CSAIL
MIT COMPUTER SCIENCE AND ARTIFICIAL INTELLIGENCE LABORATORY

Massachusetts Institute of Technology

Application of Machine Learning to Epileptic Seizure Detection

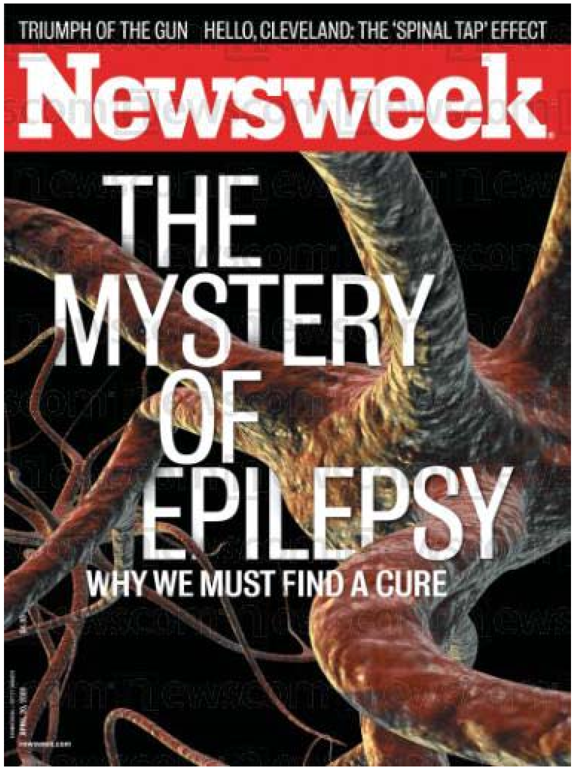
The runner-up of Best Application Paper Award, ICML 2010.

Author: Ali Shoeb, John Guttag

Prepared by Ning Wang

Epilepsy (癫痫症)

- Neurological disorder characterized by recurring seizures (发作)
- Affects 1% of world's population
  - 1 out of 3 cases not well controlled by medication
- Aftermath of seizures causes most harm

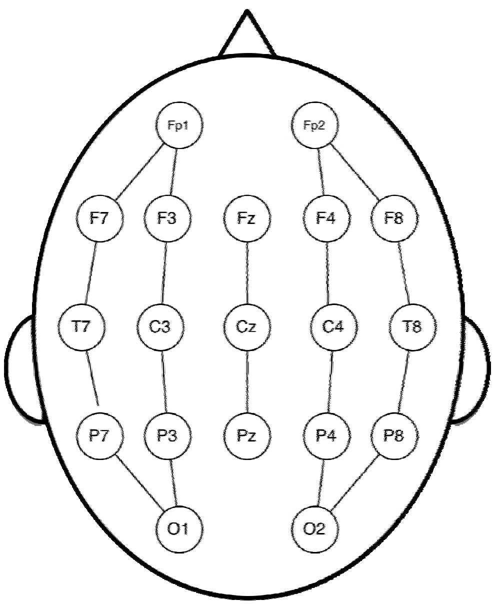


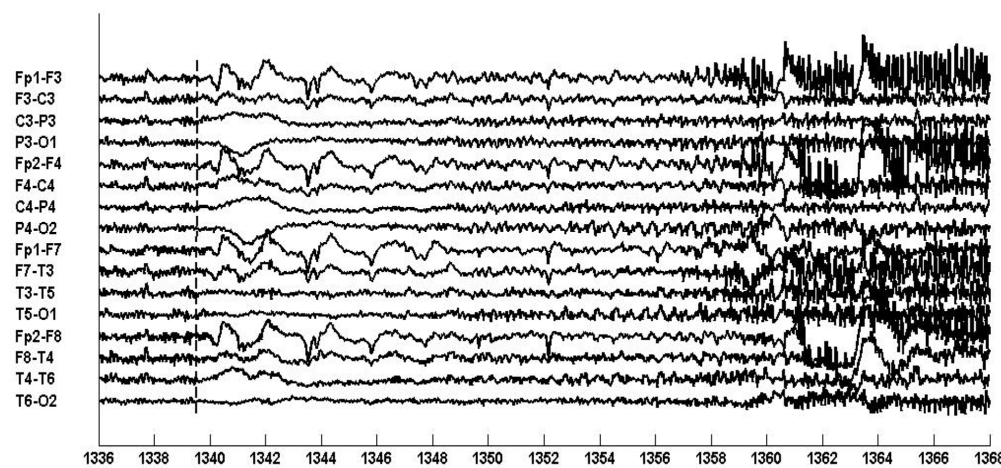
"There are currently only a few ways to treat epilepsy, and applying them is still an art as much as it is a science."

– "In the Grip of the Unknown," *Newsweek*, 20 April 2009

What Happens Today?

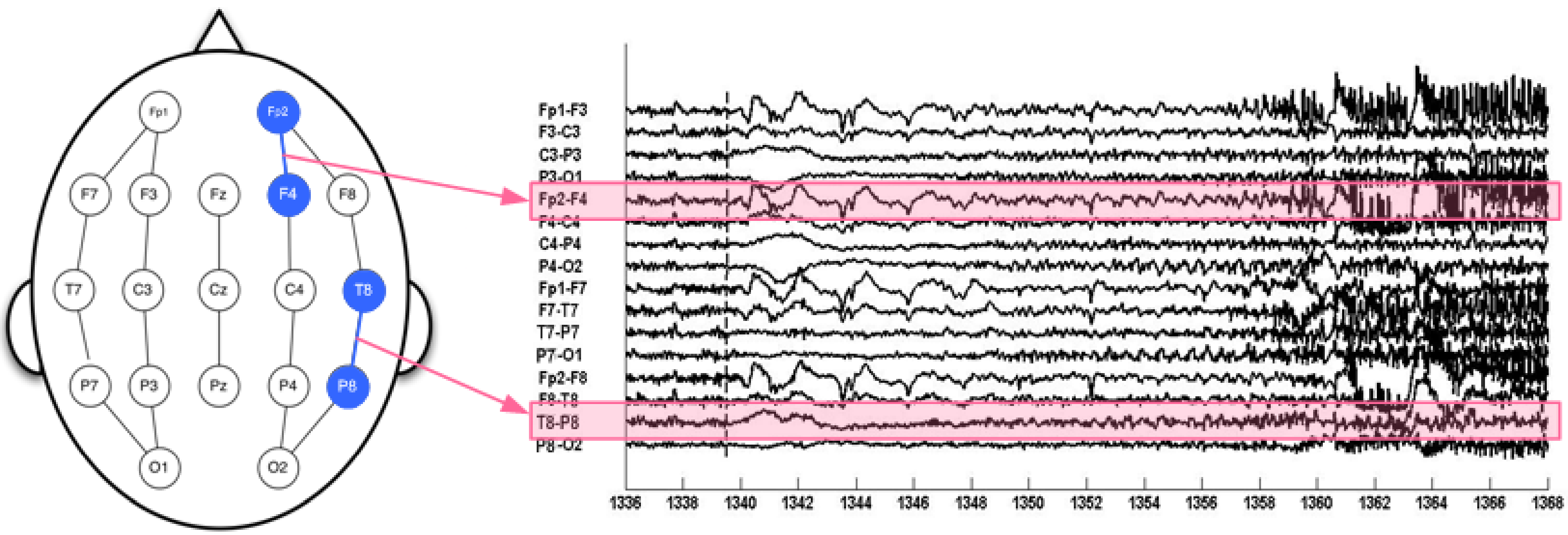
- Diagnosis using **electroencephalogram (EEG)**
  - Record electrical activity of brain using multiple electrodes
- Train a classifier to detect seizure onset using EEG data
  - Seizure onset detection restricted to clinical environment



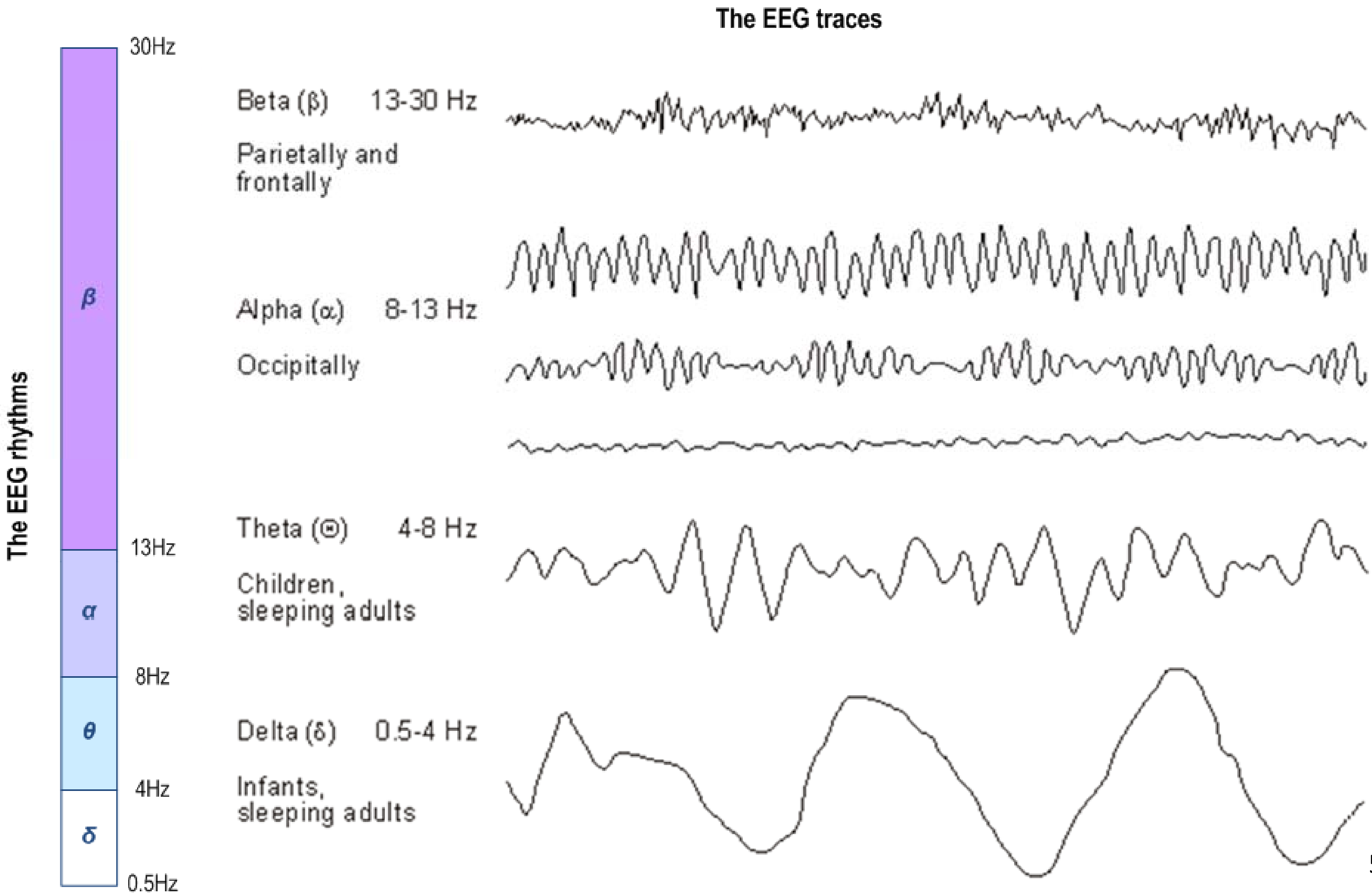


Scalp EEG

- Data recording
  - Noninvasive electrodes uniformly arrayed on the scalp.
  - Channel signal = difference between potentials measured at two electrodes.
- Scalp EEG



EEG Signal’s Rhythmic Pattern



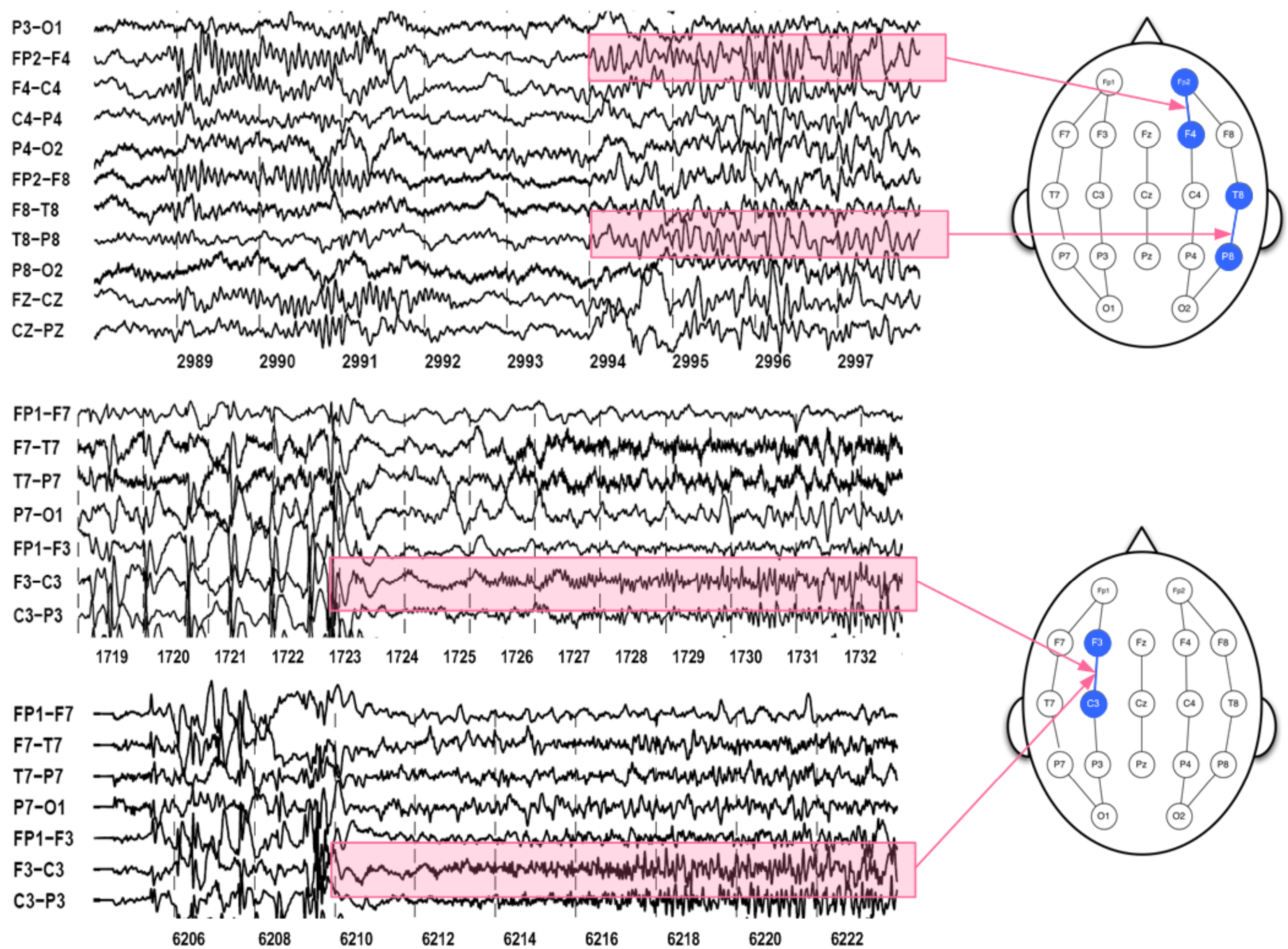
Personal Dependency

- 3 seizures from 2 patients (A and B).
- Inter-patient variability & intra-patient consistency.

Patient A
(Seizure 1)

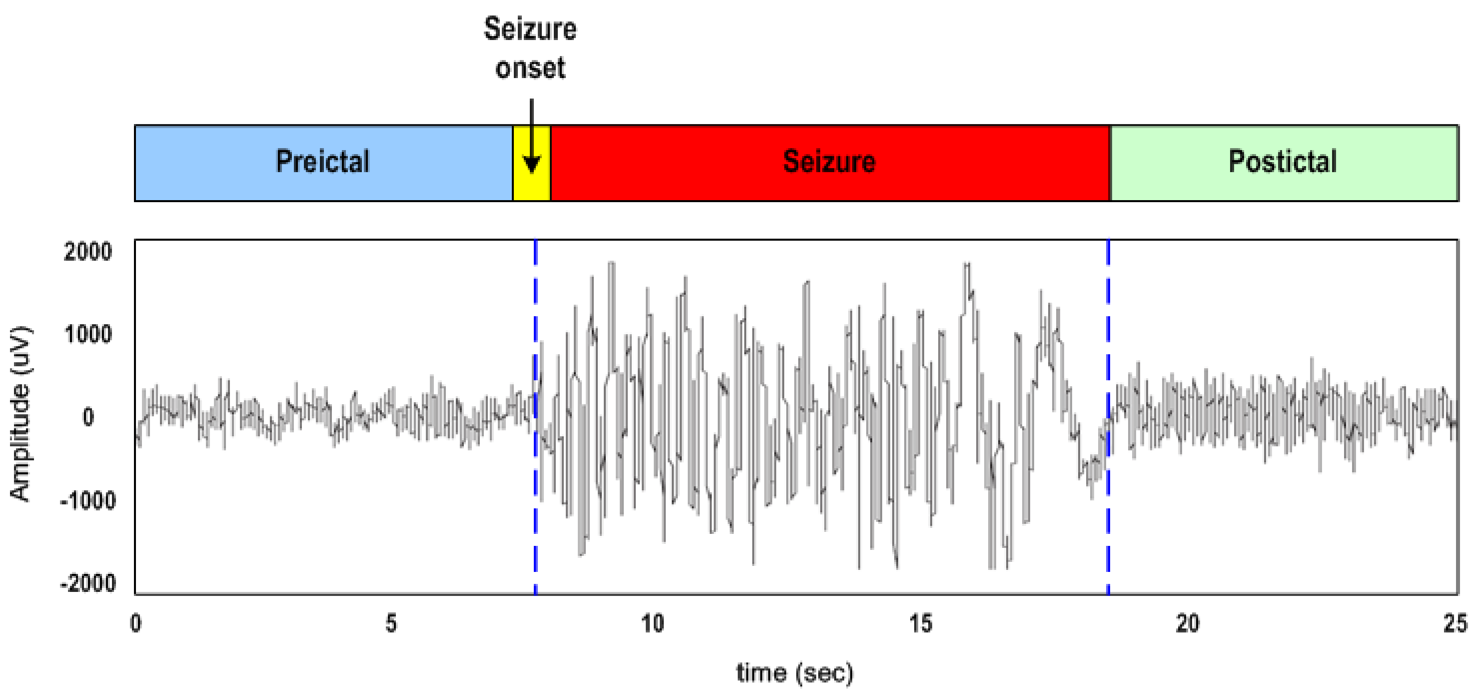
Patient B
(Seizure 1)

Patient B
(Seizure 2)



Seizure Detection Tasks & Applications

Task	Requirements	Application scenarios
Seizure event detection	• greatest possible ***accuracy***, • not necessarily shortest ***delay***.	Apps. requiring an accurate account of seizure activity over a period of time.
Seizure onset detection	• shortest possible ***delay***, • not necessarily highest ***accuracy***.	Apps. requiring a rapid response to a seizure. *e.g., initiating functional neuro-imaging studies to localize cerebral origin of a seizure.*



Seizure Detection through EEG Analysis

- Rhythmic activity following a seizure onset typically
  - Involves a set of EEG channels.
  - Contains multiple frequency components.
  - Differs in structure among patients.

Patient-specific

- EEG characteristics vary significantly across patients.
- Rhythmic patterns exhibit considerable intra-patient consistency for a same brain region.

Machine learning-based

- Identifying discriminative features.
- Supervised learning.
- Segmentation of seizure/non-seizure states → binary classification.

Challenges

- Considerable overlap in EEG associated with seizure and non-seizure states among patients.

  Specificity and sensitivity tradeoff.

- EEG constantly transitions between regimes both within seizure and non-seizure states.

  Non-stationarity.

- Medical applications require quick seizure onset detection.

  Latency and specificity tradeoff.

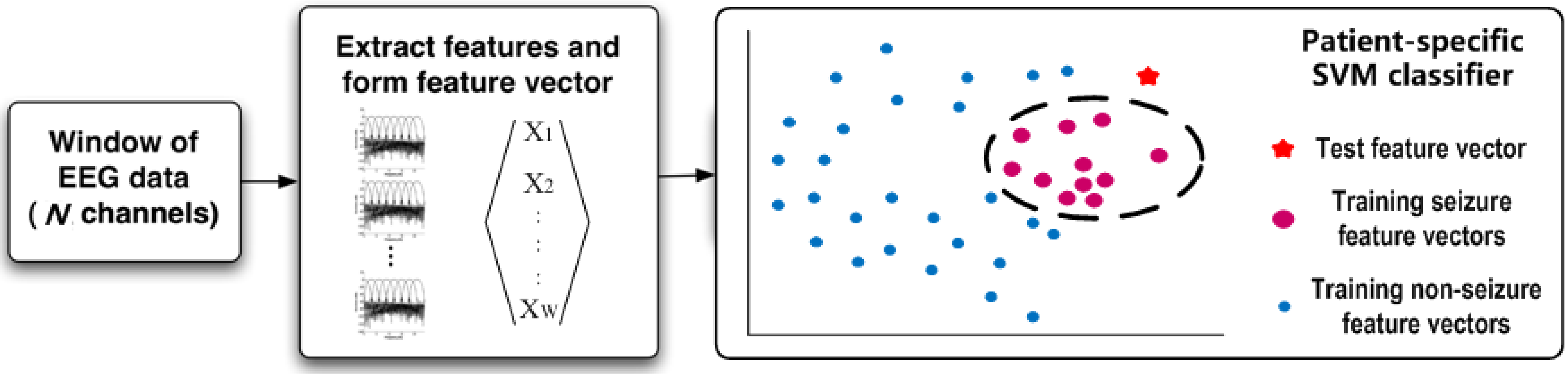
- Seizures are rare event.

  Paucity of seizure training data.

Scalp EEG Database

- CHB-MIT data set
  - 916 hours of continuous scalp EEG.
  - 23 pediatric patients at Children's Hospital Boston and one adult patient at Beth Israel Deaconess Medical Center.
  - 173 events judged to be clinical seizures by experts.
  - 18 EEG channels.

Patient-specific Detector Architecture

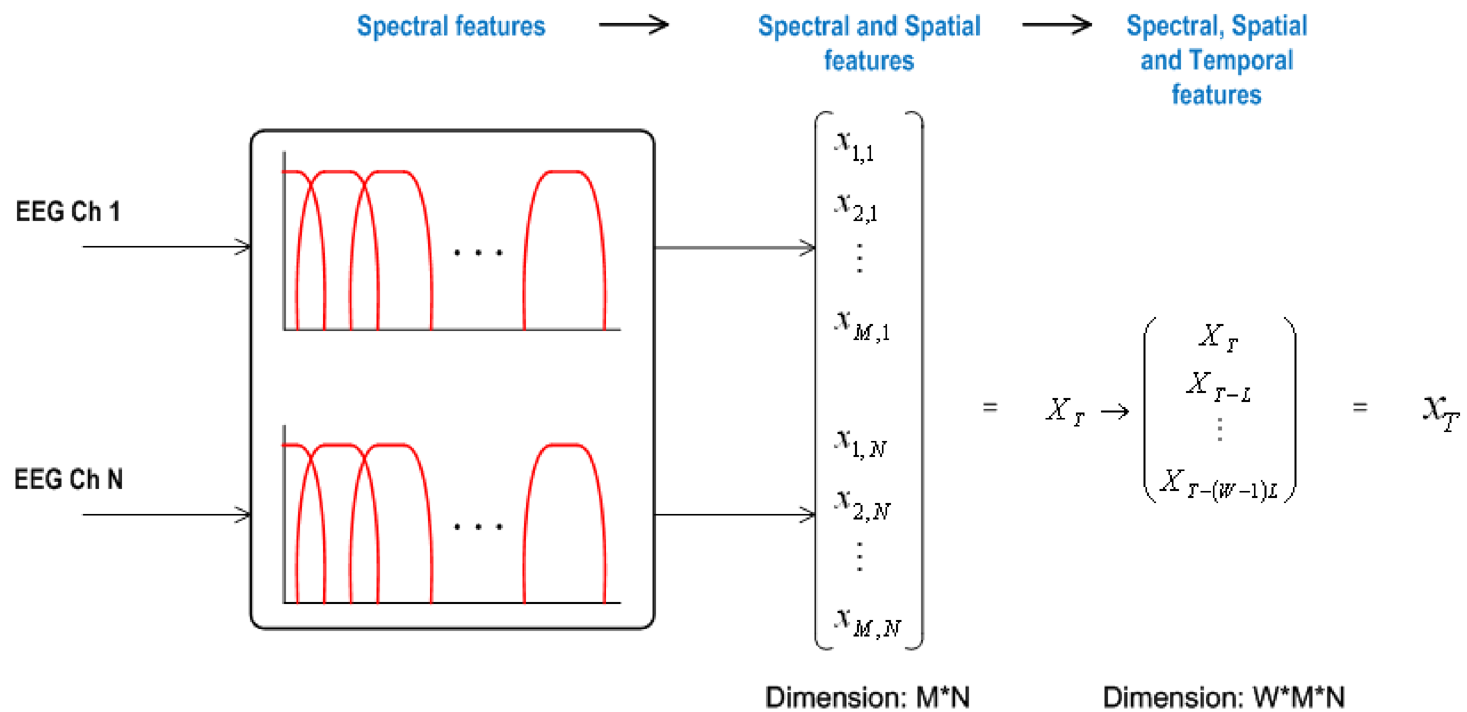


[1] Ali Shoeb, *Ph.D Thesis, MIT, 2009.*

- Algorithm examines 2 second windows that overlap by 1 second.
- Patient-specific, support vector machine classifier is learned offline using training data

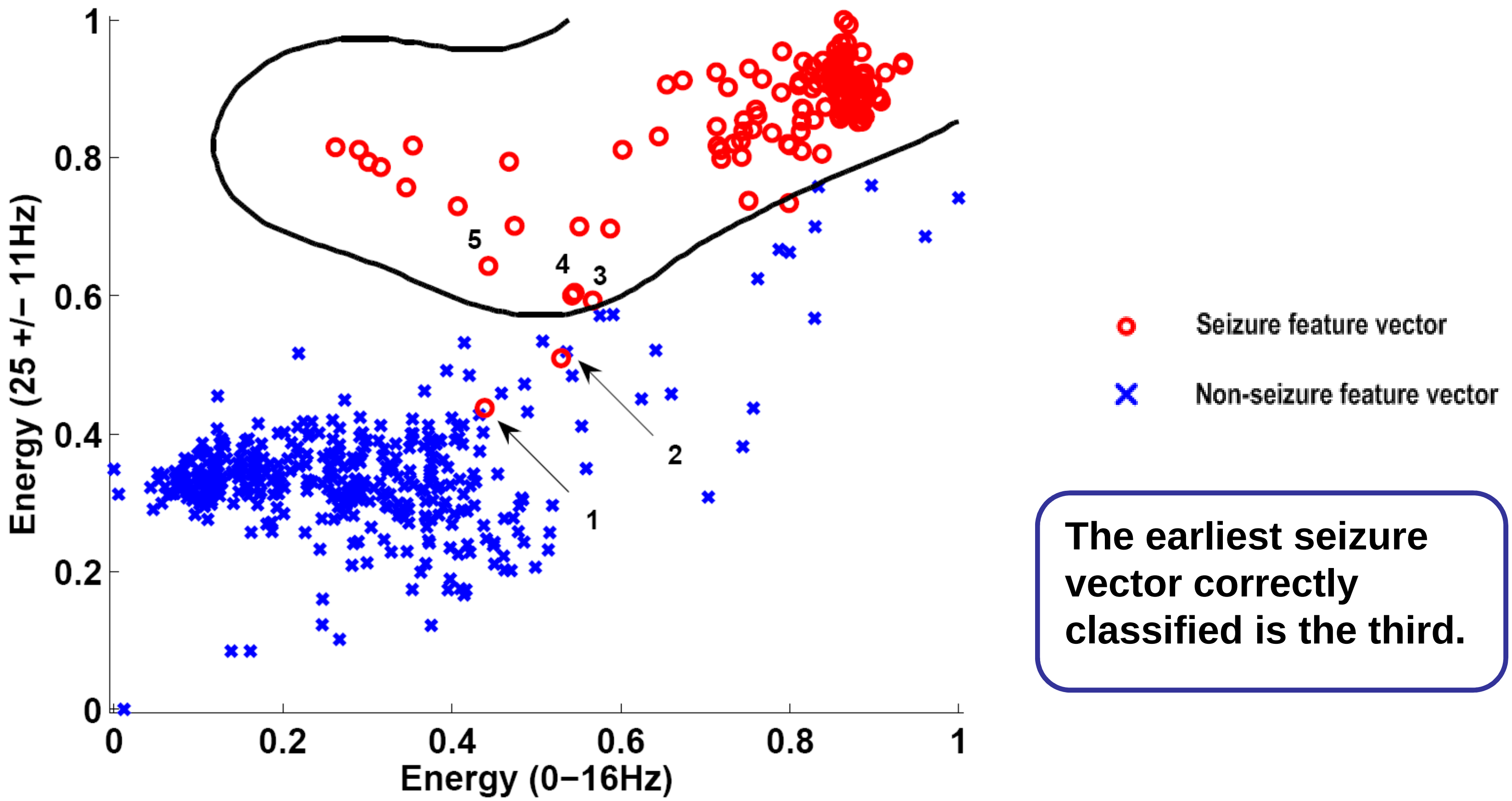
Feature Vector Design

- Features characterizing an EEG signal
  - ***Spectral*** structure
  - ***Spatial*** occupation of concerned rhythmic activity
  - Short-term ***temporal*** evolution



Feature Vector Binary Classification

- Support vector machine
- Non-linear decision boundaries using RBF kernel.



The earliest seizure vector correctly classified is the third.

Instantiating Detector Parameters

Stage	Parameter	Description
Feature extraction	$L = 2$ *sec*	EEG epoch length
	$N = 18$	Number of EEG channels
	$M = 8$	Number of filters in filterbank
	$W = 3$	Number of feature vectors that form X_T
Training	$H >= 24$ *h*	# of non-seizure training data
	$K = 3$	# of seizures used for training
	$S = 20$ *sec*	# of seizure training data
SVM classification	$\gamma = 0.1$	SVM radial basis kernel parameter
	$J = 1$	Relative cost of misclassifications
	$C = 1$	Trade-off between classification margin and error

Evaluation Methodology

- Pre-recorded data for training
  - One hour long records: seizure records, non-seizure records.
  - Number of seizures per patient: 2 to 38 (mean: 8.9)
- For each patient:
  - Create training and test data sets using both seizure and non-seizure data files
  - *leave-one-record-out* cross-validation scheme.

Evaluation Metrics

- Electrographic seizure onset detection latency $EO_{Latency}$.
  - Delay between electrographic onset and detector recognition of seizure activity.
- Sensitivity *S*.
  - Percentage of test seizures identified by a detector.
- False alarms per hour *FA.*
  - Number of times over the course of an hour, a detector declares the onset of seizure activity in absence of an actual seizure.

Evaluation Metric Measurement

N_{NS}	N_S
Number of non-seizure records	Number of seizure records

- Sensitivity & Latency
  - Training: N_{NS} non-seizure records (median N_{NS} = 33), N_S-1 seizure records (median N_S = 5).
  - Test: withheld seizure record.
  - Repeat N_S times so that each seizure record is tested.
  - Measurement:

    1. Sensitivity

$$S = \frac{1}{N_S}\sum_{m=1}^{N_S} S_m \quad \left(S_m \in \{0,1\}: \text{whether detector note the } m^{th} \text{ seizure}\right)$$

    2. latency

$$EO_{latency} = \frac{1}{K}\sum_{m=1}^{N_S} S_m \times EO_{latency,\,m} \quad \left(K: \text{total number of detected seizures}\right)$$

- Specificity
  - Training: N_S seizure records, N_{NS}-1 non-seizure records
  - Test: withheld non-seizure record.
  - Repeat N_{NS} times so that each non-seizure record is tested.
  - Measurement:

    1. False alarm FA

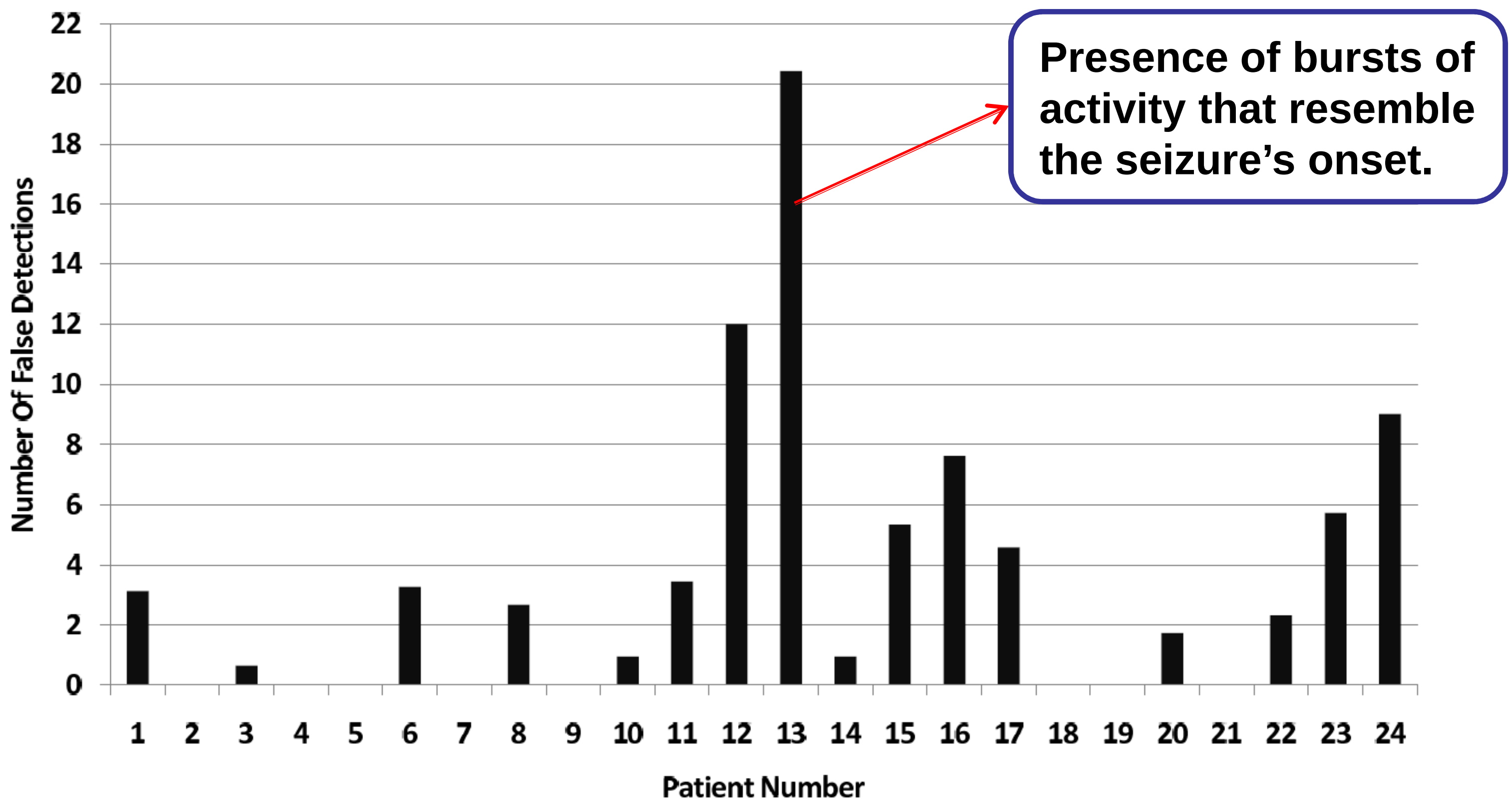
$$FA = \frac{1}{N_{NS}+N_S}\left[\sum_{n=1}^{N_{NS}} FA_{NS,\,n} + \sum_{m=1}^{N_S} FA_{S,\,m}\right]$$

Performance: Sensitivity and Latency

- *96%* of *173* test seizures detected.
- Mean latency for declaring seizure onset: *4.6* seconds.
- In specific, among the *173* seizures,
  - *50%* detected within *3* seconds.
  - *71%* detected within *5* seconds.
  - *91%* detected within *10* seconds.

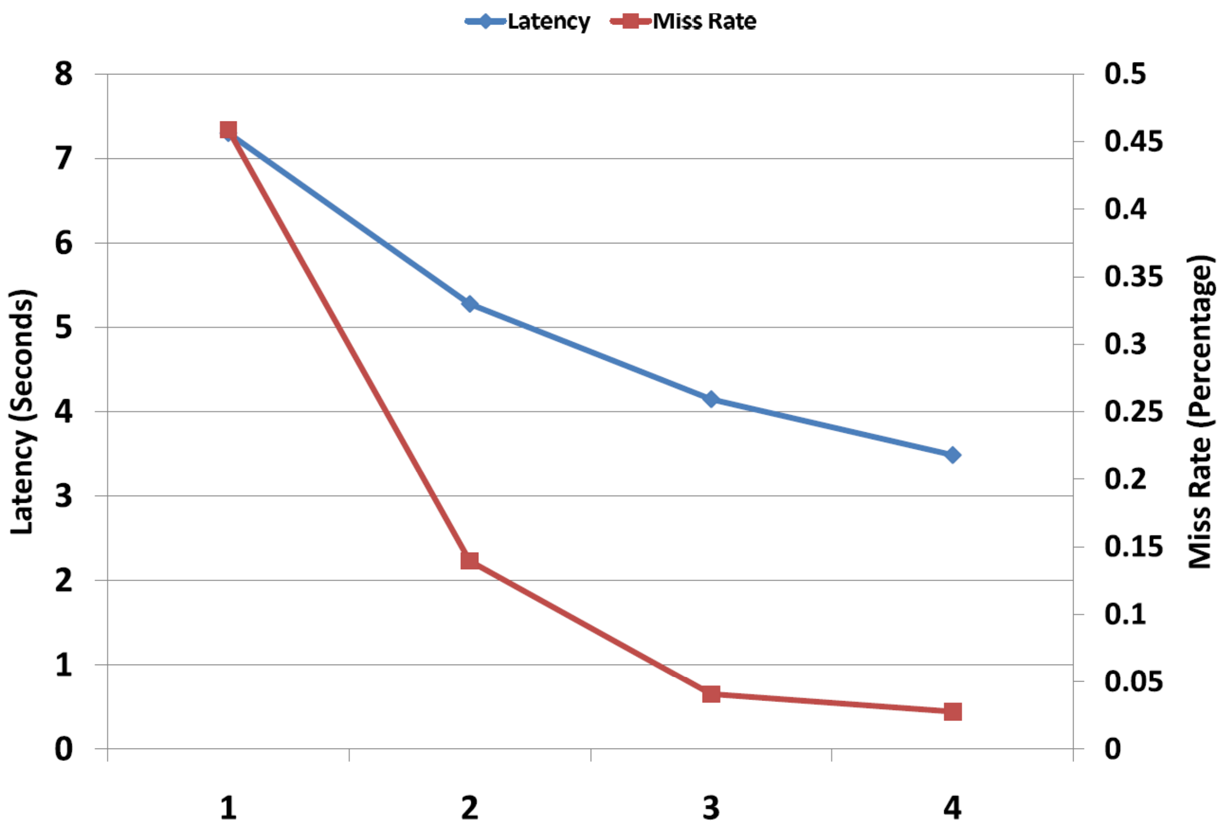
Performance: Specificity

- Patient-specific detector.
- False alarms (FA) declared per *24* hours.
- Median *FA* rate is *2 FAs/24* hour period.



Rate of Learning

- Average detection latency and miss rate decrease with an increasing number of training seizures.
- Statistics from 5 randomly selected patients.



single training seizure ➔ > 7s latency, miss 45% of test seizures;

3 training seizures ➔ 4s latency, < 5% missing detection.

Comparison with Patient Non-specific Classifier

- Reveal algorithm (Wilson et al., 2004)
  - Offline, commercially available.
  - Uses neural network.
  - Trained on hundreds of seizure and non-seizure epochs.
  - From a large number of pediatric and adult patients.
- Evaluation on Reveal algorithm
  - 61% of seizures detected.
  - 33 false detections per 24 hour period reported.

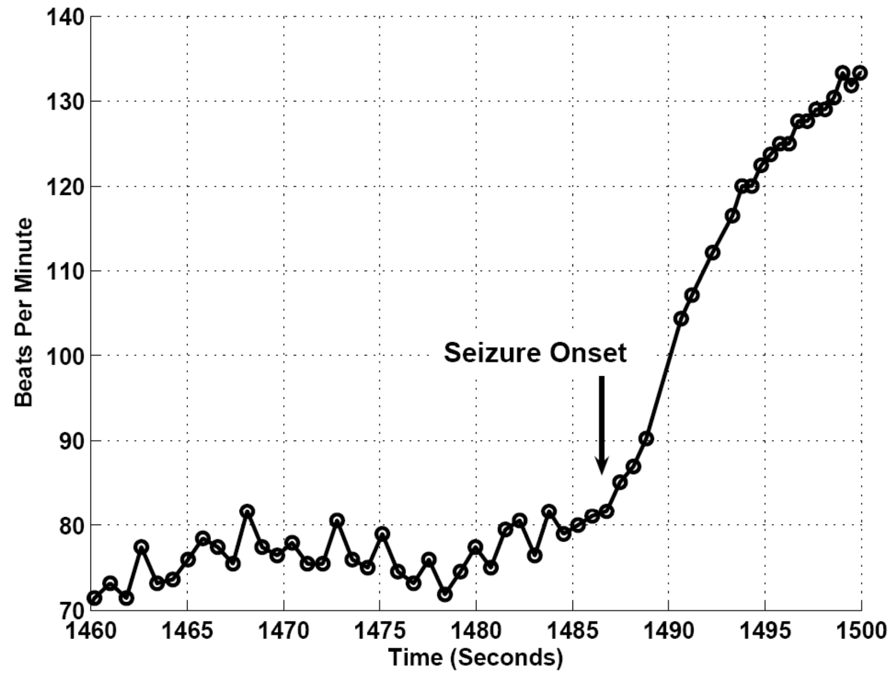
EEG-ECG based Seizure Detection

- Include **electrocardiogram (ECG)** information
  - feature augmentation by 2 dimension:

    mean heart rate,

    heart rate change information.
  - 10 seizures and 66 hours of synchronized EEG-ECG from Patient 24.

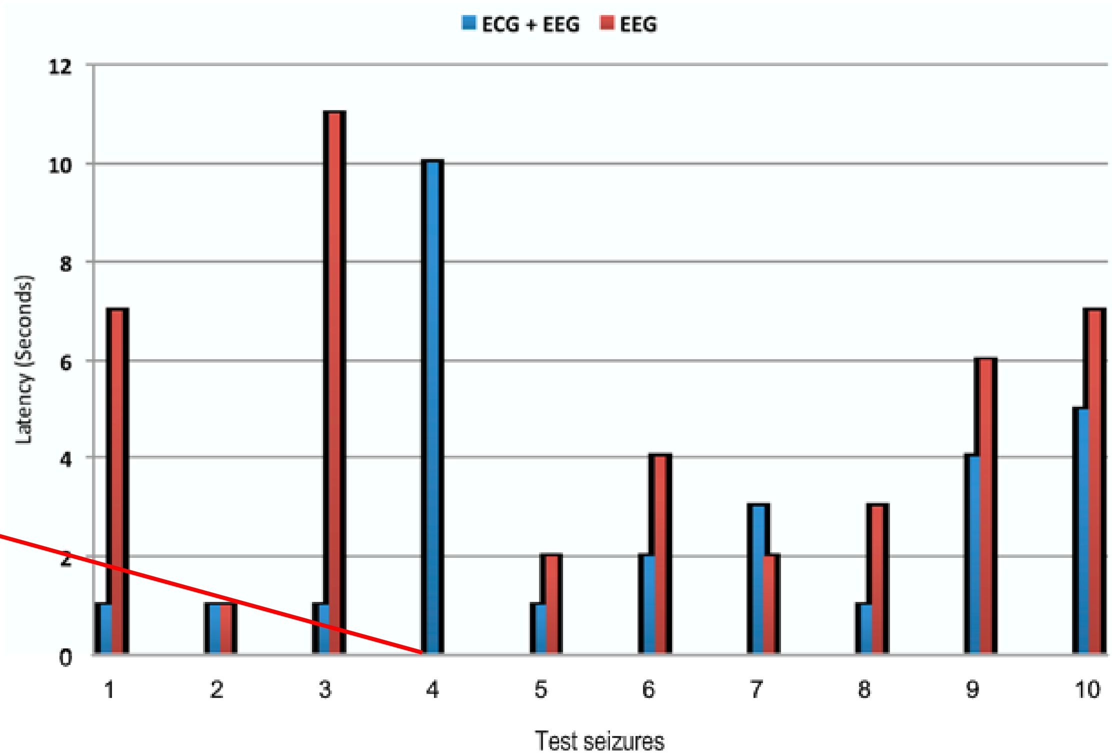
A seizure with an onset lacking rhythmic activity, but accompanies a heart-rate acceleration.



Latency Improvement

- Performance reinforcement
- Mean latency: 4.2 → 2.7 seconds
- False alarms: 9 → 5 per 24 hour period.
- Sensitivity: 100%.

The 4th seizure *cannot* be detected by the EEG-only detector.



Conclusions

- Patient-specific epileptic seizure onset detection
  - Through analysis of scalp EEG, a non-invasive measure of brain's electrical activity.
  - Formulating problem into appropriate machine learning framework.
  - Identifying features critical to discriminating seizures.
- Advantages
  - High performance.
  - Suitable for clinical use.

Thank you very much!

Q & A