Supervised Learning in Automatic Channel Selection for Epileptic Seizure Detection

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Abstract
Detecting seizure using brain neuroactivations recorded by intracranial electroencephalogram (iEEG) has been widely used for monitoring, diagnosing, and closed-loop therapy of epileptic patients, however, computational efficiency gains are needed if state-of-the-art methods are to be implemented in implanted devices. We present a novel method for automatic seizure detection based on iEEG data that outperforms current state-of-the-art seizure detection methods in terms of computational efficiency while maintaining the accuracy. The proposed algorithm incorporates an automatic channel selection (ACS) engine as a pre-processing stage to the seizure detection procedure. The ACS engine consists of supervised classifiers which aim to find iEEG channels which contribute the most to a seizure. Seizure detection stage involves feature extraction and classification. Feature extraction is performed in both frequency and time domains where spectral power and correlation between channel pairs are calculated. Random Forest is used in classification of interictal, ictal and early ictal periods of iEEG signals. Seizure detection in this paper is retrospective and patient-specific. iEEG data is accessed via Kaggle, provided by International Epilepsy Electro-physiology Portal. The dataset includes a training set of 6.5 hours of interictal data and 41 min ictal data and a test set of 9.14 hours. Compared to the state-of-the-art on the same dataset, we achieve 49.4% increase in computational efficiency and 400 mins better in average for detection delay. The proposed model is able to detect a seizure onset at 91.95% sensitivity and 94.05% specificity with a mean detection delay of 2.77 s. The area under the curve (AUC) is 96.44%, that is comparable to the current state-of-the-art with AUC of 96.29%.

Keywords: seizure detection, iEEG, Random Forest, automatic channel selection

1. Introduction

Epileptic seizure affects nearly 1% of global population but only two thirds can be treated by medicine and approximately 7 – 8% can be cured by surgery (Litt and Echauz, 2002). Therefore, seizure onset detection and subsequent seizure suppression becomes important for the patients that cannot be cured by neither drug nor surgery. Early detection can allow early electrical stimulation to suppress the seizure (Echauz et al., 2007). In this paper, we focus on how to effectively and reliably detect seizure onset based on iEEG patterns. Causes and treatment of seizure is beyond the scope of this paper.

EEG has been commonly used in brain-computer interface thanks to the convenient real-time readings and high temporal resolution of EEG signals (Zeng and Song, 2015; Zhang et al., 2013). In recent years, EEG has provided a promising possibility to detect and even predict an epileptic seizure (Tieng et al., 2016; Fatichah et al., 2014; Parvez and Paul, 2015; Saab and Gotman, 2005; Osorio and Frei, 2009; Kuhlmann et al., 2009). For seizure detection, Fatichah et al. (2014) used a combination of principle component analysis (PCA) and neural network with fuzzy membership function that can achieve accuracy rate up to 97.64% . Tieng et al. (2016) combined wavelet de-noising with adapted Continuous Wavelet Transform in their algorithm and were able to achieve sensitivity of 96.72% and specificity of 94.69% with EEG data from mice. Another remarkable method is to transform EEG signals into images so as to leverage image processing techniques (Parvez and Paul, 2015). This approach was able to obtain 98.91% sensitivity and 94.35% specificity. Zabihi et al. (2016) reconstructed EEG phase spaces using time-delay embedding method and PoinCare section. The phase spaces were then reduced by PCA before being fed to linear discriminant analysis (LDA) and Naive Bayesian classifiers. This approach achieved 88.27% sensitivity and 93.21% specificity in seizure detection.

Shoeb (2009) deployed 8 filters spanning the frequency range of 0.5–24 Hz for each 2-s EEG epoch of all channels, then concatenated 3 epochs to form a feature set to be fed to a SVM classifier. This approach was tested with the CHB-MIT EEG dataset and was able to detect 96% of 163 test seizures with a mean detection delay of 4.6 seconds. Using the same CHB-MIT dataset, EEG signal was transformed into an image representation using 2-D projection of the patient electrodes and the magnitude of 3 different frequency bands spanning the range of 0–49 Hz of each 1 s block of EEG signal (Thodoroff et al., 2016). The recurrent convolutional neural network took 30 consecutive blocks as inputs to perform feature extraction and classification. The patient-specific detectors in this method have comparable performance compared to the proposed method by Shoeb (2009).

Prominent feature extraction techniques consider characteristics in both frequency and time domain. As an efficient tool for time-frequency-energy analysis, wavelet-based filters were used to extract a ratio of seizure
content of the short foreground in comparison with the background (Saab and Gotman, 2005; Osorio and Frei, 2009). Saab and Gotman (2005) applied Bayes’ formula on extracted features to estimate the probability of seizure in EEG signals. This method achieved an impressively short onset detection delay of 9.8 s with 76% sensitivity and 0.34/h false positive rate. Kuhlmann et al. (2009) extended Saab and Gotman’s method by combining extra features to find a superior detector. Their method was able to achieve a sensitivity of 81%, a false positive rate of 0.60/h, and a median detection delay of 16.9 s on a dataset of 525 h of scalp EEG data.

The current state-of-the-art seizure detection method proposed by Hills (2014) for the dataset considered here is implemented and extended in this paper. The dataset is derived from a Kaggle seizure detection competition in which Hills (2014) scored AUC of 96.29% and announced as the winner. Description of the dataset is provided in Section 2.1. In this paper, we significantly enhanced computational efficiency of Hill’s method by employing an automatic channel selection algorithm. This enabled us to process data as accurately with reduced number of channels. Table 1 summarizes the existing EEG-based seizure detection methods in recent years.

The remainder of this paper is organized as follows. In Section 2, after describing the dataset, we propose automatic channel selection engine that helps to reduce the number of channels to be processed. This section also presents spatio-temporal feature extraction and Random Forest classifier used for seizure detection. Section 3 evaluates the performance of the proposed model with comparison against the state-of-the-art method on the same dataset. Section 4 concludes the achievement of the paper.

### 2. Proposed method

The intracranial EEG data was recorded on multiple subjects with varying number of channels and sampling rates. We propose an automatic channel selection engine to filter out channels which are less relevant to seizure. The engine accepts the raw iEEG data, their corresponding labels, and the number of channels to be selected, M, and determines indexes of channels that are most relevant for seizure detection. Indexes of these M channels are stored on hard-disk so the engine only needs to be executed one time at the beginning for each subject. Feature extraction was performed in both frequency and time domain on the selected channels. Information extracted in frequency and time domains was concatenated and fed to a Random Forest classifier. Fig. 1 presents flowchart of the proposed method.

#### 2.1. Dataset

Dataset being analyzed in this paper is obtained from Kaggle (2014). Intracranial EEG signals were recorded from 4 dogs and 8 patients with epileptic seizures. Recordings were sampled at 400 Hz from 16 electrodes for dogs, and sampled at 500 Hz or 5 kHz from varying number of electrodes (ranging from 16 to 72) for humans. The data was pre-organized into 1 s iEEG epochs annotated as ictal for seizure states or interictal for seizure-free states. Interictal data was captured not less than one hour before or after a seizure onset and randomly chosen from the recorded data. Each ictal segment also came with the time in seconds between the seizure onset and first data point of the segment. The training dataset is consisted of 41 min of ictal data and 6.5 hours of interictal data. Summary of the training dataset is presented in Table 2. Note that early ictal state in this paper is the ictal state occurring within the first 15 s from the seizure onset. The proposed method was tested with a hidden dataset provided by Kaggle. This dataset consists of 9.14 hours of unlabeled iEEG data (Kaggle, 2014).

### Table 1: Summary of existing EEG-based seizure detection methods

| Reference                     | EEG type       | No. of patients | No. of seizures | Data duration | Patient | Split data | Testing sensitivity | FDR* | Median detection delay |
|-------------------------------|----------------|-----------------|-----------------|---------------|---------|------------|---------------------|------|-----------------------|
| Saab and Gotman (2005)        | scalp          | 44              | 195             | 1012 h        | No      | 64%        | 78%                 | 0.34/h | 9.8s                  |
| Kuhlmann et al. (2009)        | scalp          | 21              | 88              | 525 h         | No      | 70%        | 81%                 | 0.60/h | 16.9s                 |
| Wang et al. (2016)            | scalp          | 10             | 44              | 72 min 121 h  | Yes     | 80%        | 91.44%              | 99.34% | n/a                   |
| Zabihii et al. (2016)         | scalp          | 24             | 161             | 2.55 h 169 h  | Yes     | 25%        | 88.27%              | 93.21% | n/a                   |
| Fatichah et al. (2014)        | intracranial   | n/a            | n/a             | 39.3 min 2.62 h | n/a    | 90%        | 94.55%              | 98.41% | n/a                   |
| Hills (2014)                  | intracranial   | 12             | 48              | 41 min 6.5 h  | Yes     | 50%        | 91.33%              | 94.02% | 3.17s                 |
| Parvez and Paul (2015)        | intracranial   | 21             | 87              | 58 h 490 h    | n/a     | 80%        | 100%                | 97%   | n/a                   |

*False detection rate (FDR) or specificity.
†Duration of ictal and interictal were not provided separately.
‡Intracranial EEG for seizure class and both intracranial and extracranial for non-seizure class.

### Table 2: Summary of the dataset

| Subject | No. of electrodes | Ictal data length (s) | Interictal data length (s) | Unlabeled data length (s) | Train/Test ratio |
|---------|-------------------|-----------------------|-----------------------------|---------------------------|-----------------|
| Dog-1   | 16                | 178                   | 418                         | 3181                      | 0.19            |
| Dog-2   | 16                | 172                   | 1148                        | 2997                      | 0.44            |
| Dog-3   | 16                | 480                   | 4760                        | 4450                      | 1.18            |
| Dog-4   | 16                | 257                   | 2790                        | 3013                      | 1.01            |
| Patient-1 | 68             | 79                    | 104                         | 2050                      | 0.08            |
| Patient-2 | 16              | 151                   | 2990                        | 3894                      | 0.81            |
| Patient-3 | 55              | 327                   | 714                         | 1281                      | 0.81            |
| Patient-4 | 72              | 20                    | 190                         | 543                       | 0.39            |
| Patient-5 | 64              | 135                   | 2610                        | 2986                      | 0.92            |
| Patient-6 | 30              | 225                   | 2772                        | 2997                      | 1               |
| Patient-7 | 36              | 282                   | 3239                        | 3601                      | 0.98            |
| Patient-8 | 16              | 180                   | 1710                        | 1922                      | 0.98            |

| Total | 2477              | 23445                | 32915                       | 0.79                       |
2.2. Automatic channels selection

The intracranial EEG data was recorded using various number of channels (16, 30, 36, 55, 64, 68, 72). Large number of channels yields higher computational complexity as it requires more data to be analyzed. This can also deteriorate the diversity of iEEG data, hence degrade the performance of seizure detection, because some channels may capture irrelevant information (Guyon and Elisseeff, 2003). One can leverage bio-medical knowledge to manually select which channels genuinely contribute to the seizure. However, it is hard, if not impossible, to disclose a set of channels that are significant for all subjects. It is required to use the expertise to analyze every subject (or group of subjects) to proclaim a list of significant channels with regards to each subject (or group of subjects) which is manifestly a time-consuming task.

We propose a novel approach for automatic channels selection (ACS) as follows. The labeled data is first transformed to obtain frequency information. Specifically, FFT is applied onto the raw iEEG data on all N channels. FFT values are then sliced to extract data in 1-Hz bins in the range of 1–30 Hz. $\log_{10}$ is then applied to the magnitudes. The transformed data is a $N \times 30$ minatrix where 30 is the number of 1-Hz bins in the range of 1–30 Hz. If the channels correlation is involved in ACS stage, it will be confusing to identify which channels are the most important based on the importance level of the correlation between each pair of channels. Therefore, the correlation among channels is disregarded in this stage. Each individual channel becomes a feature to be fed to classifiers. One or a set of classifiers determine the importance level of each feature or channel. There are several options of classifiers using different ensemble algorithms such as Gradient Boosting, AdaBoost and Random Forest. If multiple classifiers are used, the final importance level of each channel is the sum of importance values obtained from all classifiers. The measure of feature importance in this paper is implemented using scikit-learn ensemble library (Scikit-learn, 2014). The importance of a feature is estimated by how often that feature is used in split points of each individual decision tree of the ensemble classifier (Scikit-learn, 2014). It is important to note that only train dataset was involved in the ACS stage.

The output of the channel selection algorithm is a set of M channels sorted based on the level of their contribution to the detection of a seizure. In this paper, we selected the value of M through some experiments aiming at maximising the final AUC score. This selection, however, could be automated by setting a threshold on the importance value of the channels.

2.3. Feature extraction

2.3.1. Feature extraction in frequency domain

The iEEG signals from M selected channels are transformed by FFT. The transformed data then is filtered to discard high frequency noise and low frequency artifacts. Frequency range of 1–47 Hz was shown to achieve the best performance for the dataset (Hills, 2014). Eigenvalues have been used as an effective technique to discriminate ictal epochs in (Zhang and Parhi, 2016; Hills, 2014; Sardouie et al., 2015). In order to compute eigenvalues, spectral power is primarily normalized (zero mean and standard deviation of one) along each channel before estimating cross spectral matrix (Hills, 2014). Contrary to the Hills’ feature extraction, we did not use cross spectral coefficients as a feature because our empirical observation shows that such feature could worsen detection accuracy. Sample recordings and corresponding power spectrum for ictal and interictal segments of Patient–1 are illustrated in Figs. 2 and 3.

The feature set in frequency domain consists of:
– Spectral power in 1 Hz bins in range of 1–47 Hz by applying \( \log_{10} \) to the magnitude of FFT transformation, and

– Eigenvalues, sorted in descending order, of cross spectral matrix on all selected channels of the above spectral power.

Figure 2: Sample 1 s iEEG recordings. (a, b and c) interictal; (d, e and f) ictal at early state (within 15 s from seizure onset); (g, h and i): ictal after early state. iEEG signals presented in one column, (e.g. a, d and g) are recorded from the same channel.

Figure 3: Sample 1 s iEEG recordings power spectrum. (a, b and c) interictal; (d, e and f) ictal at early state; (g, h and i): ictal after early state. iEEG signals presented in one column, (e.g. a, d and g) are recorded from the same channel. Subplots in this figure are one-by-one associated with subplots in Fig. 2.

2.3.2. Feature extraction in time domain

Raw iEEG signals are firstly re-sampled to 400 Hz. Similarly to frequency domain, filtered iEEG data is normalized to zero mean and unity standard deviation along each channel prior to computing covariance matrix and its eigenvalues. As illustrated in Fig. 4, iEEG data from 16 selected channels of Patient–1 have a very low correlation to each others in interictal states. The correlation slightly increases when seizure is at early state and becomes remarkable beyond the early state.

The feature set in time domain consists of:

– Coefficients in upper triangle of correlation matrix of iEEG signals from selected channels, and

– Eigenvalues of the correlation matrix above, sorted in descending order.

2.4. Classifier

Random Forest algorithm was first proposed by Breiman (2001). The algorithm uses a large set of decision trees to acquire an average results. Random Forest has been shown with good performance on dataset with high dimensional datasets in biology and medical fields (Scornet, 2016; Huynh et al., 2016; Cabezas et al., 2016). This paper will not go in deep about its mathematical properties as they can be found in (Breiman, 2001; Scornet, 2016) but rather on fine-tuning the parameters to achieve the highest performance with the given feature sets.

Random Forest classifier in this paper is implemented using scikit-learn library (Scikit-learn, 2014). Parameters of the classifier are reused from the approach proposed by Hills (2014) with 3000 decision trees. The classifier analyses each 1 s iEEG epoch and categorizes them into 3 classes as outputs: early ictal (ictal within 15 s from the onset), ictal, and interictal. Regarding sensitivity and specificity evaluation, the Random Forest classifier is adjusted from three-class classifier to binary classifier which detects whether a 1 s iEEG signal is ictal or interictal.

3. Evaluation

In this section, we will compare the efficacy of the proposed method with the current state-of-the-art method proposed by Hills (2014) on the same dataset. Metrics used to test the proposed approach are area under the receiver operating characteristic curve (AUC), sensitivity, specificity and onset detection delay with 2-fold cross-validation. In the first fold, a half of the seizures per subject were chosen as training set, the rest were for validation. Note that each seizure only appears in either the training set or the validation set. The interictal data was divided randomly into two equal length sets, one for training and one for validation. In the second fold, roles of training and validation sets in the first fold were swapped. Final results reported in the following are the average of outputs from the two folds. We will also test with the hidden dataset consisting of 9.14 hours of unlabeled
Table 3: Comparison between state-of-the-art and proposed method on computational efficiency. ACS engine with M=16 for all subjects.

| Subject   | No. of electrodes | Data duration (min) | FA† (s) | Training (s) | Hills (2014) | Proposed method | Processing time improvement |
|-----------|-------------------|---------------------|---------|---------------|--------------|-----------------|--------------------------|
| Dog–1     | 16                | 9.9                 | 2       | 23.7          | n/a          | 1.7             | 23.7                     | n/a                      |
| Dog–2     | 16                | 22                  | 3.8     | 62.7          | n/a          | 3.5             | 62.5                     | n/a                      |
| Dog–3     | 16                | 87.3                | 15.4    | 341.8         | n/a          | 13.8            | 348.8                    | n/a                      |
| Dog–4     | 16                | 50.8                | 8.8     | 144.9         | n/a          | 8.5             | 149.2                    | n/a                      |
| Patient–1 | 68                | 2.9                 | 2.7     | 14.1          | 6.5          | 0.7             | 13.1                     | 17.9%                    |
| Patient–2 | 16                | 52.4                | 21.3    | 105.8         | n/a          | 22.3            | 106.3                    | n/a                      |
| Patient–3 | 55                | 17.4                | 7.1     | 13.3          | 10.6         | 1.5             | 11.6                     | 35.8%                    |
| Patient–5 | 64                | 45.8                | 79.1    | 519.3         | 180.3        | 29.4            | 219.7                    | 67.9%                    |
| Patient–6 | 50                | 38.5                | 80.7    | 146.2         | 93.5         | 15.2            | 108.7                    | 38.7%                    |
| Patient–7 | 36                | 53.7                | 435.3   | 171.9         | 19.1         | 244             | 219.7                    | 46.2%                    |
| Patient–8 | 16                | 31.5                | 13.3    | 59.7          | n/a          | 13.4            | 60.1                     | n/a                      |

Average 41.1%

* Automatic channel selection (ACS) time.
† Feature extraction (FA) time.

iEEG data to compare the AUC scores computed by the leader board of Kaggle for the two methods.

Table 4: AUC Comparison between state-of-the-art and proposed method with M=16 for all subjects.

| Subject   | AUC
|-----------|--------|--------|--------|--------|--------|--------|--------|--------|
|           | Hills (2014) | Proposed method |
|           | AUC$_E$ (%) | AUC$_S$ (%) | AUC (%) | AUC$_E$ (%) | AUC$_S$ (%) |
| Dog–1     | 97.59       | 99.40    | 98.49  | 97.14       | 99.11    | 98.13  |
| Dog–2     | 95.00       | 98.85    | 96.92  | 94.02       | 97.76    | 95.89  |
| Dog–3     | 96.77       | 99.52    | 98.14  | 96.57       | 99.47    | 98.02  |
| Dog–4     | 99.67       | 97.16    | 96.51  | 98.88       | 97.08    | 98.48  |
| Patient–1 | 90.94       | 98.14    | 94.54  | 96.65       | 99.00    | 97.52  |
| Patient–2 | 99.29       | 99.34    | 99.31  | 99.15       | 99.32    | 99.23  |
| Patient–3 | 87.98       | 94.25    | 91.11  | 87.63       | 92.69    | 90.16  |
| Patient–4 | 100         | 100      | 100    | 99.63       | 99.63    | 99.63  |
| Patient–5 | 83.02       | 89.38    | 86.20  | 87.54       | 90.73    | 89.13  |
| Patient–6 | 98.61       | 99.80    | 99.20  | 98.86       | 99.83    | 99.35  |
| Patient–7 | 89.97       | 96.02    | 92.99  | 93.84       | 97.58    | 95.71  |
| Patient–8 | 81.46       | 97.82    | 89.64  | 79.83       | 97.80    | 88.81  |

Average 93.37 97.47 95.42 94.18 97.50 95.84

This paper aims to detect whether a given 1 s iEEG segment represents a seizure and whether that segment is within the first 15 s (early) of its respective seizure. The metric for performance evaluation is the average of the two AUCs of the two detections Kaggle (2014), and is given by

\[
\text{AUC} = \frac{1}{2} (\text{AUC}_E + \text{AUC}_S),
\]

where,

- AUC$_E$ is AUC for two classes: ictal (including early seizure) and interictal, and
- AUC$_S$ is AUC for two classes: early seizure and

Table 5: Comparison between state-of-the-art and proposed method with M=16 for all subjects on sensitivity (SEN), specificity (SEP) and onset detection delay with corresponding threshold (Thres.) for binary classification of seizure and non-seizure states.

| Subject   | Delay (s) | SEN (%) | SPE (%) | Thres. (s) | Delay (s) | SEN (%) | SPE (%) | Thres. (s) |
|-----------|-----------|---------|---------|------------|-----------|---------|---------|------------|
| Dog–1     | 1.92      | 95.83   | 97.13   | 0.34       | 1.92      | 94.46   | 98.09   | 0.42       |
| Dog–2     | 2.25      | 92.86   | 89.29   | 0.11       | 2.25      | 92.44   | 91.82   | 0.13       |
| Dog–3     | 1.83      | 95.84   | 97.33   | 0.14       | 2.17      | 94.80   | 98.28   | 0.21       |
| Dog–4     | 1         | 89.55   | 89.90   | 0.09       | 1         | 89.55   | 90.26   | 0.09       |
| Patient–1 | 4         | 92.31   | 96.16   | 0.36       | 3         | 94.87   | 96.16   | 0.28       |
| Patient–2 | 2         | 95.03   | 99.20   | 0.29       | 2         | 95.03   | 99.20   | 0.28       |
| Patient–3 | 1.75      | 85.42   | 76.61   | 0.17       | 1.38      | 86.67   | 77.45   | 0.13       |
| Patient–4 | 1         | 90.95   | 98.25   | 0.25       | 1         | 90.73   | 97.37   | 0.23       |
| Patient–5 | 10        | 71.67   | 87.78   | 0.05       | 3.75      | 77.78   | 83.49   | 0.03       |
| Patient–6 | 1.75      | 98.24   | 98.85   | 0.19       | 2.25      | 97.35   | 99.21   | 0.26       |
| Patient–7 | 6         | 86.51   | 99.14   | 0.14       | 2         | 99.59   | 99.79   | 0.20       |
| Patient–8 | 4.5       | 92.78   | 97.90   | 0.22       | 4.5       | 92.78   | 97.90   | 0.20       |

Average 3.17 91.33 94.02 2.27 92.94 94.08

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- AUC$_E$ is AUC for two classes: ictal (including early seizure) and interictal, and
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Table 5: Comparison between state-of-the-art and proposed method with M=16 for all subjects on sensitivity (SEN), specificity (SEP) and onset detection delay with corresponding threshold (Thres.) for binary classification of seizure and non-seizure states.
non-early-seizure (including ictal states after 15 s from onset and interictal states).

Table 3 summarizes the gain in processing time, including time for feature extraction and classifier training for each subject. Since we chose M=16 in ACS engine, subjects with number of electrodes less than or equal to 16 would skip the channel selection stage; hence, the processing time of the proposed method is comparable with that of the state-of-the-art method for these subjects. Overall gain in computational efficiency for the patients with more than 16 iEEG channels is 41.1%. Therefore, the automatic channel selection is promising for real-time seizure detection application.

Table 4 summarizes cross-validation AUC scores using state-of-the-art and proposed methods for each subject. Overall cross-validation AUC scores of the two methods are comparable. The proposed method was tested with the hidden dataset and acquired an AUC score at 96.58% which is comparable with the state-of-the-art’s score at 96.29% (Hills, 2014).

Regarding sensitivity and specificity evaluation, the Random Forest classifier is adjusted from three-class classifier to binary classifier which detects whether a 1 s iEEG signal is ictal or interictal. Table 5 describes the comparison between the state-of-the-art and proposed method on sensitivity, specificity and onset detection delay. The threshold of the classifier’s output used to separate whether a 1 s iEEG segment is ictal or interictal was determined per subject. The value of threshold was selected to achieve the balance between sensitivity and specificity (ie., the higher threshold value yields the higher specificity but the lower sensitivity and vice versa).

Proposed method achieved a comparable performance to the state-of-the-art in terms of sensitivity and specificity. However, the proposed method yields a considerable improvement in mean onset detection delay. Onset detection delay indicates the time in seconds after that the classifier can detect a seizure onset. Delay is 1 s if the first 1 s ictal iEEG segment at seizure onset can be correctly detected. Since iEEG signals are divided into 1 s epochs, the minimum onset detection delay could be achieved is 1 s. Table 5 shows that the proposed model has shorter onset detection delay by 900 mins than the current best method.

4. Discussions

We presented a seizure detection method based on a novel approach for automatic iEEG channel selection that provides comparable performance to the state-of-the-art method for the dataset considered. Although this leads to an extra overhead computing time in the beginning, the impact overall processing time is negligible because the channel selection need to be executed one time only for each subject. The advantages of the automatic channel selection, on the other hand, are remarkable. Firstly, redundant and unrelated iEEG signals are eliminated which helps to improve efficacy of seizure detection system. Secondly, since the amount of data to processed is reduced, the processing time is also reduced. Gain in computational complexity becomes visible and significant for subjects with large number of channels. For instance, by reducing number of channels to be analyzed from 72 to 16 for Patient–4 (see Table 3, processing time can be improved by 67.9%.

![Figure 5: Comparison between state-of-the-art and proposed method with two set of M in terms of detection delay, number of processed channels and processing time.](image)

| Number of channels | Processing time |
|--------------------|----------------|
| Smaller triangle is better |

![Table 7: AUC Comparison between state-of-the-art and proposed method with M was optimized on the training data per subject.](image)

| Subject | Hills (2014) | Proposed method |
|---------|--------------|-----------------|
|        | AUC_E (%)  | AUC_S (%) | AUC (%) | AUC_E (%)  | AUC_S (%) | AUC (%) |
| Dog-1  | 97.59       | 99.40       | 98.49   | 96.93      | 99.11      | 98.02   |
| Dog-2  | 95.00       | 98.85       | 96.92   | 93.90      | 97.56      | 95.73   |
| Dog-3  | 96.77       | 99.52       | 98.14   | 95.67      | 99.17      | 97.42   |
| Dog-4  | 99.87       | 97.16       | 98.51   | 99.83      | 97.45      | 98.64   |
| Patient-1 | 90.94   | 98.14       | 94.54   | 96.05      | 99.00      | 97.52   |
| Patient-2 | 99.29   | 99.34       | 99.31   | 99.21      | 99.30      | 99.25   |
| Patient-3 | 87.98   | 94.25       | 91.11   | 86.29      | 93.31      | 89.80   |
| Patient-4 | 100     | 100         | 100     | 100        | 100        | 100     |
| Patient-5 | 83.02   | 89.38       | 86.20   | 87.54      | 90.73      | 89.13   |
| Patient-6 | 96.61   | 99.80       | 99.20   | 99.04      | 99.89      | 99.46   |
| Patient-7 | 89.97   | 96.02       | 92.99   | 95.01      | 97.92      | 96.47   |
| Patient-8 | 81.46   | 97.82       | 89.64   | 80.42      | 98.23      | 89.33   |
| Average | 93.37     | 97.47       | 95.42   | 94.16      | 97.64      | 95.90   |

Spectral power, correlation matrix and its eigenvalues on iEEG channels in both frequency and time domains have been shown as important features in seizure detection using iEEG recordings. The proposed subject-specific approach has a mean seizure onset detection delay of 2.27 s that is critical, for example, for an electrical stimulator to suppress the seizure on time.

In order to further gain computational efficiency, the number of selected channels M is optimized on the training
Table 6: Comparison between state-of-the-art and proposed method on computational efficiency. ACS engine with M was optimized on the training data per subject.

| Subject | No. of electrodes | M | Data duration (min) | Hills (2014) | Proposed method | Processing time improvement |
|---------|------------------|---|---------------------|--------------|-----------------|-----------------------------|
|         |                  |   |                     | FA †          | Training (s)    | ACS* FA † Training (s)      |                        |
| Dog–1   | 16               | 9 | 9.9                 | 2            | 23.7            | 6              1.5            | 19.8            17.1%       |
| Dog–2   | 16               | 10| 22                  | 3.8          | 62.7            | 15             2.8            | 49.9            20.8%       |
| Dog–3   | 16               | 8 | 87.3                | 15.4         | 341.8           | 77             9.7            | 224.5           34.4%       |
| Dog–4   | 16               | 13| 50.8                | 8.8          | 144.9           | 36             7.1            | 122.2           15.9%       |
| Patient–1 | 68              | 16| 2.9                 | 2.7          | 14.1            | 5              0.7            | 11.7            26.2%       |
| Patient–2| 16              | 11| 52.4                | 21.3         | 105.8           | 39             11.2           | 82.8            26.0%       |
| Patient–3| 55              | 8 | 17.4                | 25.5         | 80.7            | 31             4              | 45.1            53.8%       |
| Patient–4| 72              | 4 | 3.5                 | 7.1          | 13.3            | 8              0.8            | 11.1            41.7%       |
| Patient–5| 64              | 16| 45.8                | 79.1         | 519.3           | 115            28.2           | 158.1           68.9%       |
| Patient–6| 30              | 8 | 80                  | 38.5         | 146.2           | 56             9.6            | 60.6            62.0%       |
| Patient–7| 36              | 13| 58.7                | 53.7         | 435.3           | 118            15.6           | 198.6           56.2%       |
| Patient–8| 16              | 8 | 31.5                | 13.3         | 59.7            | 23             5.4            | 41.6            35.6%       |

Average 49.4%

* Automatic channel selection (ACS) time.
† Feature extraction (FA) time.

Table 8: Comparison between state-of-the-art and proposed method with M was optimized on the training data per subject on sensitivity (SEN), specificity (SEP) and onset detection delay with corresponding threshold (Thres.) for binary classification of seizure and non-seizure states.

| Subject | Delay (s) | SEN (%) | SPE (%) | Thres. (s) | Delay (s) | SEN (%) | SPE (%) | Thres. |
|---------|-----------|---------|---------|------------|-----------|---------|---------|--------|
| Dog–1   | 1.92      | 95.83   | 97.13   | 0.34       | 2.5       | 93.99   | 96.41   | 0.34   |
| Dog–2   | 2.25      | 92.86   | 89.29   | 0.11       | 2.25      | 92.44   | 89.20   | 0.11   |
| Dog–3   | 1.83      | 95.84   | 97.33   | 0.14       | 2.5       | 94.17   | 97.25   | 0.16   |
| Dog–4   | 1         | 89.55   | 89.90   | 0.09       | 1         | 92.16   | 90.61   | 0.09   |
| Patient–1| 4       | 92.31   | 96.16   | 0.36       | 3.5       | 93.59   | 97.12   | 0.38   |
| Patient–2| 2       | 95.03   | 99.20   | 0.29       | 2         | 95.03   | 99.20   | 0.26   |
| Patient–3| 1.75     | 85.42   | 76.61   | 0.17       | 1         | 90.45   | 76.19   | 0.12   |
| Patient–4| 1       | 100     | 98.95   | 0.25       | 1         | 100     | 98.95   | 0.25   |
| Patient–5| 10      | 71.67   | 67.78   | 0.05       | 4.75      | 73.89   | 65.94   | 0.04   |
| Patient–6| 1.75     | 98.24   | 98.85   | 0.19       | 2.75      | 96.48   | 99.39   | 0.33   |
| Patient–7| 6       | 86.51   | 99.14   | 0.14       | 5.5       | 87.35   | 99.14   | 0.15   |
| Patient–8| 4.5      | 92.78   | 97.90   | 0.22       | 4.5       | 93.89   | 98.19   | 0.26   |

Average 3.17 91.33 94.02 2.77 91.95 94.05

5. Conclusion

Detection of seizure, especially at its early state, is crucial for patients who cannot be treated by drugs or surgery. Precise seizure detection allows electrical stimulation to timely interrupt the alteration of consciousness and subsequent convulsions. Although high performing seizure detectors are available, translating state-of-the-art seizure detection methods into battery-saving hardware implementations in implantable seizure control devices requires greater gains in computational efficiency. This paper proposed automatic channels selection engine as a mechanism to adequately determine most informative iEEG recordings prior to feature extraction. The engine gave rise to significant computational efficiency improvements on subjects having large number of recording channels. For Patient–5, the computational efficiency was improved by 68.9% (see Fig. 6). The overall results of the proposed method are demonstrated in Tables 6, 7, and 8. The overall AUC, when tested with the hidden test dataset, is 96.44%, comparable to that of the state-of-the-art at 96.29%. Fig. 5 demonstrates the advantages of the proposed method in terms of detection delay, number of channels to be analyzed and processing time.
method were comparable with that of the state-of-the-art while it save 49.4% of the processing time and reduced the mean detection delay by 400 mins, both critical factors for real-world applications.

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