Spike sorting using a cognitive method based on fuzzy concepts

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***Abstract*—A new spike sorting algorithm is proposed. This algorithm follows the human cognition process and classifies the spikes based on fuzzy concepts obtained from morphological features of spikes and fuzzy membership degrees to clustered spike classes formed at an initial stage of the classification. After learning classification rules through a training set, the spike sorting goes through an online format classification. The proposed method is then applied to both simulated and real data from chicken's retina. The results are promising and suggest the utility of the proposed method.**

Keywords-spike sorting; cognitive; fuzzy; retina

I. INTRODUCTION

To better study the basic principles of how the neural system works, it is crucial to decipher the neural spike activities from the prevailing multi-unit recordings. Spike sorting is therefore of great importance to tackle the detection and classification problems of spikes collected from recording electrodes.

Over the past decades, assorted methods have been put forward to deal with the spike sorting issue [1]. Recent years have seen spike sorting developing and employing methods including the principal component analysis (PCA) [1, 2, 3], the neural network method [4, 5, 6], the wavelet transform method [7, 8], the support vector machine analysis (SVM) [9, 10] and non-parametric method [11, 12]. More and more methods are still being added to the ensemble of the solutions to the spike sorting issue.

However, a tendency appeared that methods proposed are being more and more sophisticated yet in essence leading to both performance and redundancy, which means hard for experimenters to comprehend and greater complexity in computing. In this paper, a cognitive sorting method based on fuzzy concepts is proposed, aiming to both provide promising performance and cut down complexity.

II. METHODS

A. Data collection and spike detection

The real data were obtained through experiments on the isolated, newly hatched chicken retinas with multi-electrode array (MEA, Multi Channel System MCS GmbH, Germany) [13]. Multi-unit photoresponses were recorded from 60 electrodes simultaneously. A 60-channel amplifier (single-ended amplifier, bandwidth 10 Hz – 3.4k Hz, amplification 1,200) was utilized to amplify the photoresponses, which were then digitized by a commercial multiplexed data acquisition system (MCRack) at a sampling rate of 20 kHz.

In this study, a spike is detected if a negative peak, being a local extreme, exceeds a prefixed threshold and then a spike cutout containing 40 sampling points is extracted. The 40 sampling points include 16 points before the peak and 23 points after the peak.

B. Feature extraction

Features extracted from the spikes are based on morphological characteristics to simulate the initial cognizing stage of human experts.

Let $X_j^m = \{u_j(i) : 1 \le i \le m\}$ denotes the j th extracted spike cutout, where m is the length of the cutout series, default value of m being 40 in this study. The features are extracted through the following:

a) $\forall u_j(i) \in X_j$, calculate each difference between values of $u_j(i)$ and $u_j(k)$ ($1 \le k \le m, k \ne i$). If a difference is no greater than a threshold value, then the corresponding $u_j(k)$ is added to a set $SX_j^{\ i}$. The threshold is designed to be the 15% of the difference between corresponding $u_j(k)$ and the nadir value of X_j.

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b) Examine each of the sets, $SX_j^{\ i}$ ($1 \le i \le m$), produced by Step 1. Select the sets that have the most elements, $SX_j^{\ p}$ ($1 \le p \le m$).

c) Find $u_j(p)$ to meet the following equation:

$$\min_{u_j(p)}(r_p) = \min_{u_j(p)} \sum_{u_j(k) \in SX_j^{\ p}} \left| u_j(p) - u_j(k) \right|^2 . \qquad (1)$$

Equation (1) is developed to find the baseline which absorbs the most series values and provides the least residual error, where r_p stands for residual error. The value of $u_j(p)$ calculated through (1) is set to the value of the baseline of X_j.

d) The spike height of X_j is estimated by the absolute difference between the values of the baseline and the nadir of X_j. The spike width of X_j is estimated by finding the nearest points to the nadir on both sides, whose distance to the baseline is less than 5% of its distance to the nadir. The overshoot height and the overshoot width can be extracted in the same way.

C. Fuzzy set and fuzzy concepts

Let X be a space. In a conventional two-state classifier, to judge if an input pattern $x \in \mathbf{X}$ belongs to a given class A is to examine whether it satisfies precise properties required for membership. In the real world, however, boundaries between classes may be ambiguous, and the membership of an input pattern to a given class is always imprecise and uncertain. To describe such input-output relations, Zadeh [14] proposed the concept of fuzzy sets. By introducing the "membership degree" with a fuzzy function μ_A, Zadeh's theory provided a mechanism for measuring the degree to which a pattern belongs to a given class: the nearer the value of $\mu_A(x)$ to unity, the higher the membership grade of x in the class.

Fuzzy concepts used in this paper are defined as the membership degree of morphological features. Thus, the overall fuzzy membership of a spike to a class is obtained by the combined evaluation of the spike's corresponding fuzzy concepts. AND operation in the fuzzy set theory is utilized to implement the combination, which is specifically defined as:

$$AND(x, \mu_A, \mu_B) \triangleq \mu_A(x) \cdot \mu_B(x) \qquad (2)$$

D. Cognitive sorting

The classification method developed in this study is composed of two phases: the sensational phase and the perceptional phase, which reflect the cognitive process of human being.

In the sensational phase, sequentially extracted spike cutouts at the beginning of the sorting process are taken as training data. Then a subtractive clustering technique [15] is employed to find out the number of the clusters, which indicate the number of neurons that contribute to the recording signal, and to classify the training data into the clusters. In this phase, the general features of the extracted spike cutouts are learned during the process and the identification of each neuron are accomplished through classification analogous to induction of human cognitive process

In the perceptional phase, the average waveform of the spike cutouts classified to each cluster in the previous phase is taken as the reconstructed template of each neuron. The fuzzy concepts of the reconstructed templates, obtained using the method described before, are utilized to generate fuzzy membership functions, Gaussian membership functions in this paper:

$$\mu(x, \sigma, c) = e^{-\frac{(x-c)^2}{2\sigma^2}} , \qquad (3)$$

where c acquires its value from the morphological features of the templates and σ from repeated trials. The spike cutouts extracted following the training data then go through the template-matching process in a sequential way. Based on the combined evaluation of the spike's corresponding fuzzy concepts, a spike cutout is classified to a neuron if the overall fuzzy membership degree to that neuron is the highest among all the neurons, when in the meantime a predetermined threshold value is attained. In this phase, the spike sorting is done in an on-line processing form and the sorting process reflects the way human perceive and judge.

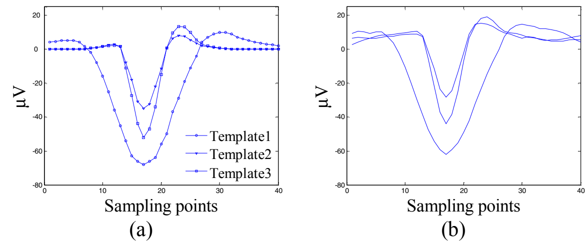

Figure 1. The waveforms representing each class of spikes. (a) The simulated spike templates. (b) The averaged waveforms of classified spikes belonging to each class using the proposed spike sorting method.

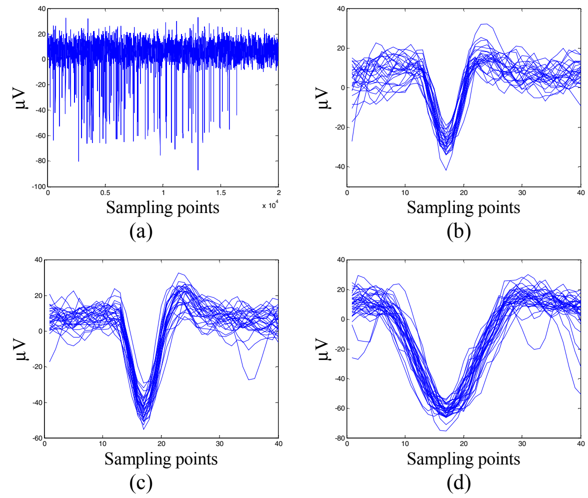

Figure 2. The task and the sorting results of the simulated data. (a) The simulated spike train using the templates and the background noise from real recording. (b), (c) and (d) Spikes classified to each class using the sorting method proposed in this paper.

III. RESULTS

The proposed spike sorting method was applied to both simulated data and real data recorded from the chicken retina. The processing program was run on a personal computer (Intel 2.4GHz, 1GB RAM) using MATLAB7.1.

A. Application to simulated data

The simulated spike waveforms use those in [2] for reference. The three simulated spikes, shown in Fig.1 (a), representing three retinal ganglion cells, were added to the background noise, which was obtained from real recording with spikes being extracted. The inter-spike interval of each instance of each template followed an exponential distribution. The simulated spike train is illustrated in Fig.2 (a).

By applying the cognitive sorting method, 94.8% of the spikes were classified and the classification results are shown in Fig2 (b)-(d). In addition, waveforms averaged from the classified results reconstructed the templates as is shown in Fig.1 (b).

In comparison, sorting method using PCA for feature extraction and direct subtractive clustering employed in [2] was

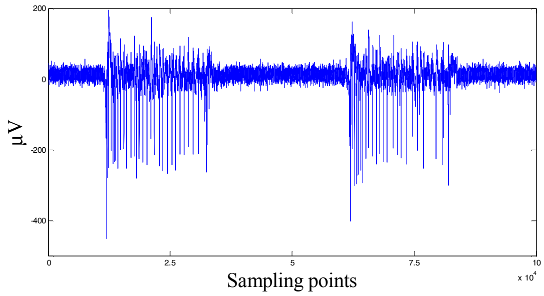

Figure 3. The recorded signal from one selected electrode under white light stimulus to the chicken's retina.

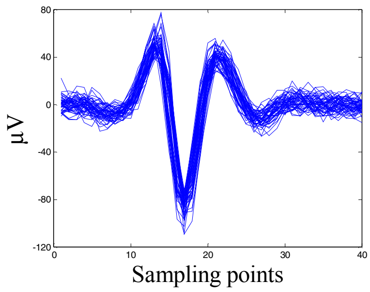

Figure 4. The ensemble of the spikes that classified to group that dominated the overall spike events processed by the proposed sorting method.

tested on the same simulated data. The sorting result was much less satisfactory as it renders a difficult balance point which would result in the increase of unclassified spikes or the inexact cluster numbers. Specific on the tested simulated data, spike data processed by method in [2] were clustered into 2 or 4 groups, while classified spikes only reached 35.42% of all detected spike cutouts when the cluster number was adjusted to 3.

The spikes that were not successfully classified using the cognitive sorting method include unclassified and mis-classified which both mainly stem from the superposition problem that will be discussed in the Discussion section.

B. Application to real data

The proposed cognitive sorting method was applied to real data recorded under white light stimulus from an isolated retina

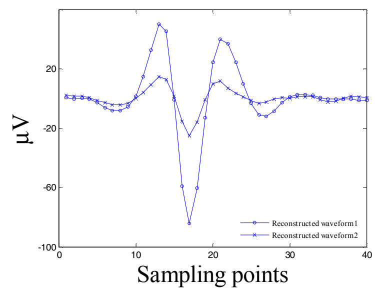

Figure 5. The reconstructed waveforms of the two classes of spikes representing two corresponding retinal ganglion cells through ensemble average.

of a newly hatched chicken. Fig.3 shows the data.

After the raw data had been high-pass filtered to counteract the effect of stimulus, the spike train went through the whole sorting method as described in the Methods section.

The cognitive sorting result showed that 75% of all classified spikes were grouped in one cluster, suggesting the dominant role of a retinal ganglion cell. The rest spikes formed a cluster that possessed less than half of the amplitude of the dominant group's, which infers that another less influencing retinal ganglion cell's activities had been collected at the same electrode. Fig.4 shows the sorting result of the dominant group. Fig.5 illustrates the reconstructed waveforms of the suggested ganglion cells.

IV. DISCUSSION

A cognitive spike sorting method based on fuzzy concepts has been presented. Despite the initial training period, the processing algorithm of this sorting method provides an online format to deal with the sequential upcoming spike data collected from the electrodes as is previously described in the perceptional phase of the cognitive sorting. The morphological features extracted from the spikes make the processing method both easy to comprehend for the experimental analysts and fast to calculate for the less computational complexity while still maintain adequate discriminative information. The fuzzy concepts employed in the method render the classification process more resemblance to the human cognition process. The results showed that the performance of this method is better than the sorting method developed in [2].

During the whole sorting process, there were some threshold values need to be settled which make this cognitive sorting method not completely independent of human supervision. However, it is worth noting that different recording methods and different research experiments would result in the variation of the statistics of the spike trains. Another confusing problem encountered in the sorting is the superposition problem, which led to the unclassified spikes and misclassified spikes as the abrupt waveforms appeared in the Fig.2 (b) (c) (d). Recently, several papers [2, 10, 16, and 17] provided possible ways to face the problem and some experimenters even deal with the problem by discarding the overlapping spikes and obtaining more forthcoming separable signals to be cost-efficient.

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