Tracking Changes in Action Potential Shapes in Chronic Multi-Unit Intrafascicular Recordings Using Neural Network Pattern Recognition Techniques

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Abstract-**A novel scheme is proposed to train an Artificial Neural Network (ANN) classifier, on a repeated basis, in order to track temporal changes in the shapes of the action potentials recorded through chronically implanted intrafascicular electrodes. This scheme uses classification results of the ANN classifier on the most recent neural recordings to label the new action potentials. The ANN classifier is retrained using the new samples so that it recognizes any changes in the shapes of the action potentials. The procedure is repeated continuously using the most recently trained ANN classifier. This scheme was tested on different simulated situations that may arise in a two unit neural recording. The results indicate that proposed method allows us to track the changes in the shapes of the action potentials in most plausible scenarios that might arise in chronic intrafascicular recordings.**

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, they could be useful in providing feedback for the control of neuroprosthetic devices and in functional electrical stimulation systems.

Since the shapes of the recorded action potentials from different units vary according to axonal diameter and distance of the unit from the recording electrode, unit separation is based upon discriminating between these subtle differences in action potential wave forms. Earlier we reported on a method that utilized an Artificial Neural Network (ANN) as a pattern recognizer to differentiate between these shapes [3]. ANNs yield higher success rates in recognizing action potentials compared to other commonly used supervised parametric and non parametric statistical tools [3, 4].

A problem that arises in chronic recordings with intrafascicular electrodes is that in time the electrode may migrate within the fascicle, causing the shapes of the recorded action potentials from some or all of the units to change. These changes are gradual enough that the recordings of a unit from one day to another are essentially the same. The manner in which these changes occur is unpredictable, except that the triphasic shape of the action potentials remain intact and the level of noise in the recording stays fairly constant during this time [5].

For a classifier to be clinically applicable on a long term basis, it must be able to track these changes without any a priori knowledge of how they occur. Clustering techniques are tools that are ordinarily used for problems of this nature, however for our recordings they did not perform effectively in separating different units.

An ANN classifier will recognize action potentials that are only slightly different in shape than the ones it was trained with. This is because the changes are small enough not to affect the outcome of classification. Based on this classification, the new action potential recordings can be grouped in to sets of homogenous classes. By selecting samples from these sets one can form training sets that are representative of the new recordings. The integrity of these training sets can be further increased by incorporating a reliability of classification metric in the selection process [6]. The training data will enable the new ANN classifier to learn the statistics of the changed action potential recordings. Performing this procedure on a repeated basis with the most recently trained classifier and the most recent action potential recordings should enable us to track changes in the action potential shapes of different units in a chronic recording.

The present study was undertaken to determine if the 'boot strap' scheme proposed above provides tracking capabilities when applied to the problem of unit classification in chronic intrafascicular recordings.

METHODS

The ANN architecture as well as the training algorithm is as described elsewhere [3]. Since the changes in the shapes of the action potentials are unpredictable, there is a need to obtain well behaved data for testing different scenarios that might arise in an actual recording situation. To this end, a simulator was written that mimics typical neural recordings much like the ones obtained our chronic implants [5] by adding pink background and uniform sampling noise to a given raw action potential shape. In addition, through frequency domain manipulations, the simulator enabled us to make desired changes in the wave forms.

Simulations

For reasons of simplicity we tackled the two unit problem first. To help explain the simulations, one can make the analogy of the continuous changes in the shapes of the means of the action potentials as movement of two clusters in feature space. The features are the values defining the

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amplitude of the waveform at different points in time, and the clusters correspond to the distribution of the action potential populations from the two units in the simulation.

Performance of the 'boot strap' scheme may degrade with time, because of errors in classifying action potentials from the new recordings. Corruption of the training sets will be most severe when the two action potential clusters converge, that is, when the shapes of the action potentials approach each other. With each step there will be more intermesh between the two clusters and hence an escalation of performance degradation. This and other plausible scenarios were simulated to quantify the performance of our ANN classification scheme.

Simulations were repeated on 6 different sets of data to produce a generalized result regarding the performance of the system.

RESULTS AND CONCLUSIONS

The following observations were made regarding the cases simulated:

1. As long as the two units remained distinct in their features and as long as the updating of the classifiers was frequent compared to the rate at which the action potential shapes changed, the 'boot strap' scheme tracked the changes.

2. As long as the movement of the two clusters was parallel to or away from the boundary drawn by the first generation classifier, the clusters could be tracked.

3. When the motion of the two clusters had a component that caused one of them to cross the boundary that the first generation classifier had drawn, subsequent generations of classifiers tended to retain the same boundary. With time one of the clusters would completely drift across the boundary and cause both clusters to be classified as one. To remedy this, estimates of the means of the clusters were calculated after every classification of the new recordings. The estimate $m_i(n)$, for the ith unit the nth recording, compared to that of the previous recording $m_i(n-1)$, indicated whether or not a movement had occurred. If this indicated a movement toward the boundary, a zone was created from which no samples were selected for training of the next generation of classifier. This zone was next to and on the side of the boundary which matched the direction of the movement of the clusters, and had a volume related to the magnitude of the movement detected. By this we were able to move the classification boundary in accordance with the movement of the two clusters and hence track the changes.

Fig. 1 is a plot of the total percentage of recognized action potentials as a function of the normalized distance between the means of the two clusters in the recording, in the case where the populations converged. Five different starting distances between the two clusters were used. The graph shows that the 'boot strap' scheme performs as well as an ANN trained with correctly labelled training samples. The graph further demonstrates that the separability of two populations is a function of the distance between their means.

These results indicate that the 'boot strap' method offers an effective alternative to unsupervised statistical clustering schemes for identifying single units in multi-unit recordings. This 'boot strap' scheme can also be used with other Bayesian classifiers in place of an ANN.

This work was supported by a grant from NINDS of NIH and by a grant of computer time from the Utah Supercomputing Institute which is funded by the State of Utah and the IBM Corporation.

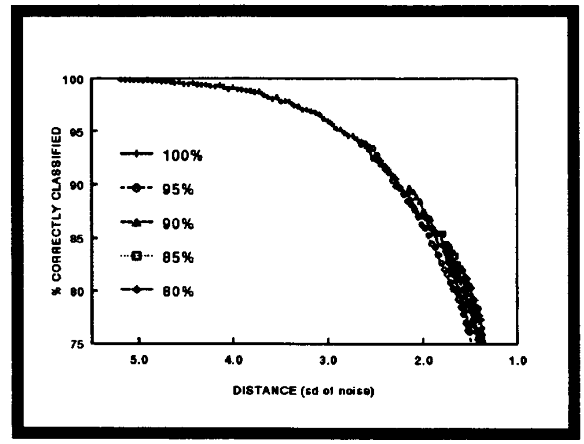

Figure 1. Classification success as a function of distance between two clusters of action potentials.

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