Characteristic of Neural Signal Feature for Spike Sorting and Detection

Tongwei Wang*
School of Astronautics, Harbin Institute of Technology, Harbin, Heilongjiang Province, 150001, China
*Corresponding author’s e-mail: 1180610908@stu.hit.edu.cn

Abstract. Neural spike plays an important role in understanding brain activities, and in neural spike sorting, the features of signal are of great importance. This paper aims to have a review on features used to discriminate different originated spikes. The features are divided into three categories: features in the time domain, features in the transformation domain, and features of dimensional reduction. For each kind of feature, the basic principle, advantages, and disadvantages are described and discussed. Results showed that features in the time domain are suitable for on-chip or real-time spike sorting, while features in the transformation domain can be used in offline spike sorting aiming at high performance. For features of dimensional reduction, it makes a large number of features available in spike sorting. In conclusion, researchers need to determine features by balancing the minimization of calculation complexity and maximizing sorting performance according to different occasions and demands. Expectations are also made for future directions of spike feature studies. The article may guide both the physiologists who want to determine features in neural spike sorting and researchers who want to work on feature extracting algorithms further to achieve better performance in experimental challenges.

1. Introduction
The rapid depolarizing ascending branch and rapid repolarizing descending branch of an action potential recorded from neurons are collectively called neural spikes [1]. It is generated by the flow of ions through ion channels and initiated at a specialized trigger region called the initial segment, which is near the origin of the axon [2]. The neural spike is the carrier of information conveyed between the brain and the other parts of the human’s body (which can be detected by placing electrodes such as microwire and glass micropipette in vivo) [3]. It plays an important role in understanding the brain activities.

The frequency of the spike events expresses the exact information conveyed in a single neuron, and the spikes detected by electrodes are generated by several neurons located in the vicinity of the electrodes. It is important to assign spikes to the neuron that produces it to understand the exact informative communication of different neurons. And this process is called neural spike sorting.

When doing neural spike sorting, the difference of spikes needs to be discerned to determine which spikes come from the same neuron. That is to say, extracting effective features of neural spikes is necessary for this process [4]. There are different features used in neural spike engineering.

In this study, features used in neural spike sorting were described. The advantages and disadvantages were summarized and compared, which can guide researchers when doing neural spiking and choosing which feature to use.
2. Procedures of neural spike sorting

Figure 1 Procedures of neural spike sorting

The procedure of neural spike sorting is shown in Figure 1. It contains four steps: spike detection, feature extraction, clustering, and back annotation. The first step is recording spikes accurately by using devices and algorithms. Different kinds of electrodes can be used in this step, such as single wire, tetrode and microelectrode array of different specifications. The second step is using features to discriminate spikes of different origins. The third and last step is determining the number of neurons detected and assign all the spikes detected. Different kinds of clustering algorithms can be used in this step, such as the k-Means algorithm [5-7], the fuzzy c-Means algorithm [8,9], the Superparamagnetic Clustering (SPC) algorithm [10,11].

In neural spike sorting, feature extraction plays an important role. It extracts numerical parameters from the non-numerical data, the original spikes. These parameters are the only bases for spike clustering, so the discrimination these parameters yield determines the performance of the spike sorting system directly. Therefore, a feature that discerns the spikes best is supposed to increase the sorting accuracy in the whole process.

3. Features used in neural spike sorting

There are many different kinds of features used in spike sorting, which can be sorted into three categories: features in the time domain, features in the transformation domain, and features of dimensional reduction.

3.1. Features in the time domain

Features in the time domain are extracted from the temporal characteristics of a spike waveform. Among them, the amplitude (such as the peak to valley amplitude [12,13] and the positive peak amplitude [14], the duration (such as the waveform duration [13,15], the core spike duration [16] and the event duration [13]) as well as the derivative features (such as the peak, e.g., positive [14,17,18] and negative [14] of the spike first derivative (FD), the peak, e.g., positive [17-19] and negative [17,18] of the spike second derivative (SD) and the highest repolarization rate [19] of spike) were the most widely used and achieved considerable results. There are also researches which adopted the area features calculated by the integration of the waveform: Gibson [20,21] used areas under the positive and negative period as features, respectively; Jahanmiri [12] utilized the sum of absolute values of the whole curve as a feature; while Kamboh [22] and Saeed [23] chose Zero-Crossing Features (ZCF) which are the sum of values before zero points (ZC1) and after zero points (ZC2).

Features in the time domain have outstanding advantages. These features can be extracted by relatively simple calculation and need no training. This makes them time-saving and suitable for use in both on-line and off-line spike sorting. Meanwhile, the features extracted are less occupied, so they do not require much space to store data. Generally, this kind of feature was frequently used in early spike sorting and real-time spike sorting.

However, it also has limitations. Since the amplitudes sensed by the electrode change with the distance between the detected neuron and the electrode, this feature can be used to distinguish different neurons when the neurons are not equidistant with respect to the electrode [24,25]. While it yields bad performance in common situations in which the electrode is planted in a three-dimensional
space filled with equidistant neurons. Besides, since it derivates from amplitude and duration information in the time domain only, the information it gets is limited, and it is likely to contain redundant components. This would also contribute to low performance in spike sorting.

3.2. Features in transformation domain

Compared with features in the time domain, features in the transformation domain can provide more information. The properties of the detected signal can be obtained by mainly three kinds of calculations or algorithms: the Fourier Transform, the wavelet transform, and the empirical mode analysis.

3.2.1. Features based on Fourier transform

The Fourier Transform is a kind of integral transformation that transforms a signal in the time domain ($x(t)$) to its frequency spectrum ($X(j\omega)$), which can be calculated according to Eq. (1). According to the frequency spectrum, a signal could be expressed by the sum of infinitely many different sine or cosine signals with different amplitudes and phases [26]. Since different signals have different frequency spectra, spectra features can be the features of their corresponding time-domain signals. In neural spike sorting, the fast Fourier transform (FFT) is the most used algorithm to complete the Fourier transform of input signals. It transforms sampling-points $x(n)$ to the frequency domain as $X(k)$ using Eq. (2).

$$X(j\omega) = \int_{-\infty}^{\infty} x(t)e^{-j\omega t}dt \quad (1)$$

$$X(k) = \frac{1}{N} \sum_{n=0}^{N-1} x(n)e^{-j\frac{2\pi kn}{N}} \quad (2)$$

Different features can be extracted from Fourier transform. The most basic features correspond to the highest amplitude densities and their corresponding amplitude densities on the amplitude spectrum. Sometimes the phase spectrum is also used in feature extraction. Besides this, features can also be extracted from the energy spectra or the power spectra. The energy spectra and the power spectra are defined in Eq. (3) and (4). Features used in the energy spectra are the frequency and the energy in the main peaks and energy measures in various frequency bands. Features used in the power spectra are similar to features in energy spectra. Still, it should be noticed that when extracting power features from a single spike, the signal needs to be expanded to a periodogram. A method based on the Welch periodogram is reported in [27]. Meanwhile, for all these three kinds of spectra, measures such as the centroid frequency, mean square frequency, root mean square frequency, frequency variance, frequency standard deviation could also be used as features in neural spike sorting.

$$G_x(\omega) = |X(j\omega)|^2 \quad (3)$$

$$\Phi_x(\omega) = \lim_{T \to \infty} \frac{1}{2T} |X(j\omega)|^2 \quad (4)$$

For the application of features based on Fourier transform, Kaku[28] used prominence of the peak frequency of the power spectrum as features to identify spike patterns in the subthalamic nucleus of parkinsonian patients. Yang [29] proposed a new robust spike classification algorithm based on both the amplitude component and the phase component of the spikes’ frequency spectra obtained by FFT. Goerg [30] proposed a frequency domain adaptation of the Expectation-Maximization algorithm based on magnitudes in amplitude spectrum or power spectrum obtained by the discrete Fourier transform which can be used in neural spike sorting.

3.2.2. Features of wavelet transform

Compared with the Fourier transform, the spectrum was calculated by using the whole length of the signal. The wavelet transform can obtain spectrum in both time and frequency aspects. Wavelet transform is a kind of integral transformation that decomposes a specific signal into the sum of different wavelet signals [31]. It is defined by equation (5), where $\alpha$ is the scale and $\tau$ is the translation of the wavelet. Through wavelet transform, we can obtain the time-frequency spectrum of a signal. It contains information about the frequency component of the signal at different times.
Wavelet transform is a kind of time frequency domain analysis. Unlike the Fourier transform, the basis function $\psi(t)$ is not fixed. Since different wavelets have different properties, so choosing different wavelet basis functions in wavelet analysis would lead to different results, and it would seriously determine the complexity of the follow-up work [32]. Accordingly, it is important to choose a proper wavelet basis in wavelet analysis.

There are mainly two kinds of features that can be extracted from the time frequency spectrum. The most widely used one is the extremum feature from the amplitude spectrum, which extracts the maximum value of the amplitude in each scale space and combines it with its corresponding scale parameter and translation parameter to construct the eigenvector. Another feature is the feature of energy distribution. For the extraction of this feature, the energy distribution of every scale space is calculated from the energy spectrum, and the scale spaces whose energy is relatively concentrated are selected. Their total energy is extracted and aligned to be the eigenvector [33].

Features of wavelet transform have been widely used in neural spike sorting. Hassan [34] proposed an efficient spike processing method with data subdivision and unification based on Harr wavelet features. Gao [35] applies variance of column vector in wavelet coefficient matrix as features to do spike sorting with template matching. Makarov [36] proposed a novel sorting method—the Parametric Wavelet sorting with Advanced Filtering (PWAF), based on the features of discrete wavelet transform coefficients.

### 3.2.3. Features of Hilbert-Huang transform

The Hilbert-Huang transform (HHT) is a method that decomposes a specific signal into the sum of different intrinsic mode functions (IMF) and then applies the Hilbert transform to them. But being different from the FT and WT, the IMF in HHT does not have a fixed form.

---

**Figure 2** The flow chart of empirical mode analysis

The Hilbert-Huang transform contains two sections, the empirical mode decomposition (EMD) and
the Hilbert spectra analysis [37]. The flow chart of this method is shown in Figure 2. In the HHT, the average envelope of the input signal is drawn according to the difference between the original signal and all IMFs obtained. Then the intermediate signal, which is the difference between the original signal and average, is calculated and judged whether it is an IMF. If yes, then it is output to be an IMF, or the steps 1 to 3 are repeated until an IMF is obtained. The IMF is continuing to be obtained until the result meets the accuracy. After all, IMFs are obtained, the Hilbert spectra analysis is applied on all IMFs to obtain the time frequency feature of the original signal. Sometimes, only the empirical mode decomposition is applied to signal analysis.

Mainly three kinds of features can be extracted from the time domain signal according to the procedures of empirical mode analysis. First, features from each IMF, mainly include amplitude feature and frequency feature, can be extracted for clustering [38]. Second, when applying Hilbert spectra analysis on all IMFs, an analytic signal of each IMF is calculated. It is defined by equation (6) [38]. Its amplitude and instantaneous frequency could also be extracted as features [39,40]. They are calculated by equations (7) and (8) [37].

\[ Z_j(t) = i \text{imf}_j(t) + HT(\text{imf}_j(t)) = A_j(t)e^{i\theta_j(t)} \]  
\[ A_j(t) = \sqrt{(\text{imf}_j(t))^2 + (HT(\text{imf}_j(t)))^2} \]  
\[ f(t) = \frac{d\theta_j(t)}{dt} = \arctan \left( \frac{HT(\text{imf}_j(t))}{\text{imf}_j(t)} \right) \]

Third, after the Hilbert-Huang transform, the Hilbert spectrum of input signal could be obtained. Features could be extracted from the Hilbert spectrum [40]. Being similar to the time frequency spectrum generated by wavelet transform, the Hilbert spectrum is a time frequency spectrum. It can be divided into Hilbert amplitude spectrum and Hilbert energy spectrum. The feature extraction from these two kinds of the spectrum is similar to it from the spectrum obtained by wavelet transform. Details can be referred to wavelet transform above.

Different researchers have applied this kind of feature to spike researches. Zhang [40] extracted the instantaneous frequencies and IMF-energy distributions from spikes as features for analyzing spikes in epilepsy. Zhu [41] used values from Hilbert amplitude spectrum as features for neural spike clustering and yielded a better effect than extracting features from waveform morphology.

3.2.4. Analysis of features in transformation domain
From the review of three different kinds of features in the transformation domain, it can be seen that different features have different attributes, advantages, and disadvantages.

Features based on Fourier transform offer frequency information of the whole spike waveform, while features of wavelet transform offer a time-frequency analysis of the signal. So, there would be more features based on WT available for researchers due to the extra real time frequency information provided by the two-dimensional spectrum. It can be concluded that features based on WT are much more advanced than features based on FT. Features from empirical mode analysis are another much advanced feature. First, like features from WT, features from HHT are also two-dimensional features. They contain information from both the time domain and frequency domain. This makes them much more suitable for analyzing non-stationary signals (spikes) than features based on FT. Second, the EMD does not depend on a fixed basis function. This makes features from it adaptive and thus better represent the original signal. But it also has its limitations. The EMD is based on empirical data, so its completeness and orthogonality cannot be proved theoretically. Therefore, the application of this kind of feature does not have a solid theoretical foundation. Besides, since the application of this kind of feature started late, few references of it can be searched around neural science. This would make researchers meet more experimental challenges when applying this kind of feature on neural spike sorting.

3.3. Features of dimensional reduction
To improve the performance of neural spike sorting, most researchers would like to extract features
from many (basically more than 10) different dimensions. Because these features are likely to contain many redundant components, which would make the whole spike sorting process much more time-consuming and occupied. It is necessary to apply dimensional reduction algorithms on these features to keep the active ingredients and filter away the superfluous ones. There are mainly two kinds of dimensional reduction algorithms applied to the features utilized in neural spike sorting: the principal component analysis (PCA) and the Laplacian eigenmaps (LE).

### 3.3.1. Principal component analysis

The most widely used component analysis of features is principal component analysis (PCA). PCA is an algorithm which projects data sets with multiple related features to coordinate system with less related features [4]. In this algorithm, a set of orthogonal basis vectors includes the largest variation of the data.

![Figure 3 Steps of principal component analysis](image)

This algorithm mainly contains four steps, as shown in Figure 3. The first step is creating the covariance matrix of the data set. Second, all eigenvalues of the covariance matrix are calculated. Then the first k eigenvalues are retained under the condition of descending order of variance. Finally, the data points are transformed by the k eigenvectors.

When applying this algorithm in feature extraction, the more original features are extracted, the more information is obtained from the original spikes, then the larger separation this algorithm yields. Moreover, the larger number of components we choose, the larger separation we can obtain as well. The experiments in [42] have proved that the first three features can provide good separation toward neural spikes for the choice of the number of components. And [43] reported that when choosing a higher number of k, the variance of higher components may be dominated by background noise. Hence, a large number of components is unsuited to spike sorting.

For the application of this feature, Huang [44] proposed a unified optimization model of feature extraction and clustering for spike sorting by iteratively performing PCA and KM-like procedures. Li [45] a novel feature fusion strategy based on the wavelet coefficients and PCA. Park proposed a deep learning-based spike classification for extracellular recordings with pseudo-labels based on PCA and K-means clustering [46].

Generally, PCA performs well in neural spike sorting. It yields a good sorting accuracy and sorting error when combined with a different clustering algorithm. And its potential is considerable with the increase of computational complexity. Its classification accuracy can improve about 30 percent when the computational accuracy is increased from $10^2$ to $10^4$. However, the disadvantage is that applying PCA will increase the computational complexity occupied hardware resources a lot, so it is only suitable for off-line sorting. Besides, PCA often requires extra offline training. This would also put considerable pressure on researchers.

### 3.3.2. Laplacian eigenmaps

The feature in the transformation domain is Laplacian eigenmaps (LE). The objective of LE is trying to find a low dimensional representation to keep the close neighbor relationship measured by weight matrix $W$ [47]. It mainly contains five steps.

In the first place, the distance matrix is computed. The distance used is mainly the Euclidean
distance. Then, the number of nearest neighbors (n) we need is determined. For every data point, the n nearest neighbors of it are found and connected.

Then, the weight matrix $W$ is then calculated according to the following equation, where $\sigma$ is a scale parameter set contingently [47].

$$W_{ij} = \begin{cases} e^{-\frac{\|x_i-x_j\|^2}{2\sigma}} & \text{if two points are connected} \\ 0 & \text{otherwise} \end{cases} \quad (9)$$

Then, the degree matrix ($D$, which is a diagonal matrix) and the Laplacian matrix ($L$) are computed according to Eq. (10) and (11). Then the eigenvalues and eigenvectors of the Laplacian matrix are calculated according to Eq. (12).

$$D_{ii} = \sum_j W_{ij} \quad (10)$$
$$L = D - W \quad (11)$$
$$Lf = \lambda Df \quad (12)$$

After that, the eigenvalues are ranked in ascending order ignoring the eigenvalue 0, and the eigenvectors are sorted correspondingly to their eigenvalues.

At last, the number of dimensions of the vectors after dimensional reduction (m) is determined, and the first m eigenvectors are kept. Then the mapping of data point $x_i$ into the lower m dimensional space can be expressed by $(f_1(i), ..., f_m(i))$.

This algorithm was shown to outperform PCA in simulated datasets in [3,48] and real signals in [3,49]. Due to the mutual satisfaction of the cost function’s locality-preserving property and the calculation of variance weighted by local density, it is generated. It yields better cluster quality compared with PCA [49]. Moreover, its intermediate results of the number and locations of the tentative cluster centers can be used to initialize in clustering. However, this method also has weak points, its steps are tedious, involving the creation of graphics and matrixes, which yields the highest computational complexity. And [3] reported that when combined with the clustering method, this algorithm would cause over-clustering on some occasions.

4. Discussion and Conclusion

In this article, three kinds of features used in neural spike sorting are reviewed: time domain features, transformation domain features, and dimensional reduction features. For each kind of feature, the basic principle, advantages, and disadvantages are described and discussed.

It can be concluded that different features have different characteristics. Time domain features are simply extracted from the waveforms, while transformation domain features are more advanced: FT offers frequency information and yields better performance in neural spike sorting; they do not need training and have good rapidity as well, so they can also be used in on-chip feature extraction; WT is even more advanced than FT, experiments have shown that features of wavelet transform yields much higher sorting accuracy, so they are suitable for spike sorting process which has a high precision requirement. Besides, wavelet transform can also achieve a good outcome of reducing neural signals' in-band noise, so the wavelet-based method can be applied on both signal pre-processing and feature extraction to optimize the whole sorting process; HHT is another advanced method that does not base on a fixed basis function, it is adaptive and has performed as high as WT.

However, the transformation domain features also have limitations: Since the transform process is necessary for feature extraction, it would result in higher computational complexity and lower speed in both on-line and off-line spike sorting. This results in a large decrease in sorting speed and makes on-line sorting impossible. Besides, the background noise frequency would seriously influence the performance of wavelet-based classification, so the extraction of this feature may require an extra noise reduction process sometimes.

When it comes to dimensional reduction features (PCA and LE), they specialize in spike sorting with many features and result in considerable performance. LE yields better performance and higher complexity. Generally, due to the accuracy requirements, more and more researchers apply features from WT, PCA, and LE instead of features from FT and the time domain. For HHT, it has a great
potential in spike signal processing, so it may be applied more in future spike sorting.

The advantages and disadvantages of different features were compared and shown in Table 1. Considering the computational complexity, features in the time domain are the most time-saving methods, while dimensional reduction processing is consuming the longest time. When it comes to the cluster validity, the dimensional reduction and features in the transformation domain showed better performance than features in the time domain.

| Feature                     | Complexity | Validity | Speed | On-line Sorting | Offline training |
|-----------------------------|------------|----------|-------|----------------|-----------------|
| Time domain features        | 1          | 3        | 1     | Yes            | No              |
| Transformation domain features | 2         | 2        | 2     | Sometimes      | No              |
| Dimensional reduction features | 3         | 1        | 3     | No             | Yes             |

Table 1 Comparison of the three features (higher number represent lower values)

There are some suggestions for researchers when selecting algorithms in spike sorting and expectations for future research through the analysis. When choosing features, the minimization of complexity and the maximization of performance need to be mutual satisfied, and the objectives can determine the most proper kind of feature. When the spike sorting process needs to be real time, the features in the time domain would be the best choice. While seeking to develop sophisticated algorithms to achieve higher sorting accuracy, the WT and PCA are worth choosing. When applying new algorithms with high potential in neural spike sorting, the HHT and LE are of high value. For the future study of features in spike sorting, there are three mainstream directions. First, more improvement of existing feature algorithms that yield better performance or solves basic problems is worth to be studied. Second, new algorithms can be exploited to meet new experimental challenges. Third, different combinations of spike detection algorithms, feature extraction algorithms, and clustering algorithms can search for better performance of the whole spike sorting process.

References
[1] Wang T. H. (2018) Physiology. People's Medical Publishing House, Beijing.
[2] Kandel E, Schwartz J. H., Jessell T. M. (2000) Principles of Neural Science. McGraw-Hill, New York.
[3] Chah E, Hok V, Della-Chiesa A, et al. (2011) Automated spike sorting algorithm based on Laplacian eigenmaps and k-means clustering. J Neural Eng. 8.
[4] Ozdemir S, Susarla D. (2019) Feature Engineering Made Easy. The Posts and Telecommunications Press, Beijing.
[5] Saif-ur-Rehman M, Ali O, Dyck S, et al. (2021) SpikeDeep-classifier: a deep-learning based fully automatic offline spike sorting algorithm. J. Neural Eng. 18.
[6] Park I.Y., Eom J, Jang H, et al. (2020) Deep Learning-Based Template Matching Spike Classification for Extracellular Recordings. Applied Sciences. 10.
[7] Do A T, Zeinolabedin S M A, Jeon D, et al. (2019) An Area-Efficient 128-Channel Spike Sorting Processor for Real-Time Neural Recording With 0.175 μW/Channel in 65-nm CMOS. IEEE Transactions on Very Large Scale Integration (VLSI) Systems. 27: 126-137.
[8] Hwang W. J., Lee W. H., Lin S. J., et al. (2013) Efficient Architecture for Spike Sorting in Reconfigurable Hardware. Sensors. 13.
[9] Yu Y, Zhao Y, Liu H, et al. (2015) Spike sorting based on PCA and improved fuzzy c-means. ICMRRA., 15: 818-822.
[10] Khan B, Bhatti A, Johnstone M, et al. (2015) Optimal Feature Subset Selection for Neuron Spike Sorting Using the Genetic Algorithm. ICONIP, 9490: 364-370.
[11] Quiroga R Q, Nadasdy Z, Ben-Shaul Y. (2004) Unsupervised spike detection and sorting with wavelets and superparamagnetic clustering. Neural Comput. 16.
[12] Jahanmiri-Nezhad F, Barkhaus P. E., Rymer W. Z., et al. (2014) Spike sorting paradigm for classification of multi-channel recorded fasciculation potentials. Comput. Biol. Med., 55: 26–35.
[13] Stewart C. M., Newlands S. D., Perachio A. A. (2004) Spike detection, characterization, and discrimination using feature analysis software written in LabVIEW. Comput. Methods Programs Biomed., 76: 239–251.
[14] Yang Z, Chen T C, Liu W. (2008) A neuron signature based spike feature extraction algorithm for on-chip implementation. Conf. Proc. IEEE Eng. Med. Biol. Soc. 1716–1719.
[15] Sonoo M, Stalberg E. (1993) The ability of MUP parameters to discriminate between normal and neurogenic MUPs in concentric EMG: analysis of the MUP “thickness” and the proposal of “size index”. Electroencephalogr. Clin. Neurophysiol., 89: 291–303.
[16] Bestel R, Daus A. W., Tielemann C. (2012) A novel automated spike sorting algorithm with adaptable feature extraction. J. Neurosci. Methods., 211: 168–178.
[17] Paraskevopoulou S E, Barsakcioglu D Y, Saberi M R, et al. (2013) Feature extraction using first and second derivative extrema (FSDE) for real-time and hardware-efficient spike sorting. J. Neurosci. Methods., 215: 29–37.
[18] Paraskevopoulou S E, Wu D, Efekhar A, et al. (2014) Hierarchical Adaptive Means (HAM) clustering for hardware-efficient, unsupervised and real-time spike sorting. J. Neurosci. Methods., 235: 145–156.
[19] Su C K, et al. (2013) Computational solution of spike overlapping using data-based subtraction algorithms to resolve synchronous sympathetic nerve discharge. Front. Comput. Neurosci. 7.
[20] Gibson S, Judy J. W., Markovic D. (2008) Comparison of spike-sorting algorithms for future hardware implementation. Conf. Proc. IEEE Eng. Med. Biol. Soc. 5015–5020.
[21] Gibson S, Judy J. W., Markovic D. (2012) Spike sorting: the first step in decoding the brain. IEEE Signal Process. Mag., 29: 124–143.
[22] Kamboh A. M., Mason A. J. (2013) Computationally efficient neural feature extraction for spike sorting in implantable high-density recording systems. IEEE Trans. Neural Syst. Rehabil. Eng., 21: 1–9.
[23] Saeed M, Kamboh A M. (2013) Hardware architecture for on-chip unsupervised online neural spike sorting. Proc IEEE EMBS Conf. Neural. Eng. 1319–1322.
[24] Henze D. A., Borhegyi Z, Csicsvari J, et al. (2000) Intracellular features predicted by extracellular recordings in the hippocampus in vivo. J Neurophysiol., 84: 390–400.
[25] Moffitt M. A. and McIntyre C. C. (2005) Model-based analysis of cortical recording with silicon microelectrodes. Ci Neurophysiol., 116: 2240–2250.
[26] Marko H. (1981) System Theory-Spectrum Transformation and Its Application. People’s Education Press, Beijing.
[27] Welch P. (1967) The use of fast Fourier transform for the estimation of power spectra: A method based on time averaging over short, modified periodograms. IEEE Transactions on Audio and Electroacoustics., 15: 70-73.
[28] Kaku H, Ozturk M, Viswanathan A, et al. (2019) Grouping Neuronal Spiking Patterns in the Subthalamic Nucleus of Parkinsonian Patients. EMBC. 4221-4224.
[29] Yang C. H., Yuan Y, Si J. (2013) Robust spike classification based on frequency domain neural waveform features. J. Neural Eng., 10.
[30] Goerg G. M. (2011) A nonparametric frequency domain EM algorithm for time series classification with applications to spike sorting and macro-economics. Statistical Analysis and Data Mining., 4: 590-603.
[31] Yu F Q. (2019) Ten Lectures on Practical Wavelet Analysis. Xidian University Press, Xi’an.
[32] Fan Y B, Pan Z K, Wang Z Y. (2011) Wavelets: Theory, Algorithms and Filter Banks. Science Press, Beijing.
[33] Zhang J Y, Zhang B, Jiang X Z. (2000) Analysis of feature extraction method based on wavelet transform. Signal processing.,16.
[34] Ul Hassan M, Veerabhadrappa R, Bhatti A. (2021) Efficient neural spike sorting using data subdivision and unification. PLOS ONE., 16: e0245589.
[35] Gao L S, Li F Q, Fu J Q. (2018) Neural Spike Sorting Based on Matched Wavelet. CCIS. 53-57.
[36] Makarov V. A., Pavlov A. N., Tupitsyn, A. N. (2008) Optimal sorting of neural spikes with wavelet and filtering techniques. SPIE. 6855.
[37] Zheng Z G, Liu L H. (2010) Empirical Mode Analysis and Wavelet Analysis and Their Applications. Meteorological Press, Beijing.
[38] Zhang X J, Zhang Q, Sun J C. (2006) Target Feature Extraction and Selection Based on Empirical Mode Decomposition. Journal of Northwestern Polytechnical University. 24: 453-456.
[39] Niu J, Liu Y X, Qin Y L, et al. (2011) A New Method of Radar Micro-motion Feature Extraction of Cone Target Based on Empirical Mode Decomposition. Acta Electronica Sinica. 39: 1712-1715.
[40] Zhang M M, Wang J, Ao T D. (2010) The Method of Spike Feature Extraction Based on HHT. iCREATe. 1-4.
[41] Zhu J D, Lin C F, Chang S H, et al. (2015) Analysis of spike waves in epilepsy using Hilbert-Huang transform. J Med Syst. 39.
[42] Wheeler B C, Heetderks W J. (1982) A comparison of techniques for classification of multiple neural signals. IEEE Tran Biom Eng. 29: 752–759.
[43] Lewicki M S. (1998) A review of methods for spike sorting: the detection and classification of neural action potentials. Network. 9: R53–78.
[44] Huang L B, Gan L, Ling B W. (2021) A Unified Optimization Model of Feature Extraction and Clustering for Spike Sorting. IEEE Transactions on Neural Systems and Rehabilitation Engineering. 29: 750-759.
[45] Li H G, Song R Q, Liu J W. (2018) Low-dimensional feature fusion strategy for overlapping neuron spike sorting. Neurocomputing. 281: 152-159.
[46] Park I Y, Eom J, Jang H, et al. (2020) Deep Learning-Based Template Matching Spike Classification for Extracellular Recordings. Appl. Sci. 10.
[47] Mohri M, Rostamizadeh A, Talwalker A. (2019) Foundations of Machine Learning. China Machine Press, Beijing.
[48] Ghanbari Y, Spence L, Papamichalis P. (2009) A graph-Laplacian-based feature extraction algorithm for neural spike sorting. Conf Proc IEEE Eng Med Biol Soc. 3142–3145.
[49] Ghanbari Y, Papamichalis P, Spence L. (2010) Graph-spectrum-based neural spike features for stereotrodes and tetrodes. IEEE Int Conf on Acoustics Speech and Signal Processing. pp598–601.