

# ROBUST SEIZURE DETECTION USING COUPLED HIDDEN MARKOV MODELS

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## ABSTRACT

Focal epilepsy is characterized by seizures originating from a discrete onset zone. Seizures can then spread to other regions through connections within the brain. We define a network of seizure propagation paths based on a coupled hidden Markov model (CHMM) to mimic the biological phenomena. We employ a variational technique to reduce the underlying parameter space. Finally, we demonstrate that our model outperforms the classic seizure detection framework.

**Index Terms**— Focal epilepsy, seizure detection, hidden Markov models, variational inference

## 1. BAYESIAN SEIZURE DETECTION

Epilepsy is a chronic neurological disorder marked by recurrent and unprovoked seizures. Among the many characterizations, focal epilepsy is characterized by seizures originating from one location and possibly spreading to other regions of the brain [1]. The standard clinical procedure for epilepsy diagnosis relies heavily on scalp electroencephalography (EEG), which uses an array of electrodes placed on the scalp in a predefined pattern to record population-level neuron firings [2]. These recordings are visually inspected by a trained neurologist, which is a time consuming procedure. Our goal is to automatically detect the seizure onset from EEG recordings by modeling the dependency between neighboring EEG electrodes.

We develop a coupled hidden Markov model (CHMM) for inferring the seizure spread in a recording of a focal seizure. The CHMM uses a 3 state left-to-right transition matrix which allows only one transition into and out of a seizure state. The transition matrix employs a coupling parameter, which increases the probability of concordance between channels. The CHMM uses a Gaussian mixture model emission for the observed EEG features. We learn the model using a mean field variational method that treats each channel as an independent hidden Markov model (HMM) chain.

## 2. RESULTS

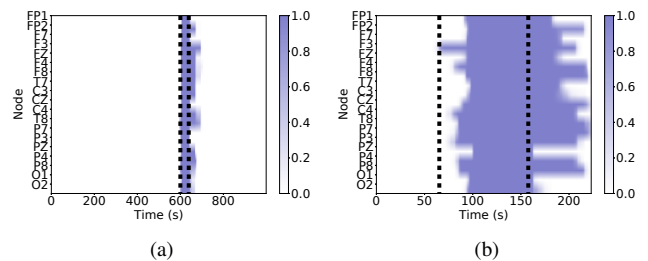
Our data was collected in the Epilepsy Monitoring Unit of the Johns Hopkins Medical Institute (JHMI). Seizure EEG recordings were extracted from 15 focal epilepsy patients for a total of 90 seizure recordings. Each recording contained one seizure with as much as 10 minutes of baseline before and after the seizure. Each recording also contained annotations marking the seizure onset and offset made by residents at the JHMI. We use a five-fold cross validation setup to verify the accuracy of our model on these 90 recordings. The input data for our model consisted of short-time spectral power, independently summed across the delta, theta, alpha, and

Model	True Positive	True Negative	AUC
SVM	17.761%	92.378%	0.719
Logistic	21.547%	92.875%	0.796
GMM	23.089%	92.954%	0.792
CHMM	66.460%	85.771%	0.846

**Table 1:** Results for each experiment. True positive indicates the portion of the seizure region correctly identified while true negative indicates the portion of the non-seizure region correctly identified.

beta frequency bands. As a baseline we also trained a support vector machine (SVM) with a polynomial kernel, logistic regression, and Gaussian mixture based classifier.

The CHMM outperforms the simpler classifiers as shown in Table 1. Two CHMM inference results are shown in Figure 1. Channels are plotted vertically with time on the horizontal axis. Color denotes the estimator’s posterior probability of a seizure event. Seizures occur in contiguous regions of time including multiple windows. The CHMM classifier is able to recognize these contiguous regions better than the logistic regression or GMM models, which perform classifications for each window independently. Our results demonstrate the importance of temporal dependencies for seizure detection. In addition, the first channel to enter the seizure state in Figure 1 (b) corresponds to the clinically verified onset. This demonstrates potential efficacy for localization.



**Fig. 1:** Detection results for the CHMM. The seizure region is denoted by the dashed black lines. (a) shows the models ability to accurately classify seizures across the whole brain. (b) shows the models ability to track seizure spread outwards from the onset zone, here shown by the early onset in F3.

## 3. REFERENCES

- [1] John W. Miller and Howard P. Goodkin, *Epilepsy*, Wiley, 2014.
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