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Automatic spike sorting by unsupervised clustering with diffusion maps and silhouettes

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ABSTRACT

Knowledge of the activity of single neurons is crucial for understanding neural functions. Therefore the process of attributing every single spike to a particular neuron, called spike sorting, is particularly important in electrophysiological data analysis. This task however is greatly complicated because of numerous factors. Bursts or fast changes in ion channel activation or deactivation can cause a large variability of spike waveforms. Another considerable source of uncertainties results from noise caused by firing of nearby neurons. Movement of electrodes and external electrical noise from the environment also hamper the spike sorting. This paper introduces an integrated approach of diffusion maps (DM), silhouette statistics, and k-means clustering methods for spike sorting. DM is employed to extract spike features that are highly capable of discriminating different spike shapes. The combination of k-means and silhouette statistics provides an automatic unsupervised clustering, which takes features extracted by DM as inputs. Experimental results demonstrate the noticeable superiority of the features extracted by DM compared to those selected by wavelet transformation (WT). Accordingly, the proposed integrated method significantly dominates the popular existing combination of WT and superparamagnetic clustering regarding spike sorting accuracy.

1. Introduction

Processing and analysing electrophysiological data face a huge challenge in biomedical engineering. Neuroscientists commonly use extracellular recording technique to understand the activities of brain. The technique in principle is to insert an electrode into the extracellular tissue of the brain to record activities of individual neurons (Fig. 1). These electrodes record the activities (referred to as ‘spikes’) from multiple neurons surrounding the electrodes rather than single neurons as desired by most of medical applications.

Spike sorting refers to the process of grouping or clustering spikes to different neurons relying on the similarity of their shapes. Activities of different recognized neurons can be specified based on resulting clusters given that each neuron tends to fire spikes of a particular shape. The ultimate purpose of spike sorting is to determine which spike corresponds to which of these neurons.

There have been a number of spike sorting methods proposed so far in the literature, e.g. see [1–5]. Quiroga [6] proposed a technique that combines wavelet transformation (WT) with superparamagnetic clustering without assumptions such as low variance or Gaussian distributions. Ventura [7] in another approach utilized both waveform and tuning information obtained from the modulation of firing rates. The new spike sorter employs an expectation-maximization maximum likelihood algorithm without any additional assumptions.

A new tool for fast and robust online classification of single neuron activity based on the fuzzy *c*-mean clustering is examined in Oliynyk et al. [8]. The method is particularly useful for the analysis of large parallel recordings, which are practically impossible or inconvenient for human supervision, and thus is helpful in the decoding of neural ensembles or other clinical applications. Hill et al. [9] on the other hand recommended that four quality metrics of false-positive and false-negative errors should accompany spike sorting regardless of the algorithm used to sort. These metrics would facilitate the assessment regarding the performance of the sorter relative to the level of contamination of the data.

Alternatively, an algorithm for automatic unsupervised detection of action potentials in extracellular recordings is introduced in Shalchyan et al. [11]. A new manifestation variable for detection is defined based on the combination of denoised wavelet coefficients over selected scales. Tiganj and Mboup [12] used an iterative application of independent component analysis and a deflation

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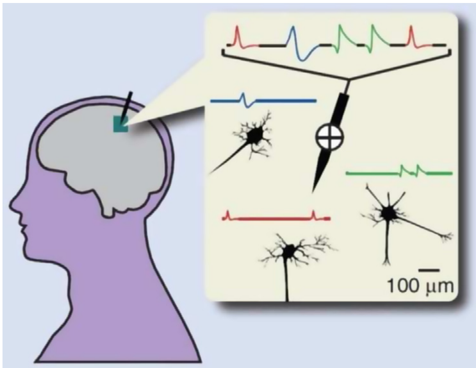

Fig. 1. A microelectrode to record the electrical signal [10].

technique in two nested loops for spike sorting with multi-channel recordings. Each loop of the algorithm improves the final sorting results and thus significantly increases the overall spike sorting performance.

More recently, Pillow et al. [13] investigated the geometry of failures of traditional spike sorting algorithms and developed a sorting model, which explicitly accounts for the superposition of spike waveforms.

Although various methods have been proposed, obtaining high accuracy in spike sorting is always a big challenge in neuroscience and biomedical engineering. Furthermore, the computational burden in spike sorting is massive. This paper presents an integrated approach that combines diffusion maps (DM), silhouette statistics, and k-means for a robust unsupervised spike sorting method. According to our best knowledge, this is the first proposal on application of the DM for spike feature extraction and the silhouette statistics for determining the number of clusters in spike sorting. The accuracy of the proposed approach is compared to the renowned benchmark spike sorting method that is a combination between the wavelet transformation (WT) and the superparamagnetic clustering suggested in [6].

The arguments are organized as follows. The next section describes details of steps of the methodology. Section 3 is devoted for experiments and results whilst discussions and concluding remarks are presented in Sections 4 and 5, respectively.

2. Methodology

The main methodology is graphically diagrammed in Fig. 2. Diffusion maps algorithm is employed for spike feature extraction. The automatic unsupervised clustering is implemented by a combination of the silhouette statistics and k-means clustering.

The first step in the methodology is spike detection that aims to identify data points that form an action potential. When spike sorting methods are applied for real data in practice where spike ground truth data are not available, the spike detection step is definitely required. However, real data often do not contain ground truth of what is right or wrong. In other words, ones do not have the exact information of how many neurons that are recorded from and which spike corresponds to which neuron. It is thus highly difficult and subjective to compare the performance of different spike sorting approaches [14].

Therefore, to evaluate and compare spike sorting methods, there are no better ways than using the synthetic data accompanied by spike ground truth. As with Quiroga et al. [6], using the ground truth data, all spikes including both detected and undetected ones are employed for evaluating feature extraction and clustering algorithms in this paper. Details of spike detection and alignment process, which are applicable to real data without ground truth, can be referred to Quiroga et al. [6]. Descriptions of comparable feature extraction and clustering methods are presented in the following sub-sections.

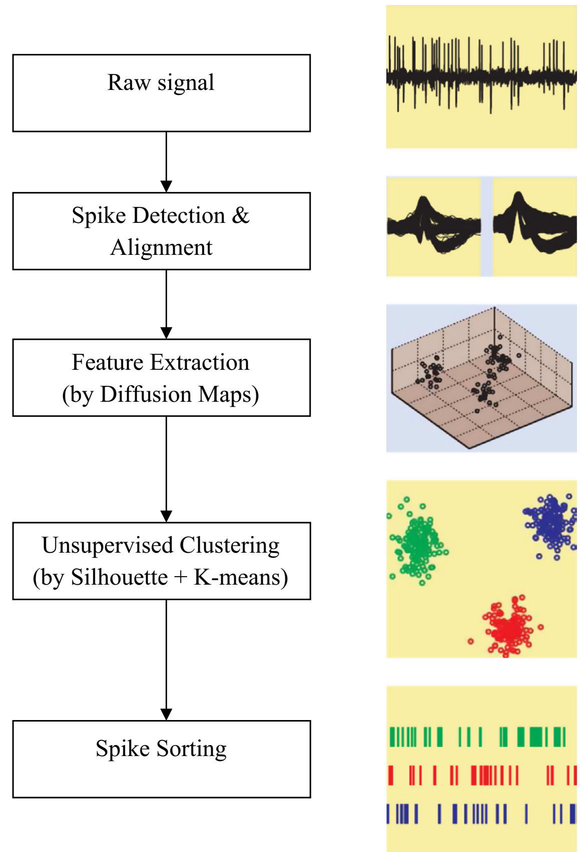

Fig. 2. Spike sorting proposed method.

2.1. *Feature extraction: Diffusion maps vs. wavelet transformation*

Feature extraction is a process in which the salient features of the spikes are derived based on spike waveshapes. The features should be able to well differentiate spikes of different neurons and preferably low-dimensional. Simple features such as peak-to-peak amplitude, maximum spike amplitude and spike width may be used [15]. These approaches however are sensitive to noise and intrinsic variations in spike shapes. Alternatively, principal component analysis (PCA) is a popular method used for feature extraction in spike sorting [16–18]. WT [19] also has emerged as a competitive feature extraction method [20–23].

2.1.1. *Wavelet transformation*

WT represents a signal in a time–frequency fashion. Once the wavelets (the mother wavelet) $\varphi(x)$ is fixed, translations and dilations of the mother wavelet can be formed $\{\varphi(x-b/a), (a,b) \in R^+ \times R\}$. It is convenient to take special values for a and b as $a = 2^{-j}$ and $b = 2^{-j}k$ where j and k are integers. One of the simplest wavelets is the Haar wavelet, which has been used in various applied mathematics applications. Haar functions can uniformly approximate any continuous function. Dilations and translations of the function φ, which is $\varphi_{jk}(x) = \text{const}.\varphi(2^j x - k)$, define an orthogonal basis in $L^2(R)$. This means that any element in $L^2(R)$ may be represented as a linear combination of these basis