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EEG Spikes Detection, Sorting, and Localization

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Abstract**—**This study introduces a new method for detecting, sorting, and localizing spikes from multiunit EEG recordings. The method combines the wavelet transform, which localizes distinctive spike features, with Super-Paramagnetic Clustering (SPC) algorithm, which allows automatic classification of the data without assumptions such as low variance or Gaussian distributions. Moreover, the method is capable of setting amplitude thresholds for spike detection. The method makes use of several real EEG data sets, and accordingly the spikes are detected, clustered and their times were detected.

Keywords**—**EEG time localizations, EEG spike detection, super-paramagnetic algorithm, wavelet transform.

I. INTRODUCTION

THE detection of neural spike activity is a technical challenge that is a pre-required for studying many types of brain functions. Most neurons in the brain communicate by firing action potentials. These brief voltage spikes can be recorded with a microelectrode or surface electrode which can often pick up the signals of many neurons in a local region. In many cases, good single-unit activity can be obtained with a single electrode and a simple hardware threshold detector. Often, however, just measuring the activity of a single neuron is a challenge due to a high amount of background noise and because neurons in a local area often have action potentials of similar shape and size. Furthermore, simple approaches such as threshold detection can bias the experiment toward neurons that generate large action potentials. In many cases, the experimental yield can be greatly improved by the use of software spike-sorting algorithms [1].

Other methods to detect and sort the spikes are achieved using software spike detection and sorting. Software spike sorting can reduce these errors detection. With modern computers and software this is easy to implementation. If the raw waveform data can be transferred to the computer for software analysis, many of the algorithms described can be implemented with simple programs using software package such as MATLAB [1].

II. OUTLINE OF THE METHOD

The spikes detection and sorting of EEG data in our procedure consist of four principal stages, which can be summarized as:

a) Normalizing the collected data.
b) Detecting the spikes automatically via amplitude thresholding.
c) Calculating the wavelet transform for each of the spikes and the optimal coefficients for separating the spike classes are automatically selected.
d) The selected wavelet coefficients then serve as the input to the super-paramagnetic (SPC) algorithm, and clustering is performed after automatic selection of the temperature corresponding to the super paramagnetic phase.

The flow chart in Fig. 1 summarizes these steps of the proposed procedure.

III. EEG PRE-PROCESSING

The spikes occur during the activity of brain cells have interval, for most cells, of no less than 10ms (20ms to 50ms) [2], [3] .Therefore, to get at least 10 samples for each spike the sampling rate should be at least 2 kHz to avoid spike misalignments, then, sampling rate of 12.5 KHz is used. The signal should be normalized before any analysis occurs using the signal spike detection. The normalization should be performed using band pass filtering the signal (30–3000) Hz, four poles Elliptic filter, and the signal amplitude must be carefully adjusted.

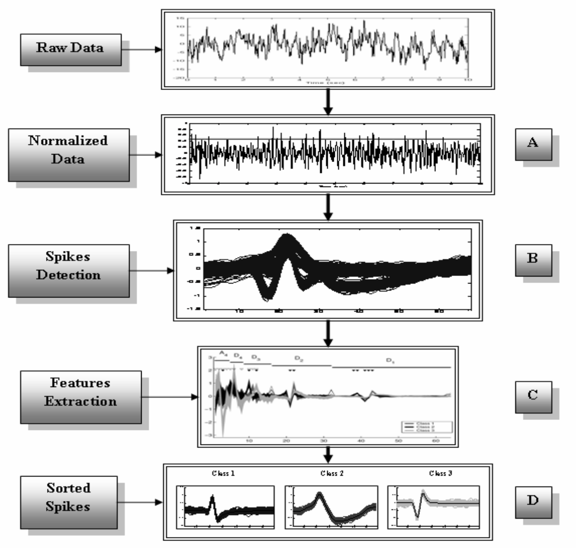

Fig. 1 Overview of the automatic clustering procedure, (A) the normalized data after filtering and setting its amplitude, (B) spikes are detected by setting an amplitude threshold, (C) a set of wavelet coefficients representing the relevant features of the spikes is selected, and (D) the SPC algorithm is used to cluster the spikes automatically

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IV. EEG Spikes Detection

Spike detection should be performed by amplitude thresholding after normalizing the data. The threshold (*Thr*) is automatically set to [2],

$$Thr = 4\sigma, \tag{1}$$

$$\sigma_n = median\left\{\frac{|x|}{0.6745}\right\}, \tag{2}$$

where **x** is the band pass-filtered signal and σ_n is an estimate of the standard deviation of the background noise [3]. Note that taking the standard deviation of the signal (including the spikes) could lead to very high threshold values, especially in cases with high firing rates and large spike amplitudes. In contrast, by using the estimation based on the median, the interference of the spikes is diminished (under the reasonable assumption that spikes amount to a small fraction of all samples). For each detected spike, 64 samples or points (i.e., ~5 ms) were saved for further analysis. All spikes were aligned to their maximum at sample number 20 [3].

V. Wavelet Coefficients of Each Spike

After spikes are detected, their wavelet transform are calculated. Four-level multi-resolution decomposition using 'Daubechies4' wavelet is implemented. Daubechies4 wavelet is chosen due to their compact support and orthogonality, which allows the discriminative features of the spikes to be expressed with a few wavelet coefficients and without a priori assumptions of the spike shapes [4]-[6]. After that, the 64 points should be tested by KS-test [7] to reduce the dimension of the inputs to the clustering algorithm. The use of wavelet coefficients for spike sorting has been proposed recently by R. Quiroga, et al (2004) [3].

VI. EEG Spikes Sorting using SPC Algorithm

This algorithm has been proposed by Blatt et al., 1996 [8]. It is based on simulated interactions between each data point and its K-nearest neighbors, i.e. the clustering index is the correlation between each set of neighboring points selected by KS-test instead of inter-point index. The SPC algorithm is executed for a wide range of temperatures spanning the ferromagnetic, super-paramagnetic, and paramagnetic phases. In order to localize the super-paramagnetic phase automatically, the temperature is varied from 0 to 20 in increments of 0.01 to look for the highest temperature at which a cluster containing more than 60 points appeared if at the next temperature increment a cluster of 60 points were detected then previous recorded temperature will be adopted. On other hand, if the next cluster has more 60 points then the increased temperature will be considered and so on. If no cluster with a minimum of 60 points was found, the minimum temperature value will be maintained.

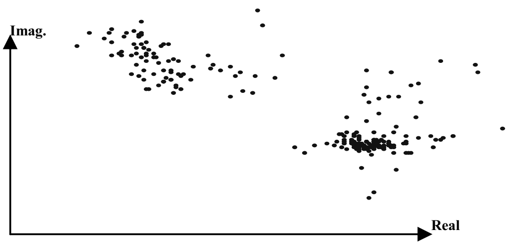
VII. Practical Results

The procedure tested using 4 examples, 2 for normal persons and 2 for epileptic persons. All data are recorded for 10 seconds. Table I shows the threshold magnitude for each example calculated in this procedure.

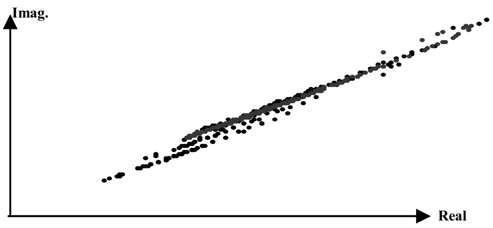
TABLE I
The Threshild Values of the Four Examples

Examples No:		*Threshold magnitude*
1	Normal I	0.4485
2	Normal II	0.4147
3	Abnormal I	0.2472
4	Abnormal II	0.2449

Fig. 2 shows the projections of the wavelet coefficients selected by the KS criterion for examples (1) and (4).



(a)



(b)

Fig. 2 The projection of the wavelet coefficients of the spikes, (a) for example (1), (b) for example (4)

Fig. 3 shows the cluster sizes as a function of the temperature for data set of example (1). At a temperature T = 2, the transition to the super-paramagnetic phase occurs. When the temperature increased the size of the cluster appears is diminished.

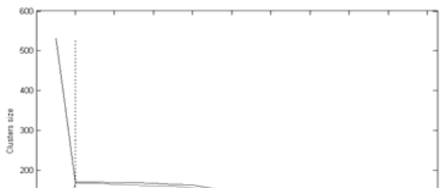


Fig. 3 The super-paramagnetic phase

Table II shows the spikes time and their class of the spikes during half second (from 2 to 2.5 sec of the recorded data for examples 1 and 4).

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TABLE II
THE SPIKES TIMES AND THEIR CLASSES

Example(1)		*Example(4)*	
Spike's times (sec)	***Class No:***	***Spike's times (sec)***	***Class No:***
2.0237	1	2.0031	0
2.0507	1	2.0174	1
2.0776	1	2.0328	0
2.1044	1	2.047	1
2.1311	1	2.0629	0
2.1579	1	2.077	0
2.1848	1	2.093	0
2.2115	1	2.1069	0
2.2381	1	2.1227	0
2.2647	1	2.1369	0
2.2916	1	2.1527	0
2.3186	1	2.1668	0
2.3452	1	2.1826	0
2.3714	1	2.1966	0
2.3984	1	2.2125	0
2.4251	1	2.2266	0
2.4521	1	2.2424	0
2.479	1	2.2566	0
		2.2723	2
		2.2864	0
		2.3022	0
		2.3163	0
		2.3319	2
		2.3461	1
		2.3617	0
		2.3761	1
		2.3923	0
		2.4065	1
		2.4228	0
		2.4368	1
		2.453	2
		2.467	1
		2.4832	2
		2.4973	0

Fig. 4 shows the traces of the segment of data (~0.5 sec) for example (1) and (4).

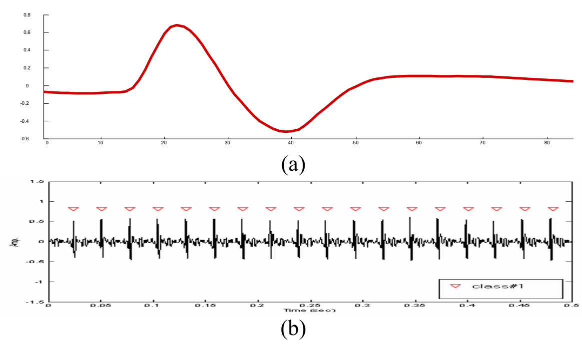

Fig. 4 Time localization of the spikes for example (1): (a) plot of the spikes, (b) time localization

Finally, Fig. 5 (a, b, and c) illustrate the traces of the spikes in class 0, 1, and 2 while Fig. 5.d illustrates the time localization of the spikes.

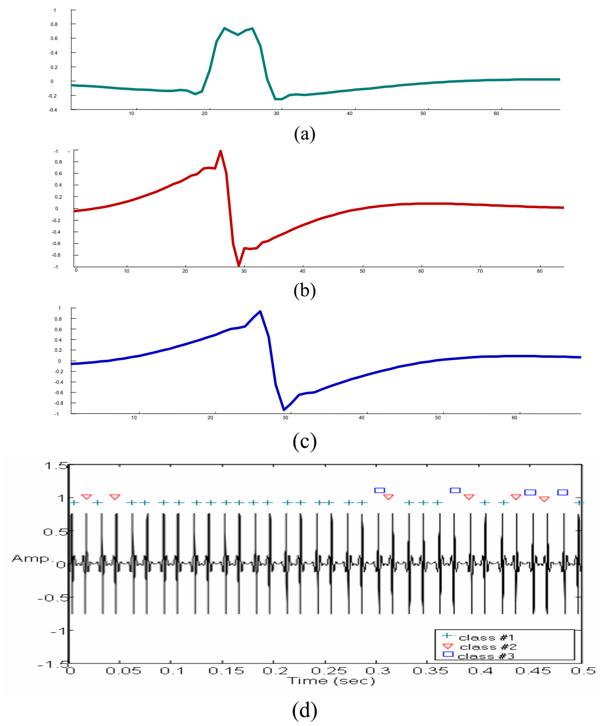

Fig. 5 Time localization of the spikes for example (4): (a) plot of the spikes' mean of class#0, (b) plot of the spikes' mean of class#1, (c) plot of the spikes mean of class#2, (d) times localization of the spikes

VIII. CONCLUSION

The procedure of spikes detection, sorting, and localization is fully unsupervised and fast. This is because of its dependence on the features of extraction from the spikes using wavelet coefficients. Thus, the procedure becomes particularly interesting for the classification of spikes for a large number of channels recorded simultaneously. Spike detection is achieved using an amplitude threshold on the high-pass filtered data. The threshold value is calculated automatically using the median of the absolute value of the normalized signal. This will gives the threshold setting only to the spikes amplitude; the resultant threshold will diminishes its dependence on the firing rate and the peak-to- peak amplitude of the spikes. The wavelet transform makes as a feature extractor tool that localized shape differences of different spikes. The information about the shape of the spikes is distributed in several wavelet coefficients. Our approach differs from R. Quiroga, et al in many aspects; first, using different digital filters and cutoff frequencies (Elliptic filter with cutoff frequencies 30-3000 Hz). Second, the method used Daubechies wavelet instead of Haar wavelet to get better localizations of the shapes differences. Finally, finding the time of each spike is important feature in the detection the spikes, which is not estimated in their approach.

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