An Empirical Mode Decomposition Based Method for Action Potential Detection in Neural Raw Data

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***Abstract*—**Information in the nervous system is coded as firing patterns of electrical signals called action potential or spike so an essential step in analysis of neural mechanism is detection of action potentials embedded in the neural data. There are several methods proposed in the literature for such a purpose. In this paper a novel method based on empirical mode decomposition (EMD) has been developed. EMD is a decomposition method that extracts oscillations with different frequency range in a waveform. The method is adaptive and no a-priori knowledge about data or parameter adjusting is needed in it. The results for simulated data indicate that proposed method is comparable with wavelet based methods for spike detection. For neural signals with signal-to-noise ratio near 3 proposed methods is capable to detect more than 95% of action potentials accurately.

***Keywords*—**EMD, neural data processing, spike detection, wavelet decomposition.

I. Introduction

INFORMATION in the nervous system is coded as firing patterns of action potentials, so action potential detection from neural data is essential in the interpretation of neural mechanisms. Neural data composed of spikes and background noise which the later is a combination of unwanted signals due to fluctuations of energy carriers like ions or electrons and action potentials produced by neurons in far field. Because background noise consist of action potentials so spectral analysis methods based on Fourier transform aren't efficient in neural data analysis [1].

So far several methods have been developed for detecting spikes embedded in neural data. The simplest and most convenient method is spike detection based on simple thresholding. In the case of low signal to noise ratios (SNRs) the efficiency of such method is significantly poor. Also recognition of overlapped spikes is impossible in simple thresholding method [2]. Methods based on neural network have been utilized for spike detection [3] but neural networks need a-priori information about signal and noise characteristics for training purposes which aren't always available in neural data processing, especially in low SNR cases. Another technique for spike detection is template matching which detects spikes based on the similarity between neural signal and a predefined template. The result of such method outperforms than simple thresholding but its performance highly depends on the template selection and predefined threshold for similarity measurements [4]. Transforms like wavelet are other choices [2]-[5] to map neural data to transform space and search the presence of action potentials in that space. However in wavelet domain select a suitable wavelet is always a question and must be survived. For example comparison between discrete wavelet transforms (DWT) and stationary wavelet transform (SWT) indicates that SWT outperforms than DWT in spike detection [5]. In multiresolution wavelet domain the method based on multiplication of wavelet coefficients in some successive detail levels has been proposed in [1] which relies on the band limited properties of action potential. This method is sensitive to a threshold for decision. For solving spike detection, method based on high order statistics has been proposed in [6]. Based on this assumption, the background noise is Gaussian in nature [7], statistics with order higher than two can be used to separate Gaussian noise and spikes.

In this paper an adaptive method based on EMD has been developed for action potential detection in an automated manner. The method is adaptive and needs no a-priori information about neural data. We have shown it is comparable with wavelet based methods.

II. Materials and Method

A. Recording from Cockroach

A single tungsten microelectrode with impedance about 1MΩ, inserted in the cockroach body, has been employed for recording real neural data. During recording, cockroach has been restrained firmly on a plastic disk. Cockroach only enables to move its antenna freely. This causes fewer artifacts to be induced on a recorded signal. The plastic disk is located on a faraday cage for electromagnetic interference reduction. The signal is applied to an electrophysiological amplifier set through a preamplifier, consist of TLC2272AC (Texas instruments, USA). Analog neural data has been amplified with a gain equal to 2000 and filtered in the range of 0.3-3 kHz. A data acquisition card is utilized to digitize analog amplified and filtered data. The sampling frequency is adjusted to 30ksample/s for satisfying nyquist theorem. Using NI-Labview8.6 (National instruments, USA) software has been prepared for controlling data acquisition includes saving and displaying acquired data. This software controls sampling frequency of data acquisition card. To increase data sample

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and reduce alignment error, recorded data has been upsampled with a factor equal 4.

B. EMD Algorithm

EMD is a method for decomposing a time series to some intrinsic mode functions (IMF). The assumption behind this method is that all time series are composed of IMFs as oscillatory modes [8]. It is a suitable tool for analyzing nonstationary signals. The most important characteristic features of IMFs are the equal numbers of extrema and zero crossing (expect one difference) and zero value for its upper and lower envelope average. EMD algorithm is briefly implemented as follows:

1) Identify all extrema (maxima and minima) of the neural signal, *x(t)*.
2) Generate the upper and lower envelopes via cubic spline interpolation among all the maxima and minima points, respectively.
3) Average two envelopes to compute a local mean series *m(t)*.
4) Subtract *m(t)* from the neural data to obtain an IMF candidate *h(t)=x(t)-m(t)*.
5) Check the properties of *h(t):*

- If *h* is not an IMF (i.e. it does not satisfy the characteristic features of IMF explained above), replace *x(t)* With *h(t)* and repeat the procedure from step 1.
- If *h* is an IMF, consider the residue *r(t)=x(t)- h(t)* as new *x(t)* and go to the next step. In this step *h(t)* is considered as the first IMF. The procedure for extracting each IMF is entitled as sifting. Usually it is time consuming to wait for achieving characteristic features of IMF, so if the difference between two successive sifting is lower than a predefined value, sifting is terminated and the result is considered as an IMF.

6) For extracting other IMFs, the procedure from step 1 to step 5 is repeated on residue. Extracting procedure is terminated if residue is a constant or a function with one extrema. After extracting all IMFs, *x(t)*-time series signal-can be expressed as (1):

$$x(t) = \sum_{j=1}^{n} C_j + r_n \tag{1}$$

where r_n is the final residue, C_j is *j-th* IMF and *n* is the number of extracted IMFs. IMFs which are extracted firstly entitled as low order IMF and those extracted later are called higher order IMF. Lower order IMFs have higher frequency content and contain higher energy of signal. The effect of high frequency noise is dominant in lower order IMFs. It has been shown that EMD acts like a dyadic filter and the ratio of data sample over extrema in successive IMFs will decrease by the factor of two [9], [10].

C. Proposed Method

As EMD acts like a dyadic filter bank [9] so each IMF contains a limited frequency content of the main signal in a manner that by increasing the order of IMFs, the frequency content of IMF will decrease by a factor of two, so the oscillation related to different component of neural signal like high frequency noise, spikes and non-spike events which are different in frequency content are included in different order of IMFs. For example each spike event has its dominant energy in some successive IMFs due to this fact that spikes are band-limited waveforms [1] but the high frequency noise which has different frequency content will be represented by different set of IMFs. This means that each spike can be represented by the summation of some successive IMFs that each of them contains a portion of spike's frequency or energy content. In time domain it is equivalent to say that the oscillations which make spike waveform appear in some successive limited number of IMFs. Another interesting feature of EMD is that it is localized in time so in temporal location of spike events, oscillations in related IMFs are expected. Therefore the idea is that by multiplication of some successive IMFs, it is possible to reinforce the spike events and debilitate other parts of signal like background noise.

For extraction of spikes from neural data, the following algorithm is proposed:

1. Select four IMFs starting the IMF with maximum amplitude. Here it has been supposed that the SNR of neural data is higher than zero so the amplitude of action potential is equal or greater than background noise.
2. Multiply the selected IMFs. The spikes are band limited signals so their related oscillations are embedded in some successive IMFs. This multiplication will attenuate the effect of background non-spike events. Multiplication of absolute value of IMFs enables our algorithm to be robust against different form of spike morphologies.
3. Multiplication result has several peaks with dominant amplitude around spike's temporal location so a decision threshold selection for eliminating small peaks is needed. For removing the necessity for such threshold, a simple soft thresholding scheme is used. If the nature of the background noise is considered to be Gaussian [7], it is possible to estimate a threshold level above the background noise from first IMF [11]. The estimation of standard deviation of background noise based on first IMF is considered by (2):

$$\delta_1 = \frac{\mathrm{median}\{|\mathrm{IMF}_1(\mathrm{t}) - \mathrm{median}\{\mathrm{IMF}_1(\mathrm{t})\}|\}}{0.6745} \tag{2}$$

estimating the standard deviation of background noise based on (2) is less sensitive to outliers than the traditional calculation of the sample standard deviation [5]. By calculating δ_1, other IMF noise levels can be derived [11] from δ_1 based on (3).

$$\delta_k = \frac{\delta_1}{\sqrt{2}^{k-1}} \tag{3}$$

where *k* is the order of IMF. By calculating the noise level for each IMF, it is possible to determine a threshold above background noise [12] for each IMF by (4) to obtain the smoothed version of each IMF.

$$\tau_k = \delta_k \sqrt{2\log(m)} \tag{4}$$

In (4) m is the IMF length and k is the order of IMF. Values of signal lower than τ contain background noise. Between selected IMFs, the IMF with maximum value is chosen and soft thresholding with correspond threshold value of τ_k is applied to it. Soft thresholding causes all non-spike events in final multiplication to be removed so the necessity of the threshold on multiplication result is discarded. Any peaks above zero in final multiplication represent spike in real data. If multiple peaks be detected in duration lesser than spike's length, peak with maximum value is selected. After determining peak location in the multiplication result, a window with a length of approximately 1ms automatically is located on neural data in determined peak location. Due to the special morphology of spikes 0.1ms of window is located before the peak location and 0.9ms of window is located after peak location. Portion of neural data located in 1ms window is selected as action potential. 1ms is the approximate duration of action potential of spikes in the nervous system [7].

D. Construct Simulated Data

The main difficulty in evaluation of the spike detection algorithms is the absence of a ground truth data which the temporal location of spikes and their exact number can be specified clearly. To eliminate such problem a noisy spike synthesizer is used which can generate signals for which the ground truth is known [13]. Synthesized data used in this paper contains two target neurons. Some correlated and uncorrelated spike trains based on spike's templates of target neurons are produced which have Poisson distribution and added to desired templates. Finally white Gaussian additive noise is added to simulate a real data. In this data, exact time and template of spikes are clearly specified.

III. Results

In this section the ability of proposed EMD based algorithm in spike detection for different neural data set (real and simulated data) and for different SNRs is examined. The SNR is defined as the ratio of powers for targeted signal waveforms and noise as (5):

$$SNR = \left(\frac{action\ potential\ waveforms(p-p)}{pure\ noise\ segment(p-p)}\right)^2 \quad (5)$$

The action potential waveforms in the simulated data are specified so the average action potential peak-to-peak is applied in (5).

A. Results for Real Data

For investigating the ability of proposed algorithm, small portion of a real neural waveform from our recorded data which contains one dominant spike is selected. In Fig. 1 the neural data is displayed in upper trace and the location of dominant spike's peak is specified by a thick dot. The four selected IMFs are depicted in the middle traces in Fig. 1. In the vicinity of spike's peak, there are some peaks in multiplication result. Dominant peak is selected and its location is displayed in Fig. 1 (lower trace). Note that a threshold based on (4) has been exerted on the first IMF to eliminate the necessity for any manual threshold selection on the multiplication result. Also all detected spikes from our whole recorded data are depicted in Fig. 2 (a). This real data is inspected visually by an expert person and the presence of two templates of action potential is determined. The projection of all detected spikes on first and second principal components obtained by principal component analysis (PCA) is displayed in Fig. 2 (b). The existence of two clusters in PCA analysis emphasizes the existence of two spike templates.

B. Comparison with other Techniques Using Simulated Data

To compare the proposed EMD based algorithm, simple thresholding and a method proposed in [1] based on wavelet transform have been used. In traditional thresholding a threshold is adjusted manually. To quantify the performance of algorithm (6) is used [6].

$$Hit\ Rate = \frac{N_{cds}}{N_{trs}} * 100$$
$$Precision = \frac{N_{cds}}{N_{ds}} * 100 \quad (6)$$

where N_{cds} is the number of correct detected spikes, N_{ds} is the number of detected spikes and N_{trs} is the number of true spikes. Hit rate and precision near 100% are ideal. Fig. 3 shows the results for implementation of proposed EMD algorithm, wavelet based algorithm and simple thresholding for spike detection in simulated data. In wavelet based method 'db3' wavelet has been used as mother wavelet which gave the best result and 5 decomposition levels have been used. The results for hit rate and precision for simulated data in different SNR have been shown in Fig. 3.

IV. Discussion and Conclusion

In this paper a new algorithm based on empirical mode decomposition (EMD) for neural spike detection has been proposed. Due to the band limited properties of action potentials, their frequency content is concentrated in a limited number of adjacent frequency windows. The main idea behind the proposed method is that as EMD acts like a dyadic filter bank [9], [10] it can extract the oscillations embedded in a signal (IMF extraction) in the frequency windows. It means that each oscillation contains a portion of signal's frequency content. It is expected that oscillations that construct an action potential are included in some successive IMFs in the related temporal location of action potential.

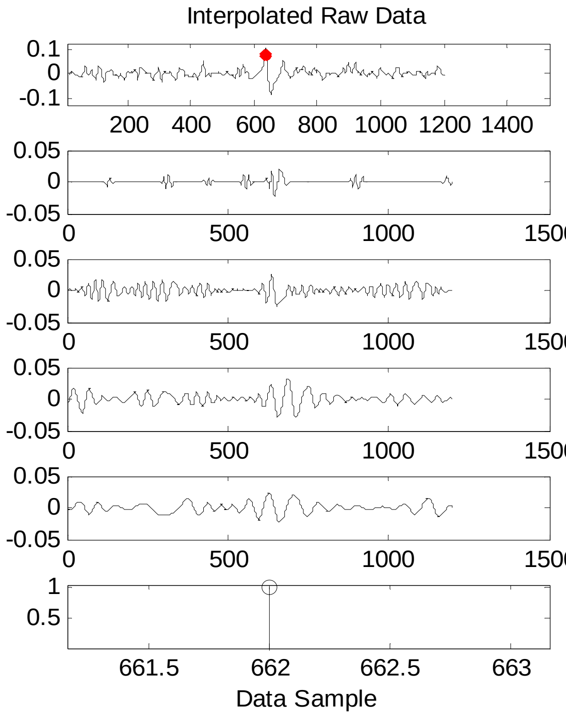

Fig. 1 A portion of recorded waveform from cockroach (upper window) Selected 4 first IMFs (middle) Result of multiplication of selected IMFs (lower). A threshold has been applied to first IMF as discussed in methods

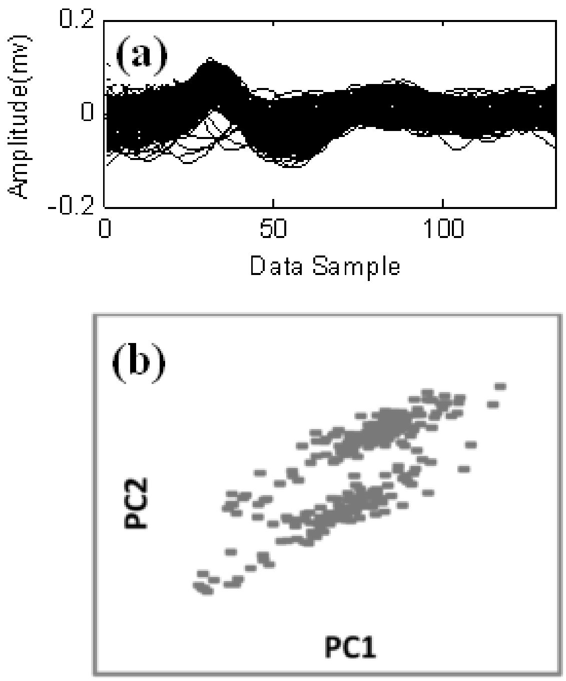

Fig. 2 Detected spikes using EMD based method from raw data (a) The projection of detected spikes on PCA space (b)

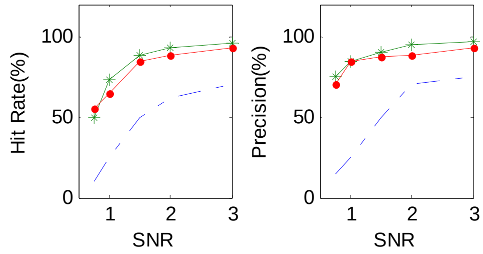

Fig. 3 Hit Rate & Precision for simulated data: simple thresholding (dashed line), EMD based method (star mark) and Wavelet based method (dot mark)

This means that spike event exhibits its effect in IMFs as the same temporal location as event occurs. Consequently spike event energy is demonstrated by localized oscillations in some limited numbers of successive IMFs while other non-spike events are expressed by different set of IMFs. By multiplying some successive IMFs, a peak will be appeared in the neighboring location of action potential's peak. Fig. 1 shows the Implementation of proposed EMD method on a short real neural data from our recorded data which contains one dominant spike. The lower trace in Fig. 1 shows that proposed method can determine action potential temporal location accurately. Note that multiplication of some successive IMFs reinforces spike events as band limited events and attenuates non-spike events. The result in Fig. 2 shows all detected spikes by EMD algorithm from whole real neural data. An expert person visually inspected the presence of two templates in our recorded data which is proved by PCA analysis which depicted in Fig. 2 (b) and shows the presence of two clusters as the existence of two templates in our data. The results depicted in Fig. 3 indicate that for simulated data as a ground truth data with SNR greater than 1.5, proposed algorithm can detect more than 95% of spikes accurately that is slightly better than wavelet detection based method [1]. As can be seen in Fig. 3 the proposed algorithm detects action potential more superior than simple thresholding method which its performance deteriorates in low SNRs. Also the wavelet based methods for action potential detection are highly dependent on selection of mother wavelet. Varieties of wavelets have been used for this aim [1]-[5] in literature. In spite of the wavelet based methods, employing EMD helps to have an adaptive method which its result only depends on desired signal. Based on the soft thresholding that have been proposed in materials and method, our EMD based algorithm needs no predetermined threshold and all peaks above zero in multiplication of selected IMFs will be considered as a sign of action potential existence in raw data. Of course in some cases which the aim is detection of dominant spikes with high amplitude, user can adjust the threshold on multiplication of IMFs to avoid detection of spikes with lower energy.

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