Real-Time Seizure State Tracking Using Two Channels: A Mixed-Filter Approach

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***Abstract*—Accurate and cost-effective seizure severity tracking is an important step towards limiting the negative effects of seizures in epileptic patients. Electroencephalography (EEG) is employed as a means to track seizures due to its high temporal resolution. In this research, seizure state detection was performed using a mixed-filter approach to reduce the number of channels. We first found two optimized EEG features (one binary, one continuous) using wrapper feature selection. This feature selection process reduces the number of required EEG channels to two, making the process more practical and cost-effective. These continuous and binary observations were used in a state-space framework which allows us to model the continuous hidden seizure severity state. Expectation maximization was employed offline on the training and validation data-sets to estimate unknown parameters. The estimated model parameters were used for real-time seizure state tracking. A classifier was then used to binarize the continuous seizure state. Our results on the experimental data (CHB-MIT EEG database) validate the accuracy of our proposed method and illustrate that the average accuracy, sensitivity, and false positive rate are 85.8%, 91.5%, and 14.3% respectively. This type of seizure state modeling could be used in further implementation of adaptive closed-loop vagus nerve stimulation applications.**

I. Introduction

Roughly 50 million people worldwide live with epilepsy and this disease is not localized to a specific age range, and affects people as early as 3 years old [1], [2]. Seizures are the defining symptom of this disorder and are characterized by a period of abnormal synchronous excitation of neurons in one or both hemispheres that can lead to permanent or temporary brain damages [3], [4]. During an epileptic seizure, the patient may undergo a loss of bladder or bowel control, violent muscle movements, and/or a loss of consciousness [5], [6]. Thus, unmannaged seizure symptoms may not only restrict epileptic patients from performing activities that require reliably uninterrupted attention, but can also negatively affect their daily lives. Medical attention for epileptic patients entails the use of medicine [7] or vagus nerve stimulation [8], which requires surgical implementation [9]. Reliable and accurate seizure severity detection may lead to a reduction in serious brain injuries and unsafe operating conditions, and may allow patients to immediately seek medical attention.

Electroencephalography (EEG), the recording of electrical activity produced by the brain at the scalp [10], has been proposed as a signal modality for seizure detection due to the reliable acquisition, high temporal resolution, portability, and relatively low cost. EEG analysis is typically accomplished with the use of machine learning algorithms [11], such as convolutional neural networks [12], [13], recurrent neural networks [14], [15], spiking neural networks [16], Support Vector Machines (SVM) [17]–[19], and Linear Discriminant Analysis (LDA) [20]. These machine learning algorithms typically result in binary classifications, meaning information about the seizure severity would be lost. Information about seizure severity can be used with vagus nerve stimulators to reduce a subject's epileptic symptoms by online frequency or amplitude adaptation [21], [22].

State-space modeling of seizures provides us with continuous estimation, which contains information about the severity of the seizure and can be implemented in a closed-loop vagus nerve stimulator. In order to improve the feasibility of the whole process and reduce the potential cost to the end user, we used an LDA classifier to find two optimized EEG features to reduce the required number of EEG channels to two for reliable classification. We then propose a state-space approach to formulate the hidden seizure tracking problem.

Using the chosen two features (i.e. continues and binary) and employing a mixed-filter approach, we performed seizure state detection [23]–[25]. We considered mixed-filters that manipulate two variables, rather than one, because a single-feature filter would lose the ability to accurately classify if the single input feature was noisy, whereas a double-feature filter would not [26]–[28]. Expectation Maximization (EM) algorithm was then applied to find the unknown state-space model parameters [27], [29]. Since our prediction is continuous, rather than only detecting the presence of a seizure, information about the severity of the seizure is also obtained [30], [31]. The successful and reliable detection of seizure

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activity and its severity allow for closed-loop system design for vagus nerve stimulation applications. Accurate seizure detection may also lead to a reduction in the possibility of serious brain injuries in a closed-loop manner [32]–[35].

II. Methods and Materials

A. Data Acquisition

The original data-set (CHB-MIT Scalp EEG Database) was collected at the Boston Childrens Hospital in 2010 [36]. The continuous EEG of 22 pediatric subjects (5 males, ages 3-22, and 17 females, ages 1.5-19) with intractable seizures was measured for several days following the cessation of anti-seizure medication with the intent to assess each subject's viability for surgical intervention. EEG signal collection was accomplished using a 21-electrode headset at 256 Hz sampling frequency. Data was provided in a bipolar montage where each channel is obtained from two electrodes. Further information on the original data collection can be found in [36].

B. Feature Extraction

In order to determine the optimum set of features for use in the detection of a seizure, the EEG data from a single subject is divided into three data-sets: training set, validation set, and testing set. The first seizure recorded within the subject's collected data is reserved as the training set, the second recorded seizure is used as the validation set, and all remaining seizures are included in the testing data-set, which will be used to test and compare the validity of this process. The authors would like to note that the proportions are not analogous to the typical training, validation, and testing data-set splits seen in machine learning researches. This is due to the stated desire to minimize the required number of seizures by the intended end user, thereby ensuring the highest level of comfort for acquisition of the training and validation sets.

Since we are analyzing data collected between multiple sessions, the EEG features are normalized by employing min/max normalization based on the statistical characteristics of the feature derived from the first minute of each session. By using only the first minute for normalization, the real-time applicability of this method is maintained.

An assumption inherent to the filter selected for this research is that the continuous feature must be monotonic in relation to the unknown seizure state. Since EEG signal information is oscillatory in nature, it is not possible for the amplitudes to be monotonic in relation to the seizure state [37]. For this reason, EEG band powers are instead chosen as candidate features for this process.

Each channel is decomposed into the absolute power of four characteristic EEG band powers: Delta (<4 Hz), Theta (4-7 Hz), Alpha (8-15 Hz), and Beta (16-31 Hz). The Gamma band power (31+ Hz) is not included, because this band is typically contaminated with electromyographic (EMG) data. These absolute band powers are found by using a Fast Fourier Transform (FFT) with a sliding window using the one second interval immediately preceding the desired estimation point.

C. Feature Selection

To find the best continuous and binary features, a wrapper feature selection is utilized using (i) LDA, a simple linear computationally-efficient classifier, as the predictive model, (ii) F1 score as evaluation metric, (iii) greedy forward selection as the subset selection policy, and (iv) a stopping criteria of using only one feature [38].

To find the continuous feature, the raw feature values are converted from amplitude squared to dB to make it always positive as required by the selected filter. Then, an LDA classifier is trained on each converted feature of the training set separately. The LDA classifier is modified so that the misclassification cost of seizures is set to the proportion of non-seizures to seizures in the training set, as labeled by expert clinicians from the original data protocol. This is necessary as the duration of non-seizure period within each session greatly outnumbers the duration of the seizure itself. Prospective converted EEG features from all possible channel and band power combinations from the validation set are then passed through the corresponding trained LDA individually and the resulting arrays are compared to the true seizure states of the validation set. It is important to note that the use of the validation set is to find features that are generalizable. If the features were validated on the training set instead of the validation set, the feature selection process would choose features based on overfitting rather than predictivity. To compare the relative usefulness of each prospective feature, F1 scores are compared rather than absolute accuracy. F1 score is selected for comparisons due to its emphasis on the effects of precision and recall, which is represented with the following equation,

$$F1 = 2 \cdot \frac{precision \cdot recall}{precision + recall}. \tag{1}$$

The F1 score is chosen instead of accuracy because the data is highly imbalanced towards non-seizure and using accuracy alone could lead towards selecting a feature with a high accuracy for non-seizure periods, rather than for seizure periods. The feature with the highest F1 score is chosen as the continuous feature.

The binary feature selection process essentially follows the same protocol as the method described for the continuous feature. The raw EEG feature data is then binarized and, therefore, there is no need for a dB transformation. LDAs are trained on the training set and validated on the validation set. The F1 scores based on the validation set are compared and the highest performing feature is selected. For binarization of this selected feature, another LDA is trained on both the training set and validation set (with a misclassification cost derived based on the true seizure to non-seizure proportion in the training and validation sets). This LDA is then used to create binary features for the test set.

An example of this process is provided in Figure 1. This figure indicates that both the binary and continuous features have a clear relationship with the true seizure state in that

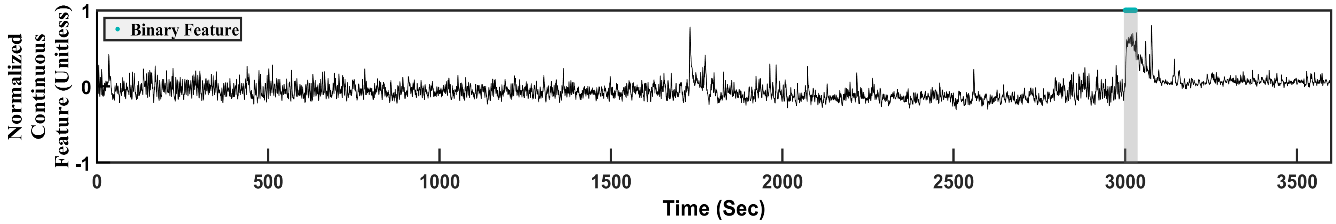

Fig. 1: **Feature Selection.** The grey region marks the period of EEG activity designated as the true seizure state. Feature selected from subject 1 training set.

the binary feature only exists during the seizure, whereas the continuous feature has much higher activity during the seizure.

D. Mixed-Filter Algorithm

The filter process described here treats seizure status as a hidden biophysical state in a state-space formulation and results in a continuous seizure state estimation. A continuous state estimation, in addition to providing information as to the presence of a seizure, also provides information about the severity of a seizure. Further reasoning behind the decision to choose this filter in tracking the subject-specific continuous seizure state is based on the filter's success in incorporating both binary and continuous features in order to estimate a hidden state [26]. If only one feature is used for prediction, noise in that feature would lead to poor performance generally. With at least two features, a single noisy channel doesn't necessarily prevent accurate prediction. The following presents a mathematical formulation for the mixed-filter algorithm.

We first assume that the model of the continuous seizure state, x_k, can be represented as the following first-order auto-regressive process [33], [39]–[43],

$$x_k = \rho x_{k-1} + \nu_k \tag{2}$$

where $0 < \rho < 1$ represents an unknown forgetting parameter and ν_k is an independent Gaussian random variable representing the process noise, i.e. $\nu_k \sim \mathcal{N}(0, \sigma_\nu^2)$, where σ_ν^2 is the unknown variance of the process noise. Let,

$$x = [x_0, x_1, \cdots, x_K] \tag{3}$$

be the unobserved state vector. Our observation model for the continuous feature will be using power, r_k (amplitude squared), of a frequency band power. In order to make r_k unbounded, as required by our filter, we converted it from amplitude squared to dB by taking $10 \cdot log(r_k)$ to form z_k, where α and β are unknown parameters and ε_k is an independent Gaussian random variable, i.e. $\varepsilon_k \sim \mathcal{N}(0, \sigma_\varepsilon^2)$, where σ_ε^2 is the unknown variance of the continuous measurement noise.

We assume that the binary variable, n_k, can be represented by the Bernoulli probability model:

$$Pr(n_k|x_k) = (p_k)^{n_k}(1-p_k)^{1-n_k}. \tag{4}$$

The binary variable n_k (derived from the raw amplitude squared EEG data) is selected using the process described in section II-C. The observation model is defined as:

$$p_k = \frac{e^{\mu+x_k}}{1+e^{\mu+x_k}}. \tag{5}$$

This choice of a logistic function for this specific filter design is that the probability function, p, should be bounded between zero and one. The parameter μ is estimated for each subject individually and from chance probability, p_{chance}, as described in [26], [44]. The chance probability used within this model is selected as the training set and validation set duration of seizure divided by the total duration of the combined sessions. In order to get the continuous seizure state predictive model, we employ the EM algorithm on the combined training set and validation set for the optimization of the unknown state-space parameters:

$$\theta = (\rho, \alpha, \beta, \sigma_\nu^2, \sigma_\varepsilon^2, x_0). \tag{6}$$

The EM process is an iterative method that finds the maximum likelihood of θ by alternating between expectation and maximization steps. During the expectation stage, the algorithm creates a log-likelihood function using initial values of the parameters. The maximization stage finds parameters that maximize this log-likelihood function [23], [27]. These parameters are then used to reformulate the log-likelihood function in the next expectation stage. The process repeats until the parameters converge to constant values. The EM algorithm is as follows:

1) Expectation Step: At $(l+1)^{th}$ iteration of the algorithm, we compute the expectation of data log likelihood in the estimation step given selected continuous and binary features and $\theta^{(l)}$, which contains the parameter estimates from l^{th} iteration.

a) Forward Filter: We estimate seizure severity state variable, $x_{k|k}$ and its variance $\sigma_{k|k}^2$, given $\theta^{(l)}$, using a recursive non-linear filter algorithm [26], [45]. Notation $k|j$ denotes the expectation of the state variable at k given the responses up to j.

$$x_{k|k-1} = \rho^{(l)} x_{k-1|k-1} \tag{7}$$

$$\sigma_{k|k-1}^2 = \rho^{(l)2}\sigma_{k-1|k-1}^2 + \sigma_\nu^{2(l)} \tag{8}$$

$$C_k = (\beta^{(l)2}\sigma_{k|k-1}^2 + \sigma_\varepsilon^{2(l)})^{-1}\sigma_{k|k-1}^2 \tag{9}$$

$$x_{k|k} = x_{k|k-1} + C_k\Big[\beta^{(l)}(z_k - \alpha^{(l)} - \beta^{(l)}x_{k|k-1}) + \sigma_\varepsilon^{2(l)}(n_k - p_{k|k})\Big] \tag{10}$$

$$\sigma^2_{k|k} = \Big[(\sigma^2_{k|k-1})^{-1} + p_{k|k}(1-p_{k|k}) + (\sigma_\varepsilon^{2(l)})^{-1}\beta^{(l)2}\Big]^{-1} \tag{11}$$

for $k = 1, \cdots, K$.

b) Backward Smoother: Equations (10) and (11) result in the posterior mode estimates $x_{k|k}$ and its variance $\sigma^2_{k|k}$, respectively. A fixed interval smoothing algorithm [46] is employed to compute $x_{k|K}$ and $\sigma^2_{k|K}$. This algorithm is given as follows [26]:

$$x_{k|K} = x_{k|k} + A_k(x_{k+1|K} - x_{k+1|k}) \tag{12}$$

$$A_k = \sigma^2_{k|k}(\sigma^2_{k+1|k})^{-1} \tag{13}$$

$$\sigma^2_{k|K} = \sigma^2_{k|k} + A_k^2(\sigma^2_{k+1|k} - \sigma^2_{k+1|K}) \tag{14}$$

for $k = K-1, \cdots, 1$ and initial conditions $x_{K|K}$ and $\sigma^2_{K|K}$.

c) State-Space Covariance Algorithm: The state-space covariance algorithm [47] is utilized to estimate the covariance $\sigma_{k,u|k}$ as follows [26]:

$$\sigma_{k,u|k} = A_k\sigma_{k+1,u|k} \tag{15}$$

for $1 \leq k \leq u \leq K$.

Moreover, the variance and covariance terms, $W_{k|K}$ and $W_{k-1,k|K}$ are computed as follows [26]:

$$W_{k|K} = \sigma^2_{k|K} + x^2_{k|K} \tag{16}$$

$$W_{k-1,k|K} = \sigma_{k-1,k|K} + x_{k-1|K}x_{k|K} \tag{17}$$

2) Maximization Step: The expectation of data log likelihood is then maximized with respect to $\theta^{(l+1)}$ as follows [26]:

$$\rho^{(l+1)} = \sum_{k=1}^{K} W_{k-1,k|K}\Big[\sum_{k=1}^{K} W_{k-1|K}\Big]^{-1} \tag{18}$$

$$x_0^{(l+1)} = \rho x_{1|k} \tag{19}$$

$$\sigma_\varepsilon^{2(l+1)} = K^{-1}\sum_{k=1}^{K} z_k^2 + K\alpha^{2(l+1)} + \beta^{2(l+1)}\sum_{k=1}^{K} W_{k|K} - 2\alpha^{(l+1)}\sum_{k=1}^{K} z_k - 2\beta^{(l+1)}\sum_{k=1}^{K} x_{k|K}z_k + 2\alpha^{(l+1)}\beta^{(l+1)}\sum_{k=1}^{K} x_{k|K} \tag{20}$$

$$\begin{bmatrix}\alpha^{(l+1)} \\ \beta^{(l+1)}\end{bmatrix} = \begin{bmatrix} K & \sum_{k=1}^{K} x_{k|K} \\ \sum_{k=1}^{K} x_{k|K} & \sum_{k=1}^{K} W_{k|K}\end{bmatrix}^{-1} \begin{bmatrix}\sum_{k=1}^{K} z_k \\ \sum_{k=1}^{K} x_{k|K}z_k\end{bmatrix} \tag{21}$$

$$\sigma_\nu^{2(l+1)} = K^{-1} \sum_{k=1}^{K}\Big[W_{k|K} - 2\rho^{(l+1)}W_{k-1,k|K} + \rho^{2(l+1)}W_{k-1|K}\Big] \tag{22}$$

During EM estimation process, the seizure prediction seemed to be following the continuous feature more than the binary feature. To overcome this issue, the EM algorithm is modified so that the parameters of observation equation regarding the continuous feature is frozen after the Pearson correlation coefficient between the estimated seizure state and the continuous feature reaches 0.95. In this way, the seizure prediction better follows both the binary and continuous features.

The next step in this process involved applying the parameters and features found with the training set and validation set in order to track the continuous seizure state in the test set. In the analysis of this data-set, we use the state parameters found from the training and validation sets to directly estimate the continuous seizure state. For this stage, instead of using both a forward filter and a backward smoother, we solely use the forward filter to be able to analyze data in real-time. A backward smoother would not be applicable for analyzing data in real-time.

E. Binary Seizure Classification

A final LDA is trained using the continuous seizure state prediction output from the EM algorithm based on the training set and validation set to output a binary seizure state. The selected features, state-space parameters, the trained feature binarization LDA, and the trained seizure state binarization LDA are then applied to the testing data-set. This process outputs a binarized form of the seizure state prediction so that comparisons can be made between the above described algorithm and past attempts to classify this data-set by other studies. Specifically, we will be assessing three performance criteria based on True Positives (TP), True Negatives (TN), False Positives (FP), False Negatives (FN), and False Positive Rate (FPR):

$$Sensitivity = \frac{TP}{TP+FN} \cdot 100\% \tag{23}$$

$$Accuracy = \frac{TP+TN}{TP+FN+TN+FP} \cdot 100\% \tag{24}$$

$$Specificity = \frac{TN}{TN+FP} \cdot 100\% = 100 - FPR \tag{25}$$

III. Results

An example of our continuous seizure state prediction is shown in Figure 2. Even though the binary feature failed to predict a lack of seizure in the 1500 to 2000 ms range, the model, using both features, still successfully predicted seizure state during this period. As expected, neither the binary nor

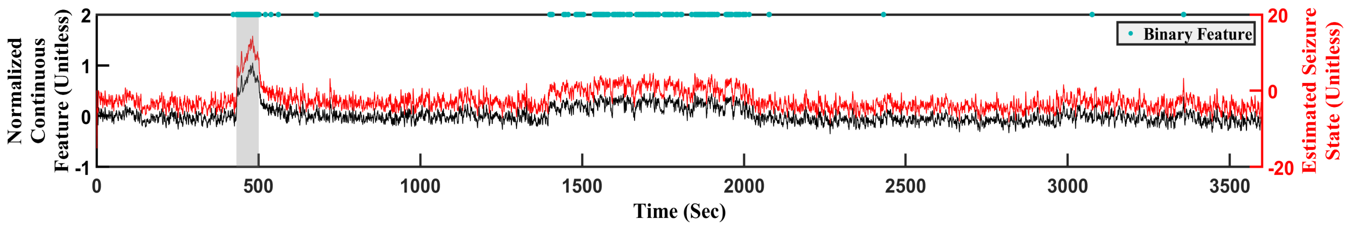

Fig. 2: **Continuous Seizure State Estimation.** The red curve represents the unitless estimated seizure state and corresponds to the right y-axis. The black curve represents the unitless normalized continuous feature and corresponds to the left y-axis. Feature selected from subject 3 test set.

continuous feature alone could outperform the simultaneous use of both variables. However, the combination of the two variables together clearly finds a pronounced seizure state that matches well with the true seizure state. The seizure state binarization LDA is then applied to the continuous seizure state output from the EM algorithm for the test set to produce a binary seizure state prediction. In order to compare this algorithm to past attempts to classify this data, the accuracy (Ac), specificity (Sp), and sensitivity (Se) between our binary seizure state predictions and the true seizure state are calculated for the testing data-sets of each subject. These results are presented in Table 1. While comparing statistics on number of false detections per hour would have been interesting, it is not considered a legitimate comparison as the length of each segment this process analyses is significantly smaller, i.e. 30 seconds compared to 1/256 of a second, and would consequently have significantly higher false detection rates.

Table I provides a comparison of our results with previous studies. In [36] and [48], the authors calculated feature vectors as inputs for an SVM classifier, whereas [49] instead used an LDA for classification. The feature vectors each created are also more computationally demanding than our proposed method, with [36] using temporal and spectral statistics, [48] employing fuzzy entropy, and [49] calculating wavelet coefficients. It is also important to note that all three studies classify segments of time, rather than predicting in a point-by-point basis. Additionally, these studies were using the full range of available electrodes, whereas the proposed algorithm is detecting based on the information from only two channels. Finally, all three studies performed binary classification, which means information regarding the severity of a seizure is lost.

In addition to performance statistics, the proposed algorithm also provides insight as to the possible focus of the seizure. While the original data-set did not include any information as to the focus of the seizure, our results can be compared against results from a previous study that performed channel importance analysis. *Das et al.* [50] employed wavelet analysis to design channel-specific input vectors for an SVM classifier. In Table I, the channels that provided the highest specificity and highest accuracies for subjects 1, 2, and 10 (the only subjects of the first ten reported by [50]) matched the channels found by the proposed feature selection process.

The algorithm proposed in this research demonstrates a feasible real-time channel-minimized method of utilizing a continuous and binary representation of EEG features for the detection of epileptic seizure events. The seizure state prediction is continuous, meaning that, in addition to the detection of a seizure event, the algorithm also provides information on the severity of a seizure. Understanding the severity of a seizure will allow adaptive vagus stimulation applications as different levels of seizure severity may require different stimulation amplitudes or frequency adjustments. Furthermore, following the first two seizures of a specific subject, this process only uses the information from two channels so that, following the training and validation stages, further continuous estimation would need only two channels, rather than a full array of EEG electrodes. The use of only two channels would allow for customizable EEG headsets, which would reduce the cost and improve the comfort of the end user. Outside of seizure detection, the proposed algorithm also helps in our understanding of a subject's epileptic event. The wrapper feature selection process finds the highest performing channel/band power combination, which provides information as to the brain region of focus for the epileptic event.

The primary goal for this detection algorithm is to demonstrate the feasibility of real-time seizure detection with a restricted number of channels. The method described in this research uses a wrapper feature selection process, which employs an LDA predictive model and compares the resulting F1 scores of candidate features. The candidate features are the collection of four band powers for each of the EEG channels. Two high performing features were found separately and an LDA classifier was used to transform one feature into a binary feature. The results for this feature selection process essentially matched previous results from another study that assessed the performance of individual channels [50]. Further research is needed on the application of this algorithm on a data-set where the true seizure focus is known in order to understand how well the selected channels match the seizure focus.

The optimized set of a continuous and binary features was used in a state-space approach. An EM algorithm was employed to optimize the state-space parameters. The output of this process is a seizure state predictive model. Using an online forward filter with the the optimized parameters, the model outputs a continuous estimation of the seizure state, which allows for an understanding of both the timing

TABLE I: **A Comparison Among Different Studies that Analyzed The Same Data-set.** In the performance statistics section, we compare Accuracy (Ac), Specificity (Sp), and Sensitivity (Se) values of our proposed method to other studies. The best channels section shows that our selected channels match the highest performing channels of the three subjects reported by [50] (*Das et al.* [50] only reported the results for subjects one, two, and ten among the first ten subjects).

	Performance Statistics								Best Channels				
	Accuracy			Sensitivity			Specificity		Cont.	Bin.	Se.	Sp.	Acc.
Sub.	*	[48]	[49]	*	[36]	[48]	*	[48]	*		[50]		
1	94	99	94	92.7	100	99	94.1	99	F8-T8	T8-P8	T7-P7	F8-T8	F8-T8
2	75.1	100	80	100	100	100	75.1	100	T8-P8	T8-P8	FT9-FT10	T8-P8	T8-P8
3	82	98	95	91.4	100	97	81.8	98	CZ-PZ	P7-O1			
4	89.9	97	77	93.3	100	96	89.9	98	F4-C4	FZ-CZ			
5	96.8	98	76	98.2	74	98	96.8	98	P4-O2	P8-O2			
6	61.1	96	74	78	86	96	61.1	96	F7-T7	FT9-FT10			
7	86.6	97	84	84.9	100	97	86.6	97	FP2-F8	F8-T8			
8	75.8	96	81	95.3	100	96	74.7	96	CZ-PZ	P4-O2			
9	96.6	96	88	95.9	100	95	96.6	96	T7-FT9	F3-C3			
10	99.6	98	73	85.7	100	98	99.8	96	T7-P7	F7-T7	T8-P8	T7-P7	F7-T7
Avg.	85.8	97.5	82.2	91.5	96	97.2	85.7	97.4					

* indicates results obtained through the current study.

and severity of a seizure. To compare our results to past research that analyzed this data-set, our continuous seizure estimation was binarized by a final LDA. Our model shows reasonably comparable performance statistics when compared against other studies [36], [48], [49]. It is important to note that all three of the compared studies used all electrodes available without the stated focus of real-time detection.

Further research may see benefits from focusing improvements in several key aspects: channel count restrictions, type of features to include, and global seizure state acquisition. While this particular filter only uses two channels, the specific area of seizure activity in the brain can produce significant relationships with more than two channels. It may be a beneficial to locate all affected channels during the training stage, rather than a maximum of two, in order to detect a seizure more accurately. This would increase the number of necessary channels in a practical application. Another area where this algorithm could be improved is in using a filter that uses more than one continuous feature. The filter described in this research uses a single continuous and single binary feature, but, as described in the methods section, steps had to be taken to avoid overfitting to the continuous feature as the algorithm seemed to favor the continuous feature over the binary feature. Future filter design could instead take as inputs two or more continuous features, in addition to the sole binary feature. If, however, future applications do not require any form of channel restriction (i.e. due to a reduced cost in EEG headsets), the above algorithm could use a Kalman filter to find a global seizure state based on channel-specific seizure estimations. While this negates the goal of channel-restriction since information from all EEG channels would be necessary, the ability to predict in real-time would be maintained and, by using all channels, it is expected to achieve higher performance.

The above algorithm has shown that it is indeed possible to perform real-time seizure detection using EEG with a limited number of channels to track the continuous seizure state, which provides us information about the timing and severity of the seizure. This can be implemented in a closed-loop system with a frequency or amplitude adaptive vagus nerve stimulator to help reduce the symptoms of the seizure.

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References

[1] I. Osorio, H. P. Zaveri, M. G. Frei, and S. Arthurs, *Epilepsy: the intersection of neurosciences, biology, mathematics, engineering, and physics*. CRC press, 2016.

[2] K. Starnes, K. Miller, L. Wong-Kisiel, and B. N. Lundstrom, "A review of neurostimulation for epilepsy in pediatrics," *Brain sciences*, vol. 9, no. 10, p. 283, 2019.

[3] D. S. Wickramasuriya, L. P. Wijesinghe, and S. Mallawaarachchi, "Seizure prediction using hilbert huang transform on field programmable gate array," in *2015 IEEE Global Conference on Signal and Information Processing (GlobalSIP)*. IEEE, 2015, pp. 933–937.

[4] H. E. Scharfman, "The neurobiology of epilepsy," *Current neurology and neuroscience reports*, vol. 7, no. 4, pp. 348–354, 2007.

[5] L.-T. Huang, M. Cilio, D. Silveira, B. McCabe, Y. Sogawa, C. Stafstrom, and G. Holmes, "Long-term effects of neonatal seizures: a behavioral, electrophysiological, and histological study," *Developmental Brain Research*, vol. 118, no. 1-2, pp. 99–107, 1999.

[6] M. R. Amin and R. T. Faghih, "Tonic and phasic decomposition of skin conductance data: A generalized-cross-validation-based block coordinate descent approach," in *2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2019, pp. 745–749.

[7] Y. M. Hart and S. D. Shorvon, "The nature of epilepsy in the general population. i. characteristics of patients receiving medication for epilepsy," *Epilepsy research*, vol. 21, no. 1, pp. 43–49, 1995.

[8] D. Labar, J. Murphy, E. Tecoma, E. V. S. Group *et al.*, "Vagus nerve stimulation for medication-resistant generalized epilepsy," *Neurology*, vol. 52, no. 7, pp. 1510–1510, 1999.

[9] I. Osorio and M. G. Frei, "Vagal nerve stimulation techniques for treatment of epileptic seizures," Jan. 22 2002, uS Patent 6,341,236.

[10] M. Dümpelmann, J. Fell, J. Wellmer, H. Urbach, and C. E. Elger, "3d source localization derived from subdural strip and grid electrodes: a simulation study," *Clinical Neurophysiology*, vol. 120, no. 6, pp. 1061–1069, 2009.

[11] A. Craik, Y. He, and J. L. Contreras-Vidal, "Deep learning for electroencephalogram (eeg) classification tasks: A review," *Journal of neural engineering*, 2019.

[12] U. R. Acharya, S. L. Oh, Y. Hagiwara, J. H. Tan, and H. Adeli, "Deep convolutional neural network for the automated detection and diagnosis of seizure using eeg signals," *Computers in biology and medicine*, vol. 100, pp. 270–278, 2018.

[13] N. Lashkari, J. Poshtan, and H. F. Azgomi, "Simulative and experimental investigation on stator winding turn and unbalanced supply voltage fault diagnosis in induction motors using artificial neural networks," *ISA transactions*, vol. 59, pp. 334–342, 2015.

[14] L. Vidyaratne, A. Glandon, M. Alam, and K. M. Iftekharuddin, "Deep recurrent neural network for seizure detection," in *2016 International Joint Conference on Neural Networks (IJCNN)*. IEEE, 2016, pp. 1202–1207.

[15] K. M. Tsiouris, V. C. Pezoulas, M. Zervakis, S. Konitsiotis, D. D. Koutsouris, and D. I. Fotiadis, "A long short-term memory deep learning network for the prediction of epileptic seizures using eeg signals," *Computers in biology and medicine*, vol. 99, pp. 24–37, 2018.

[16] S. Ghosh-Dastidar and H. Adeli, "A new supervised learning algorithm for multiple spiking neural networks with application in epilepsy and seizure detection," *Neural networks*, vol. 22, no. 10, pp. 1419–1431, 2009.

[17] Y. Liu, W. Zhou, Q. Yuan, and S. Chen, "Automatic seizure detection using wavelet transform and svm in long-term intracranial eeg," *IEEE transactions on neural systems and rehabilitation engineering*, vol. 20, no. 6, pp. 749–755, 2012.

[18] J. An, T. Yadav, M. B. Ahmadi, V. S. A. Tarigoppula, and J. T. Francis, "Near perfect neural critic from motor cortical activity toward an autonomously updating brain machine interface," in *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2018, pp. 73–76.

[19] S. Parshi, R. Amin, H. F. Azgomi, and R. T. Faghih, "Mental workload classification via hierarchical latent dictionary learning: A functional near infrared spectroscopy study," in *2019 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI)*. IEEE, 2019, pp. 1–4.

[20] Y. U. Khan, N. Rafiuddin, and O. Farooq, "Automated seizure detection in scalp eeg using multiple wavelet scales," in *Signal Processing, Computing and Control (ISPCC), 2012 IEEE International Conference on*. IEEE, 2012, pp. 1–5.

[21] S. Moeller, C. Lücke, C. Heinen, B. H. Bewernick, M. Aydin, A. P. Lam, T. W. Grömer, A. Philipsen, and H. H. Müller, "Vagus nerve stimulation as an adjunctive neurostimulation tool in treatment-resistant depression," *JoVE (Journal of Visualized Experiments)*, no. 143, p. e58264, 2019.

[22] D. S. Wickramasuriya, M. Amin, R. T. Faghih *et al.*, "Skin conductance as a viable alternative for closing the deep brain stimulation loop in neuropsychiatric disorders," *Frontiers in neuroscience*, vol. 13, p. 780, 2019.

[23] D. S. Wickramasuriya and R. T. Faghih, "A novel filter for tracking real-world cognitive stress using multi-time-scale point process observations," in *2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2019, pp. 599–602.

[24] M. R. Amin and R. T. Faghih, "Inferring autonomic nervous system stimulation from hand and foot skin conductance measurements," in *2018 52nd Asilomar Conference on Signals, Systems, and Computers*. IEEE, 2018, pp. 655–660.

[25] D. S. Wickramasuriya and R. T. Faghih, "Online and offline anger detection via electromyography analysis," in *2017 IEEE Healthcare Innovations and Point of Care Technologies (HI-POCT)*. IEEE, 2017, pp. 52–55.

[26] M. J. Prerau, A. C. Smith, U. T. Eden, Y. Kubota, M. Yanike, W. Suzuki, and E. N. Graybiel, A. M.and Brown, "Characterizing learning by simultaneous analysis of continuous and binary measures of performance," *Journal of Neurophysiology*, vol. 102, pp. 3060–3072, 2009.

[27] D. S. Wickramasuriya and R. T. Faghih, "A bayesian filtering approach for tracking arousal from binary and continuous skin conductance features," *IEEE Transactions on Biomedical Engineering*, 2019.

[28] D. D. Pednekar, M. R. Amin, H. F. Azgomi, K. Aschbacher, L. J. Crofford, and R. T. Faghih, "A system theoretic investigation of cortisol dysregulation in fibromyalgia patients with chronic fatigue," in *2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2019, pp. 6896–6901.

[29] D. S. Wickramasuriya and R. T. Faghih, "A cortisol-based energy decoder for investigation of fatigue in hypercortisolism," in *2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2019, pp. 11–14.

[30] R. T. Faghih, M. A. Dahleh, and E. N. Brown, "An optimization formulation for characterization of pulsatile cortisol secretion," *Frontiers in neuroscience*, vol. 9, p. 228, 2015.

[31] R. T. Faghih, "From physiological signals to pulsatile dynamics: a sparse system identification approach," in *Dynamic Neuroscience*. Springer, 2018, pp. 239–265.

[32] I. Iturrate, M. Pereira, and J. d. R. Millán, "Closed-loop electrical neurostimulation: challenges and opportunities," *Current Opinion in Biomedical Engineering*, vol. 8, pp. 28–37, 2018.

[33] H. F. Azgomi, D. S. Wickramasuriya, and R. T. Faghih, "State-space modeling and fuzzy feedback control of cognitive stress," in *2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2019, pp. 6327–6330.

[34] H. Taghvafard, M. Cao, Y. Kawano, and R. T. Faghih, "Design of intermittent control for cortisol secretion under time-varying demand and holding cost constraints," *IEEE Transactions on Biomedical Engineering*, 2019.

[35] A. Vassileva, D. van Blooijs, F. Leijten, and G. Huiskamp, "Neocortical electrical stimulation for epilepsy: Closed-loop versus open-loop," *Epilepsy research*, vol. 141, pp. 95–101, 2018.

[36] A. H. Shoeb, "Application of machine learning to epileptic seizure onset detection and treatment," Ph.D. dissertation, Massachusetts Institute of Technology, 2009.

[37] G. Buzsáki and A. Draguhn, "Neuronal oscillations in cortical networks," *science*, vol. 304, no. 5679, pp. 1926–1929, 2004.

[38] V. Kumar and S. Minz, "Feature selection," *SmartCR*, vol. 4, no. 3, pp. 211–229, 2014.

[39] D. S. Wickramasuriya, C. Qi, and R. T. Faghih, "A state-space approach for detecting stress from electrodermal activity," in *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2018, pp. 3562–3567.

[40] M. R. Amin and R. T. Faghih, "Sparse deconvolution of electrodermal activity via continuous-time system identification," *IEEE Transactions on Biomedical Engineering*, 2019.

[41] R. T. Faghih, M. A. Dahleh, G. K. Adler, E. B. Klerman, and E. N. Brown, "Deconvolution of serum cortisol levels by using compressed sensing," *PloS one*, vol. 9, no. 1, p. e85204, 2014.

[42] X. Deng, R. T. Faghih, R. Barbieri, A. C. Paulk, W. F. Asaad, E. N. Brown, D. D. Dougherty, A. S. Widge, E. N. Eskandar, and U. T. Eden, "Estimating a dynamic state to relate neural spiking activity to behavioral signals during cognitive tasks," in *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2015, pp. 7808–7813.

[43] R. T. Faghih, M. A. Dahleh, G. K. Adler, E. B. Klerman, and E. N. Brown, "Quantifying pituitary-adrenal dynamics and deconvolution of concurrent cortisol and adrenocorticotropic hormone data by compressed sensing," *IEEE Transactions on Biomedical Engineering*, vol. 62, no. 10, pp. 2379–2388, 2015.

[44] R. T. Faghih, "System identification of cortisol secretion: Characterizing pulsatile dynamics," Ph.D. dissertation, Massachusetts Institute of Technology, 2014.

[45] M. J. Prerau, A. C. Smith, U. T. Eden, M. Yanike, W. A. Suzuki, and E. N. Brown, "A mixed filter algorithm for cognitive state estimation from simultaneously recorded continuous and binary measures of performance," *Biological cybernetics*, vol. 99, no. 1, pp. 1–14, 2008.

[46] A. Graybiel, W. Suzuki, and E. Brown, "Dynamic analysis of learning in behavioral experiments," *J Neurosci*, vol. 24, p. 447461, 2004.

[47] P. D. JONG and M. J. Mackinnon, "Covariances for smoothed estimates in state space models," *Biometrika*, vol. 75, no. 3, pp. 601–602, 1988.

[48] J. Xiang, C. Li, H. Li, R. Cao, B. Wang, X. Han, and J. Chen, "The detection of epileptic seizure signals based on fuzzy entropy," *Journal of neuroscience methods*, vol. 243, pp. 18–25, 2015.

[49] N. Rafiuddin, Y. U. Khan, and O. Farooq, "Feature extraction and classification of eeg for automatic seizure detection," in *2011 International Conference on Multimedia, Signal Processing and Communication Technologies*. IEEE, 2011, pp. 184–187.

[50] A. B. Das, M. J. H. Pantho, and M. I. H. Bhuiyan, "Discrimination of scalp eeg signals in wavelet transform domain and channel selection for the patient-invariant seizure detection," in *2015 International Conference on Electrical & Electronic Engineering (ICEEE)*. IEEE, 2015, pp. 77–80.