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Experimental Study on Neuronal Spike Sorting Methods

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Abstract

When recording extracellular neural activity, it is often necessary to distinguish action potentials arising from distinct cells near the electrode tip, a process commonly referred to as spike sorting or action potential sorting. Sorting of neuronal spikes plays a very important role in coding of neural information, which is a prerequisite for studying the brain function. In this paper, five major action potential classification methods including Template Matching, Wavelet Transform, Principal Component Analysis, Back-Propagation (BP) Neural Network, Two-stage Radius Basis Function Network are studied. Under the conditions of different levels of background noise, the performances of these methods are tested. This work may be helpful to choose classification method.

1. Introduction

Most neurons in the brain transmit information by firing action potentials [1-2]. These time-voltage action potentials can be recorded with a microelectrode, which can often acquire the signals of many neurons in a brain region [3]. The neurophysiologist wish to make the functions of each neuron understood, therefore, discriminating these signals from the others is the first step, and also critical step [4-5]. Spike sorting is the process of detecting action potentials from extracellular signals and assigning them to individual neurons. Early development aims at assisting researchers in studying brain functions off-line. Recent applications include brain-computer interfaces and neural prostheses for people suffering from nervous system traumas. These efforts all build on the capability of accurate automatic decoding of neuronal signals, which imposes a statistical computing task replete with open problems [2]

In many cases, this work can be accomplished with a simple threshold method. Often, however, just measuring the voltage of neurons to do classifying is a challenge due to a high amount of background noise, and also because neurons in a local area often have action potentials of similar shape and size. Therefore, it is necessary to do further research in spike-classifying algorithms.

2. Methodology

2.1. Second-order headings

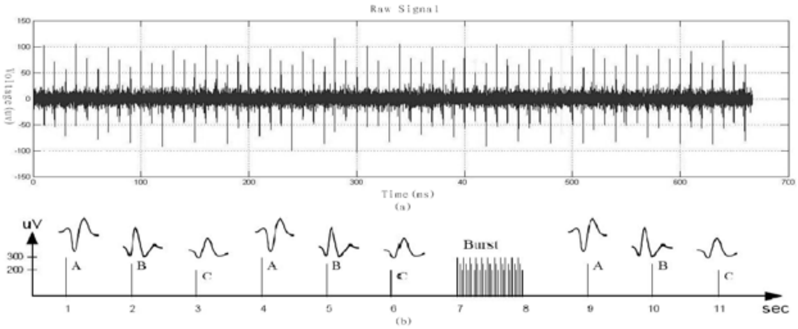

Figure1. a)Waveforms of the Raw Signal from the Simulator; b). Specifications of the Action Potential from the Simulator

The signals used in the paper are from the Neural Signal Simulator. The raw signal is in Fig.1.a. The Neural Signal Simulator produces three different shaped action potentials on each of 128 output channels(Fig.1.b). The circuit simulates the output of a Cyberkinetics 100 ┌ electrode array. Each virtual electrode is simulated as detecting microvolt signals from three separate neurons located at different distances from the recording site. The amplitudes of the three action potentials as well as the kinetics of their responses differ in a manner consistent with real world signals.

The simulation on each output channel consists of a sequence of three individual action potentials that ‘fire’ one after the other at a 1s intervals. This firing sequence repeats nine times. Then, every 10 seconds, a one-second burst of activity is simulated. The burst consists of the same train of three individual action potentials, but they are repeated with an inter action potential interval of 10 milliseconds (Fig.1.b). To achieve the results of the method of detection and classification in a range of different degrees of the noise in the environment, we construct the noised data by adding white Gaussian noise to the raw signal in the measurement of dB that is the scalar of SNR which specifies the signal-to-noise ratio(Fig.2). The background noise is added using the function Awgn() in Matlab. This function adds white Gaussian noise to the vector signal. The scalar SNR specifies the signal-to-noise ratio in decibels. This syntax assumes that the power of the vector signal is 0 dB.

2.2. Template Matching

In order to recognize an object, we compare it to action potentials of the similar objects that we have stored in memory. By comparing with variety of stored candidates, we can identify the object by the one that it most closely resembles [6-11].

2.3. Wavelet Transform

There is a generally observation that the differences between action potentials primarily come to transient differences in high frequency features (like sharp edges and steep leading or trailing slopes) and/or in low frequency features (like the duration of the re-polarization phase). Thus in this paper, we adopt the Wavelet based Spike Classifier (WSC) method, where it use the quantification of energy found in specific frequency bands at specific time locations during each action potential profile to classify different waveforms[12-14].

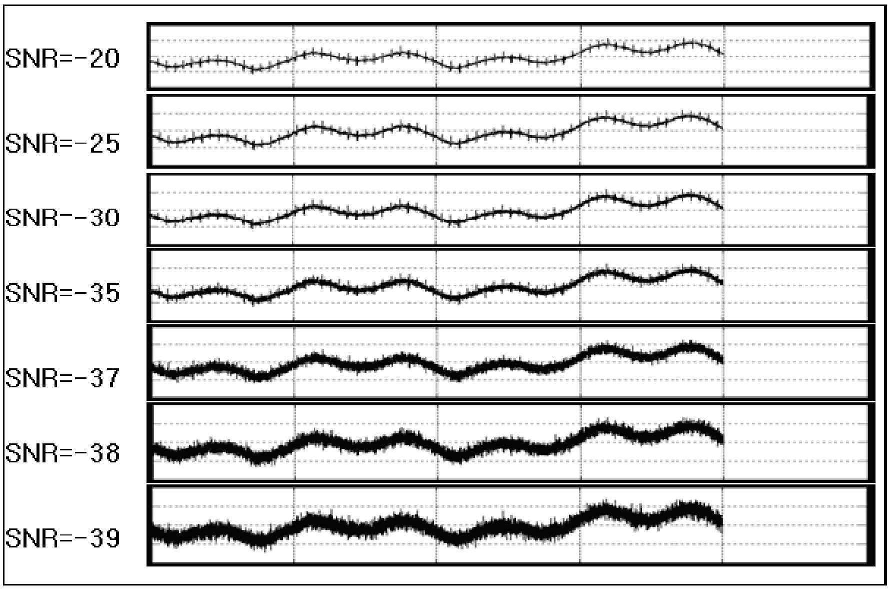

Figure2. Signals Added White Gaussian Noise in Different SNR

2.4. Principal Component Analysis

Principal Component Analysis (PCA) has been widely used in feature extraction from complex and high dimensional data in many fields, such as signal processing, image processing and pattern recognition. It reduces the dimensionality of the feature space by creating new features that are linear combinations of the original features [15-18].

2.5. K-means Cluster

K┌ means clustering is a simple unsupervised learning algorithm. It can be divided into 4 steps. a).Initialize the cluster center. b).Update the cluster that every sample belongs to. c).Update the centers of every cluster. d).If the termination condition is reached, terminate the iteration, else go to step b)[19-20].

2.6. Back-Propagation (BP) Neural Network

BP neural networks uses Back┌ Propagation algorithm to learn the weights. The back┌ propagation algorithm is as follows: a). Forward┌ propagate the input from input layer to output layer; b). Back┌ propagate the error from output layer to input layer. Update the weights matrix between input layer and hidden layer, and the weights matrix between hidden layer and output layer; c).If the termination condition is met, the algorithm ends, else returns to a)[21-23].

2.7. Two-stage Radius Basis Function Network

There are three layers in typical RBF networks, input layer, hidden layer and output layer. Input layer is made up of conception units, which receive input from outside. Hidden layer applies a nonlinear transformation between input layer and hidden layer. Output layer calculates the linear weighted sum of hidden units' output and provides a result after a linear transformation [24-26].

3. Experiment Design

Original spike signals for sorting are from Neural Signal Simulator as mentioned in part A. signal source. As said before, there are three types of spikes produced from the simulator, with high SNR. Hence we can detect every spike exactly and construct a group of action potentials for classifying. For those original action potentials (fig), we can easily utilize these five methods to cluster them into 3 types, as the standard to evaluate the correct rate of other classification methods later. After that, white noise is added to original clean spikes to create different SNR signals (0, -10, -15, --20, -25, -30, -35) to check the effectiveness of these methods on spike sorting.

4. Results

Applying the five methods to classify simulated action potentials in different SNR, we get the correct ratio of these five methods in Table 1 and Fig.3.

Table 1. Correct ratio of these five methods in different SNR

SNR(-dB)	Template Matching	PCA	RBF	BP	Wavelet Transform
5	1	1	1	1	1
21	1.0000	0.9767	0.9900	0.9810	1.0000
22	1.0000	0.9687	0.9830	0.9470	0.9987
23	1.0000	0.9673	0.9820	0.9660	0.9973
24	1.0000	0.9653	0.9720	0.9410	0.9947
25	0.9987	0.9573	0.9640	0.9050	0.9873
26	1.0000	0.9493	0.9630	0.9080	0.9861
27	1.0000	0.9453	0.9610	0.8790	0.9773
28	0.9973	0.9313	0.9610	0.8520	0.9653
29	0.9853	0.9407	0.9230	0.8500	0.9487
30	0.9873	0.9247	0.9050	0.8090	0.9367
31	0.9747	0.9107	0.8670	0.7930	0.9127
32	0.9700	0.8907	0.8320	0.7540	0.8933
33	0.9500	0.8707	0.8050	0.7150	0.8680
34	0.9207	0.8513	0.7760	0.6180	0.8313
35	0.8913	0.8253	0.7390	0.6210	0.7993

36	0.8713	0.7927	0.7030	0.6070	0.7627
37	0.8420	0.7433	0.7120	0.5940	0.7387
38	0.8473	0.6833	0.6870	0.5540	0.6887
39	0.7707	0.7007	0.6540	0.5490	0.6527
40	0.7293	0.6413	0.6260	0.5020	0.6080
41	0.6606	0.6013	0.5850	0.5090	0.5933

From the Table 1 and Fig 3, we find that all methods can accurately classify the three action potentials. However, as the lower of the SNR, these performances are much different. The correct ratio of template matching method has no significant change until the SNR is -30dB, and it is the best in the five methods, and BP is the worst. When the SNR decreases to a certain degree, less than -30dB, all these methods cannot competently classify the three action potentials accurately. And the waveforms of action potentials in the noised signal have become chaos on the whole.

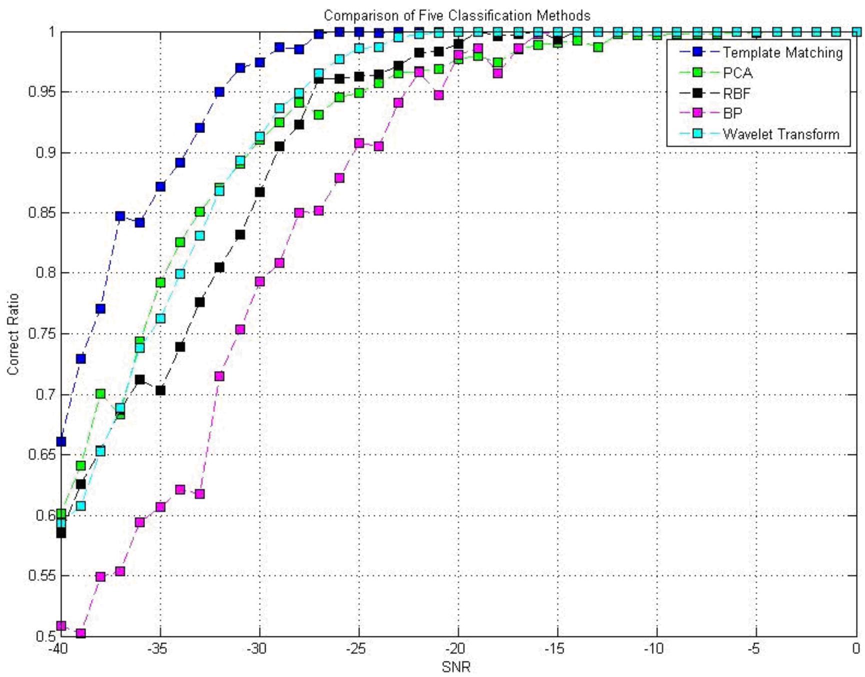

Fig.3. Correct ratio comparison of these methods in different SNR

5. Discussion

Firstly, we make comparisons between RBF network and BP network methods used in this article. The result shows that RBF network performed better than BP network in action potentials classification. The two-stage RBF network has short training time, but RBF centers selected by K-means method have great influence on its performance. Because the amount of data is small in our experiment, the RBF centers account for a relatively larger proportion of the total data. Thus, the centers can easily reflect the distribution of the input samples, which helps to improve the correct ratio of discrimination. In this paper, the initial centers are selected by 'farthest points' method instead of being randomly selected. So the RBF centers can reflect the distribution of the samples better, which makes the correct ratio of discrimination with RBF networks relatively stable.

Secondly, we make comparisons between DWT and PCA methods used in this article. Since the amplitude and peak are key features in discriminating action potentials, while the shape of waveform is not easy to quantify. Therefore, using S.D. of DWT coefficients as feature extracting vectors, takes well advantage of wavelet properties. Compared with widely used PCA method, we got higher correct rate in sorting and have more specified physiological explanation. More importantly, DWT served as both filtering and classification functions in the processing, because it will not result in shape distortion of the original signal.

From all the methods, template-matching methods yielded the best classification accuracy compared to spike-shape features, principal components, and other methods. Moreover, it can classify the action potentials online.

6. Conclusion

Sorting of neuronal spikes plays a very important role in coding of neural information, which is a prerequisite for studying the brain function. There are still many problems that limit the robustness of many of the current methods, such as non-stationary background noise, electrode drift and proper spike alignment. Possibly the most restrictive assumption of most methods is the assumption of stationary spike shapes. And currently there are no methods that can accurately classify highly overlapping groups of bursting action potentials. Decomposing overlapping action potentials with non-stationary shapes is largely an unsolved problem. Techniques that use multiple electrodes and incorporate both action potential shape and action potentials timing information are promising in surmounting this problem.

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