

# Model Parameter Estimation As Features to Predict the Duration of Epileptic Seizures From Onset

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**Abstract**—The durations of epileptic seizures are linked to severity and risk for patients. It is unclear if the spatiotemporal evolution of a seizure has any relationship with its duration. Understanding such mechanisms may help reveal treatments for reducing the duration of a seizure. Here, we present a novel method to predict whether a seizure is going to be short or long at its onset using features that can be interpreted in the parameter space of a brain model. The parameters of a Jansen-Rit neural mass model were tracked given intracranial electroencephalography (iEEG) signals, and were processed as time series features using MINIROCKET. By analysing 2954 seizures from 10 patients, patient-specific classifiers were built to predict if a seizure would be short or long given 7 s of iEEG at seizure onset. The method achieved an area under the receiver operating characteristic curve (AUC) greater than 0.6 for five of 10 patients. The behaviour in the parameter space has shown different mechanisms are associated with short/long seizures.

**Clinical relevance**—This shows that it is possible to classify whether a seizure will be short or long based on its early characteristics. Timely interventions and treatments can be applied if the duration of the seizures can be predicted.

## I. INTRODUCTION

Epilepsy is a common neurological disorder that is associated with abnormal brain activities known as seizures. Although 70% of patients' symptoms can be relieved using medication or surgery, the remainder remain refractory to treatment [1]. Seizure prediction has been studied to help these patients with their everyday lives to alert them prior to a seizure, enabling them to seek help from the doctor or stay away from dangerous environments[2]. Though some prediction methods have achieved high accuracy [3], the mechanisms that cause seizures remain unknown [4].

Scalp and intracranial electroencephalography (EEG) record electrical activity signals captured on the scalp or the surface of the brain, respectively. These signals primarily represent spatially and temporally smoothed version of cortically generated electrical potentials [5]. Modelling is a way to bridge the EEG data and the underlying neurophysiological processes[6].

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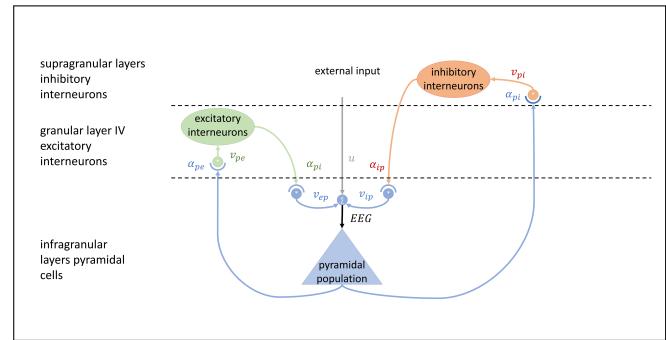


Fig. 1. Structure of the Jansen & Rit model. The model consists of three populations: pyramidal neurons, inhibitory interneurons and excitatory interneurons. The output of each population is a firing rate, which is transformed to changes in the mean membrane potentials of connected neural populations.

It is known from previous research that it is possible to predict whether a seizure will be short or long from the seizure onset [7]. Brain modelling makes it possible to additionally understand how seizures evolve both spatially and temporally [8], [9]. Here, we implement brain modelling combined with machine learning to predict seizure durations for individual patients, so that we can also understand patterns of short and long seizures in the models.

## II. METHODS

### A. Neural Mass Model

We focus on the Jansen-Rit neural mass model (NMM) [10], [11], which is commonly used to model cerebral cortex, illustrated in Fig. 1. It is a three-population neural field model that can generate an EEG signal based on pyramidal population output. The spatially averaged postsynaptic potential (PSP) of population  $m$  arising as a result of firing-rate input from pre-synaptic population  $n$ ,  $\phi(v_n(t'))$ , is expressed as

$$v_{mn}(t) = \alpha_{mn} \int_{-\infty}^t h_{mn}(t-t') \Phi(v_n(t')) dt' \quad (1)$$

where  $\alpha_{mn}$  is the population averaged synaptic connectivity strength and  $h_{mn}$  is the PSP kernel, and  $\Phi(v)$  is a sigmoid function that transforms the membrane potential to a firing rate given by

$$\Phi(v) = \frac{1}{2} \left( \text{erf} \left( \frac{v - v_0}{\varsigma} \right) \right) \quad (2)$$

The convolution in (1) can be also written as two coupled, first-order, ordinary differential equations [12],

$$\frac{dv_{mn}}{dt} = z_{mn} \quad (3)$$

$$\frac{dz_{mn}}{dt} = \frac{\alpha_{mn}}{\tau_{mn}}\Phi_{mn} - \frac{2}{\tau_{mn}}z_{mn} - \frac{1}{\tau_{mn}^2}v_{mn} \quad (4)$$

where  $\tau_{mn}$  is the lumped time constant.

We aim to estimate the parameters of the Jansen-Rit NMM. The parameter vector is defined as  $\theta = [u \ \alpha_{pe} \ \alpha_{pi} \ \alpha_{ip} \ \alpha_{ep}]^T$  (Fig. 1). This set of parameters corresponds to the input  $u$  to the model and the population averaged connection strengths between the three populations. We assume the synaptic gains of the model to be constant to simplify the estimation problem.

### B. LSTM Filter

The LSTM (long short-term memory) Filter is a novel data-driven approach to accurately estimate the state variables and parameters of the Jansen-Rit NMM [13]. It was trained on simulated EEG data generated by the Jansen-Rit NMM using a wide range of parameters [14]. Given an observation signal, the trained LSTM filter can predict the state variables and parameters that can recreate the observation signal using the NMM.

### C. MINIROCKET

Time series classification typically focuses on traditional signal processing methods for feature extraction. Frequency band power [15] and Hjorth parameters [16] are often used as features. Convolutional kernels constitute a single mechanism that is able to capture many of the features that previously required specific analysis techniques. Convolutional neural networks for time series classification have been shown to be effective [17].

ROCKET generates a large number of random convolutional kernels, which capture random features that could be relevant for time series classification [18]. Even though a single random convolutional kernel may approximately capture a relevant feature, a large number of random kernels can capture more features that are useful for classification. Compared to other time series classification methods, ROCKET is effective as it can achieve high classification accuracy with lower training time. Furthermore, MINIROCKET has simplified the process by using a small, fixed set of convolutional kernels, which makes it significantly faster while maintaining essentially the same accuracy [19].

### D. Data

Seizure intracranial EEG (iEEG) data from 10 NeuroVista patients were analysed in this paper [20], [21]. Each patient was implanted with 16 iEEG electrodes over the brain quadrant thought to contain the epileptogenic zone. Recordings were made at 400 Hz and with a common average reference. Five patients were removed due to low numbers of seizures.

### E. Analysis

The second to the seventh seconds from the seizure onset of iEEG were considered for processing, as most seizures last at least 7 s. The first second was excluded in case of clinician error in marking seizure onset.

The process of building and testing the model is illustrated in Fig. 2. The LSTM filter estimated states and parameters for 7 s of recording. Since we consider that the parameters of the NMM provide the necessary information about brain behaviour [8], we subsequently used the external input and connectivity strengths. To further reduce the number of parameters, we have selected  $\alpha_{pi}$ ,  $\alpha_{ip}$  and  $u$  as features. Thus, the LSTM filter was used to generate 3 parameters from each channel for each iEEG sample. As a result, 48 parameters (16 channels) were generated per sample.

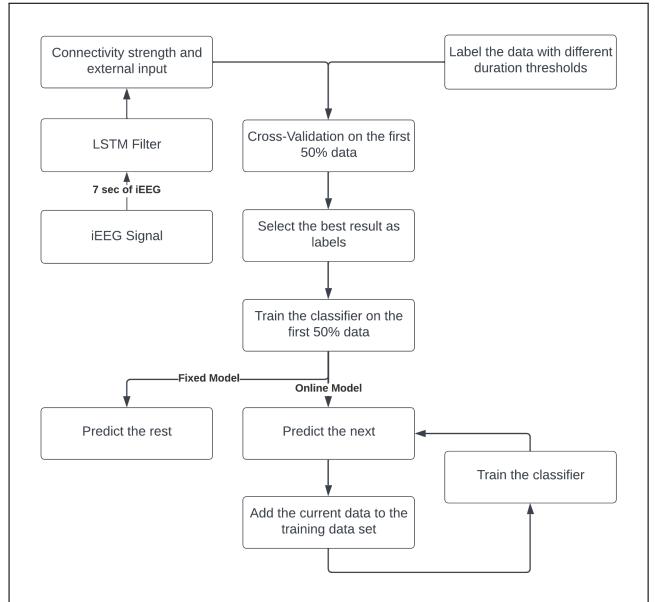


Fig. 2. Process of building and testing a model. Parameters are generated from the LSTM filter, combined with dynamic labelling, and the best results are selected through a cross-validation process.

Parameters generated from the LSTM filter were then processed by MINIROCKET for feature extraction [19]. MINIROCKET applied convolutional kernels to the time series data and generated approximately 10,000 features. With the MINIROCKET built-in classifier, these features were then used in a linear classifier, which was either logistic regression or ridge regression. However, we only used the feature extraction part and discarded the built-in classifier, and built non-linear classifiers using gradient boosting to avoid the class imbalance problem [22].

Due to a large number of features (10,000) and small number of examples for patient-specific training (71-484), we applied feature selection to reduce than number of features to the more useful features. ANOVA F-value between all features and labels was computed on the training dataset to identify useful features [23]. According to the number of examples from each patient, the top 10% were selected for further training.

Short and long seizures were defined in a patient-specific manner as there is no universal definition. Therefore, for each patient, we separated the seizures into two classes by considering different short/long seizure duration thresholds [7]. The median duration for each patient was identified first and was set as the initial threshold, then the threshold was

TABLE I

CROSS-VALIDATION (CV) AND TESTING RESULT OF THE TEN SELECTED PATIENTS. FOR EACH PATIENT, THE TOTAL NUMBER OF SEIZURES IS GIVEN AS WELL AS NUMBERS OF SEIZURES CONSIDERED TO BE SHORT WITHIN THIS NUMBER. THE CV AND TEST RESULTS ARE AUC VALUES WHEN CONSIDERING THE GIVEN SPLIT BETWEEN NUMBERS OF SHORT AND LONG SEIZURES. THE GREEN HIGHLIGHTS SHOW THE SPLIT CHOSEN TO BE OPTIMAL FOR EACH PATIENT BASED ON THE CV RESULT.

Pat. 1	# Seizures	121					
# Short	37	45	53	60	70	77	80
CV	0.82	0.69	0.69	0.69	0.64	0.65	0.59
Test	0.64	0.50	0.63	0.61	0.48	0.49	0.50
Pat. 3	# Seizures	341					
# Short	86	136	174	213	230	250	
CV	0.82	0.74	0.77	0.69	0.71	0.74	
Test	0.62	0.60	0.66	0.68	0.66	0.62	
Pat. 6	# Seizures	71					
# Short	25	27	29	31	33	35	37
CV	0.50	0.54	0.57	0.86	0.68	0.85	0.73
Test	0.50	0.50	0.50	0.62	0.48	0.39	0.48
Pat. 7	# Seizures	246					
# Short	44	67	96	120	148	168	
CV	0.75	0.75	0.78	0.77	0.78	0.60	
Test	0.52	0.49	0.51	0.58	0.65	0.52	
Pat. 8	# Seizures	466					
# Short	27	71	159	231	285	308	322
CV	0.54	0.60	0.54	0.52	0.64	0.56	0.50
Test	0.50	0.49	0.47	0.53	0.48	0.52	0.55
Pat. 9	# Seizures	204					
# Short	66	81	96	102	113	126	135
CV	0.59	0.58	0.63	0.63	0.67	0.66	0.67
Test	0.46	0.52	0.48	0.49	0.47	0.48	0.54
Pat. 10	# Seizures	484					
# Short	108	144	180	201	221	239	250
CV	0.70	0.63	0.62	0.64	0.70	0.68	0.66
Test	0.53	0.50	0.53	0.49	0.49	0.48	0.49
Pat. 11	# Seizures	463					
# Short	111	134	160	188	208	231	254
CV	0.77	0.71	0.71	0.75	0.70	0.72	0.71
Test	0.65	0.58	0.65	0.61	0.59	0.58	0.57
Pat. 13	# Seizures	481					
# Short	49	83	151	228	286	323	347
CV	0.66	0.61	0.60	0.57	0.57	0.57	0.60
Test	0.57	0.46	0.49	0.47	0.50	0.51	0.47
Pat. 15	# Seizures	77					
# Short	29	34	37	42	46	49	51
CV	0.57	0.50	0.50	0.65	0.70	0.78	0.66
Test	0.66	0.50	0.50	0.53	0.49	0.58	0.53

adjusted around the median. Normally the step of adjustment is 5% of the total number of seizures, but patient might have several seizures with the same duration, which was also taken into consideration for the step of adjustment to ensure the threshold does not split seizures with the same duration. The classifiers were trained using the first 50% of the data labelled with different thresholds and the optimal threshold for each patient was determined using a cross-validation process. Five-fold forward chaining was applied to calculate the cross-validation score [24] as the seizures are temporally ordered making them unsuitable to shuffle randomly.

To assess the testing performance of the final classification model and to complete the cross-validation, the area under the receiver operating characteristic curve (AUC) was

computed. AUC is a common measurement of classification performance [25] that overcomes the shortcomings of other metrics such as accuracy that can be less robust if there is class imbalance. The threshold that had the highest cross-validation AUC score was selected as the optimal threshold. Testing was then done on the last 50% of the data.

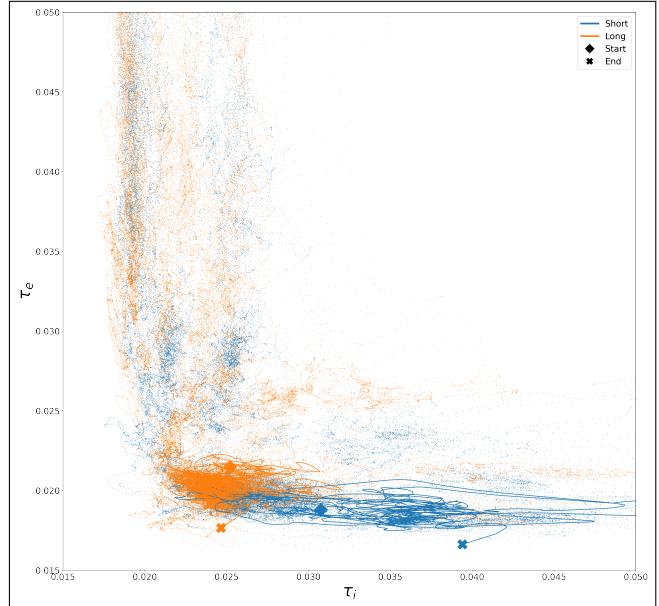


Fig. 3. Patient 3 seizure onsets from the first to the seventh second in the parameter space. Scatter points are the samples, while solid lines are selected as a typical short seizure and a typical long seizure. Diamond and cross indicate the starting point and the end point respectively.

### III. RESULTS

Table I shows the results of the cross-validation (CV) analyses used to select the optimal threshold between short and long seizures and the testing results. The thresholds selected for each patient, based on maximal CV AUC, are highlighted in green.

Five out of ten patients showed testing AUC scores higher than 0.6. Several patients showed a much higher cross-validation score than their testing score; for example, patient 1 had a CV score of 0.82 but a testing score of 0.64. This might be caused by an uneven distribution of short/long seizure across the training and testing data sets.

We did not achieve a testing AUC score higher than 0.5 for Patients 8, 9 and 10, and Patient 13 also had a low testing score of 0.57. This is very similar to our previous work where these four patients achieved low testing scores [7]. These patients all had higher numbers of seizures compared to other patients, which sometimes can be difficult because the properties of seizures may change over time.

An example of seizure onset time constant features is shown in Fig. 3 for Patient 3. Each data point represents the feature values at each sample point. Seizures considered ‘short’ are shown as blue and seizures considered ‘long’ are shown as orange. One of each type is traced with a line starting from the diamond and finishing at the cross. Most seizures are clustered around the bottom left, but short seizures tend to cluster more to the right. Some seizures, both

short and long, are scattered on the upper left of the graph, possibly causing misclassifications. Two example traces of seizures are shown, one short (blue) and one long (orange). They commence at the diamond points and end at the crosses, and show very different trajectories through the parameter space.

#### IV. CONCLUSIONS

We have proposed a method to classify the duration of seizures by using EEG recordings from the seizure onset period and tracking the spatiotemporal evolution of seizures. This work provides a potential way to interpret the behaviour as the tracking within the parameter space can reveal how seizures evolve in the parameter space. Although the performance is worse compared to the model using signal processing and online method which achieved an average AUC of 0.7 for 5 patients [7], the model can be improved by conducting online learning method. Future work will focus on the classification algorithm to improve the performance and make it more interpretable.

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#### ETHICS STATEMENT

The data used in this paper is approved by Human Research Ethics Committee, St Vincent's Hospital, Melbourne – approval LRR145/13.

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