Communications

Classification of Action Potentials in Multi-Unit Intrafascicular Recordings Using Neural Network Pattern-Recognition Techniques

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Abstract—**Neural network pattern-recognition techniques were applied to the problem of identifying the sources of action potentials in multi-unit neural recordings made from intrafascicular electrodes implanted in cats. The network was a three-layer connectionist machine that used digitized action potentials as input. On average, the network was able to reliably separate 6 or 7 units per recording. As the number of units present in the recording increased beyond this limit, the number separable by the network remained roughly constant. The results demonstrate the utility of neural networks for classifying neural activity in multi-unit recordings.**

I. INTRODUCTION

The development of chronically implantable intrafascicular electrodes has made it possible to record neural activity from small subsets of nerve fibers in peripheral nerves [1], [2]. If the firing patterns of single units (individual nerve fibers innervating peripheral mechanoreceptors) could be extracted from these multi-unit recordings, such recordings could be useful in providing feedback for the control of neuroprosthetic devices and in functional electrical stimulation systems [3].

Unit separation is based on identifying similarities in the shapes of the action potentials from any one unit, and differences in the shapes of action potentials from different units. We have reported elsewhere on a template-based method for classifying single units from intrafascicular recordings [4], [5]. In this method, templates were constructed based on the shape of action potentials from identified single units in the recording, and classification depended on fitting recorded action potentials to these templates. Although the template-matching method was successfully implemented in real time, it could separate only a limited number of units in the intrafascicular recordings.

Separation by theoretically more effective methods generally involves measuring the statistical distance between an observed pattern and a set of expected patterns. In the case where action potentials from different units are all about the same amplitude and duration, and thus have similar energy contents, one might use a set of matched filters tuned to the expected patterns. In the latter case we want to find: max $\sum\{O(i) \cdot W(i)\}$, where $O(i)$ are the digitized values of the action potential to be classified, and $W(i)$ are the weights for a given matched filter.

Multiplying a vector of input values by a vector of weights is the same operation used in linking layers of a neural network. The network can be considered an adaptive matched filter, with the flexibility of deducing nonlinear boundaries between patterns.

Neural networks have proven to be valuable tools in complex pattern-recognition problems, including signature verification and hand-written digit recognition [6]–[9]. Although Bayesian classifiers have been suggested as optimal, particularly when the noise is not white [10], [11], it has been shown that neural-network classifiers trained by backward error propagation perform as well as, and sometimes better than, conventional Bayesian classifiers, especially when the noise distribution is different than that assumed in the latter [12], [13]. Performance of neural networks is found to be close to that of k-nearest neighbor and quadratic Gaussian classifiers when Gaussian distribution of the patterns are assumed [12]. In most real world problems, including classifying action potentials from intrafascicular recordings, the noise is not stationary and white Gaussian, and statistical classifiers fail to accommodate practical issues, such as rejection of artifacts [8], [13].

The present study was undertaken to determine the feasibility of using artificial neural networks to classify single-unit activities in multi-unit intrafascicular recordings. Although confined to a restricted set of experimental conditions, the results indicate that such networks are particularly powerful in this application.

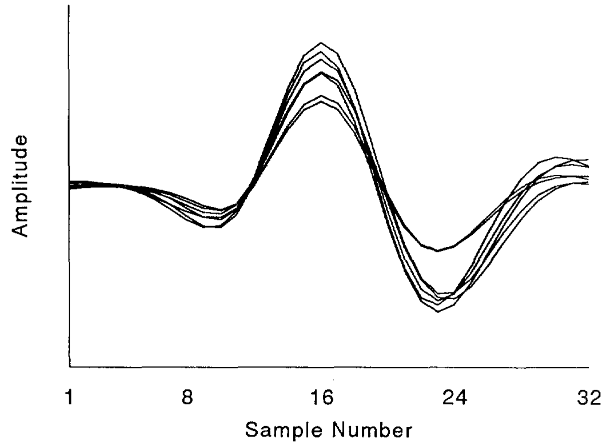

Fig. 1. Means of action potentials from seven of ten different units in a single recording. The seven units were separable using neural-network classification, but were not separable using the template method of Goodall and Horch [4]. The remaining three units were separable by both methods. The signal to noise ratios of the units shown ranged from 2.0 to 4.0.

II. METHODS

Recordings of multi-unit neural activity were made with intrafascicular electrodes implanted in peripheral nerves of cats (as described elsewhere [2]). Action potentials evoked by mechanical stimulation of individual cutaneous receptors (units) were detected by a threshold crossing criterion and digitized into 32 samples at a rate of 28.5 kHz. This procedure was repeated for all the units in the recording which could be individually activated. An example of the action potential shapes from different units seen in a single recording is shown in Fig. 1. Two types of noise contribute to the difficulty of uniquely classifying individual action potentials in these recordings: bandwidth limited 1/f noise from the signal source and recording electronics, and phase noise due to variability in timing between when an action potential occurs and when digitization occurs.

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TABLE I
CONFUSION MATRIX FOR THE TEN UNITS IN THE RECORDING FROM WHICH FIG. 1 WAS MADE

		Assigned Unit										
		1	2	3	4	5	6	7	8	9	10	nm
	1	75	5	0	4	0	2	0	0	4	0	10
	2	5	80	0	0	0	2	0	0	2	0	11
	3	0	0	98	0	0	0	0	0	0	0	2
	4	2	2	0	86	0	2	0	0	0	0	8
Source	5	0	0	0	0	88	0	2	0	2	0	8
unit	6	2	2	0	2	0	80	0	0	2	0	12
	7	0	0	0	0	0	0	96	0	0	0	4
	8	2	0	0	0	0	0	0	92	0	0	6
	9	2	0	0	0	0	0	0	0	90	0	8
	10	0	0	0	0	0	0	0	0	0	100	0

Note: The rows represent the actual units from which the action potentials came, the columns represent the unit to which the action potentials were assigned. Numbers are expressed as percents, nm= no match.

A three-layer, feedforward, connectionist network was used. Three layers have been shown to be adequate for most complex pattern-recognition tasks [8]. The number of nodes in the first layer of the neural network was selected to make full use of all the data points available (32) plus one bias node. In preliminary studies, the size of the second layer (32 nodes plus one bias node) was determined to be sufficient to maximize the performance of the network on this task. The number of nodes in the third layer was set equal to the number of units to be classified. Supervised backward error propagation was used to train the network [14].

Two primary procedures of training and testing were adopted. The first procedure used a limited (approximately 50) set of action potentials recorded from each of the units in a given recording. The network was trained and tested with the same data set. The second procedure used a large (order of several hundred) set of action potentials from each unit for training. The trained network was then tested with a different set of action potentials from each of the units.

Classification success was assessed by comparing the assigned sources of action potentials in the testing set to their actual sources [4]. An action potential was classified as belonging to the unit corresponding to the output node of the network having the largest value, provided that the value was greater than 0.25. If no output satisfied this criteria, the action potential was classified as not matched. A unit was rated as separable if the error rate in classification met the criteria established by Goodall and Horch [4] (inclusion error rate $<$ 0.15 and exclusion error rate $\leq$ 0.25).

III. RESULTS

Table I shows the confusion matrix for the units in the recording from which Fig. 1 was derived. All ten units in the recording were separable with the neural network. Of the 189 units present in the recordings studied from chronically implanted electrodes, 89 (46%) could be separated with neural networks when the same data set was used for testing and training. This was a statistically significant (Chi-squared test, $p < 0.001$) improvement over the 16% success rate obtained with the same data using the template method described earlier [4].

To see if these results were an artifact of training and testing with the same data set, three networks were trained with a different set of data obtained from recordings not included in the earlier study. When training and testing were performed with the same sets of action potentials, the networks separated 20 of the total of 23 units present in the three recordings. When different data sets were used for training and testing, the networks separated 16 of the 23 units.

Unit separability with the neural network depended on signal-to-noise ratio [Fig. 2(a)] and on the number of units in the recording

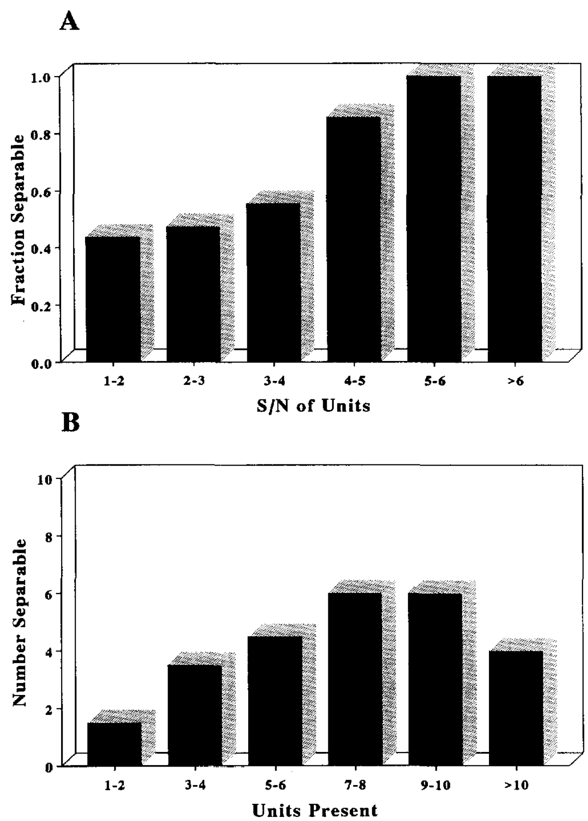

Fig. 2. Determinants of unit separation success. Plotted are the fraction of separable units as a function of signal-to-noise ratio (A) and the number of units in a recording that could be separated as a function of the total number of units in the recording (B). Data were averaged from 20 different recordings and grouped into bins. Classification success in individual recordings often exceeded the values shown here.

[Fig. 2(b)]. Units with higher signal-to-noise ratios were more likely to be separable than those with lower signal-to-noise ratios. As the number of units in the recording increased beyond 8 or 9, the number of separable units did not increase beyond a limit of approximately 6, but rather declined.

IV. DISCUSSION

Since training and testing with different action potentials gave results similar to training and testing with the same (limited) population of action potentials, the results presented here are indicative of the expected performance of neural-networksystems in typical applications, where the system would be used to separate activity recorded subsequently to recording the training data.

Three factors determine the separability of units in a multi-unit recording. The first is the similarity of the action potential shapes from the different units. Separability requires differences in the shapes of the externally recorded action potentials. These differences arise from differences in the conduction velocities of the nerve fibers and in the distances between the sources of the signals and the electrode [15].

The second factor is signal-to-noise ratio. Noise present in the recordings corrupts the action potential features and limits the ability of template systems to separate different units [4]. The same is true when neural networks are used. Thus, it is not surprising that units with high signal-to-noise ratios are separated more frequently.

The third factor is the number of units in the recording. With these single-channel recordings, the neural network could typically separate a maximum of about 6 units. If more than ten units were present in the recording, the actual number of separable units declined from this maximum. Recordings limited to 10 or fewer units have proven to be useful in providing information about natural external stimuli, in part because this is below the point where superposition of action potentials becomes a problem [4], [5]. Thus the ideal number of units in a multi-unit recording with intrafascicular electrodes appears to be on the order of 7 to 10.

Although the present study utilized a single neural-network architecture and a limited data set, the results appear generalizable. Work currently under way in our laboratory, using a more extensive data set, indicates that equivalent results are obtained with a variety of different architectures [5]. Thus artificial neural networks provide an effective unit-separation method, characterized by ease of implementation under the real-world constraints imposed on attempts to uniquely identify, on line and in real time, the source of single unit activity in multi-unit recordings.

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Ultrasound Scattering from Blood with Hematocrits Up to 100%

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Abstract— **The backscattering coefficient of saline suspensions of porcine red blood cells was measured for hematocrits up to about 90%. It was found that the coefficient peaks at approximately 15%, but then, contrary to what a simple "gap theory" might suggest, it decays smoothly to zero, without showing another peak at high hematocrits. A one-dimensional (1-D) slab scattering model, in which the number of slabs per unit length represents the hematocrit and whose thickness and acoustical properties are similar to red cells/plasma, was also used to investigate the relation between the backscattered power and hematocrit. Monte-Carlo simulations performed for randomized boundary conditions show a similar relation to that of the 3-D system. The experimental data is compared to the Percus-Yevick theory for the packing of hard spheres, and the simulated data is compared to the Percus-Yevick theory for infinite slabs.**

I. INTRODUCTION

Understanding the scattering of ultrasound by blood is of fundamental importance in the use of Doppler ultrasound as a non-invasive means of assessing blood flow as well as in the use of ultrasonic measurements for studying blood rheology. It is now well established [1] that in the hematocrit range of a few up to about 50%, the backscattering coefficient (BSC) of saline suspensions of red cells initially increases with hematocrit, reaches a peak in the range of 15–20% (depending on the flow conditions), and decreases thereafter. Such a behavior is in fairly good agreement with model predictions based on various particle packing theories (see [2], [3], or [4] for comprehensive reviews). Little attention has been paid to scattering from blood with hematocrits much beyond 50%, perhaps because this is beyond the average normal human value of 45%. Nonetheless, the clinical significance of the range beyond 50% is demonstrated by the fact that fetal blood is normally 60% and that Chaplin *et al.* [5] have reported values from 9% to 82%. In addition, the strengths and validity of various scattering theories can be more fully examined if the range from a few percent up to 100% is used.

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