A Review on Different Algorithms and Methods used for Neural Spike Detection

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Abstract – *Identification of neural spike activities has been a challenging task for a researcher which is a prerequisite for understanding various types of brain function. Computing the activities of each neuron with maximum accuracy can be a tricky task since the acquired signal form neurons have large amount of noise, therefore it becomes difficult for detection. This article reviews various algorithms and different techniques used for detection and classification of neural spike sorting. The article firstly shows the challenges faced for the measurement of neural activities and preliminary issues of signal detection and classification. Further this paper reviews and demonstrates algorithms and methods that have already been applied to various spike sorting problems. Also the advantages and limitations of each algorithm and methods along with its applicability have been discussed in this paper.*

Key Words: Neural Spike, monitoring, Detection, human brain,

1. INTRODUCTION

One of the latest research in today's era is monitoring and studying neural activities of human brain. This research is the most challenging, upcoming and interesting field of biomedical engineering. This technology dig out all the hidden and useful information from nervous system. This may help various patients such as empowering amputees to control advanced prosthetic limbs. Other medical applications like treatment of epilepsy, paralysis and various other disorders have been recorded and demonstrated as well. Apart from all this neural activities are being interfaced with human brain which is called as brain computer interfacing (BCI) system. Presently neural probes providing more than 1000 arrays of information has been recorded as neural activities happening inside the brain [1]. Whenever the neural activities are occurring inside the brain an electrical signal is produces along the scalp of head. These signals consist of many hidden information along with huge amount of noise which produces a neural spike which can be detected with a proper signal processing technique

[2].Moreover these signals transferred from neuron to electrode are weak in nature also they gets reshaped in terms of amplification because of the characteristics of transfer path [3].

The neurophysiologist may wish to sorting neural signal acquired by assigning a particular spike to a particular neuron which is fully dependant on the goals of the experiment and it may also have some level of reliability. In most of the cases a simple hardware setup with single microelectrode are used for single unit activity [4]. However neural activities to be measured for single neuron is pretty challenging task, since there is lot of noise involved due to other neural activities whose signals may be similar in shape and size. Again some easy approach like threshold detection can distinguish the experimental results of each neuron which has large action potentials [5]. In most of the cases the experimental result can be improved using software based spike sorting algorithms. This paper provides a useful review of different methods developed for this purpose. Various researchers have used spike sorting method to study neural populations. In few cases the measurement of population activity using multiple electrodes which are placed far enough apart from each other that the signals of each neuron does not interfere others signal. And using this method spike activities can be measured on individual channel [6]. Also auto classification can greatly reduce the time which is required to measure such activity and also the accuracy of measurements can be improved. An added benefit of spike sorting is that it is likely to learn limited populations of neurons that are too close to permit segregation by conventional practice. If the activity of numerous neurons can be measured with a solitary electrode, it is probable with spike sorting to precisely assess the neural activity, even in cases when two or more neurons fire at the same time. This ability is particularly vital for experimental investigations of neural codes that use spike timing [7].

This review article is framed as follows, firstly we will discuss about the basic problems and issues which are involved for reliable measurement of neural activities. Next the article will review on various techniques used for detection of neural activities along with their advantages and disadvantages. Finally the article will end by concluding some of the current directions of research are this area and their challenges.

2. MEASUREMENT OF NEURAL ACTIVITIES

The initial step required for studying the neural signal is to detect action potentials between various noise sources and brains background activities. These action potentials are usually called as spike signals which demonstrate all the physical activities of either brain or any other organs. The amount of transmitted data and errors which are caused due to neighboring cells can be reduced with the help of spike detection techniques which has became a major area of research in the field of neuroscience and neural prosthetics applications. The block diagram of implantable neural signal recording system is shown in figure 1, where the preprocessor which detects the neural signal spikes, sorts them and also reduces the dimension of transmission data is also indicated in figure 1.

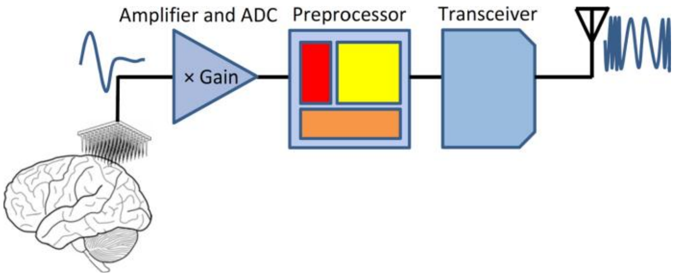


Figure -1: Neural Signal Recording System

Practically the neural signal recording system works in an electrically noisy surrounding where detection of spike signal is very difficult. Further the system also needs to adjust solely when the surrounding environment changes without human intervention. The spike signals in noisy surroundings are detected using various algorithms having their advantages and disadvantages [8]. Traditionally various researchers used to extract different features of neural signals [9]. Although these researchers were skillful but the surrounding environmental situations may cause fake results. Further if the neural signals are investigated by human beings then it consumes much more time [10]. Therefore computerized methods have been proposed for detection of spike signals. Further it is notable that existing computerized techniques for neural spike detection needs initial patient training on how strong processors located out of the patients body [11].

A number of computerized processing techniques have been initiated and applied to spike detection systems. The most popular and widely used technique is amplitude thresholding. This technique simply relies on the amplitude of the received signal without any pre or post processing. This technique is attractive because of its simplicity and ease in hardware implementation, but is vulnerable to noisy signals [12] Artificial neural networks (ANN) are the other alternative for adaptive spike signal detection. ANN methods are used in different areas of biomedical signal processing and efficiently improve the detection algorithms but they have the drawbacks of pre-training and difficult hardware realization [13]. There are other algorithms based on the energy of the signals for spike detection. These techniques consider that within the same time intervals, the energy of the spike is greater than that of the noise [14]. One of the popular and simple methods to extract a spike signal out of a noisy signal is a nonlinear energy operator (NEO) which is based on the energy disparity between spike and noise in a sample interval. Since this technique demonstrates high efficiency and accuracy in detecting the action potentials, and because of its simplicity, it gathers more attention than other methods. In this method, a semi-constant coefficient is used to scale the threshold. The accuracy of this method is strictly dependent on accurate selection of that coefficient.

2.1 PROBLEMS IN SPIKE SORTING

The basic problem of spike sorting is shown in figure 2. After taking a look at the waveform it can be observed that the waveform is not uniform and there are many action potentials. So the basic problem arises that are there several different neurons? If yes, then how to establish an conclusion? Further it can be seen that the waveform is full of noise which could due to the use of amplifier or some small spikes from other neurons located in the same local region. So the big question arises that how can we reliably classify individual neurons in the presence of such background noise? Another remark can be seen that spikes of different cells overlap each other. Therefore how do we classify these overlapping signals? To find out the answers we will discuss firstly a simple algorithm and further will discuss such other challenges [15].

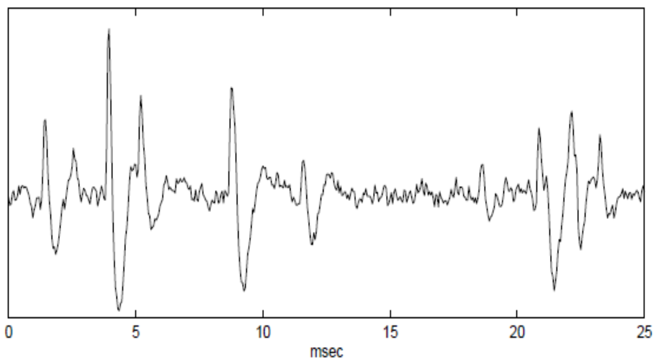


Figure -2: Sample Neural Signal from

2.2 THRESHOLD DETECTION

Ideally, the spikes of the waveform are related with the activity of neuron located in a local population. But this method is not useful since spikes at different instant of times are different also some of the neurons produces various different action potentials due to which the shape of signal changes. In many neurons the most important feature of spike signal is its magnitude or it can also be referred as the height of spike [16]. One of the easiest ways to measure this activity of neuron is with the help of voltage threshold trigger which is recorder with the help of recording electrodes. The electrodes records the spikes generated by a neuron which is of interest and is separated from background noise. The pulse signal is generated whenever neural activity is triggered beyond the threshold value of voltage [17]. But this method is the most common way to measure neural activity. The main advantage is that it requires very less hardware setup further coding required is also not complicated. The big disadvantage is that it is not possible to achieve acceptable isolation. This isolation can be tested just by observation of overlaid spiked as can been seen from figure 3. Figure 3 (a) reflects an example of properly isolated neuron signals and figure 3 (b) resembles an example of poorly isolated example. It can be observed that figure 3 (a) still has some background noisy spikes which has minor effect on quality of isolation whereas figure 3 (b) has two different spike shapes and it is not possible to select a threshold value of isolation [18].

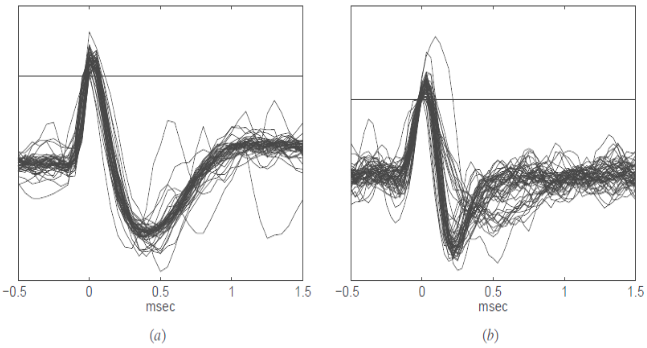


Figure -3: neuron signal with and without proper isolation

3. DETECTION OF MULTIPLE SPIKE SHAPES

In threshold detection spike analysis had many limitations since it was just able to detect as per the height or magnitude of voltage spike obtained from electrode. But it is the simplest and faster method of doing analysis with unfortunate limitations [19]. Detection of simultaneous multiple spikes shapes will be reviewed in this section starting from a very simple algorithm and ending on a very well built up algorithm.

3.1. FEATURE EXTRACTION

The wave shape shown in figure 3 clearly shows two action potentials nearly having equal magnitude but different frequency i.e. different wave shapes. If this some statistical characteristics are determined of each wave shape then it is possible to classify each spike differently. Now the main question arises that how to determine the statistical characteristics? The best solution is to determine the spike height and width or to find magnitude to magnitude value. These techniques by far are the oldest methods of spike sorting. These methods were mostly chosen since it gave the better discrimination with minimum sets of features [20]. Further it may be noted that for improving the accuracy of discrimination more amount of features can be extracted using any of the signal processing techniques available. Figure 4 shows the clear classification of neuron spikes where each spike width shows some different neuron characteristics.

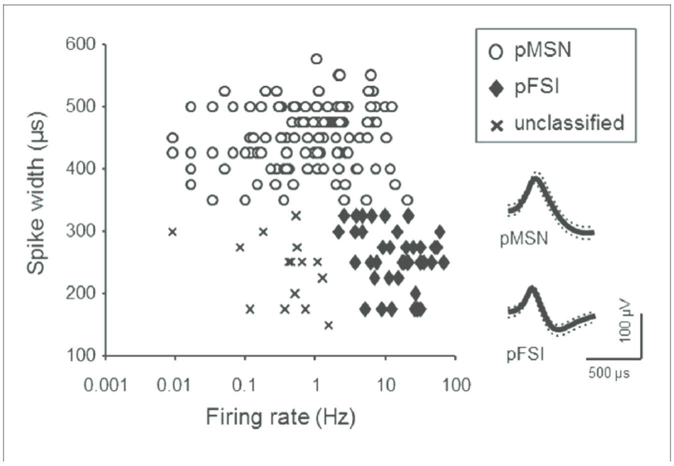


Figure -4: Scatter plot

Here it is observed that there are two different clusters which have different spike width for different firing rate which overlaps each other so again the question arises that how do we sort different spikes. For that a simple solution is using cluster cutting technique [21]. In this technique boundaries are defined for a particular set of data features. If the sample data set falls inside that boundary then it is classified or discriminated. If any sample features falls beyond that data sets then it can be removed.

For offline analysis, cluster boundaries are determined after different sets of data have been collected and analyzed. Whereas for online analysis the data is analyzed while the data is being collected, this is only possible if the data sets of clusters are stable. Again one of the important question remains is that what happens if some bad features are selected for classification? The answer is to perform principal component analysis where features are selected automatically based on the nature of signal wave shapes [22].

3.2. CLUSTER ANALYSIS

For determining multidimensional data sets cluster analysis is done. Cluster analysis also classifies the data based on the cluster determined. The basic idea underlying is that all the results from different independent classes can be described by its relatively simple model and this idea is best in case of spike sorting of different neurons [23]. The first task of clustering is to describe both the cluster location and the variability of the data around that location. The second task is, given a description of the clusters, to classify new data. Various researchers have discussed many methods for clustering [24]. The very simplest approach is the use of neareast – neighbor of k-means clustering, where the location of clusters is fixed for each data type. And when a spike is recorded then its features are compared with the closest mean using Euclidean distance. A sample spike classification with separate boundaries is shown in figure 5. Here all the lines inside figure are indicated as the decision boundary lines for nearest neighbor clustering

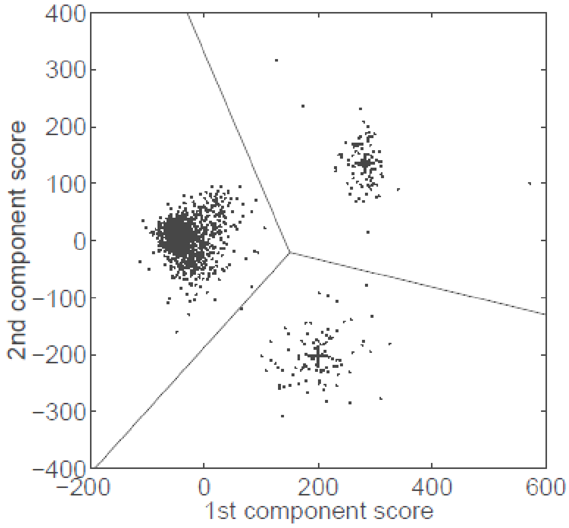


Figure -5: Decision Boundaries for nearest – neighbor clustering

Classification in this manner is possible and appropriate when the distribution of data is within the cluster and all are well separated from each other. But when the cluster overlaps then it is impossible to classify using this technique.

3.3. BAYESIAN CLUSTERING AND CLASSIFICATION

The most common method of clustering is by modeling each cluster with multivariate Gaussian. Thus Gaussian is centered on the cluster which is given by

$$p(x|c_k, \mu_k, \Sigma_k) \quad \text{.....................} \quad (1)$$

Where,
x is the spike data vector and μ_k and Σ_k are the mean and covariance matrix for class c_k.

3.3.1. BAYESIAN CLUSTERING

The application of Bayesian clustering showing three sigma error contour is shown in figure 6. Where figure 6 (a) shows four different clusters where one cluster overlaps other cluster and the line indicates the Bayesian decision boundaries. Whereas figure 6(b) shows the data sets of nine clusters and the line below all the clusters is the three sigma error contour of the largest cluster [25].

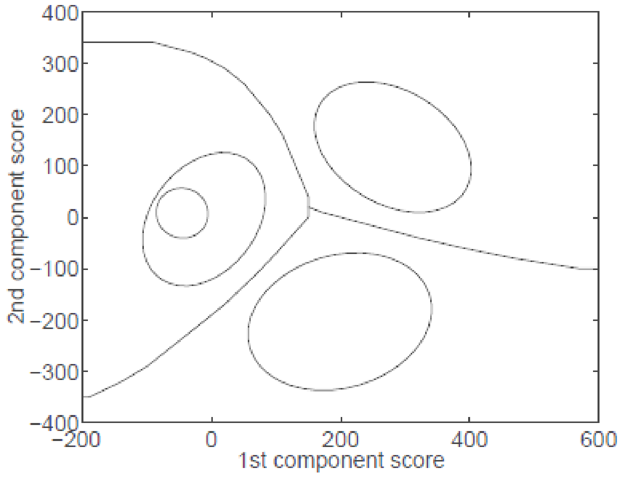


Figure -6 (a): Application of Gaussian Clustering to Spike Sorting for four clusters

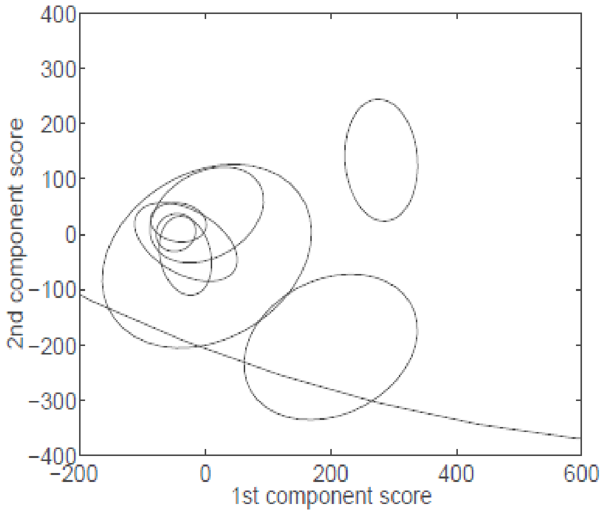
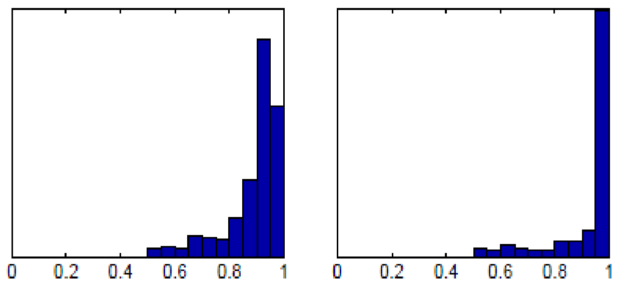


Figure -6 (a): Application of Gaussian Clustering to Spike Sorting for Nine clusters

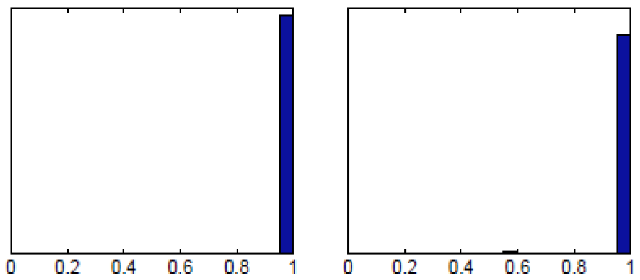
3.3.2. BAYESIAN CLASSIFICATION

The main benefit of Bayesian framework is that it provides the possibility to quantify the certainty of classification which provides an additional useful aid for isolating the spikes in various different clusters. The probability of spike which can be classified in well defined cluster generates a peculiar probability of each cluster [26]. By observing the distribution of probabilities it is possible to gain some idea that how all clusters are separated from each other. The histogram shown in figure 7 provides the distribution of probabilities for most probable class of the data sets.



(a) Class 1 (b) Class 2

Figure -7 (a): Application Histograms of the probability of the most probable class for the data.



(c) Class 3 (d) Class 4

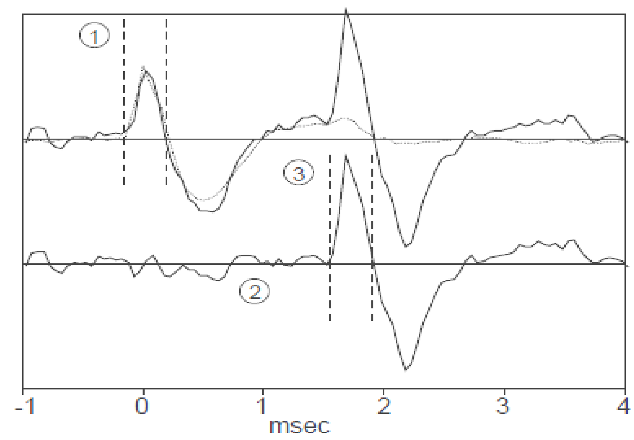
Figure -7 (b): Application Histograms of the probability of the most probable class for the data.

. In classes 3 and 4, nearly all of the data have probability equal 1.0, indicating that these points are assigned to their respective clusters with near certainty. For classes 1 and 2, only 26% and 68% of the points, respectively, have a class conditional probability greater than 0.95. This type of measure is particularly useful for monitoring the quality of the isolation during a prolonged period. A drop in isolation quality can indicate background noise or electrode drift.

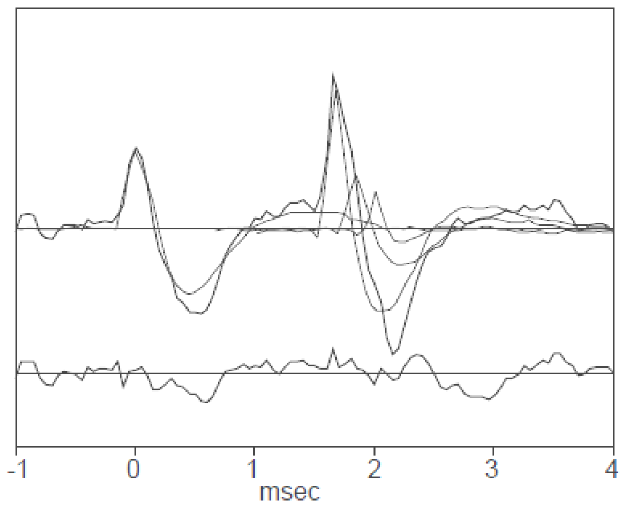
3.4. OVERLAPPING SPIKES

Among all the methods discussed earlier none of the method is capable to detect the neural spike when two spikes overlap each other. On other hand if the features of spikes are separated from each other sufficiently in time then it is possible to adopt one of the methods mentioned earlier in this review paper. With the hybrid approach of cluster cutting and Bayesian classification it is possible to investigate the cluster with very bad overlaps. This enables the researchers not to compromise results. There are many other situations where both detection and accuracy is desired for overlapping action potentials. So in order to classify the event properly the simplest method is to subtract a spike from the wave form when it is classified as an event.

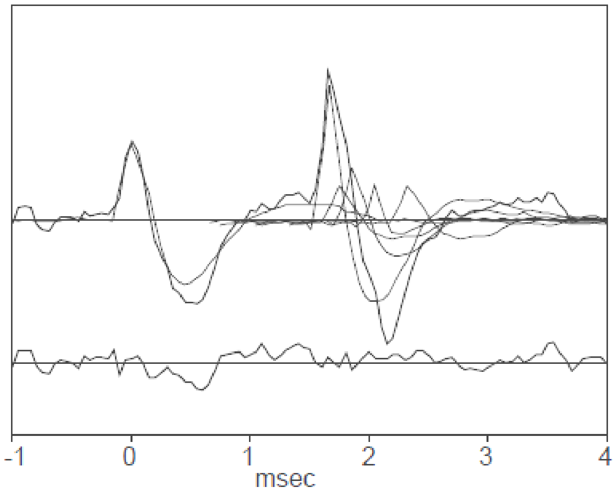
With an understanding that it will help to improve the classification of subsequent spikes. But this method can introduce noise when the spike is subtracted from the wave form. Another method is to use neural network where it learns all the boundary conditions and give proper classification [27]. However, is that the network must be trained using labelled spikes; thus the decision boundaries that are learned can only be as accurate as the initial labelling. Like the subtraction methods, these methods can only identify overlaps that have identifiable peaks. The overlap decomposition algorithm of [28] is illustrated in figure 8. The first step is to find a peak in the extracellular waveform. A region around the peak (indicated by the dashed lines) is selected. These data are classified with the k-dimensional tree which returns a list of spike sequence models and their relative probabilities. Each sequence model is a list of spikes (possibly only a single spike) and temporal positions relative to the waveform peak. The residual waveform (the raw waveform minus the model) of each remaining model is expanded until another peak is found



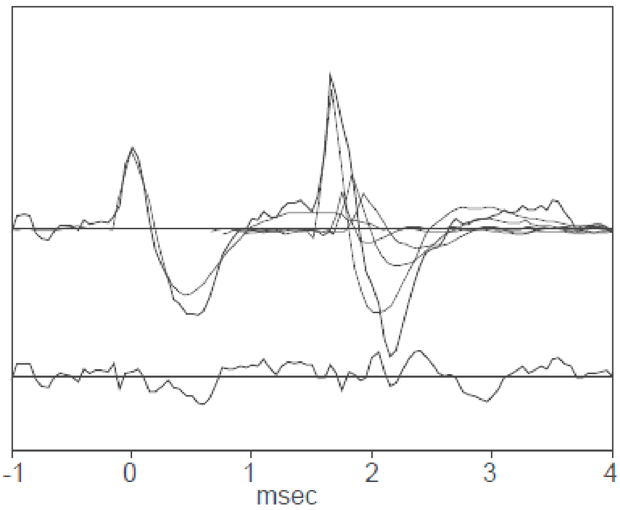
(a)



(b)



(c)



(d)

Figure -8: Overlap decomposition method.

4. CONCLUSIONS

An early comparison of feature-based methods was done by Wheeler and Heetderks who concluded that template-matching methods yielded the best classification accuracy compared to spike-shape features, principal components, and optimal filters. Lewicki compared template-based, Bayesian clustering and classification to the commercial package Brainwaves, which relied on the user to define the two-dimensional cluster boundaries by hand. The methods gave similar results for well separated clusters, but the Bayesian methods were much more accurate for spike shapes that were similar. Template-based methods can fail for neurons that burst and can become increasingly inaccurate if there is electrode drift. The cluster grouping method of Fee et al gives better classification in this situation compared to template-based methods. For overlapping action potentials, the method of Lewicki was shown to be nearly 100% accurate for action potentials that are significantly above the noise level. Perhaps the most promising of recent methods for measuring the activity of neural populations is not an algorithm. But the simplest method used by many researchers is still a single electrode with threshold detection.

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