34th Annual International Conference of the IEEE EMBS
San Diego, California USA, 28 August - 1 September, 2012

An efficient spike-sorting for implantable neural recording microsystem using hybrid neural network

Hongge Li* *Member IEEE*, Pan Yu, Tongsheng Xia

Abstract—**Automatic efficient spike sorting is one of the biggest challenges for the neural recording microsystem online. An unsupervised spike sorting method is proposed in this paper, based on the hybrid neural network with principal component analysis network (PCAN) and normal boundary response (NBR) self-organizing map network (SOMN) classifier. The PCAN extracted the spike features with the dimension reduced and correlation eliminated; The SOM network perform the spike distribution in the feature space, thus after convergence, the weights of the neurons demonstrate the spike cluster distribution in the feature space; At last the spike sorting was finished by computing the neurons' Normal Boundary Response (NBR) which determined the neurons' classes. The experimental results show that, based on hybrid neural network spiking sorting algorithm, it can achieve the accuracy above 97.91% with signals containing five classes. The novel classification algorithm proposed is to further improve the efficient and adaptive of classification system.**

I. INTRODUCTION

Over the last decades, neuroscientists have successfully applied the recording brain signals to control artificial acquisition, which is the prototype of brain-machine interface [1-5]. The spike detecting and sorting, which distinguishes between the neurons of different types contributing to activity in a recording system, decrease the tolerant information and encode completely different information [3]. Requirements for spike sorting unit should be accurate, unsupervised automatic and low complexity [4]. The classification of spike has been performed on theory algorithm and hardware implementation with many unsupervised and supervised methods[5], which depend on a particular pre-processing, of which most popular are as principal component analysis (PCA) and wavelet analysis. However, a mainly problem is that the wavelet with high spike dimension has the characteristic of being time-consuming [6]. Moreover, most clustering algorithms need a pre-determined classes number or require clustering validity assessment to determine the spikes data sets of represent each cluster [7-8].

In this paper, the hybrid artificial neural network (HANN) is presented. The first layer employ the PCA neural network, which extracting the spike features for the waveform data pre-processes; The next neural network layer of the proposed methodology implement spike clusters distribution within the feature space and then identifies the number of clusters, using a proposed self-organization (SOM) neural network. The traditional SOM has several outputs corresponding to the clusters number within the feature space. This method just needs two extra epochs SOM training without modifying the weights of neurons to compute the NRB of each neurons, and then one simple comparison will identify the clusters.

*Resrach supported by National Natural Science Foundation of China (60971084), and was supported by Science Foundation for The Excellent Youth Scholars of Ministry of Education of China (20091102120046).

Hongge Li is with School of Electronic Information Engineering.Beihang University Beijing, China (corresponding author to provide phone: 0086-10-82339209; e-mail: honggeli@buaa.edu.cn).

II. METHODS

The architecture of the hybrid neural network classifier is shown as Fig.1. It performs the spike feature extraction and the data clustering to implement the spike sorting.

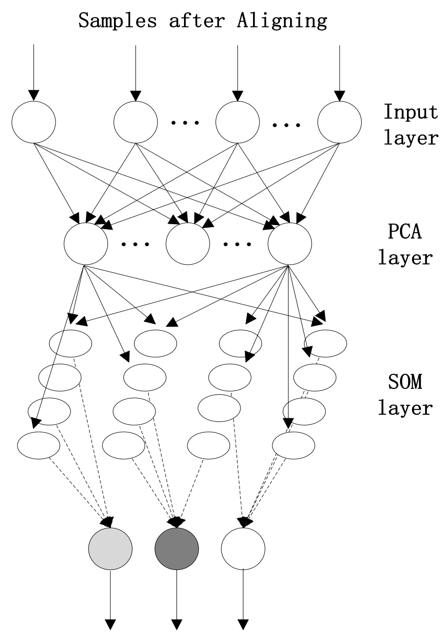

Figure. 1 Architecture of unsupervised spike classifier

A. Aligning and feature extraction

Usually, spike segments are to be aligned at a particular point after detection. This method aligns spikes at the peak points, identified by the changing slope criterion(the sign of the slope of five sequential points changes when a new point is added on the right side and the first point on the left side is excluded). The spike data is a 64 dimensional vector and its peak appears at the 20th point. After alignment, the spikes are used to train the PCA network layer based on the GHA rule [9]. It is shown as follow,

$$y_j(t) = \sum_{i=1}^{m} w_{ij}(t) x_i(t)$$

$$\Delta w_{ij}(t) = \gamma \cdot \left[y_j(t)x_i(t) - y_j(t)\sum_{k \le j} w_{ik}(t)y_k(t) \right].$$

Where *x(t)* is input vectors, *y*(*t*) is layer's output vectors with *m* dimension, and W_{ij} is the weight-matrix connecting from inputs to outputs. The learning rule is exactly the learning rule for Oja's subspace algorithm.

B. Clustering in feature space

The SOM neural network proposed performed the spike classification after the spike features extracted by the PCA layer. The SOM neural network model consists of 2-dimensional neuron array. The neighboring neurons compete in their activities by means of mutual later interactions, and develop adaptively into specific detectors of different signal patterns. Therefore, the neurons become specifically tuned to various input signal patterns or classes of patterns through an unsupervised learning process. In our system, the neurons of SOM layer are fully interconnected [10]. It implements the self-ordering process or obtain the best match with an input spike and each classifier of the internal map. Usually, The Euclidean distance map and the learning rule is used by,

$$d_j = \|\mathbf{w}_j - \mathbf{y}\| = \sqrt{\sum_{i=1}^{n_y} (w_{ij} - y_i)^2}$$

$$\Delta w_j(t) = h_{cj}(t)[y(t) - w_j(t)].$$

Where $\boldsymbol{w}_j$ is the weights of the *j*th neuron of the SOM layer, n_y is the features' dimension. $h_{cj}(t)$ determines the modification of the weights in the winning neuron and its neighbor neurons.

C. Type identification

Since the basic SOM network have no prior knowledge of the number of clusters, the number of SOM neurons is selected more than the factual number of clusters. Then, if each neuron converge into same region, it results in the over classification problem for the spike signals. To address this problem and perform the neurons classes, we propose an extensive version of SOM based on neurons Normal Boundary Response (NBR) .

At the end of the training of the SOM, assuming adequate training epochs, the neurons in SOM layer be mapped to the feature space. Usually, the distance of the furthest training vector from the winning neuron is then found, and this value is then used to set the boundary surrounding the neuron as shown in Fig.2 (dotted line). This boundary value is then used to test whether the neurons belong to the same class or not. By comparing the distance of the neighbor neurons with their boundary value, it is possible to determine whether the vector lies inside the boundary or not as shown in Fig.2 (dotted line). If the output of the SOM falls inside this value, it will then be identified as the same class.

Absolutely, some buried problems exist in the furthest boundary Response(GBR). It is mainly because that there are some overlapping spikes and the data noise. These singularities, adversely affecting the boundary identification, often result in that it is much greater to classify the neurons corresponding to other spike cluster. Additionally, the standard learning rule of the SOM makes a few neurons have less opportunity to be trained and move to the cluster center sometimes, and as a result, these neurons will lie at the low-density area. When identifying the boundary of these neurons, the value is possibly great due to the singularities and the feature vectors at the cluster edges.

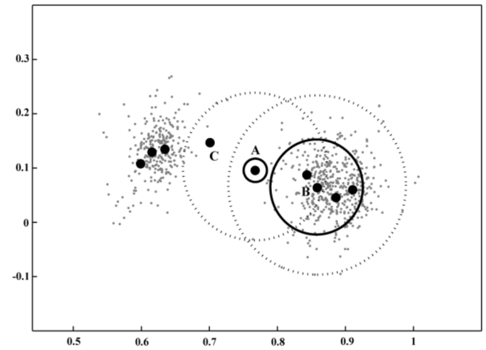

Figure. 2 Demonstration for NBR (dotted line) and adjusted response boundary (state line) of SOM neurons

We introduce two extra learning epochs' training to identify a normal boundary of individual neurons which overcome the adverse effect by singularities and impose restriction on neurons at low-density areas.

(1) The first epoch:

Initialize winning counter for each neuron: $WINCNT_j$ = 0, (j = 1, 2, …, n)

sum of the distance of the jth neuron and the sample make it winner:

$SUMDIS_j$ = 0, (j = 1, 2, …, n)

sum of the square of the distance above:

$SUMSQDIS_j$ = 0, (j = 1, 2, …, n)

for each sample in T (spike set),find the winning neuron *j* and record the distance DIS_j;

$SUMDIS_j = SUMDIS_j + DIS_j$;

$SUMSQDIS_j = SUMSQDIS_j + DIS_j^2$;

$WINCNT_j = WINCNT_j + 1$;

compute the mean distance of each neuron and the winning sample set:

$MEANDIS_j = SUMDIS_j/WINCNT_j$;

the derive of the distance above:

$DEVDIS_j = SUMSQDIS_j/WINCNT_j - MEANDIS_j^2$;

if $WINCNT_j$ < Nsample/Nneuron

$WINFREQ_j = WINCNT_j$/Nsample/Nneuron;

(2) The second epoch:

for each sample in T (spike set), find the winning neuron *j* and record the distance DIS_j;

if $WINCNT_j$ < Nsample/Nneuron

if $DIS_j * WINFREQ_j > NBR_j$

$NBR_j = DIS_j * WINFREQ_j$;

else keep NBR_j;

else if $DIS_j > NBR_j$ && $DIS_j < MEANDIS_j + k*DEVDIS_j^{1/2}$

$NBR_j = DIS_j$;

In the pseudo-code above, the $DEVDIS_j^{1/2}$ represents the samples' derive from the mean distance, usually when k = 2~3, it was considered the samples were too far from the winning neuron, which was going to be removed. Thus the normal boundaries of each neuron were determined. The following step was identifying the neurons classes. The distance of the two neighbor neurons is less than at least one of the neuron's boundary.

III. RESULTS

Five of these spike data sets were employed in training. To apply the extracted waves to the classifiers as raw input, a window with a length of 64 data points is employed in the spike peak. Five types of signals of these spike data consisted of the differential samples of spike, as 1018, 978, 933, 501, 272 are shown in Fig.3. Each spike data is normalized after alignment. The spike signals applied for testing the classifiers has eliminated the signal noise for the preprocessing NEO algorithms spike detection [12].

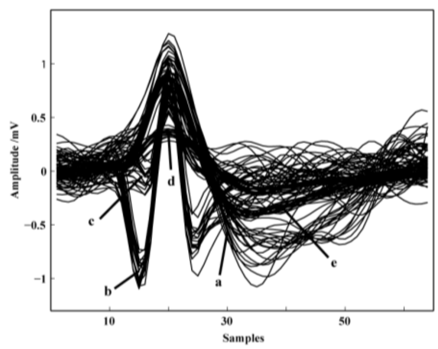

Figure. 3 Spikes of 5 types after alignment

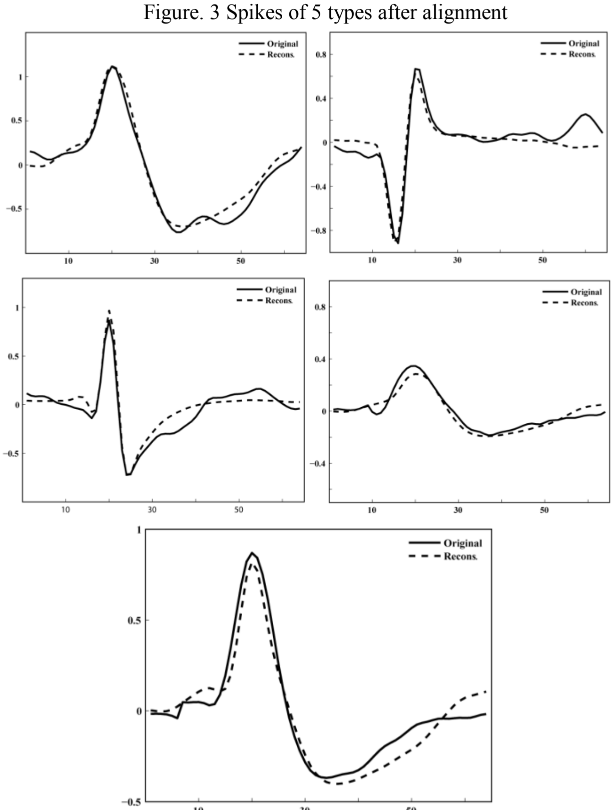

Figure. 4 Comparison of original and reconstructed spikes of five types

A. Representativity and separability

The samples projected to the feature space must keep the cluster characteristics of the original spike set. That means the samples thought to be of the same type should be closer in the feature space to each other than the samples belonging to another type. In the worst case, the samples should not present admixtures. Fig.4 shows the examples of the five spikes (dotted line) of different types in the data set, and their corresponding reconstructed spikes (solid line) from the feature vectors, intuitively the spike waveforms were coincident with the reconstructed ones, successfully reconstructed by the extracted principal components. The samples of one type keep closely clusters spacing distinct to each other, making it easy to determine the spike types.

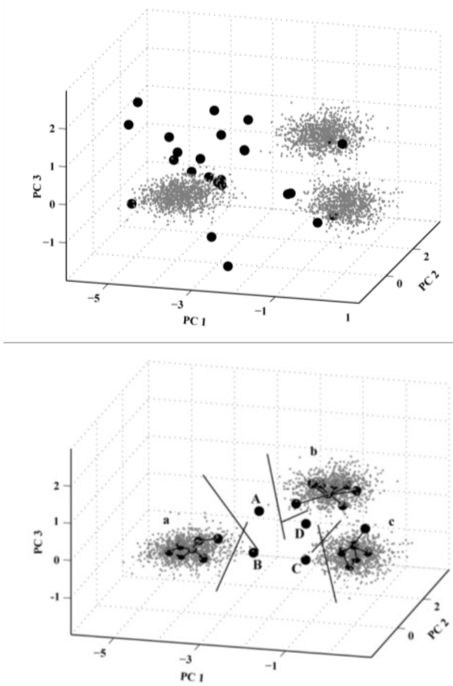

Figure. 5 Distribution of spike feature space cluster with three classes data

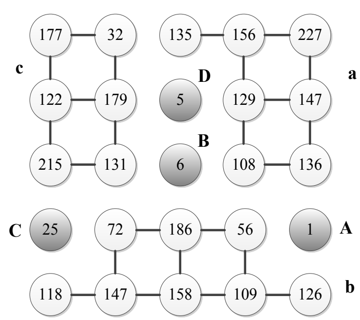

Figure.6 Distribution of spike feature space and topology

B. Feature classification

For the demonstration of the proposed PCA-SOM network classification function, we generated a pattern of combination of SOM neurons within both feature space and topology in Fig.5. Fig.5 shows the three dimensional space distribution of spike data after feature extraction with PCAN and the distribution of the converged SOM neuron location. After neuron type identification using the method proposed, the main three types of neurons were confirmed and separated by the neurons within low density. Fig.6 shows the distribution of spike feature space and topology, the neurons with low density usually has so limited winning samples that the NBRs can be very small to avoid misclassification. After the additional training to obtain the NBRs and identify SOM neuron types, the final classification of spikes can be identified.

C. Feature classification

For the demonstration of the proposed PCA-SOM network classification function, we generated a pattern of combination of SOM neurons within both feature space and topology in Fig.5. Fig.5 shows the three dimensional space distribution of spike data after feature extraction with PCAN and the distribution of the converged SOM neuron location. After neuron type identification using the method proposed, the main three types of neurons were confirmed and separated by the neurons within low density. Fig.6 shows the distribution of spike feature space and topology, the neurons with low density usually has so limited winning samples that the NBRs can be very small to avoid misclassification. After the additional training to obtain the NBRs and identify SOM neuron types, the final classification of spikes can be identified.

D. Classification accuracys

The classification accuracy were computed under different spike set, as a standard reference, the classical K-means' results were also computed shown in Table 1. First, The average precision is calculated as follow,

$$\mathrm{Pre}(\%) = \frac{\sum \text{Sorting Number}}{\sum \text{Sample Number}}.$$

When the cluster number is 2, i.e. the spike set II, the K-means perform the highest accuracy level of 100%, and the classifier proposed is 98.32%. However, with the number of the spike clusters increasing, the accuracy of K-means decrease distinctly since there is a greater probability of misclassification. Comparing with the K-means' instability [11], the classification system proposed keeps a stable and high accuracy level above 97.91%, much higher than the classical method. While the data set is in high complexity, the hybrid neural networks shows adaptively its advantages, according to the distribution of the feature vectors, the SOMN neurons converged optimally keeping a high accuracy for the different spike type. Namely, the NBR-NN proposed implements the high classification accuracy and high stable average precision with spike type increasing as shown in Table 1.

IV. CONCLUSION

This paper introduces a novel two-stage classification system based on hybrid artificial neural networks for the automatic extraction and the high accuracy classification for the spike recording microsystem. The presented approach implement the data preprocessing, feature extraction, and classification function using the PCA network and adjusted SOM network. The classifier displays the best performance in terms of average precision (larger than 97.91% at 5 classes), and is trained with NBR hybrid neural network algorithm with the preprocessing data. Comparison with other tradition methods shows that, automatic hybrid neural network achieves a significant improvement in the high accuracy classification for many spike class, and implementing low time-consuming online. An additional advantage of the proposed method is that it greatly decreases the number of feature when compared with the other method based on the same reconstruction error.

Table 1 Classification accuracy compared with k-means according to the different spike set

spike set	Spike types	Sample number	Correction sorting		Average precision/%	
			This work	K-means	This work	K-means
II	a	1043	1043	1043	98.32	100
	b	977	943	977		
III	a	1043	1021	940	99.00	90.35
	b	977	970	977		
	c	883	883	706		
IV	a	1043	1040	967	97.91	88.34
	b	977	943	928		
	c	883	876	712		
	d	501	474	400		
V	a	1043	1038	858	99.13	82.26
	b	977	974	832		
	c	883	877	752		
	d	501	483	500		
	e	272	272	82		

REFERENCES

[1] J. Clausen, "Man, Machine and in between," Nature, 457, pp.1080-1081, 2009.

[2] Z. G. Wang, X. Gu, X. Lü, et al. Microelectronics-embedded channel bridging and signal regeneration of injured spinal cords. Progress in Natural Science, vol.19,pp.1261-1269, 2009.

[3] S. Gibson, W. Judy and D. Markovic, "Comparison of Spike-Sorting Algorithms for Future Hardware Implementation," 30th IEEE EMBS Conference, Canada, pp.5015-5020, 2008.

[4] M. Sawan, "Brain-Machine-Brain Wireless Interfaces for Intracortical Biosensing and Subsequent Treatments" in Talk by DL Mohamad Sawan at SSCS-New York and Santa Clara in May and June," IEEE Solid-State Circuits Magazine, Vol.3, No.4, pp.34-37, 2011

[5] M. Rizk, I. Obeid, S. Callender, D. Wolf. A single-chip signal processing and telemetry engine for an implantable 96-channel neural data acquisition system, J. Neural Eng., vol.4, pp.309-321, 2007.

[6] M.S.Lewicki, A review of methods for spike sorting: the detection and classification of neural action potentials. Network Comput Neural Syst. Vol.9, pp.53-78, 1998.

[7] R Quiroga, Z. Nadasdy, Y. Ben-Shaul. Unsupervised spike detection and sorting with wavelets and superparamagnetic clustering. Neural Computation. Vol.16, pp.1661–1687, 2004.

[8] P.M. Horton, A.U. Nicol, et al. Spike sorting based upon machine learning algorithm (SOMA). Journal of Neuroscience Methods. vol.160, pp. 52-68, 2007.

[9] D.Terence Sanger. Optimal unsupervised learning in a single-layer linear feedforward neural network. Neural Networks, vol.2, pp.459-473,1989.

[10] T. Kohonen, Self-organizing maps. Springer-Verlag. 1995.

[11] R. Silverman, A.Y. Wu. An efficient k-means Clustering Algorithm: Analysis and Implementation. IEEE transaction on Pattern Analysis and Machine Intelligence. Vol. 24, pp.881-892, 2002.

[12] H.G. Li, Q.C. Xu, Sub-threshold-based Ultra-low Power Neural Spike Detector, Electronics Letter. Vol.47, pp367-368, 2011.