Feature Extraction from EEG using Wavelets: Spike Detection Algorithm

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Abstract

This paper combines wavelet transforms with basic detection theory to develop a new unsupervised method for robustly detecting and localizing spikes in noisy neural recordings. The method does not require the construction of templates, or the supervised setting of thresholds, it is based on a Bayesian detector where the noise is modeled to be Gaussian in nature. We present simulations on actual EEG recordings under different recording conditions. We further demonstrate that falsely detected spikes corresponding to our method resemble actual spikes more than the false positives of other techniques such as amplitude threshold. Moreover, the simplicity of the method allows for nearly real-time execution.

1. Introduction

On discussions with neurologists specializing in sleep related disorders and epilepsy, we were made aware of the tediousness of diagnosing sleep related disorders and epilepsy.Diagnosis involves accurate detection and localization of the individual spikes and spike trains from EEG signals acquired from sleep tests, which are recorded for several hours.

Recorded spike trains are inevitably corrupted by noise. The source(s) for the noise are highly varied. Perhaps most importantly, the activity of distant neurons may appear as noise which is highly correlated with the useful signal. Another difficulty is that the spikes (EEG spike trains/EEG spikes are used synonymously) both are have the shapes and amplitudes that are highly variable. All of these issues make the problem of spike detection challenging.

2. Wavelet based Detection Method (WDM)

The methodology developed here is a combination of processes developed from Wavelet theory, Statistical Signal Processing and Detection theory. Stating the algorithm up font as it would make the developed process more transparent.

1. Preprocessing
2. Perform multiscale decomposition of the signal using an appropriate wavelet basis.
3. Separate the signal and noise at each scale.
4. Based on results from 1. and 2. perform Bayesian hypothesis testing at different scales to assess the presence of spikes.
5. Combine the decisions at each level.
6. Estimate the arrival times of individual spikes.

Two assumptions about the noise are used throughout this paper, the background noise is: a) Stationary; b) Gaussian. Although these assumptions are not crucial for implementation, they insure the mathematical rigour of the algorithm. When they are violated, the performance of the algorithm may be different from the expected results. The stationarity of external and neural noise (both constitute the noise present) cannot be assumed in general. If the stationarity ever becomes a concern, the data can be broken into shorter segments that can be analyzed separately. Also, wavelet bases of compact support are well suited for representation of nonstationary signals. The Gaussian nature is also justified in the paper.

3. The Detection Process

We apply the continuous wavelet transform, with a restricted set of scales (similar to dyadic scales) and translations, we obtain a multiscale representation of the signal in terms of its wavelet coefficients. Selection of the wavelet functions and choice of its scales are important factors.

The continuous wavelet transform defined operates on a continuous set of scales and translations. Hence, the basis functions are not orthogonal and the representation of the signal by its wavelet coefficients is redundant. One can choose dyadic scales and translations from a discrete set , so that the corresponding wavelets form an orthonormal basis . Here, we will restrict the set of scales and translations in a different manner. Practically, all EEG signals are sampled in discrete time. Thus, we choose the set of basis function translations to be finite, where this set is determined by the sampling rate of the signal *Fs* and its duration *T(s)* , i.e., where $B=\{0,1\ldots k\ldots N-1\}$ where $N=TFs + 1$ is the number of samples of the discrete signal (time series). Therefore, in the continuous wavelet transform the set of translations coincides with the discrete time vector.Similarly, biophysical considerations of the duration of the spikes can be used to restrict the relevant scales of the wavelet basis functions. Despite their variability in shape and amplitude, the vast majority of spikes are highly localized in time, with a characteristic duration[1] .

The problem of detecting spikes in a noisy signal can be seen as a binary hypothesis testing problem, where under the null hypothesis *H0* the signal is not present, and under the alternative *H1* both signal and noise are present. For purposes of unsupervised signal detection, we must separate these coefficients by estimating the noise level in each coefficient from the sampled data. To obtain these estimates, we borrow ideas from Donoho and Johnstone [2] who studied the problem of nonlinear estimation of signals from noisy data under a sparse representation. We formulate the detection problem as a sequential binary hypothesis test at each scale . Hence the methodology involves

a) Combining the decisions at individual scales.

b) Estimating the spike arrival times.

a)Combining the decisions at individual scales: Because they are highly localized in time, the samples corresponding to spikes occupy contiguous subsets of the discrete time vector *B.* This property of transients is often referred to as a *temporal contiguity*. Temporal contiguity translates into the contiguity of the coefficients in the wavelet domain [3] i.e., the wavelet coefficients corresponding to the same spikes tend to be neighbors in both time and scale. Since we use the continuous wavelet transform with the basis functions of compact support roughly matched to the scale of spikes, the temporal contiguity in the wavelet domain is inherently preserved. The scale contiguity follows from a broad frequency spread of a time-limited signal, namely if a scale is thought of as an approximation of the frequency, a time-limited spike will be spread across many scales. The presence of noise, however, may obscure the picture at the scales that are not relevant. The scale contiguity can also be viewed in the present context as a cross-correlation (redundancy) of the wavelet coefficients (decisions) at different scales.

b) Estimation of Spike Arrival Times: We now turn to the issue of estimating the spike arrival times from the wavelet coefficients supporting the acceptance of *H1* . In a noise-free environment, the wavelet basis function that provides the maximum correlation with the spike to be detected, corresponds to a wavelet coefficient of maximum magnitude. The time associated with the translation index of the basis function with maximal coefficient can be taken as a good approximation to the occurrence time of the underlying transient. Because we choose the set of translations *B* with time resolution down to the sampling period, this approximation is essentially as good as the sampling period. Tracking of modulus maxima of the wavelet coefficients across scales has been proposed for the detection of signal singularities [4]. In a noisy environment, there is naturally a jitter associated with the location of this maximal coefficient. This jitter can be reduced by averaging the locations of the maxima across different scales. This is the idea behind our approach.

4. Performance

The performance of the Wavelet Detection Methodology was compared against other methods including the power detection method (PDM), the single amplitude thresholding method (SATM) ,and the double amplitude thresholding method (DATM). Since the spike polarity might change during the course of an experiment, the SATM may be inadequate (e.g., a positive threshold is bound to miss the majority of negative going spikes). For truly unsupervised applications, we introduce the DATM, where either positive or negative threshold crossings indicate the presence of spikes. The performance of these methods was assessed using the receiver operating characteristic (ROC). The ROC curve compares the probability of (correct) detection versus the probability of false alarm . The ROC curve for each combination of Firing Rate and SNR was obtained by averaging the performance over 100 trials. The Appendix in the paper details our averaging methodology.
A recent detection method using a nonlinear energy operator (NEO) [5] reports a successful detection under nearly 0 dB, where, the authors defined SNR as a peak-to-peak amplitude of the smallest spike template divided by the noise standard deviation. However, without specifying the amplitudes and relative frequencies of other templates, followed by averaging, as discussed in this paper , SNR can be manipulated to any desired value. In other words, such a definition of SNR does not provide an objective measure of the noisiness of the data, as larger amplitude spike templates will have larger SNRs. We tested the performance of the NEO detector under a properly defined SNR and realistic neural noise model and found its performance at best comparable, and often falling short.
Despite the large number of existing algorithms for detection of extracellular potentials in noisy observations, robust,fully automated detection algorithms have been scarce.We presented a novel detection scheme and compared its performance to many commonly used spike detection methods. The detection is cast in the standard hypothesis testing framework and since the signals to be detected are unknown, the detector performance is representation dependent. Spike transients have historically been detected by a simple amplitude thresholding, where the threshold level is chosen with respect to the (estimated) standard deviation of the noise. We have shown how this can yield erroneous results, especially if no signal is present. Spike waveforms are not just samples whose average amplitude exceeds some baseline level. They also have a characteristic shape and duration. Using wavelets we are taking advantage of this additional information that is ignored by amplitude or power thresholding methods. The algorithm is completed by combining detection, which arises from sequential hypothesis testing, and parameter estimation, where the occurrence times of individual spike transients are the parameters of interest. Additional postprocessing of estimated arrival times may be necessary. This may result in inability to resolve the transients that are within a millisecond of each other. However, the same problem is inherent to any other detection method, and there have been some attempts to provide solutions [6], [7], although in the context of spike classification rather than spike detection. The findings are: a) the Wavelet Detection Method provides a significant improvement under extremely low SNRs and low Firing Rates(FR), a situation commonly found in actual experiments; s) for a single choice of detection parameter, the Wavelet

Detection Method offers more consistent performance under different SNR-FR scenarios; 3) therefore, it is possible to come up with a single parameter that performs well for a wide range of SNRs and FRs, which is very useful for unsupervised on-line applications; 4) the jitter in estimated spike arrival times and its variance are comparable for WDM and commonly used amplitude thresholding; 5) falsely detected spikes of WDM are likely to be caused by the activity of distant neurons and can be utilized as neural data, as opposed to false positives of amplitude thresholding methods, which typically represent random fluctuations (noise).We conclude this paper by noting that the Wavelet Detection Method is also suitable for off-line analysis, where by trading off the cost of omission and false alarm, the user can modify the sensitivity of the method, similar to changing the threshold level in amplitude thresholding method.

5. Selected References

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