Comparison of Feature Extraction Methods for Spike Detection with Artificial Neural Networks: A Focal Epilepsy Case Study

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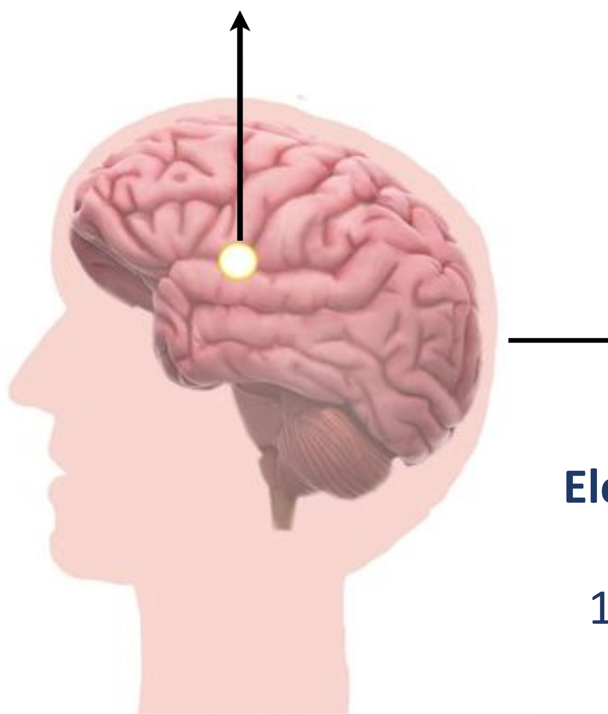
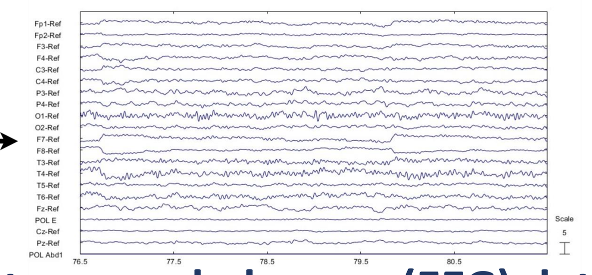
MOTIVATION &METHODS

Refractory Focal Epilepsy



Interictal epileptiform discharges must be accurately marked to localize the epileptogenic zone for surgery and tDCS treatment [1]



Electroencephalogram (EEG) data (22x1 hour)
19 electrodes , 200 Hz sampling frequency

① Problem

The standard Spike marking performed by epileptologists is **time-consuming** and **subjective**[1]

② Preprocessing:

- 0.5-75 Hz bandpass [3]
- 50 Hz notch filter
- 12-channel bipolar longitudinal montage
- Epoched into 1 second [4]

③ Labeling Data

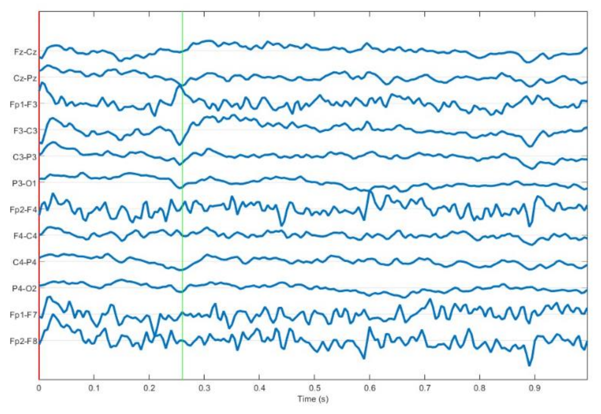
EEG data marked by three Epileptologists: a large inter-rater variability [1],[5]

3.a. ORmarking Data
label an as spike(1) if marked by **at least one epileptologist**.

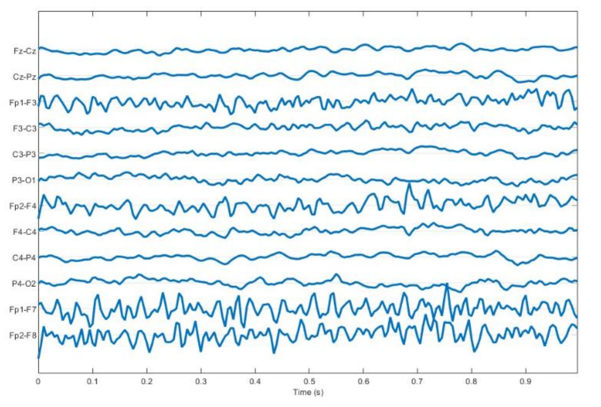
3.b. ANDmarking Data
label as spike(1) if marked **by all three epileptologists**.

④ Balancing Data

Random Undersampling [6]



Spike-Data: a 1-second epoch that contains a spike (**1**)

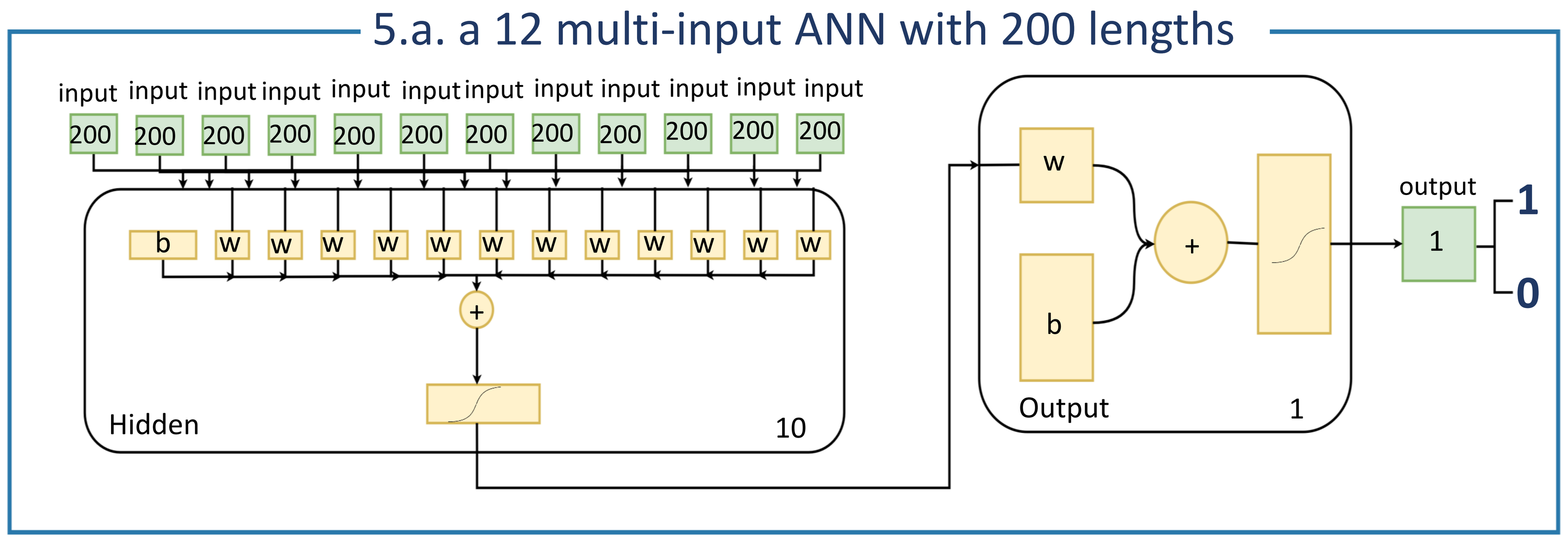


Non-Spike-Data: : a 1-second epoch that does not contain a spike (**0**)

Segmented EEG data	ORmarking Data	ANDmarking Data
Number of Spike-Data	10656	1162
Number of Non-Spike-Data	69198	78692

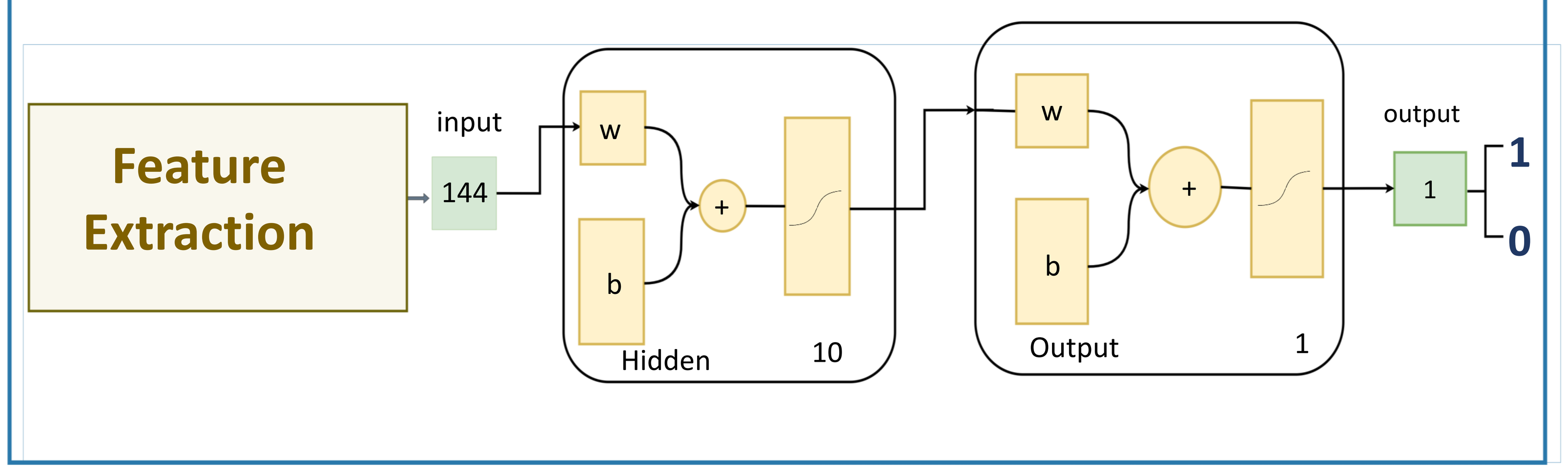
12x200

5.a. a 12 multi-input ANN with 200 lengths



all processes were performed using MATLAB R2021b

5.b. an ANN with feature lengths



Features

Statistical Features [7]
Mean, Standard Deviation, Skewness, Kurtosis

Chaotic Features [8], [9]
Higuchi FD, Katz FD, Lyapunov Exponent

Frequency Features [10]
Welch's Power Spectral Density(PSD) estimate power of the EEG sub-bands

⑤ Classification

using Artificial Neural Networks(ANN) [5],[11]

5.a. The original data was given as input to the 12 multi-input ANN

5.b. The 12-channel data is represented by extracted features and given as input to an ANN

RESULTS

- The Statistical Features(Mean amplitude value, Amplitude standard deviation , Amplitude skewness Amplitude kurtosis), Higuchi Fractal Dimention(HFD), Katz Fractal Dimention(KFD), Lyapunov Exponent(LE), The power of the EEG sub-bands (P_alfa, P_beta, P_gamma, P_theta,P_delta) is extracted with the PSD and used as a feature.
- The EEG is represented with new features and classified with ANN and 10-fold cross-validation. The performance of the classifier is determined by accuracy, sensitivity, specificity, precision, f score, Cohen's Kappa Score and geometric mean score(gmean) [12].

Tables show performance Metrics Results for ORmarking Data and ANDmarking data

FEATURE EXTRACTION	ORmarking Data						
	accuracy	sensitivity	specificity	precision	f score	Cohen's Kappa	gmean
-	0.7208	0.7398	0.7024	0.7024	0.7229	0.7207	0.7208
P_gamma+ P_beta	0.6373	0.6754	0.5991	0.6277	0.6507	0.6372	0.6361
P_alfa, P_beta, P_gamma, P_theta,P_delta	0.7358	0.6544	0.8167	0.7800	0.7117	0.7357	0.7311
HFD	0.7271	0.7164	0.7369	0.7155	0.7160	0.7269	0.7266
LE	0.7536	0.7630	0.7447	0.7409	0.7518	0.7535	0.7538
Statistical Features	0.8001	0.7796	0.8199	0.8073	0.7932	0.8000	0.7995
KFD+ LE+Statistical Features+P_gamma+ P_beta	0.8756	0.9185	0.8346	0.8418	0.8785	0.8756	0.8755
KFD	*0.8799*	*0.9493*	*0.8129*	*0.830*	*0.8858*	*0.8798*	*0.8785*
KFD+ LE+Statistical Features	0.8813	0.9203	0.8413	0.8560	0.8870	0.8812	0.8799
KFD + Statistical Features	*0.8822*	*0.9198*	*0.8450*	*0.8545*	*0.8860*	*0.8822*	*0.8816*

FEATURE EXTRACTION	ANDmarking Data						
	accuracy	sensitivity	specificity	precision	f score	Cohen's Kappa	gmean
-	0.7181	0.7273	0.7094	0.7018	0.7143	0.7172	0.7183
LE	0.8943	0.8807	0.9068	0.8972	0.8889	0.8939	0.8937
HFD	0.9071	0.9083	0.9060	0.9060	0.9041	0.9067	0.9071
P_alfa, P_beta, P_gamma, P_theta,P_delta	0.9251	0.9189	0.9310	0.9273	0.9231	0.9248	0.9250
Statistical Features	0.9292	0.9252	0.9328	0.9252	0.9252	0.9289	0.9290
P_gamma+ P_beta	0.9381	0.9626	0.9160	0.9115	0.9364	0.9378	0.9390
KFD	*0.9690*	*0.9558*	*0.9823*	*0.9818*	*0.9686*	*0.9689*	*0.9689*
KFD+ HFD	0.9735	0.9825	0.9643	0.9655	0.9739	0.9733	0.9733
KFD+ Statistical Features	0.9823	0.9825	0.9821	0.9825	0.9825	0.9822	0.9823
KFD+ LE+Statistical Features +P_gamma+ P_beta	*0.9823*	*0.9815*	*0.9831*	*0.9815*	*0.9815*	*0.9822*	*0.9823*

DISCUSSION

- **Well-trained ANN can even outperform the sensitivity and specificity of expert markers.**
- ANN classification improved by feature extraction methods.
- Katz FD best represented the spikes for both ANDmarking and Ormarking data.
- Limitations: Only one person's data was classified. Its general use is restricted.

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