therefore, an automated real-time detection system may function as an alerting mechanism, allowing for immediate medical assistance.

The necessity of such an automatic seizure detection system has paved the way to a considerable number of studies in the past few decades. In one of the earliest studies, Gotman [5] presents an automated seizure detection method based on half-wave decomposition of EEG. This method is evaluated on a scalp EEG dataset obtained from 16 patients and intracranial EEG recorded from 4 patients. The author reports a detection accuracy of 76% and a false detection rate of 1 per hour. Similarly, Gabor et al. [4] propose a method to detect epileptic seizures using wavelet based filtering and self organizing neural networks. The algorithm is tested on 24 long term scalp EEG recordings obtained from 22 patients. The authors report a detection accuracy of 90% with a mean false detection rate of 0.71 per hour. Even though these early studies emphasize requirement of a more robust methods, they have identified the main characteristics of seizure EEG, as self-similar oscillatory patterns.

The time-limited oscillatory features of the seizure EEG have led researchers to use various time-frequency analysis methods [1, 4, 6, 7] for seizure detection. Though wavelet based time-frequency techniques are capable of capturing the oscillatory patterns of seizure EEG, these methods are still handcrafted and require user defined parameters which may not be prudent for developing a robust and efficient seizure detection algorithm. Therefore, it is desirable to design a system that 'learns' the more intricate features of seizure EEG to perform robust seizure detection. Among learning models for seizure detection, artificial neural networks (ANN) have largely been absent in the epileptic seizure detection literature.

Based on electrode placement, EEG can be segmented into intracranial and scalp recordings. The intracranial EEG (iEEG) is recorded using electrodes placed invasively under the scalp. The iEEG are generally artifact free and contain more information recorded at higher frequencies. Conversely, the scalp EEG is recorded non-invasively, and typically prone to external noise and signal attenuation due to the skin, skull, cerebrospinal fluid, etc. between the electrodes and the brain. However, scalp EEG is more popular and widely used in clinical applications due to the ease of use, low cost, and no requirement of surgery.

The ANNs, specifically the recurrent neural networks are quite adept at processing time-series data [8-10]. The RNNs contain feed-back connections in addition to the regular feed-

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forward connections among its neurons. These feedbacks allow the RNN to accumulate and maintain past knowledge when processing time sequence data. The RNN utilizes the past knowledge, or context, when processing future input elements of the time sequence. EEG can be considered as time sequence data, which makes RNN an appropriate tool to process EEG signals. Until now, very few studies have utilized RNNs to process EEG for seizure detection [11, 12]. Petrosian et al. [12] use an RNN to predict seizures using intracranial and scalp EEG. The authors utilize a three layered RNN with one recurrent hidden layer to perform the detection task. Trained on both raw and wavelet decomposed input EEG, the authors findings show that the RNN can successfully predict seizure onset with intracranial data. However, tests with the more challenging scalp EEG have shown less success [12].

In this work, we propose a novel deep bidirectional recurrent neural architecture (DRNN) to process time-sequence EEG for seizure detection. The bidirectional information flow is a recent improvement in recurrent networks [13], which enables the use of past as well as future context in sequential data. In addition, we believe that the spatial location and the disperse patterns of seizure activity may hold valuable insights into accurate and timely detection. Therefore, simultaneous processing of all EEG electrodes may adequately capture these spatial features rather than processing each electrode separately. In order to learn both temporal and spatial features simultaneously, we propose a unique mapping method of the EEG montage to the deep architecture. This montage mapping method allows for an efficient design of the deep bidirectional recurrent architecture. This study uses scalp EEG for the analyses of the proposed DRNN in seizure detection.

Section II of this paper provides background information on cellular neural networks and bidirectional recurrent networks. Section III introduces the proposed DRNN architecture for patient specific seizure detection. Section IV discusses the long term EEG data used in the analysis, the preparation of EEG montage for processing, and outlines the network parameters used for the seizure detection task. Section V presents and analyzes the experimental results, and section VI concludes the findings.

II. BACKGROUND

A. Cellular Neural Network

Cellular neural networks (Cellular ANN's) are a unique type of ANN architecture that consists of cells with identical elements arranged in some geometric pattern [14]. Each element (cell) of the Cellular ANN may vary from a simple artificial neuron to a complex ANN. An example cellular architecture is shown in Fig. 1.

Cellular ANNs in Fig. 1 may efficiently process input patterns that contain some inherent geometric structures. Each cell of the network processes the corresponding element (e.g. a timely electrode output in an EEG montage) of an input pattern, enabling efficient distributed processing. Though each element may be processed independently by the corresponding cell, the interactions between neighboring cells allow for processing local geometric patterns in 2D input. The cellular structure also utilizes network weight sharing between each cell. This helps processing large input patterns with relatively small number of training weights.

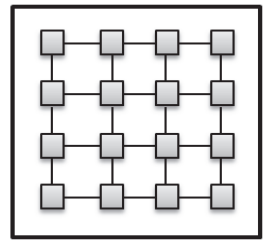

Fig. 1. Typical cellular architecture of a 4×4 CNN. Interactions between cells are depicted by connecting lines.

B. Bidirectional Recurrent Neural Network

A classic recurrent network (RNN) is unidirectional, which suggests that the RNN processes a data sequence in one direction (i.e. left to right processing of a 1D data sequence).

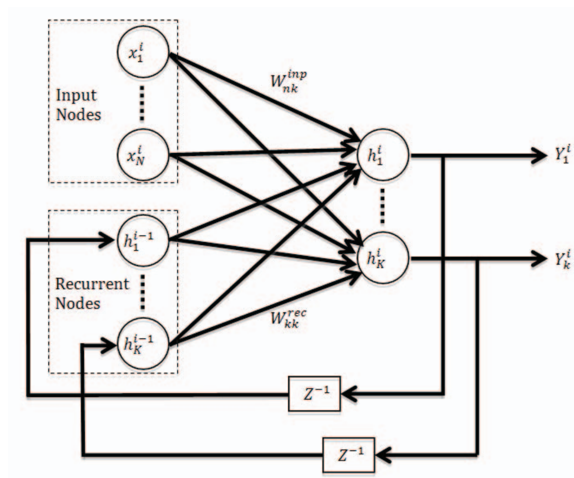

Fig. 2. A 2 layer unidirectional recurrent neural network architecture.

Fig. 2 shows a 2 layer unidirectional RNN structure.

The forward propagation function of above RNN architecture is given in (1),

$$Y_k^i = f\left[\left(\sum_{l=1}^{N} W_{lk}^{inp}\, X_l^i\right) + \left(\sum_{m=1}^{K} W_{mk}^{rec}\, Y_m^{i-1}\right)\right] \quad (1)$$

Where Y_k^i is the output from the hidden node k at i^{th} time point in the data sequence. W_{lk}^{inp} is the weight connecting l^{th} input component, X_l^i at time i, with hidden unit h_k^i. Similarly, weight W_{mk}^{rec} connects the previous (recurrent) output component Y_m^{i-1} with the hidden unit h_k^i.

Note that eqn. (1) can be expanded backwards through the data sequence from $i-1$ until the initial element of the input sequence. This reveals that the current output Y^i of the RNN depends on the current input X^i as well as the context accumulated through the previous outputs. This way of processing however, may not be quite efficient, especially if the whole data sequence is available, as the future context is unused. Moreover, the unidirectional model often fails to form proper responses to the first few inputs of a sequence due to lack of past context.

The bidirectional RNN (BRNN) [13] alleviates these problems by making use of the past as well as the future context of a data sequence. BRNN can be thought of as a straightforward extension of the classic RNN, where it maintains two different recurrent layers for each direction (one for processing from left to right (RNN^{d_1}), the other from right to left (RNN^{d_2})). BRNN then combines the outputs of RNN^{d_1} and RNN^{d_2} using an additional output layer. Fig. 3 shows the general composition of a BRNN.

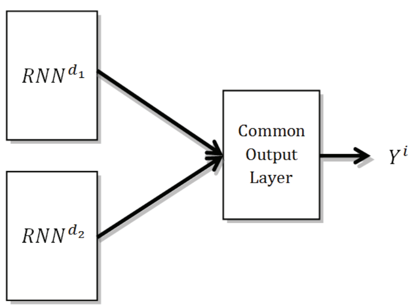

Fig. 3. Bidirectional RNN (BRNN) architecture

The RNN^{d_1} and RNN^{d_2} in Fig. 3 are recurrent neural networks such as the one shown in Fig. 2. The common output layer combines outputs from each directional RNN to produce the final output Y^i for the i^{th} element in the data sequence. Note that this bidirectional setup ensures constant amount of contextual influence in processing any element i of the input data sequence.

III. METHODS

The proposed DRNN holds a bidirectional recurrent neural network as the core element of its cellular external architecture.

A. The DRNN Architecture

The bidirectional model in Fig. 3 including RNNs (Fig. 2) in each direction constitutes the core network element of the proposed DRNN architecture. The final architecture of the DRNN is shown in Fig. 4.

Note that the cellular structure of the proposed network matches with that of the 2D input pattern. Therefore all the attributes of a Cellular ANN architecture (discussed in section II-*A*) are preserved in the DRNN. Each 2D element of the input pattern is processed simultaneously by each corresponding cell of the DRNN. Also, each cell of the DRNN communicates with its neighbors. The Bidirectional RNN cores in the proposed architecture produces outputs as shown in Fig. 3. These outputs are combined and processed using a multi-layered perceptron (MLP) to obtain the final output of the network. Therefore, the DRNN architecture further extends the

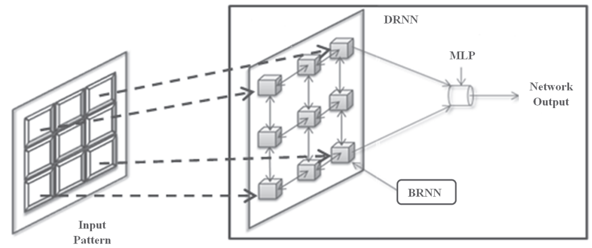

Fig. 4. Proposed DRNN architecture

capabilities of bidirectional recurrent neural networks for efficient processing of 2D data. Moreover, this unique structure of DRNN enables learning and recognizing both temporal and spatial patterns simultaneously. These traits make the DRNN an excellent architecture to process EEG time-series montages.

B. The DRNN Training

The recurrent architectures inhibit the use of standard back-propagation for obtaining the derivatives of the network for training. Instead, the natural choice is to use back-propagation through time (BPTT), which accurately computes the derivatives of RNNs using a temporal 'unfolding' process [15]. This is essentially a time extension to generic back-propagation. However, with the complexity of neural architecture, derivative computation through BPTT may get quite complex, and error-prone. The combination of cellular architecture with bidirectional recurrent networks makes the proposed network even more intricate and, hence, the use of BPTT undesirable.

Therefore, this study uses a Jacobian free Unscented Kalman filer (UKF) based parameter optimization method for training DRNN. The UKF has been successfully used for training recurrent architectures [16, 17]. We propose to use the UKF based training algorithm to train the DRNN for the seizure detection task.

IV. EEG TIME-SEIRIES PROCESSING WITH DRNN

A. EEG Dataset

The EEG data utilized in this study is extracted from the CHB-MIT EEG database [18]. The database consists of long term bipolar referenced EEG recordings from pediatric patients with intractable seizures. This study uses continuous EEG recorded from 5 subjects (e.g., 'chb01, 'chb03', 'chb05', 'chb07', and 'chb11') for the analysis of DRNN in seizure detection. For each chosen subject, the long term EEG is recorded in continuous segments of 1 to 4 hour duration, which includes one seizure event. All the EEG recordings of this dataset are sampled at 256 samples per second, at 16-bit quantization. Most of the cases contain 23 bipolar EEG signals derived from electrodes placed according to International Federation of Clinical Neurophysiology 10-20 placement system.

All EEG data are pre-processed using a band-pass filter between 3Hz and 30 Hz since most seizure activity at ictal state occurs within this frequency range [1, 5].

B. EEG Montage Processing with DRNN

As mentioned in section IV-*A*, the patient specific EEG data are recorded as 23 or more bipolar signals. However, this study requires the EEG signals to be organized in a grid like arrangement. Therefore, we propose to map 18 representative signals that can be best utilized to form a grid like pattern. The proposed montage of 18 EEG signals and its grid like mapping is shown in Fig. 5. The blue lines in the montage (Fig. 5(a)) correspond to the signal obtained by bipolar referencing of the electrodes at each end. The corresponding 2D grid approximation of the signal locations are shown in Fig. 5(b). Note that the proposed mapping of 2D grid takes the general shape of a 2D input pattern typically used with cellular networks (see Fig. 4). Therefore, this mapping of input data is used for the proposed DRNN to process EEG for seizure detection. The raw EEG signal at each location of Fig. 5 (b) is considered as the external input x for each corresponding cell. The EEG are segmented into 1 sec non overlapping epochs (256 samples per epoch) prior to analysis with DRNN. This ensures a 1 sec context region for each processing element i of the input EEG sequence at each cell.

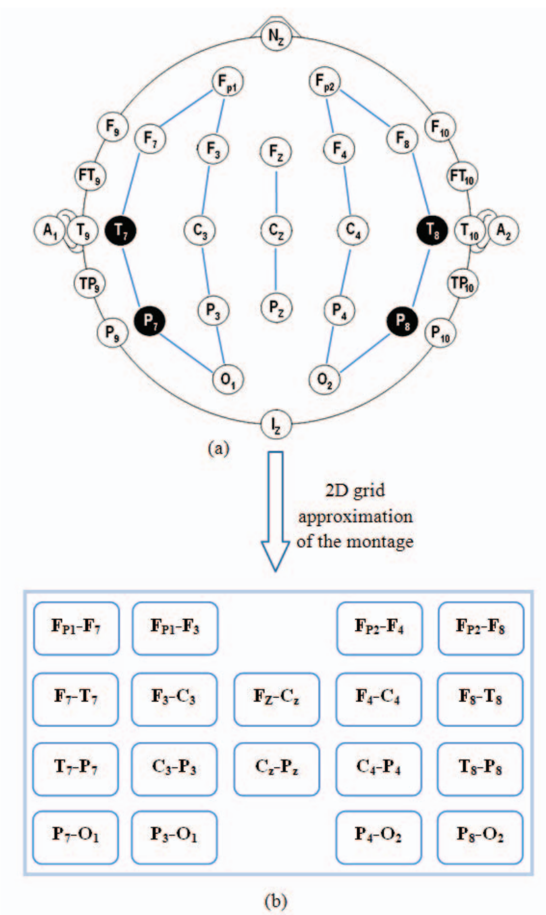

Fig. 5. (a) The long term EEG bipolar signal montage used in the study. (b) The 2D grid approximation of the montage

The core RNN of the DRNN architecture used in the study consists of $K = 5$ active recurrent neurons (tanh) in the hidden layer. Output to the neighboring cells is chosen to be the output of final (5th) hidden recurrent neuron. The common output layer of the core consists of 1 active neuron (tanh). Therefore, each cell in the DRNN produces 1 output. The MLP (see Fig. 4) consists of 2 layers. The input layer (layer 1) to MLP is the collection of all the cell outputs. The 2nd (final) layer is an activated neuron (logistic sigmoid) which classifies each sample in an EEG epoch as seizure or non-seizure. The final classification for each 1 sec epoch is obtained by applying 3 patient specific post processing steps: (1) A box filter is first applied over all the output samples. (2) Next, the outputs are thresholded at a patient specific value. This value is experimentally obtained in training by observing the network output given seizure or non-seizure class input. (3) Finally, the mode over each epoch is used to classify that epoch.

The training and testing is conducted using a patient specific leave one out cross-validation scheme. Suppose long term EEG recordings of one patient contain Z number of seizure events. The classifier is trained using $(Z-1)$ continuous EEG segments. The testing is done on the withheld continuous EEG segment with seizure event. As mentioned in section III-A, each continuous EEG segment contains 1 hr or more EEG. Therefore the proposed detector is tested on sufficient duration of seizure and non-seizure activity.

V. RESULTS AND DISCUSSION

The performance of the proposed DRNN seizure detector is analyzed in terms of: (1) Seizure detection sensitivity (true positives), (2) Amount of false positives (specificity) per hour of EEG, and (3) seizure detection latency (delay). Sensitivity provides percentage of seizures correctly detected in the test dataset. Specificity gives the number of false positive classifications per hour of EEG. Latency is the time (in sec) between the seizure detected by the algorithm and the seizure onset provided in the database.

The proposed architecture is implemented using MATLAB 8 with a workstation: Intel Xeon 2.6GHz and 32 GB of RAM.

A. Seizure Detection Performance of DRNN

The proposed DRNN architecture successfully detects all 25 seizures, which is an overall sensitivity of 100%. The detailed results for patient specific seizure detection sensitivity along with total number of seizures are shown in Fig. 6.

Seizure detection delay is an important factor for an automated detector, especially for accurate onset detection. Real-time seizure detection with minimal latency may allow adequate time for medical personnel to intervene and administer pertinent medication. The average patient specific seizure detection delay of the DRNN is shown in Fig. 7. The overall detection delay for the dataset is approximately 7.0 sec with a standard deviation (stdev) of 2.7 sec.

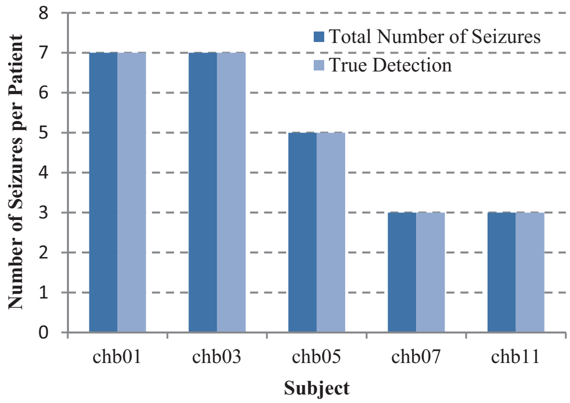

Fig. 6. Seizure detection results for each patient

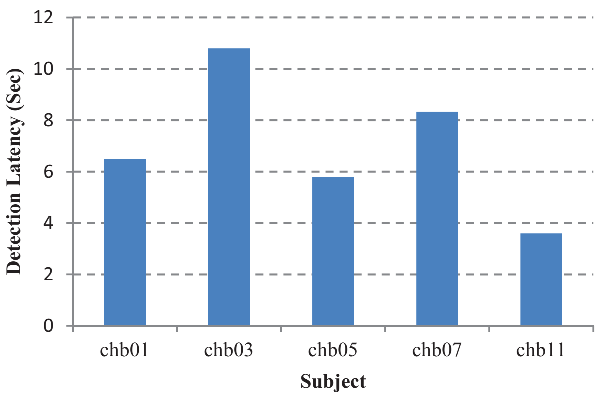

Fig. 7. Seizure detection latency for each patient

Unlike the accuracy, the delay in seizure classification heavily depends on the onset characteristics of the seizure. For example, a seizure event that develops its inherent characteristics over time rather than from the onset or a seizure onset that is corrupted by artifacts may result in considerable detection delay. The output thresholding technique utilized in this study (section IV-B) has a substantial effect on the detection delay. This patient specific thesholding value obtained using the DRNN output on the training data essentially compromises between the sensitivity, specificity and detection delay. Figure 8 shows an example DRNN response to an EEG segment that contains a seizure event. The large peak of the graph shows that DRNN successfully detects the seizure event. However, note the relatively small fluctuations in the DRNN response for surrounding non-seizure EEG. This requires the classification threshold to be increased to a larger value to avoid false positives. Increasing the threshold in turn increases the detection delay. For this study, we increase the threshold value to maintain a minimal ($0.08\ h^{-1}$) false classifications, and maximum true detections,

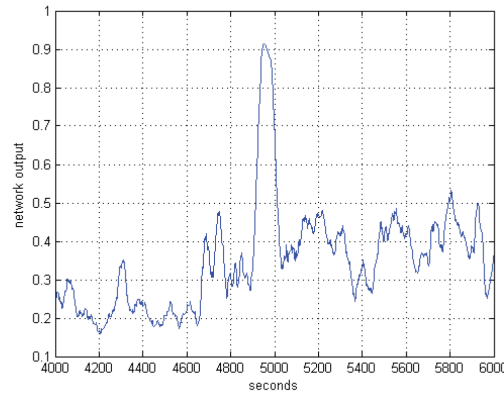

Fig. 8. DRNN response (smoothed) for an EEG segment containing a seizure event (seizure event from 4920 sec to 5006 sec)

compromising the detection delay.

B. *Performance Comparison*

In order to establish the performance of the proposed seizure detector, we compare our preliminary results with several other state-of-the-art scalp EEG based seizure detection methods reported in literature. The comparison with performance metrics are summarized in Table I.

From the studies used in comparison, Saab et al. [1], and Kuhlman et al. [4] utilize wavelet decompostion methods for seizure detection. Zandi et al. uses an improved multi-resolution wavelet packet based method, yielding an accuracy of 91% with 9 second detection delay, improving upon [1] and [4]. On the other hand, Shoeb et al. [2] uses a filter bank based feature extraction method coupled with an SVM classifier yielding a sensitivity of 96% with a detection delay of 4.6 sec. Note that the EEG data used in this preliminary study is extracted from the larger dataset used in [2], which allows for a direct comparison of outcomes. Accordingly, the seizure detection specificity of DRNN proposed in this study is comparable to that of Shoeb et al. [2] while the detection delay is slightly higher. However, the DRNN performs much better with regards to the sensitivity. We point out that the delay and specificity can be regulated in the selection procedure of DRNN output thresholding values as discussed earlier.

TABLE I
SEIZURE DETECTION METHOD PERFORMANCE COMPARISON

Seizure Detection Algorithms	Sensitivity (%)	Specificity (False Detections h^{-1})	Detection Delay (Sec)
Saab et al. [1]	78	0.86	9.8 (median)
Shoeb et al. [2]	96	0.08	4.6 (mean)
Zandi et al. [3]	91	0.33	9 (mean)
Kuhlmann et al. [4]	81	0.60	16.9 (median)
Proposed Method	**100**	**0.08**	**7 (mean)** **2.7 (stdev)**

Furthermore, unlike Ref. [2] where features are hand-crafted, proposed method in this work automatically learns the inherent characteristics of seizure data. In addition, the classic time-frequency evaluation techniques tend to be highly complex and resource intensive. For instance, Zandi et al [19] with wavelet packet transform reports a run time of 330ms to process 2 sec epoch of 15 channel EEG. Whereas, DRNN takes a processing time of approximately 30ms for 1 sec epoch of 18 channel EEG. Additionally, the overall DRNN architecture designed for seizure detection in this study utilize only 142 trainable weights. The fast run-time and sparse use of weights in this study suggest the potential for real-time use of DRNN.

VI. Conclusion

This paper proposes a novel DRNN architecture for patient specific epileptic seizure detection with scalp EEG. A novel mapping of input seizure pattern is also proposed to facilitate use of a fast derivative free UKF training algorithm for the DRNN. The combination of EEG montage mapping with deep recurrent architecture aids in learning both spatial and temporal features of seizure EEG. The network is tested on long term scalp EEG data consisting of approximately 34 h of EEG obtained from CHB-MIT database. The DRNN architecture successfully detects 100% seizure events with a mean detection delay of 7 sec and a 0.08 h^{-1} false classification rate. The results obtained from these preliminary experiments suggest that the seizure detection performance of the DRNN is better than that of current state-of-the-art seizure detection techniques in literature. Furthermore, the quick run-time of DRNN coupled with extremely sparse use of computing resources makes DRNN desirable for real-time use.

In future, we plan to further improve DRNN architecture for both scalp and intracranial EEG processing. The improvements may include further automation of patient specific thresholding for better detection delay, and utilization for real-time seizure detection. We also plan to expand the use of DRNN beyond seizure detection and process EEG for other purposes such as brain computer interfacing.

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