2018 7th IEEE International Conference on Biomedical
Robotics and Biomechatronics (Biorob)
Enschede, The Netherlands, August 26-29, 2018

Accuracy Optimization of the Spike Sorting Algorithm for Classification of Neural Signals

Emiliano Noce[1], Anna Lisa Ciancio[1] and Loredana Zollo[1]

Abstract— **The Spike Sorting is an algorithm that allows extracting peculiar features from the neural signals and uniquely identifying the neurons that contributed to the generation of the recording. The literature shows that researches on this topic do not pay the due attention to the optimization process of the algorithm parameters. Here, an optimization process based on the multimodality approach is presented. It was aimed to select the best set of features to increase the accuracy of classification of neural signals. Simulated recordings were used to validate the approach. We demonstrated that triplets of optimized features were able to discriminate among 10 classes with an accuracy of $\sim$ 95%; on the other hand, a fixed triplet reached an accuracy of $\sim$ 90%. Moreover, accuracy decay with respect to the classes was slower and surprisingly more predictable.**

I. INTRODUCTION

Spike Sorting Algorithm (SSA) is a well-known mathematical process that aims to identify from a neural recording the characteristics of the neurons nearby the recording site. It has been demonstrated that the shape of the action potential is influenced not only by the orientation and the distance w.r.t. the recording electrodes but also by the intrinsic features of the neurons, such as the dendritic tree and the distribution of the ion channels [1]. Knowing this kind of information can help better understanding the inner mechanism of the central and the peripheral nervous system.

The SSA includes three phases. The first one, called *spike detection*, aims to locate the action potentials inside the recording. The second phase is the segmentation of the spikes and the extraction of its peculiar and distinctive features. The third one involves machine learning algorithms in order to correctly classify, by means of the aforementioned features, the activity of the neurons.Despite the EMG signals represent the most adopted means to control an upper limb prosthesis in the last years the letterature showed an increased interest in the use of neural electrodes implanted in peripheral nerves to control prostheses with ENG signals and to provide tactile feedback to the amputees [2], [3], [4], [5], [6].

In the last decades, different research groups have analyzed real as well as simulated recordings with a fixed setting of all the parameters involved in the algorithm, such as the threshold for the spike detection of the features for the classification. For example, the spike detection is performed applying fixed amplitude threshold [7], [8], [9] or blindly selecting the features to extract from the signal [10], [11].

[1]Emiliano Noce, Anna Lisa Ciancio and Loredana Zollo are with Unity of Biomedical Robotics and Biomicrosystems, Università Campus Bio-Medico in Rome, Via Alvaro del Portillo 22, Rome, Italy e.noce, a.ciancio, l.zollo@unicampus.it

Template matching can be a solution to fit the parameters according to the characteristics of the recording [12], [13]. Convolving the signals with a template that resembles the action potential can help both the detection [14] and the classification phases [15]. Unfortunately, the process can be mathematically expansive and the shape of the action potential can vary from session to session, making the effort almost useless.

The problem of these approaches, in fact, is that they do not consider the possible variability of the informative content of the signal. It is implicitly assumed that the recordings from the same site generate an electrical activity with already known features. However, the shapes of the action potential depend on too many factors that are not possible to know before the first recording. Fixing the SSA parameters, then, can negatively impact the performance of the whole process, i.e. it may lead to low accuracies. It can even be cumbersome to identify manually a set of features that greatly fits the registrations. Finding a way to optimize the SSA can be paramount to achieve higher accuracy especially if it can be performed blindly, i.e. without knowing the characteristics of the neural recordings.

In this work, this problem is tackled searching for a reliable method that identifies the best set of features and rigorously increase the SSA performance, searching in rich and defined pool. Before the training of the classifier, a group of temporal features are extracted from the detected action potentials. From them, by means of a muldimodality test, the most discriminative ones are selected and used during the classification phase. This way, the user does not have to speculate which features better represent the recorded action potentials certain that he will achieve the greatest accuracy possible. The paper is structured as follows: in Section II the methods and the algorithms are presented, both for spike detection and for feature extraction; In Section III the results and the discussion will be depicted while the conclusions will be drawn in Section IV.

II. MATERIALS AND METHODS

A. Spike Detection

According to the model presented in [16], the action potentials closer to the recording site have a higher amplitude than the background noise. The task of identifying the firings inside the neural recording can be easily solved by means of an amplitude threshold that exploits the statistical characteristics of the signal, i.e. the mean (μ) and the standard deviation (σ). A simple amplitude threshold can then be computed as follows

$$Thr = \mu + N\sigma \tag{1}$$

where N is a constant that can vary from 2[8] to 5[9]. Based on the quality of the acquisition, the value of N can be negative when the spikes have a negative predominant peak [17].

Generally, the background noise is a zero-mean process, thus μ can be omitted. The standard deviation, highly sensitive to the presence of the action potentials, can be calculated from the *Median Absolute Deviation*[18] (MAD) to increase the robustness of the threshold as

$$\sigma \approx 1.4826MAD \tag{2}$$

where MAD is

$$MAD = median\big(|X - median(X)|\big). \tag{3}$$

Instead of using only a noisy segment of the signal, it is possible to use the whole recording. The SD computed by means of eq. (3) is less dependent on the sample size and the presence of outliers [19] that are, with respect to (w.r.t.) the background noise, the neural spikes.

The aim of the detection phase of the SSA is to reduce the number of False Positives (FPs), i.e. noisy segments of the signals with such an amplitude to overtake the threshold. Similarly, the number of False Negatives (FNs), i.e. the not correctly detected spikes, have to be as low as possible. In order to limit this problem, before thresholding, the signal can be manipulated to enhance the amplitude of the action potentials and lower the noise.

To this purpose, the *Non-linear Energy Operator* (NEO)[20] and the *Moving Average Algorithm* (MAA)[21], [22] will be used in this work.

The NEO algorithm considers that the neurons increase their amplitude in the time domains and spread their band in the frequency domain. The MAA, instead, takes into account the higher energy carried by the spikes.

NEO, in its digital formulation, is expressed as

$$Y[n] = x^2[n] - x[n-k] \cdot x[n+k] \tag{4}$$

where $x[n]$ is the signal and k is a tuning parameter that enhances a particular frequency of the signals f (w.r.t to the sampling frequency Fs) computed as $Fs/(4 \cdot k)$.

MAA is computed as

$$Y[n] = \frac{1}{W} \sum_{n-\frac{W}{2}}^{n+\frac{W}{2}} \big(x[n] - x_M\big)^2 \tag{5}$$

where W is the window in which the moving average is computed, $x[n]$ and x_M are the signal and its mean, respectively. MAAs behave as low-pass filters where the cut-off frequency is the inverse of the length of W. Lower Ws smoothen the signal less strongly, increasing the likelihood of detecting FPs. The opposite, instead, augments the chance of missing action potentials, i.e. more FNs.

TABLE I

SELECTED FEATURES. THE SPIKE IS REFERRED AS S. WFL AND WFLT ARE, RESPECTIVELY, WAVEFORMLENGTH AND WAVEFORMLENGTHTOT.

Name	Formulation	Note
MAV	$\frac{\sum S}{N}$	
Max	$max(S)$	
SlopePost	$\frac{S_{max} - S_{max+5}}{5}$	
MaxFirstDer	$max(\dot{S})$	
MinFirstDer	$min(\dot{S})$	
MaxSecDer	$max(\ddot{S})$	
MinSecDer	$min(\ddot{S})$	
SimilClass	$xcorr(Temp, S)$	Temp is an action potential randomly selected after Spike Detection phase
WFL	$\sum \lvert S_i - S_{i-1} \rvert$	
WFLT	$\sum \sqrt{\lvert S_i - S_{i-1} \rvert^2 + 1}$	
a		Minor radius of the ellipse of the feature cluster
b		Major radius of the ellipse of the feature cluster

B. Feature extraction and classification

Several features and approaches were identified during the last decades to discern the shapes of different action potentials. Both temporal[10] and wavelet features[18] as well as Principal Component Analysis (PCA) [23] were employed with success. In this work, temporal features are chosen due to the simplicity of their computation. In Table I, the list of the features adopted in this work is presented.

A Support Vector Machine (SVM) in its 1-vs-1 configuration[24] and with a RBF kernel has been chosen as pattern recognition algorithm. It was implemented using the library *libSVM 3.22*, available online and free to use. Each set of features was divided randomly into a Training Set (TrS) and a Testing Set (TS). SVM was trained by means of the TrS (80% of the data) and tested with the TS (20% of the data). This procedure was applied 50 times for each simulation and the accuracy was computed each time the procedure was performed.

C. Simulated recordings

The optimization of the spike sorting algorithm will be performed using a dataset of simulated neural recordings available at `http://www135.lamp.le.ac.uk/hgr3/`. The dataset is made of 95 simulations in which it is possible to classify from 2 to 20 different action potentials. They are generated with a sampling frequency of 96 kHz and downsampled to 20 kHz. The signals are filtered between 300 and 6000 Hz. Along with the shape of the spikes, the dataset provides their exact positioning; this makes it a good tool to test this type of algorithms. More details about the rationale of the simulations can be found in [16]. An example of a simulated recording is shown in Fig. 1.

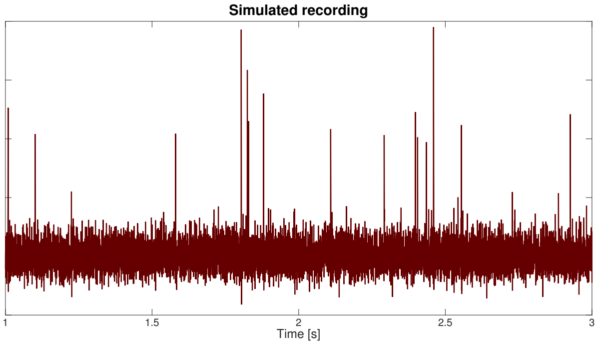

Fig. 1. Example of 2 seconds of a simulated neural recording (i.e. nr. 22).

D. Data analysis

The best spike detection approach guarantees the highest number of Real Positives (RPs) w.r.t. the number of FPs erroneously collected. Hence, ten simulated signals are randomly selected from the database and segmented in order to have 1000 action potentials each. The best spike detection algorithm is selected among: i) the Plain threshold, applying the eq. 1; ii) the NEO with parameters k = 1, 3 and 5 (respectively 6000, 2000 and 1200 enhanced frequencies); iii) the MAA with the length of the window of 48, 72 and 96 samples. Considering the selected values in this analysis, with a sampling frequency of 24 kHz, $48 - 96$ samples correspond to $2 - 4$ ms.

The choice of the triplet of features for each simulated recording will be automatically performed by means of a multimodality test, in particular the Lilliefors modification of the Kolmogorov-Smirnov Test. The Multimodality Score (MS) is expressed as

$$MS_{feat} = max(|F_{feat} - G_{feat}|) \tag{6}$$

where the F is the the cumulative distribution function and the G is the Gaussian distribution with the same mean and variance.

The MS value was computed from each set of feature and the three higher values identify the *best triplet*.

The comparison is carried out with a *reference triplet*, composed of the Maximum of the First Derivative and the Maximum and the Minimum of the Second derivative as in [10]. The reference triplet was selected as it showed good performance and ease of calculation also in an implantable neuroprosthetic device [25]. The reference triplet was not changed through the analysis. Three features were used for the easiness to represent them in a 3D space and to be consistent with [10] from which the *reference triplet* was selected.

Data were analyzed in Matlab 2014b on a Mac OSX environment.

III. RESULTS AND DISCUSSIONS

A. Spike detection

The results of the spike detection phase are presented in Table II. As it can be noted, the *NEO* allows achieving the best results in terms of RPs, but undoubtedly it is the worsts if FPs are taken into account. The main problem of the NEO is that parameter k has to be selected w.r.t. to the main frequency of the neural recording. This information may vary from recording to recording. Conversely, the *MAA* requires only that the duration of the action potentials is given.

TABLE II
RESULTS OF THE SPIKE DETECTION PHASE

Method	RP	FP
Plain Threshold	836.6 ± 61.6	53.4 ± 21.1
$NEO_{k=1}$	868.4 ± 65.3	263.9 ± 86.7
$NEO_{k=3}$	872.6 ± 53.2	176.4 ± 108.7
$NEO_{k=5}$	849.2 ± 53.8	82.4 ± 67.8
$MAA_{W=48}$	840.8 ± 42.3	43.0 ± 17.4
$MAA_{W=72}$	808.6 ± 92.1	25.2 ± 12.8
$MAA_{W=96}$	765.8 ± 49.5	30.2 ± 11.7

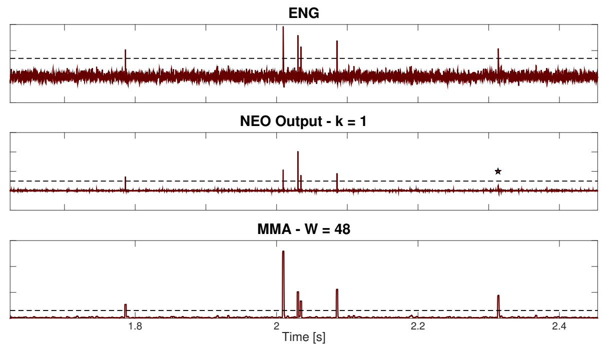

Fig. 2. Output of the *NEO* and the *MAA* related with the original signal. The dashed line is the applied threshold. The star represents the missed spike due to a bad tuning of the parameter k for the computation of the *NEO* output.

Information about the frequency content is difficult to obtain before or during the acquisitions, thus it may be complicated to tune the NEO accordingly, to maximize its performance. An example of this issue is shown in Fig. 2. It is possible to see that a spike that could be easily detected from the original signal or from the MAA output is lost after the NEO processing. This happened because parameter k was not sensitive enough to enhance the presence of that action potential. For the not-processed ENG, the threshold was computed as 4 times the SD. For both the MAA and the NEO, the N value is higher and set as 9. The SD was calculated as in eq. 2.

Using the *MAA* was easier and brought good results. As it is possible to see in Tab. II the number of FPs is dramatically lower than the ones collected with the *NEOs*. Comparing the number of FPs obtained with the two algorithms, the NEO allows obtaining better results (i.e., a high number of RPs) even if the differences are not remarkable as for the FPs. The best in terms of RPs, in fact, is the worst in terms of FPs ($NEO_{k=5}$). Thus, we can say that the *MAA* permits to increase the performance of the spike detection phase better than *NEO*, since the former detects less FPs. For this reason, the following feature extraction and classification

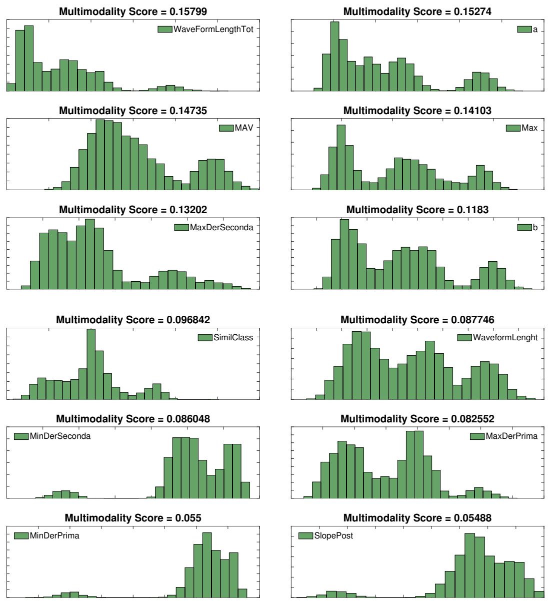

Fig. 3. Representation of the distribution of the 12 features from the highest to the lowest Multimodality Score. The simulated recording was characterized by 6 different neurons.

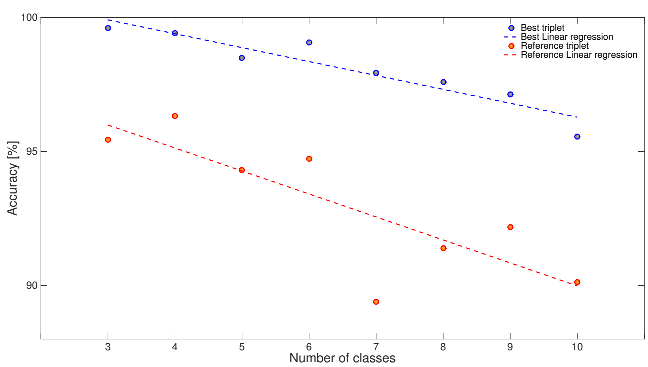

Fig. 4. Comparison between the accuracy obtained with the best (in blue) and the reference (in red) triplets.

are performed implementing the $MAA_{w=48}$ in the spike detection block.

B. Classification

As in [26] it is shown that the spike sorting algorithm is able to correctly identify no more than 8 - 10 different neurons, here the number of different neurons in the simulations ranged from 3 to 10.

In Fig. 3, an example of the features distribution for a simulated neural recording is shown. *WaveformLengthTot*, *MAV* and *a* represent the best triplet in that specific case. The pattern recognition algorithm, then, was trained by means of these features, assuring the highest possible accuracy. Finally, in Fig. 4 the results of the classification algorithm are shown. The best triplets are always better than the reference triplets, even though the number of classes is lower (Nclasses = 3). In fact, accuracy is 99.60% for the best triplet and is 95.44% for the reference triplet. For 10 classes the accuracy of the *best triplet* is 95.56%, while is about five points lower (90.13%) for the *reference triplet*.

Moreover, the Least Square method highlights that the data points correlate better for the best case w.r.t. the reference case (R^2 = 0.88 vs R^2 = 0.66). If the increase of accuracy could be expected, the improved correlation with a linear trend was less predictable. The optimization, in fact, improves the prediction of the algorithm behaviour when the number of classes increases. Furthermore, if we take into account how the accuracy decays when the number of classes increases, optimized feature selection gives more robust results w.r.t. to a not optimized set. Taking into account the angular coefficient of the linear regression, the best triplets decay in terms of accuracy is slower than the reference ones (m = -0.52 vs. m = -0.86).

The *a priori* selection of the features is problematic because of the variability of the shape of the action potential, due to intrinsic and extrinsic factors [1]. The temporal features takes into account the shape of the spikes. Different neurons can fire with similar action potentials and the values of a particular features may be alike and, thus, not appropriate for separating them. Trying to identify the most discriminative features can dramatically increase the chances of better separating spikes with similar shapes. Even if it is necessary to extract more information from the recordings (in this case 12 features versus the more canonical 3), the process does not harm an online application of this method. In fact, the training phase can be performed off-line, and once the best features are found, the on-line algorithm can be arranged to extract only the best triplet for the neural signals.

IV. CONCLUSIONS

In this paper, the optimization of the SSA was performed. Firstly, the best processing algorithm was found to increase the chance of detecting the highest amount of RPs and the lowest of FPs between the NEO and the MAA, opting for the latter due to the better results. Even if the number of RPs collected by the MAA is lower, the amount of FPs is greatly reduced ($\sim$ 82 vs $\sim$ 43). Secondly, a multimodality test was applied on a set of 12 features to find the best triplet to maximize the accuracy of the pattern recognition algorithm. The optimized set of features, in fact, increases accuracy of $\sim$ 5% w.r.t. the reference triplet up to 10 classes.

We demonstrated that this approach enhances the performance of the pattern recognition in terms of accuracy, rate of decay, and predictability of the outcome when the number of classes increases.

Moreover, the choice of the best triplet does not harm a possible on-line application since the training phase, i.e. the one that identifies the best set, can be performed off-line. During an on-line application, the algorithm can be set accordingly to extract the features that are considered as the best ones.

The paper, however, exploits only a dataset of simulated recording and it is a limiting factor since that the results are biased from these signals. In the future, the authors intend to record real neural data during the execution of motor commands to strenghten these findings and tune the algorithm with the aim to increase the accuracy. Once real neural recordings are acquired, it will be possible to verify if the approach is invariant to the noise generated by the instrumentation or by the muscles. But, since the choice of the features is not fixed but regulated by a mathematical approach, we are confident that these disturbances can be compensated. Moreover, the authors want to implement these algorithms in a more performing language such as C or Python to speed up the process and exploit, especially for the latter, the capabilities of Deep Learning.

V. Acknowledgement

This work was supported by the National Institute for Insurance against Accidents at Work (INAIL) with PPR2 project "Control of upper-limb prosthesis with neural invasive interfaces" (CUP: $E58C13000990001$), with PPR AS $1/3$ project "Implantable System for the control of an upper-limb prosthesis with invasive wireless neu-ral interfaces" and PCR $1/2$ project "New methods in the treatment of limb amputation, finalized to the application of bionic prostheses" (CUP: $E57B16000160005$).

References

[1] C. Gold, D. A. Henze, C. Koch, and G. Buzsaki, "On the origin of the extracellular action potential waveform: a modeling study," *Journal of neurophysiology*, vol. 95, no. 5, pp. 3113–3128, 2006.

[2] S. Raspopovic, M. Capogrosso, F. M. Petrini, M. Bonizzato, J. Rigosa, G. Di Pino, J. Carpaneto, M. Controzzi, T. Boretius, E. Fernandez *et al.*, "Restoring natural sensory feedback in real-time bidirectional hand prostheses," *Science translational medicine*, vol. 6, no. 222, pp. 222ra19–222ra19, 2014.

[3] A. L. Ciancio, F. Cordella, R. Barone, R. A. Romeo, A. D. Bellingegni, R. Sacchetti, A. Davalli, G. Di Pino, F. Ranieri, V. Di Lazzaro *et al.*, "Control of prosthetic hands via the peripheral nervous system," *Frontiers in neuroscience*, vol. 10, p. 116, 2016.

[4] R. Barone, A. L. Ciancio, R. A. Romeo, A. Davalli, R. Sacchetti, E. Guglielmelli, and L. Zollo, "Multilevel control of an anthropomorphic prosthetic hand for grasp and slip prevention," *Advances in Mechanical Engineering*, vol. 8, no. 9, p. 1687814016665082, 2016.

[5] A. L. Ciancio, F. Cordella, K.-P. Hoffmann, A. Schneider, E. Guglielmelli, and L. Zollo, "Current achievements and future directions of hand prostheses controlled via peripheral nervous system," in *The Hand*. Springer, 2017, pp. 75–95.

[6] E. Noce, C. Gentile, F. Cordella, A. Ciancio, V. Piemonte, and L. Zollo, "Grasp control of a prosthetic hand through peripheral neural signals," in *Journal of Physics: Conference Series*, vol. 1026, no. 1. IOP Publishing, 2018, p. 012006.

[7] C. Pouzat, O. Mazor, and G. Laurent, "Using noise signature to optimize spike-sorting and to assess neuronal classification quality," *Journal of neuroscience methods*, vol. 122, no. 1, pp. 43–57, 2002.

[8] P. Horton, A. Nicol, K. Kendrick, and J. Feng, "Spike sorting based upon machine learning algorithms (soma)," *Journal of neuroscience methods*, vol. 160, no. 1, pp. 52–68, 2007.

[9] M. Chiappalone, A. Novellino, I. Vajda, A. Vato, S. Martinoia, and J. van Pelt, "Burst detection algorithms for the analysis of spatio-temporal patterns in cortical networks of neurons," *Neurocomputing*, vol. 65, pp. 653–662, 2005.

[10] S. E. Paraskevopoulou, D. Y. Barsakcioglu, M. R. Saberi, A. Eftekhar, and T. G. Constandinou, "Feature extraction using first and second derivative extrema (fsde) for real-time and hardware-efficient spike sorting," *Journal of neuroscience methods*, vol. 215, no. 1, pp. 29–37, 2013.

[11] A. M. Kamboh and A. J. Mason, "Computationally efficient neural feature extraction for spike sorting in implantable high-density recording systems," *IEEE transactions on neural systems and rehabilitation engineering*, vol. 21, no. 1, pp. 1–9, 2013.

[12] A. Diedrich, W. Charoensuk, R. J. Brychta, A. C. Ertl, and R. Shiavi, "Analysis of raw microneurographic recordings based on wavelet de-noising technique and classification algorithm: wavelet analysis in microneurography," *IEEE Transactions on Biomedical Engineering*, vol. 50, no. 1, pp. 41–50, 2003.

[13] S. Kim and J. McNames, "Automatic spike detection based on adaptive template matching for extracellular neural recordings," *Journal of neuroscience methods*, vol. 165, no. 2, pp. 165–174, 2007.

[14] A. Salmanpour, L. J. Brown, and J. K. Shoemaker, "Spike detection in human muscle sympathetic nerve activity using a matched wavelet approach," *Journal of neuroscience methods*, vol. 193, no. 2, pp. 343–355, 2010.

[15] P. M. Rossini, S. Micera, A. Benvenuto, J. Carpaneto, G. Cavallo, L. Citi, C. Cipriani, L. Denaro, V. Denaro, G. Di Pino *et al.*, "Double nerve intraneural interface implant on a human amputee for robotic hand control," *Clinical neurophysiology*, vol. 121, no. 5, pp. 777–783, 2010.

[16] J. Martinez, C. Pedreira, M. J. Ison, and R. Q. Quiroga, "Realistic simulation of extracellular recordings," *Journal of neuroscience methods*, vol. 184, no. 2, pp. 285–293, 2009.

[17] D. A. Adamos, E. K. Kosmidis, and G. Theophilidis, "Performance evaluation of pca-based spike sorting algorithms," *Computer methods and programs in biomedicine*, vol. 91, no. 3, pp. 232–244, 2008.

[18] R. Q. Quiroga, Z. Nadasdy, and Y. Ben-Shaul, "Unsupervised spike detection and sorting with wavelets and superparamagnetic clustering," *Neural computation*, vol. 16, no. 8, pp. 1661–1687, 2004.

[19] C. Leys, C. Ley, O. Klein, P. Bernard, and L. Licata, "Detecting outliers: Do not use standard deviation around the mean, use absolute deviation around the median," *Journal of Experimental Social Psychology*, vol. 49, no. 4, pp. 764–766, 2013.

[20] K. H. Kim and S. J. Kim, "Neural spike sorting under nearly 0-db signal-to-noise ratio using nonlinear energy operator and artificial neural-network classifier," *IEEE Transactions on Biomedical Engineering*, vol. 47, no. 10, pp. 1406–1411, 2000.

[21] U. Rutishauser, E. M. Schuman, and A. N. Mamelak, "Online detection and sorting of extracellularly recorded action potentials in human medial temporal lobe recordings, in vivo," *Journal of neuroscience methods*, vol. 154, no. 1, pp. 204–224, 2006.

[22] E. Noce, L. Zollo, A. Davalli, R. Sacchetti, and E. Guglielmelli, "Experimental analysis of the relationship between neural and muscular recordings during hand control," in *Biomedical Robotics and Biomechatronics (BioRob), 2016 6th IEEE International Conference on*. IEEE, 2016, pp. 1104–1109.

[23] E. Wood, M. Fellows, J. Donoghue, and M. Black, "Automatic spike sorting for neural decoding," in *Engineering in Medicine and Biology Society, 2004. IEMBS'04. 26th Annual International Conference of the IEEE*, vol. 2. IEEE, 2004, pp. 4009–4012.

[24] C.-W. Hsu, C.-C. Chang, C.-J. Lin *et al.*, "A practical guide to support vector classification," 2003.

[25] M. Zamani and A. Demosthenous, "Feature extraction using extrema sampling of discrete derivatives for spike sorting in implantable upper-limb neural prostheses," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 22, no. 4, pp. 716–726, 2014.

[26] C. Pedreira, J. Martinez, M. J. Ison, and R. Q. Quiroga, "How many neurons can we see with current spike sorting algorithms?" *Journal of neuroscience methods*, vol. 211, no. 1, pp. 58–65, 2012.