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A New Spike Sorting Algorithm Based on Continuous Wavelet Transform and Investigating Its Effect on Improving Neural Decoding Accuracy

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Abstract—Spike sorting is an essential step in extracting neuronal discharge patterns which help to decode different activities in the neural system. Therefore, improving the spike sorting accuracy can improve neural decoding performance subsequently. Although many methods are suggested for spike sorting, few studies have evaluated their effect on neural decoding performance. In this paper, a method of spike sorting based on an optimized selection of the parameters in the continuous wavelet transform (CWT) is proposed. The proposed algorithm was tested on a simulated dataset and two publicly available benchmark datasets to evaluate its performance in spike sorting. To evaluate the effect of utilizing different spike sorting algorithms on neural decoding performance, real data was used in which the aim was to decode the force applied by the rat's hand to a pedal continuously from the intra-cortical data of the primary motor area of the cortex. The extracted neuronal firing rates by the spike sorting algorithms were applied to a partial least squares regression to decode the force signal. In the simulation study, the proposed spike sorting algorithm based on optimized wavelet parameter selection outperformed both the WaveClus spike sorting and traditional PCA-based spike sorting algorithms. The results showed the superiority of the spike sorting algorithm based on optimal wavelet parameters compared to classical discrete wavelet transform (DWT) or PCA-based spike sorting methods in decoding real intracortical data. Overall, the results indicate that it is possible to improve neural decoding performance by improving the spike sorting accuracy.

Key words: continuous wavelet transform, neural decoding, optimization, partial least squares, spike sorting.

INTRODUCTION

Neurons are the smallest unit of the nervous system that transmit information via electrical signals generated by the action potential (Kandel et al., 2000). The collection of these activities is processed in the nervous system and created to produce outputs in response to the internal or external needs of the body such as hand movements.

Extracellular recording of brain single-unit activity is known as a popular method in neuroscience research. The electrical signal recorded by the microelectrodes in the extracellular space includes the action potentials produced by all the neurons surrounding the electrode. The shape of the created spikes depends on the relative position of the recording electrode to each neuron, in addition to several cell characteristics, such as its type and geometry (Gibson et al., 2011). To obtain the time and discharge rate of single neurons, we must sort them using the differences of single spike waveforms which is called spike sorting. It is difficult to perform such clustering at a low signal-to-noise ratio (SNR) due to the reduction of the differences between the waveform of the spikes. For this reason, different groups are trying to make their proposed spike sorting algorithms more efficient and improving them to deal with the errors in low SNRs.

After detecting and separating the spike waveforms from the extracellular signal, appropriate distinctive features must be extracted from the obtained spikes. The use of simple features such as signal samples in the time domain reduces the efficiency and accuracy of the spike sorting due to the strong influence of noise on the waveform. As an alternative method, Principle Component Analysis (PCA) algorithm can be employed, which uses the sample covariance matrix to calculate two or more of the directions of largest variability in the waveforms to build a more efficient feature set for separation of multi-class waveforms (Rey et al., 2015). It has been shown that the separation of spike waveforms whose differences are only in the latter part of the peak point will be highly error-prone with the PCA algorithm and it has also been shown that clustering error with PCA may be significant if this difference belongs only to

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the former part (i.e., before the peak point) (Pavlov et al., 2007). Considering these points, it can be concluded that using the PCA features for spike sorting is not necessarily appropriate in all conditions.

In recent years, the good performance in the spike sorting algorithms that used wavelet coefficients as features has encouraged research groups to use this transform. In the study (Letelier and Weber, 2000) discrete wavelet coefficients were extracted by selecting Daubechies-8 as the mother wavelet and implementing a five-level multiresolution decomposition. To select the coefficients with maximum impact on clustering, the standard deviation criterion was used.. In the study (Hulata et al., 2002) spikes have been sorted using a wavelet packet algorithm with Coiflet-3 mother wavelet and selecting the optimal packets with the help of Shannon's information cost function. They compared their algorithm with PCA and showed that the performance of the proposed algorithm is higher than PCA. The work (Quiroga et al., 2004) can be regarded as an important study on this topic. In this study, by using Haar discrete wavelet transform (DWT) coefficients at four levels of dyadic decomposition, they selected the features that had the most deviation from the normal statistical distribution for spike sorting. In that study, it was shown that the variance-based data projection using the PCA algorithm doesn't differentiate well between clusters, instead, a higher performance would be achieved by analyzing data using DWT and selecting a limited number of coefficients using a statistical criterion such as the Kolmogorov–Smirnov test.

Most wavelet-based spike sorting algorithms in previous studies have used DWT (as a few examples (Letelier and Weber, 2000; Hulata et al., 2002; Shalchyan et al., 2012; Yang and Mason, 2016)) in which the scale parameters are limited to a finite amount by dyadic sampling. However, to find the best wavelet features capable of separating spikes well, one may need to project spikes on basis functions that are scaled to some scales other than dyadic 2^j scales. This restriction can prevent us from achieving the optimal values of the scale parameter. The use of continuous wavelet transform (CWT) does not have the limitations of DWT on the fixed basis function scales, although there is a need for a powerful method to choose and optimize the scale and translation parameters in CWT. In the study (Pavlov et al., 2007), using CWT for feature extraction and comparing it with PCA features, it was shown that by selecting appropriate coefficients, the defects of the PCA algorithm can be covered and system performance can be improved. Although that study did not provide a complete algorithm for optimization of the CWT parameters, it showed the superiority of CWT features over both PCA and DWT features in some spike sorting examples.

In the current study, we presented a spike sorting algorithm that selects optimal CWT parameters for feature extraction. For this purpose, the most effective coefficients were obtained using Euclidean Distance and area under curve (AUC) criteria. For the evaluation, the proposed algorithm was tested on two simulated datasets constructed at different SNRs as well as two public simulated datasets of previous studies. The obtained results were compared to both PCA-based and DWT-based spike sorting algorithms.

In many studies, spike sorting is used to calculate the discharge rate, to decode the nervous signals to obtain a response to stimulation, or to estimate the output of the nervous system to organs. For instance, studies related to Brain–Computer Interface (BCI) systems in which limb movement parameters such as movement, velocity, or force are decoded out of the activity of neurons of the motor cortex (Carmena et al., 2003; Gupta and Ashe, 2009; Wu and Hatsopoulos, 2008). In the majority of these studies, the question of whether or not decoding accuracy would be increased if more advanced spike sorting techniques were used has not been addressed. This issue is generally overlooked since, in most of decoding studies, simple spike sorting algorithms are used.

Studies on neural decoding using spike sorting can be classified according to the type of algorithms used. Some studies use popular algorithms such as PCA via commercial electrophysiological recording systems software to sort the recorded and detected spikes (Ma et al., 2017). Most of the time, after using such systems, the supervision of an expert on the results is required for validation (Wu et al., 2004; Perge et al., 2013). Christie et al. (Christie et al., 2014) compared BCI decoder performance in a center-out reaching task when using threshold-crossing events versus sorted spikes. For their spike sorting, the first four principal components of the waveforms were used as features. They demonstrated that their PCA-base spike sorted data performance is slightly higher than that of thresholded data for one animal but not the other. However, Todorova et al. (Todorova et al., 2014) showed that spike sorting adds value to the threshold-crossing methods employed in BMI decoding. Overall, few groups have used advanced spike sorting algorithms for decoding. For example, in (Bansal et al., 2011) density grid contour clustering algorithm has been used manually and in a supervised manner before neural decoding. However, in that study, no comparison was made between decoding performance using the proposed method and other common spike sorting methods.

In this study, we used the algorithm presented in the following section for spike sorting on the recorded signals of the study (Khorasani et al., 2016) to decode the force signal continuously and compared its results with the decoding results when using a PCA-based spike sorting and the DWT-based spike sorting method presented in (Quiroga et al., 2004).

EXPERIMETAL PROCEDURES

The proposed spike sorting algorithm

In this section, the proposed optimized wavelet parameter-based (OWP) spike sorting algorithm is described.

Spike detection

The first step is spike detection. For the detection, a threshold-crossing peak detection method was used as

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in (Quiroga et al., 2004). The threshold value was estimated from the following relationship:

$$Thr = 4.\sigma_n \tag{1}$$

$$\sigma_n = median\left\{\frac{x}{0.6745}\right\} \tag{2}$$

where x denotes a single-channel signal in this study. For each detected spike peak, 64 samples (approximately 2.5 ms at a sampling frequency of 24 kHz) were extracted for each detected spike so that the peak point of each spike was assigned to sample 20. To improve the spike peak alignment, all waveforms were upsampled to 256 samples by and interpolation using cubic splines and the spikes were aligned to their peak at sample 80.

Feature extraction and classification

In this work, optimized wavelet coefficients were used as the main features for spike sorting. Wavelet transform projects a signal into transient and finite-energy wavelet basis functions. Unlike the Fourier basis functions, different wavelet bases can be used for spanning the time–frequency representation of the signal. Projecting the signal on the bases of wavelet functions can also be considered as filtering the signal by a set of different bandwidth filters. The bandwidth of the filters is regulated by the wavelet scaling parameter. The ability to generate optimal resolution in the time–frequency domain and also to analyze non-stationary signals are two major advantages of it over other transform analysis methods like Fourier transform (Soman, 2010). CWT is defined as follows;

$$W(a,b) = \int f(t)\frac{1}{\sqrt{|a|}}\psi_{a,b}(t)dt \tag{3}$$

$$\psi_{a,b}(t) = \psi\left(\frac{t-b}{a}\right) \tag{4}$$

in which the function $f(t)$ is the waveform of the signal, $\psi(t)$ is called the mother wavelet function, and the parameters a and b are the scaling and translation parameters respectively. Each wavelet coefficient $W(a,b)$ represents the degree of correlation or similarity of the original signal to the scaled waveform of the mother wavelet with the scaling parameter a around the time point b. Given that the permissible values for both two parameters a and b can be continuously varied over all real values, the corresponding wavelet coefficient can be obtained at any time point and for any arbitrary scaling value. Therefore CWT provides unlimited flexibility for building optimal basis functions in signal analysis. In this work, we proposed a method for selecting optimal values of the parameters a and b for spike sorting.

After performing spike detection and peak alignment, the spike templates need to be found before the wavelet feature extraction to select the optimal wavelet features. The first two principal components of the spikes were extracted and an initial clustering was performed using the k-means clustering. Spike waveforms of each cluster were averaged to find the template spike for each neuron. According to the research findings in (Pavlov et al., 2007), the initial and final phases of the waveform of each neural spike may have different frequency content. Because of this difference in the frequency content, the optimum scaling and shift parameters in each of the two waveform phases should be selected separately. Therefore, each spike from the peak point was divided into two parts corresponding to the two starting and ending phases, and the analysis was performed separately for both parts. Thus, the first part of each spike waveform contains 80 samples and the second part contains 176 samples.

In the next step, to optimize the selection of the wavelet transform parameters (a,b), a two-step process was carried out by first selecting the optimal a parameter and then selecting the optimal $b$parameter. To select the parameter a, we subdivided the available frequency range of the data into 10 Hz intervals and calculated the scale value proportional to the available frequencies and the corresponding mother wavelet function.

For every pair of spike templates, we seek an optimal scaling parameter a that maximizes the Euclidean distance between the wavelet feature vectors of the two spike templates.

At this stage, for the scaling parameter obtained, the best value for the shift parameter b should be sought. The optimal value for this parameter is selected based on the resolution of the cluster distribution at different values of b. Receiver operator characteristic (ROC) curve was used for this purpose. The ROC diagram shows the resolution of two classes at different threshold values. Its horizontal and vertical axes are false positive rate and true positive rate, respectively, and the area below is called the area under the curve (AUC). The value of this area indicates the probability of how well the separator tested will work. Based on the description given, it is clear that the point that will generate the most area will be the desirable feature. Therefore, for each pair of spike templates in each of the first and second parts of the waveform the optimal scaling and shift parameters (a,b) were determined and the wavelet coefficient made of these parameters are obtained as the desirable features for separating the two templates. By repeating the above procedure for all pairs of templates and their two parts, different wavelet coefficients were selected for sorting the spike classes by using the k-means clustering algorithm.

The proposed feature extraction and classification methods are described in the following steps for a more precise and concise explanation:

1. Initial spike clustering using the first two principal components features
2. Obtaining the waveform of each action potential by averaging the pre-classified spikes. To reduce the computational burden and increase the algorithm speed (averaged waveforms are used to the end of the fourth step).
3. Splitting each spike into two time-segments and applying CWT at different values of a and b

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4. Obtaining the optimum scale to maximize the distance between the wavelet coefficients of both clusters.
5. And finally, finding the optimal shift parameter using the ROC criterion.
6. Accurate clustering of all identified spikes using optimized wavelet features and k-means algorithm.

A block diagram of the steps for implementing the proposed OWP spike sorting algorithm including spike detection, feature extraction, and classification methods is depicted in Fig. 1.

The proposed OWP spike sorting method was applied to three different synthetic datasets and a real dataset. The synthetic datasets include one new dataset we simulated ourselves for this study and two other publicly available synthetic datasets for the evaluation purpose.

The ratio of the number of correctly classified spikes to the total number of spikes was used as a measure of spike classification accuracy. In other words, the accuracy value is equal to the number of true positives divided by the sum of the numbers of true positives and false positives.

In the following sections, the synthetic and real evaluation datasets are described in detail.

Evaluation datasets

Synthetic datasets. Simulated dataset. In evaluating neural spike sorting methods, the use of signal simulation using true spike waveforms is a conventional and efficient way to evaluate methods based on predetermined labels. Given the spatial geometry of neurons, what has been studied in most previous studies in spike sorting has been the evaluation of the problem on three different spike waveforms in terms of complexity (Letelier and Weber, 2000; Quiroga et al., 2004; Wang et al., 2006), which we also examined in this study. Therefore, two simulated signals are made, each with three different spike waveforms. The waveforms of spike templates used are taken from a publicly available database of the University of Irvine. This dataset contains seven different spike waveforms that are presented with a sampling frequency of 20 kHz (see more details in (Nenadic and Burdick, 2004)). The templates were interpolated to 24 kHz to increase the detail and soften the waveforms.

Background noise from the real data (the experimental extracellular recording that will be probed in this paper)

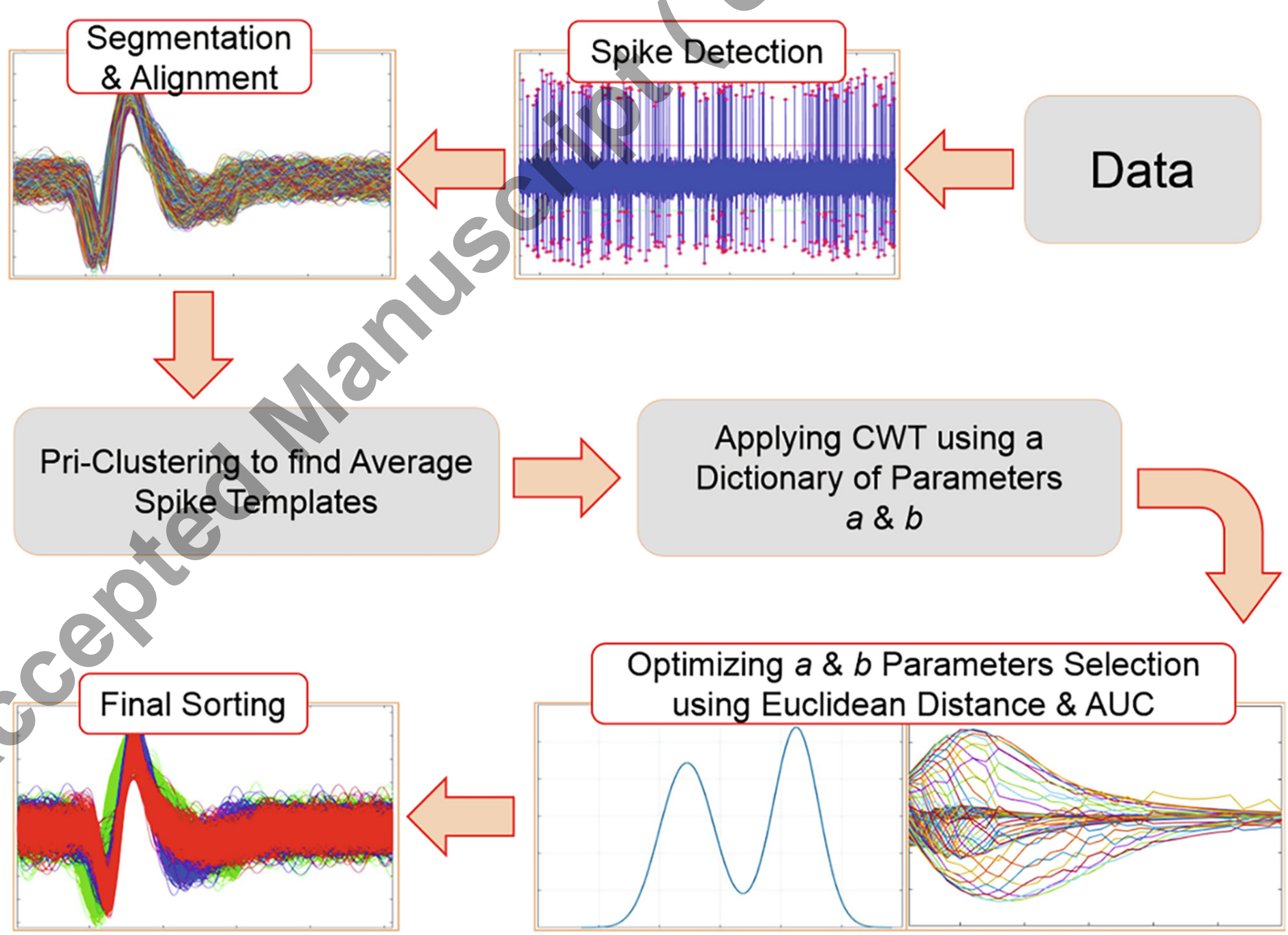

Fig. 1. Block diagram of OWP spike sorting method.

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was used to simulate background noise to create a better similarity between simulated data and real data. A signal segment from the real data containing only background noise and lacking any neuronal spike was isolated by an expert and was used to generate an Autoregressive moving average (ARMA) model of the background noise. Different models with different parameters were investigated and it was found that ARMA (7,3) can model the recorded background noise with good accuracy. Model coefficients were obtained by the Bayesian information criterion method (Maragos et al., 1993). Due to the presence of spikes in the frequency range between 300 and 5000 Hz, the modeled noise was filtered using a third-order Butterworth filter before spikes were distributed in the background noise.

Simulated signals from the combination of spike templates and simulated background noise from the above model were generated for 9 different SNRs from 2 to 6 with steps of 0.5. The SNR value was defined by dividing the maximum amplitude of the spike waveforms used in the dataset by twice the standard deviation of the noise waveform (Vargas-Irwin and Donoghue, 2007).

Spike templates were randomly distributed over the background noise, with an average of 1300 spikes in each dataset. According to the description given above, two simulated data each containing three different spike templates were constructed. The spike templates used in the datasets are shown in Fig. 2.

Public synthetic dataset 1. The first public simulated dataset used in this study is the simulated dataset used to evaluate the spike sorting algorithm known as OSORT (Rutishauser et al., 2006).

The simulated raw data is made up of an average of 150 waveforms of well-separated recorded neurons. To generate random background noise, many of these waveforms are randomly selected, randomly scaled, and added to noise traces. Background noise is used to generate different data with different noise conditions and background noise is generated with standard deviations of 0.05, 0.1, 0.15, and 0.2. In the end, three distinct neurons with a (renewal Poisson process) with a refractory period of 3 ms and a constant firing rate

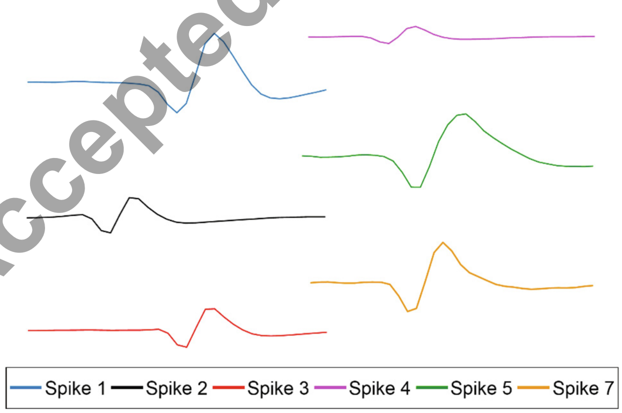

Fig. 2. The spike templates used to construct two simulated data. The simulated data1 used the spike templates from neurons 1, 2, 3 whereas the simulated data2 used the spike templates from neurons 4, 5, 7.

between 1 and 10 Hz are added to the original noise (Rutishauser et al., 2006). In this dataset, we have some overlapped spikes, forasmuch as our goal in this study we ignored them in our analysis.

Public synthetic dataset 2. The second public simulated dataset used in this study is the simulated dataset used to evaluate the spike sorting algorithm known as WaveClus (Quiroga et al., 2004). The simulated signals were generated using a database of 594 different average spike shapes collected from the recordings in the neocortex and basal ganglia. To generate background noise, spikes were randomly selected from a database overlapped at random times and ranges. The background noise is generated by a random selection of spikes from the database and their aggregation. Its basis is to mimic the background noise of real recordings created by the activity of distant neurons. Then, trains of three separate spike shapes (selected from the same database) are mounted on the noise signal at random times. The amplitude of the three spike classes was normalized to peak 1, and the noise level was considered to be 0.05, 0.1, 0.15, and 0.2 to the spike peak amplitudes (Quiroga et al., 2004). Similar to Public dataset 1, we ignored overlapped spikes in our analysis.

Experimental data. Recording. As the real dataset, the experimental recordings from the lab research work were used in the study (Khorasani et al., 2016). A brief description of the recording method is presented in the following. Three male Wistar rats (300–400 g) were prepared for a task where they had to press a static pedal using their right hand. When the amount of the applied force passed a predefined threshold (0.15 N), a drop of water was given to the rats as a reward. Data were recorded from the cerebral cortex in the primary motor area of rats using a (16-channel) micro-ware array (Microprobes Inc., Gaithersburg, USA). The resistance of each wire was between 500 and 800 kHz. Pre-amplifiers (2 * MPA8I) of the recording device (USB-ME16, Multichannel system, Germany) were connected to the implanted array connector (Omnetices Connector, USA) and recorded raw data by a sampling rate of 10KHz, simultaneously force was also recorded by a sampling rate of 30 Hz (Khorasani et al., 2016).

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Pre-processing and spike sorting. In the beginning, all recorded signals were filtered between 300 and 4950 Hz to remove the low-frequency part and preserve only the spike components. For this purpose, a 6th order Butterworth filter (forward and backward) was used. Next, a stationary wavelet denoising technique was employed to remove the interfered noise from all recordings. Using Bior1.3 mother wavelet the recorded data were decomposed into four scaling levels and were shrunk using hard thresholding. To keep the spike shapes as good as possible, the threshold level criterion was considered as 80% of the known MiniMax criterion (Rabbani and Vafadoost, 2006). This criterion was obtained empirically by testing on the simulated data to preserve the spike shape. In the next step, the complete

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OWP ← spike sorting

PLS ←

OWP spike sorting algorithm was applied to the data from each recording channel.

We used another two spike sorting algorithms, including PCA and the WaveClus, to evaluate and compare them to our algorithm in decoding the real data.

Force signal decoding. The neural impulse train obtained from each single-unit spike was smoothed using a 60 ms Gaussian window to extract the smoothed firing rate.

Finally, a Partial least squares (PLS) regression algorithm was used as in (Khorasani et al., 2017) to decode the force signal from the firing rates. To decode the force signal at a specific time instance, the spike firing rates were used in the PLS decoder during the previous 200 ms.

To evaluate the accuracy of our algorithm in force decoding, we used the correlation coefficient criterion. Using the following formula, the shape similarity between the real force and the predicted one is determined;

$$Corr_{f,\tilde{f}} = \frac{\sum_i (f_i - \bar{f})(\tilde{f}_i - \bar{\tilde{f}})}{\sqrt{\sum_i (f_i - \bar{f})^2 \sum_i (\tilde{f}_i - \bar{\tilde{f}})^2}} \tag{5}$$

where f fand $\tilde{f}$ represent real and predicted force respectively. The mean value of each signal has been shown with a barline on them.

RESULTS

spike sorting

First, the performance of the OWP method is investigated on the simulated data, and then the results of applying this algorithm to the real data are presented to decode continuous force signal.

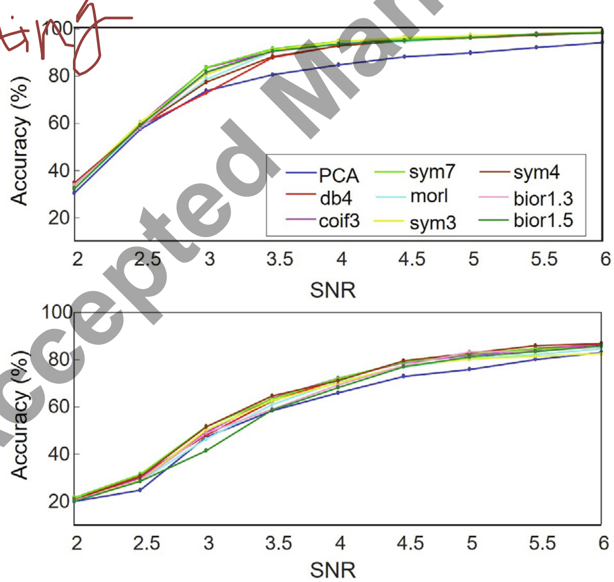

Fig. 3. Comparison of clustering accuracy of spike sorting algorithm achieved from proposed OWP method using various mother wavelet and also PCA method on two simulated datasets structured in this study for different SNRs.

Simulated data

First, the classification accuracy of the proposed OWP spike sorting algorithm which uses the optimized wavelet coefficient features was compared to PCA algorithm features on two simulated datasets constructed in our study. OWP algorithm with different mother wavelet functions was applied to two simulated datasets and the results for different SNR values are shown in Fig. 3 in two graphs. Eight of the most popular mother wavelet waveforms used in previous studies of wavelet-based spike sorting were used and evaluated. Finally, the results were compared with the classification accuracy obtained from the features extracted by the PCA algorithm. As shown in Fig. 3, the OWP algorithm using Sym4, Sym7, Morl, and Coif3 mother wavelets outperforms the PCA algorithm for all SNR $\geq$ 3 values and on both simulated datasets. The results also showed that using the Sym7 mother wavelet was better than other mother wavelets on average, although no clear difference was seen between the classification accuracies by using different mother wavelet at values of SNR $\geq$ 4.5. Therefore, because the algorithm is almost insensitive to the selected mother wavelet, from this point onwards, the Sym7 has been used as the mother wavelet at all stages. Table 1 shows a numerical comparison of classification performances obtained

Table 1. Comparison of the classification accuracy of spike sorting algorithms based on OWP and PCA methods on simulated datasets constructed in this study for different SNRs and public dataset 1 for different noise standard deviations

Datasets	Name	Accuracy (Mean ± SEM)	
		OWP Method	PCA
Simulated Data 1	SNR 2.0	**33.75 ± 1.1**	30.10 ± 2.0
	SNR 2.5	**59.14 ± 2.5**	57.51 ± 1.9
	SNR 3.0	**83.59 ± 2.4**	73.72 ± 3.7
	SNR 3.5	**91.52 ± 3.4**	80.53 ± 4.6
	SNR 4.0	**94.71 ± 3.1**	84.71 ± 2.8
	SNR 4.5	**95.78 ± 2.2**	88.17 ± 4.1
	SNR 5.0	**96.55 ± 3.0**	89.82 ± 3.4
	SNR 5.5	**97.97 ± 0.8**	92.13 ± 2.2
	SNR 6.0	**98.65 ± 0.5**	94.17 ± 2.6
Simulated Data 2	SNR 2.0	**21.68 ± 2.6**	19.96 ± 1.8
	SNR 2.5	**31.45 ± 4.1**	24.69 ± 2.4
	SNR 3.0	**51.67 ± 3.1**	47.15 ± 2.1
	SNR 3.5	**63.40 ± 3.3**	58.38 ± 1.6
	SNR 4.0	**71.94 ± 2.1**	65.95 ± 2.6
	SNR 4.5	**78.92 ± 2.7**	72.91 ± 2.4
	SNR 5.0	**82.39 ± 4.5**	75.87 ± 3.7
	SNR 5.5	**84.52 ± 2.7**	80.10 ± 3.3
	SNR 6.0	**85.25 ± 3.1**	83.07 ± 4.1
Public Dataset 1	Noise std 0.05	**93.71 ± 2.4**	93.66 ± 1.5
	Noise std 0.10	86.28 ± 2.6	**88.46 ± 2.6**
	Noise std 0.15	**74.52 ± 4.2**	65.14 ± 3.2
	Noise std 0.20	**61.21 ± 3.5**	56.72 ± 0.4

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using OWP and PCA methods on our two mentioned simulated datasets as well as on the public dataset 1.

As can be seen, OWP proposed algorithm performs better than PCA except for one noise level (std = 0.10). It is also notable that based on this public dataset, the accuracy of the proposed OWP spike sorting algorithm in noise level values of greater than or equal to 0.15 is higher than the PCA-based spike sorting method.

To further evaluate the OWP algorithm, the public dataset 2 (Quiroga et al., 2004) was used to compare its classification accuracy with the PCA and the WaveClus spike sorting methods. The result of this comparison is shown in Table 2. According to this table, we can compare the performance of all three spike sorting algorithms at different background noise levels. The results show that the proposed OWP algorithm outperformed the other two methods in most of the cases. In particular, the proposed OWP method demonstrated better classification accuracies compared to the PCA and WaveClus spike sorting algorithm for the Difficult2 dataset for all noise levels.

Real data

We used the OWP and two other spike sorting methods as described in previous sections to decode continuous force signals from firing rate functions obtained after the spike sorting. For the cross-validation purpose, here we used a sevenfold cross-validation scheme. Table 3 shows the number of trials per recording day. It can be seen that the data for Rat1 and Rat3 have been recorded for three different days and Rat 2 has been recorded for only two different days. It should be noted that the intervals between the different days of recording in rats varied from 1 to 14 days. Also, the lowest number of recorded trials was related to the third day of recording of Rat 1, whereas from Rat 3 we recorded the highest number of trials on the third day of recording. The average values of the force exerted by each rat and the range of force signals on different days of recording are shown in the fourth and fifth rows of Table 3.

Fig. 4 shows the result of the average force decoding efficiency, based on the correlation coefficient between real force and decoded signal of the test folds when either of the three evaluated methods including OWP, PCA, or WaveClus was used for spike sorting. In this figure, the horizontal axis represents the different days of recording for each rat, and the vertical axis shows the average correlation coefficient obtained by the three methods. As can be seen in the figure, using the OWP algorithm for the five days in eight days of recording for three rats significantly ($p < 0.05$) improved the signal decoding performance compared to PCA and WaveClus. These five days include the second and third days of Rat 1 and Rat 3 and the second day of Rat 2. Also in the other three days, including the first days of the three rats, OWP-based spike sorting significantly ($p < 0.05$) improved the decoding performance with respect to PCA-based spike sorting. However, using these three-day data, the proposed OWP-based spike sorting did not make a significant difference in decoding performance compared to WaveClus-based spike sorting ($p > 0.05$).

The time required to run the proposed OWP spike sorting algorithm on a one-minute segment of the real dataset using a personal computer with a PC with Intel® Core™ i5-5200U CPU, @2.2 GHz was measured. Taking into account the optimization time on the full space search of both a, b parameters, the execution time of the proposed algorithm took about 190 s.

In Fig. 5, the scatter plot and the histogram of the distribution of optimal parameter values for all three rats

Table 2. Comparison of clustering accuracy of spike sorting algorithms achieved from OWP, WaveClus, and PCA methods on two groups of public dataset 2 for various noise standard deviations

	Name	Accuracy (Mean ± SEM)		
		OWP Methodsdfsdfdsdf	WaveClus	PCA
Public Dataset 2	Difficult1 Noise0.05	**98.73 ± 1.0**	95.24 ± 1.1	83.17 ± 1.8
	Difficult1 Noise0.10	**90.56 ± 2.1**	87.25 ± 1.2	81.22 ± 2.3
	Difficult1 Noise0.15	91.23 ± 2.3	**93.58 ± 2.0**	78.37 ± 1.1
	Difficult1 Noise0.20	**74.45 ± 1.4**	72.17 ± 1.7	61.34 ± 1.5
	Difficult2 Noise0.05	98.01 ± 1.3	**98.8 ± 1.1**	89.49 ± 2.1
	Difficult2 Noise0.10	95.31 ± 2.2	**97.5 ± 1.0**	81.58 ± 2.4
	Difficult2 Noise0.15	**89.84 ± 1.5**	85.85 ± 2.2	75.55 ± 1.5
	Difficult2 Noise0.20	**84.18 ± 1.6**	82.45 ± 1.4	56.76 ± 1.3

Table 3. The information of the trials in each day

		Rat 1	Rat 2	Rat 3
Number of trials	Day 1	51	65	44
	Day 2	41	57	74
	Day 3	34	–	89
Mean of force (N)		31	37	35
Range of force value (N)		0–0.95	0–0.79	0–0.71

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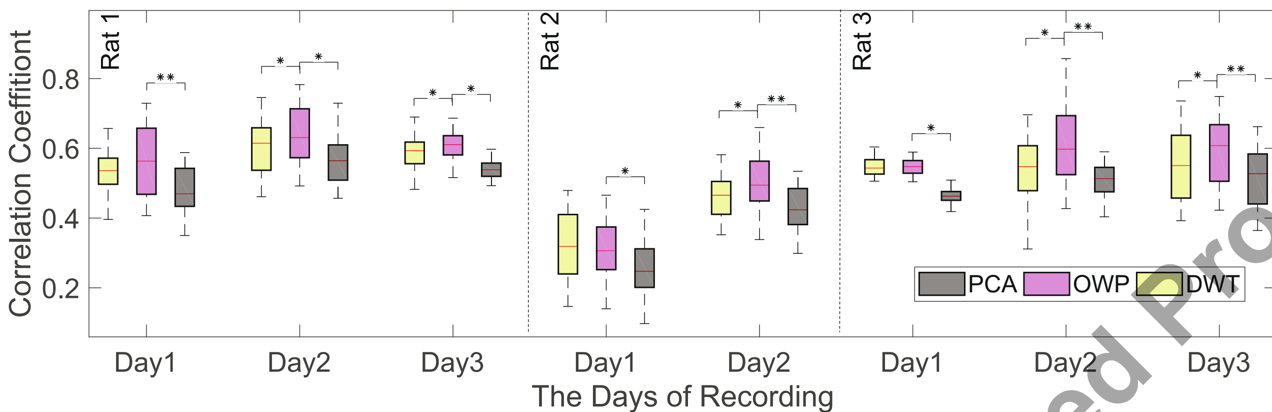

Fig. 4. Comparison of the mean correlation coefficients of rat hand signal strength for different days of recording with the output of the decoded-rhythmic signal output resulted from the implementation of WaveClus, OWP and PCA spike sorting algorithms. The symbols * and ** represent statistically significant superiority $p < 0.05$ and $p < 0.01$, respectively, based on the Wilcoxon signed-rank test.

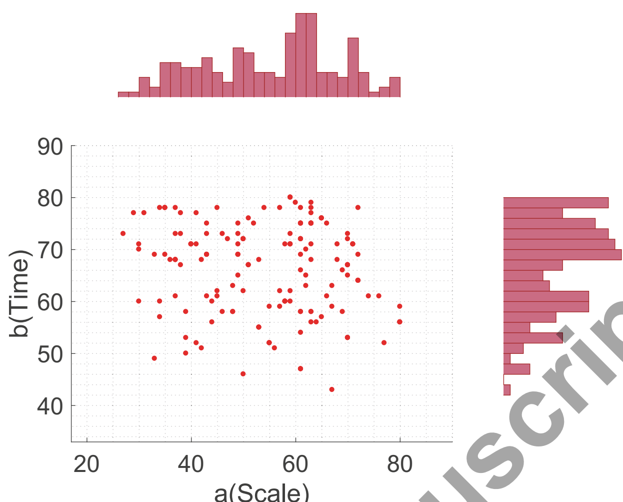

Fig. 5. The scatter plot and the histogram of the distribution of the optimal parameter values for all three rats on different days.

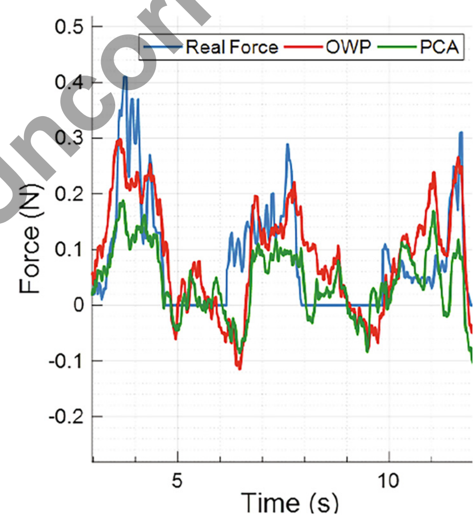

Fig. 6. Real force and the results of decoding using OWP and PCA algorithms with correlation coefficient 0.67 and 0.62, respectively.

on different days are shown. In this figure, the horizontal axis represents the values of the parameter *a* and the vertical axis represents the values of the parameter *b*.

Fig. 6 shows an example of real and decoded force signals. In this figure, the real force signal is displayed in blue and the signal decoded by the proposed OWP spike sorting algorithm is shown in red and the decoded signal in the PCA-based spike sorting algorithm is displayed in green. In this figure, the superiority of the decoding performance using the OWP proposed method over the PCA-based method can be seen.

DISCUSSION

In this paper, a spike sorting algorithm is presented that uses continuous wavelet coefficients with optimized parameters in the feature extraction stage. In this algorithm, a primary clustering is applied using PCA features to achieve the average waveform of the neurons in the data. In the next step, with the help of spike templates, the appropriate wavelet transform parameters are obtained to create the most discrimination between the spikes in the wavelet coefficient space. Using several simulated datasets at different SNRs, it was shown that the extraction of features by the proposed algorithm was more efficient than the other common features in the previous spike sorting studies, such as PCA features or DWT features.

Wavelet transform is a signal analysis method that allows the signal to be represented simultaneously in time and frequency domains, and this factor has led to the widespread use of this method. In this study, unlike most studies in this field, CWT was used instead of a discrete wavelet so that optimal values of the scale parameter could be obtained more accurately. In this way, the signal is analyzed in optimal frequency sub-bands and it will be possible to extract finer time–frequency features to separate the spike waveforms.

As mentioned in the previous sections, in most studies, spike sorting algorithms have been tested on simulated data so far, and therefore the effect of using different algorithms in decoding real signals has not been studied much. In this study, to evaluate the effect of using the proposed spike sorting method on the efficiency of the decoding algorithm, real data was used in which the aim was to decode the force applied by the rat's hand to a pedal continuously from the intra-cortical data of the primary motor area of the brain. After making the necessary preprocessing and extracting the neuronal firing rates by the spike sorting algorithms, the decoding of the signal was performed using the PLS regression method. The results of this study show the superiority of the spike sorting algorithm based on CWT using optimal wavelet parameters (i.e., OWP) compared to classical DWT or PCA-based spike sorting methods in decoding real intracortical data (Fig. 4).

Comparing the proposed algorithm with the WaveClus algorithm as the states-of-the-arts in spike sorting, we tried to show that the OWP algorithm is competitive due to its strength in optimally selecting CWT parameters in the feature extraction step, despite using the simple k-means method in the classification step. The results of the comparisons showed well this competitiveness and even in some cases the superiority of the proposed algorithm over WaveClus. Therefore, in later studies, by maintaining the feature extraction step of this algorithm, more efficient methods can be used for the classification step.

Distortion of recorded signals due to noise is one of the most important reasons for the decline in the performance of spike sorting algorithms. Noise can confuse the shape of the spikes and reduce the possibility of differentiation between them. In this study, in analyzing the real signals, we tried to reduce such errors as much as possible by using a wavelet denoising method.

Given that in the proposed algorithm, it is possible to select different types of mother wavelets, we applied some of the most widely used functions of mother wavelets on simulated datasets to see the effect of this choice on the output of the algorithm. The results show that the accuracy of the algorithm's performance, especially in the SNR (above 4.5), is not dependent on the waveform of the mother wavelet function (Fig. 3). This can be seen as a strength of this algorithm. However, we cannot easily generalize this result to all spike signals, because we used a limited number of spike waveforms in the study's simulated datasets. But since we tried to use a variety of typical extracellular spike templates, the generalization of this is not far off the mark. However, in the current study, the use of Symlets family and especially Sym7 on average showed better results. Due to the similarity of the shape and waveform of Symlet functions and spike waveforms, many functions of spike detection or spike sorting studies use these functions, and in this sense, the results of the current study are consistent with other studies.

Various studies in the field of decoding neural signals have examined different aspects of the recorded data so far. Some have used sorted spike information and some have used only detected multiple-unit spike data without sorting them. A comprehensive study was conducted in 2014 to show the effect of sorting on decoding output (Todorova et al., 2014). In that study, using the results obtained from four spike sorting algorithms, it was concluded that spike sorting will prevent the removal of useful information and will increase the performance of the method compared to multi-unit. Other articles have shown that when unsorted spikes are used, some useful information is missed, which reduces the performance (Ventura, 2008; Kloosterman et al., 2014). Research (Bansal et al., 2011) also showed that using the sorted spikes will result in better performance. Given that, in our study, we have focused on providing an algorithm for spike sorting because it is still important in much of the work done in this area to obtain information on individual neurons.

In this study, we tried to show that optimizing CWT parameters can improve the spike sorting performance and consequently improve neural decoding performance. These findings can be used in decoding studies of single-unit neuronal discharge information on a variety of topics in the field of neuroscience. However, due to the wide search range of the wavelet transform parameters for optimization, the current algorithm requires a relatively large computational time, so that like many other advanced spike sorting algorithms, it is not suitable for BCI online applications.

The coefficients obtained from the continuous wavelet algorithm, although highly redundant, instead provide a wider space for searching and finding optimal features for spike separation, which is a strength of this algorithm.

In contrast, the breadth of the search space can increase the computational cost and execution time of the algorithm compared to simpler methods, and therefore is not suitable for fast and online applications which can be considered as a disadvantage for this method. However, in many applications of neuroscience studies based on offline analysis, prolonging the execution time of this algorithm is not a disadvantage.

Another point to note about the limitations of the proposed method is that this optimization algorithm is designed to run on a computer processing system. Obviously, in applications where we need to implement all spike sorting processes on the hardware, the use of DWT will be much more cost-effective than the OWP algorithm in terms of processing. There is a trade-off between the simplicity of implementation and the performance of the algorithm, which we focus on in this study to increase the performance of the algorithm.

One of the topics that can be considered in future studies with the pure neuroscience approach in evaluating spike sorting methods is the study of the relationship between the features extracted from PMA neuronal spikes in different neuronal fire scenarios such as silence period, standard activation, or burst epoch.

In this study, the effect of spike sorting on the modulation of single-neurons was not investigated and our main focus in this study was to evaluate the effects of different sorting algorithms on the result of force signal decoding from all information of a neuronal

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population. The study of neuronal dynamic properties and their effect on the output of sorting as well as their physiological interpretation has not been performed in this study. Evaluating them can be effective in determining physiological relationships, neuronal classification, and functional characterization of the dynamical firing properties of the resulting PMA single neuronal units.

The bursting activity and the complex-spike problem have not been investigated in this study and our aim in this study was to further use the spike features and improve the spike separation based on the properties extracted from the optimized CWT.

In the case of long-term neuronal recordings, the relative shape of the recorded spikes may change and become unstable over time as the relative position of the electrodes and neuronal tissue may shift, and therefore clustering neural spike data over a long period is challenging (Shalchyan and Farina, 2014). On the other hand, using data that has been recorded in different sessions as single data can increase the classification error. One of the challenges of this study was the use of all recorded data during a single day as single data. This can make the registered spike waveforms non-stationary and thus erroneous in the process of selecting the optimal wavelet parameters. Therefore, we can expect that applying algorithms to integrated and short-term data will lead to better results. One straightforward solution to the problem of waveform changes, in the long run, is to divide the data into shorter time intervals, and in these short periods update the optimal wavelet parameters.

REFERENCES

Bansal AK, Truccolo W, Vargas-Irwin CE, Donoghue JP (2011) Decoding 3D reach and grasp from hybrid signals in motor and premotor cortices: spikes, multiunit activity, and local field potentials. J Neurophysiol 107:1337–1355.

Carmena JM, Lebedev MA, Crist RE, O'Doherty JE, Santucci DM, Dimitrov DF, Patil PG, Henriquez CS, et al. (2003) Learning to control a brain-machine interface for reaching and grasping by primates. PLOS Biol 1 e42.

Christie BP, Tat DM, Irwin ZT, Gilja V, Nuyujukian P, Foster JD, Ryu SI, Shenoy KV, et al. (2014) Comparison of spike sorting and thresholding of voltage waveforms for intracortical brain-machine interface performance. J Neural Eng 12 016009.

Gibson S, Judy JW, Marković D (2011) Spike sorting: The first step in decoding the brain: The first step in decoding the brain. IEEE Signal Process Mag 29:124–143.

Gupta R, Ashe J (2009) Offline decoding of end-point forces using neural ensembles: application to a brain-machine interface. IEEE Trans Neural Syst Rehabilitation Eng 17:254–262.

Hulata E, Segev R, Ben-Jacob E (2002) A method for spike sorting and detection based on wavelet packets and Shannon's mutual information. J Neurosci Methods 117:1–12.

Kandel ER, Schwartz JH, Jessell TM, Department of B (2000) Molecular Biophysics. In: Thomas J, Siegelbaum S, Hudspeth AJ, editors. Principles of neural science. New York: McGraw-hill.

Khorasani A, Beni NH, Shalchyan V, Daliri MR (2016) Continuous force decoding from local field potentials of the primary motor cortex in freely moving rats. Sci Rep 6:35238.

Khorasani A, Foodeh R, Shalchyan V, Daliri MR (2017) Brain control of an external device by extracting the highest force-related contents of local field potentials in freely moving rats. IEEE Trans Neural Syst Rehabilitation Eng 26:18–25.

Kloosterman F, Layton SP, Chen Z, Wilson MA (2014) Bayesian decoding using unsorted spikes in the rat hippocampus. J Neurophysiol.

Letelier JC, Weber PP (2000) Spike sorting based on discrete wavelet transform coefficients. J Neurosci Methods 101:93–106.

Ma X, Ma C, Huang J, Zhang P, Xu J, He J (2017) Decoding lower limb muscle activity and kinematics from cortical neural spike trains during monkey performing stand and squat movements. Front Neurosci 11:44.

Maragos P, Kaiser JF, Quatieri TF (1993) On amplitude and frequency demodulation using energy operators. IEEE Trans Signal Process 41:1532–1550.

Nenadic Z, Burdick JW (2004) Spike detection using the continuous wavelet transform. IEEE Trans Biomed Eng 52:74–87.

Pavlov A, Makarov VA, Makarova I, Panetsos F (2007) Sorting of neural spikes: when wavelet based methods outperform principal component analysis. Nat Comput 6:269–281.

Perge JA, Homer ML, Malik WQ, Cash S, Eskandar E, Friehs G, Donoghue JP, Hochberg LR (2013) Intra-day signal instabilities affect decoding performance in an intracortical neural interface system. J Neural Eng 10 036004.

Quiroga RQ, Nadasdy Z, Ben-Shaul Y (2004) Unsupervised spike detection and sorting with wavelets and superparamagnetic clustering. Neural Comput 16:1661–1687.

Rabbani H, Vafadoost M (2006) Wavelet based image denoising based on a mixture of Laplace distributions. Iran J Sci Technol Trans B Eng 30:711–733.

Rey HG, Pedreira C, Quiroga RQ (2015) Past, present and future of spike sorting techniques. Brain Res Bull 119:106–117.

Rutishauser U, Schuman EM, Mamelak AN (2006) Online detection and sorting of extracellularly recorded action potentials in human medial temporal lobe recordings, in vivo. J Neurosci Methods 154:204–224.

Shalchyan V, Farina D (2014) A non-parametric Bayesian approach for clustering and tracking non-stationarities of neural spikes. J Neurosci Methods 223:85–91.

Shalchyan V, Jensen W, Farina D (2012) Spike detection and clustering with unsupervised wavelet optimization in extracellular neural recordings. IEEE Trans Biomed Eng 59:2576–2585.

Soman KP (2010) Insight into wavelets: From theory to practice. PHI Learning Pvt. Ltd..

Todorova S, Sadtler P, Batista A, Chase S, Ventura V (2014) To sort or not to sort: the impact of spike-sorting on neural decoding performance. J Neural Eng 11 056005.

Vargas-Irwin C, Donoghue JP (2007) Automated spike sorting using density grid contour clustering and subtractive waveform decomposition. J Neurosci Methods 164:1–18.

Ventura V (2008) Spike train decoding without spike sorting. Neural Comput. 20:923–963.

Wang G-L, Zhou Y, Chen A-H, Zhang P-M, Liang P-J (2006) A robust method for spike sorting with automatic overlap decomposition. IEEE Trans Biomed Eng 53:1195–1198.

Wu W, Black MJ, Mumford D, Gao Y, Bienenstock E, Donoghue JP (2004) Modeling and decoding motor cortical activity using a switching Kalman filter. IEEE Trans Biomed Eng 51:933–942.

Wu W, Hatsopoulos NG (2008) Real-time decoding of nonstationary neural activity in motor cortex. IEEE Trans Neural Syst Rehabilitation Eng 16:213–222.

Yang Y, Mason AJ (2016) Frequency band separability feature extraction method with weighted Haar wavelet implementation for implantable spike sorting. IEEE Trans Neural Syst Rehabilitation Eng 25:530–538.

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