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Simulation and Classification of the Efferent Activity in Brachial Nerves

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Abstract— **A computational model linking stochastic neural innervation processes and functional neuromuscular excitation is developed to investigate peripheral nerve interface based limb prostheses. A means of classifying the virtual nerve data is presented by using both a time domain feature set and a spike detection algorithm. Some intrinsic parameters in recording and classification, such as brachial fiber activation, analysis window length and feature selection, are discussed to achieve good neural signal recognition. Recommendations for optimal performance are made, with regard to information content and window length.**

I. Introduction

CURRENTLY, commercially available artificial limbs include mechanical cable prostheses, myoelectric prostheses, and mixed control by both. Because these conventional prosthetic limbs are limited by the problems of insufficient function, and slow and unnatural control, researchers and engineers have been developing many new devices and control methods for decades. Since the available recording sites on residual muscles may be limited after amputation, myoelectric signals (MES) provide inadequate motor information, and more functions need to be restored as the amputation level increases. Moreover, muscle fatigue and electrode location sensitivity may change the features of the MES. On the other hand, neural signals are not as affected by fatigue levels, are highly reproducible, and are less susceptible to interferences. As such, they may be considered as an alternative source for extracting control signal in prosthesis. A brain-computer interface (BCI) method [1-3], in which electrodes were implanted into the cranial cavity of a primate, was used to provide motor information from the intracranial EEG signals which were generated from the motor area of the cortex [2]. This procedure is clinically risky and can only record electrical activities of the motor neurons in a very localized neighborhood, and very a few human studies [3,14] have been reported. Using multiple electrodes to collect EEG signals from the scalp avoids these problems, however the surface EEG has a low signal-to-noise ratio and is difficult to interpret.

Because of the above difficulties a peripheral nerve interface approach is proposed for powered prosthetic control. In this approach, based on the unique structure of somatotopic organization [4-5] in the peripheral nerve system, motor information is extracted from the descending nerve fibers rather than the brain. The motor information is concentrated in the peripheral nerves due to their small diameters, and the electrodes can obtain most of the movement information with little risk. Intrafascicular electrodes for neural signal recording are available, such as the Utah slanted electrode array (USEA) [6-7].

Although the detection of both cortical and peripheral neural information has been investigated in a number of experiments on animals, the reports of neural control based prostheses with human subjects are rarely seen, due to the complexity of human trials. As a result, in this work we developed a neuromuscular model for simulation of a pattern-recognition based controller using a peripheral nerve interface. It offers a foundation for investigations involving innervation of muscles by selective excitation of peripheral nerves. Furthermore, we discuss a few factors, including the contraction duration, analysis window length, and the axonal recruitment, which may affect classifying different contractions with data acquired from simulated peripheral nerve signals. Since the virtual implantation levels were chosen at or above the elbow, this model is suitable for investigation of neural control prostheses with above-elbow amputation.

II. Simulation and Analysis Methods

A. Development of the Model

1) Model Simulation: We developed the computational model [9] according to the relevant functional branches within three major brachial limb nerves, the median nerve (MN), ulnar nerve (UN), and radial nerve (RN). These are selected according to six wrist and hand contractions: hand closing (HC), hand open (HO), wrist flexion (WF), wrist extension (WE), wrist pronation (WP), wrist supination (WS). Although the articulations of different muscles and muscle groups are synergistic with multiple agonists involved, as a starting point we modeled the fascicles innervating only prime mover muscles for each contraction. The required musculature is sufficient to satisfy the independent control of a two degree-of freedom wrist and one degree-of freedom

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prosthetic hand [8].

2) Apparatus: We modeled the Utah Slanted Electrode Array (USEA) to acquire virtual nerve signals from simulated functional nerve fascicles which innervate the intrinsic muscles [10]. Electrodes are placed at the elbow and 1/8 arm length distal to the level of medial epicondyle, where the relevant nerve fascicles innervating the required muscles of forearm can be clearly observed [9]. This approach avoids the limitations of crosstalk, signal attenuation of deep muscles, and lack of control sources in high level amputations.

3) Signal Classification: A simple linear discriminant analysis (LDA) classifier was applied to discriminate intended motions of the wrist and hand in these simulated data during volitional intent. A time domain (TD) feature set [12] and a spike count (SC) feature [11] have been investigated in previous studies. Both feature sets showed distinctive patterns when fibers near the detection electrode were activated to execute a certain movement. Above six wrist and hand contractions were six classes in the classification. Figure 1 shows the representations of each feature during the classification of one good virtual channel.

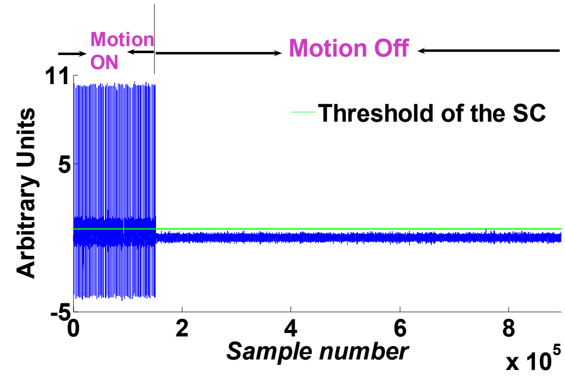
For SC, it is easy to see the clear evidence of the all-or-none nature of neural activation. Mean absolute value (MAV) and waveform length showed the expected differences between periods of contraction-on and contraction-off, because neural action potentials (APs) modulated the value and variability of waveform amplitude voltage. Multiple spike waveforms could add more zero crossings (ZC) and slope sign changes because the frequency of neural signals is higher than the background noise that mainly consists of EMG signals [13], but it is also clear these features are comparatively noisy. Since SC and TD have their own unique patterns, both can perform neural signal classification.

B. Parameters of the Model

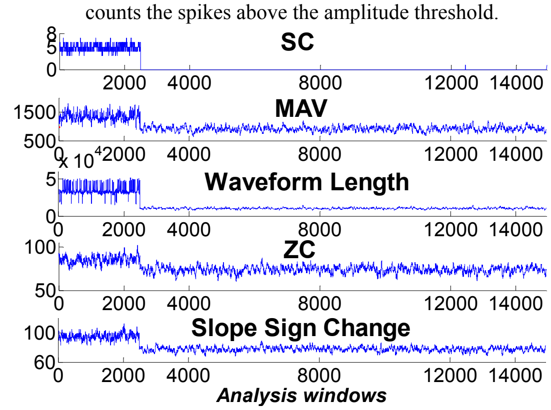
Intrinsic factors existing in the virtual recoding and signal analysis, such as the duration of motions, analysis window length in classification, and the effect of nerve fiber activation, can affect the classification performance when using information in the brachial nerves.

1) Duration of Contractions: It is essential that sufficient data be provided to adequately train a classifier. It is therefore important to know how long an isometric contraction should last. The contraction duration was based on a virtual subject in a typical scenario, which incorporated 50% activated nerve fibers and 40% encapsulated electrodes (intrafascicular electrodes will be encapsulated to a varying amount with a visible fibrous tissue growth [10] due to the physiological immune response).

The virtual subject was assumed to perform five trials (a trial was considered to be a consecutive execution of six motions, with the order of HC, HO, WE, WF, WP, and WS) in the training session. The contraction duration of these five trials was varied over 1 sec/contraction, 2 secs/contraction, 5 secs/contraction, 7 secs/motion, 10 secs/contraction to generate a training set. A single, 2 second test set was also



(a) A good channel (Analysis window length is 80 ms). SC approach counts the spikes above the amplitude threshold.



(b) Characteristics of each feature during classification

Fig. 1. Representations of each feature during the classification of one good channel.

generated for assessment of classification performance.

2) Activation of Nerve Fibers: The number of active fibers has a strong influence on the classification performance because it determines the information abundance.

Thus the simulation work took different recruitment levels (10%, 20%, and 50% of fibers within the entire fascicle) to represent different levels of isotonic voluntary contraction.

3) Analysis Window Length: Pattern recognition was performed on an analysis window from which features can be computed and provided to a pattern classifier. It is desirable to have the analysis window size as small as possible, as this determines the response time of the system in providing a decision of movement intent. On the other hand, fewer data will result in a larger feature estimation error [12].

III. Simulation Results

A. Effect of Motion Duration

The initial investigation focused on the effect of the duration of each contraction, with the purpose of determining the amount of data required to adequately train the classifier. From Figure 2, the result shows that there is no significant difference among the contraction durations considered (t-test: $p>0.05$), classified by both of spike count (SC) and time domain (TD) features. As shown in the plot, the accuracy was not compromised when the duration was short (the vertical bar representing the standard deviation over test sets). In the end, the duration was chosen to be 2 seconds on each motion, in order to reduce computing and training time. This selection will be implemented in all subsequent data collection sessions.

B. Effect of Analysis Window Length

The investigation was performed for analysis window lengths over 10 to 150 ms at a signal-to-noise ratio (SNR) level of 5 dB (the SNR is defined as the log ratio of the nerve signal peak value to the EMG RMS value, and expressed in dB). The results are illustrated in Figure 3.

It is desirable to have the analysis window size small, while achieving adequate classification performance. Consequently, the effect of window length on classification accuracy was carefully examined in this study. Data were acquired from a case of 50% fiber recruitment and 40% electrode encapsulation. From Figure 3, the analysis window length has a strong influence on classification performance, for both SC and TD features. When the length ranged from 10 ms to 60 ms, the classification accuracy improved tremendously. Beyond 80 ms, the performance of both the TD and the SC did not increase significantly, with performance nearing 80-90% accuracy. This is a very encouraging result, as 80 ms is an exceptionally good response time, much less than most current EMG-based systems, which are on the order of 100-300 ms. The analysis window length of 80 ms was also used throughout the analyses in this project.

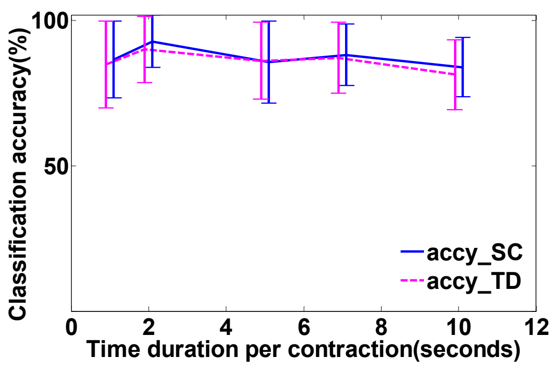


Fig. 2. Comparison of classification accuracies with different contraction durations. The label 'accy_feature' here means classification accuracy for SC and TD features.

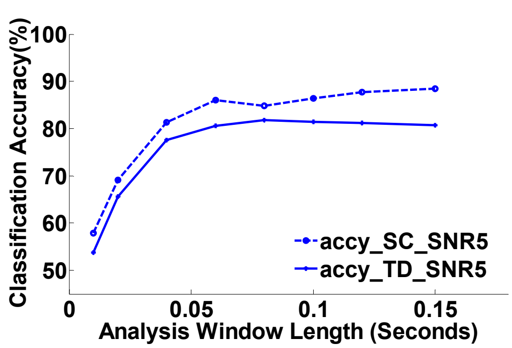


Fig. 3. Effect of different analysis window length at classification.

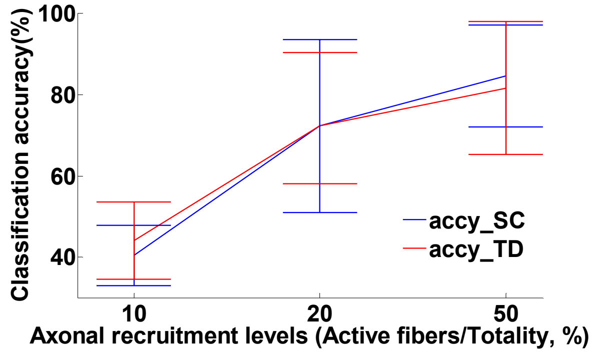


Fig. 4. Effect of different nerve fiber activations in training.

C. Effect of Nerve Fiber Activation

In Figure 4, the mean and standard deviation of classification accuracy over 10 test sets are shown for each of the recruitment levels and feature sets. The classification when 50% of the nerve fibers were activated produces the highest classification accuracy, approximately 80%. This is to be expected, as a larger number of active neurons provide more information about each class, while the classifier may not be appropriately trained at lower levels of active fibers. Therefore, the user would be required to perform reasonably high levels of contraction in an application in order to achieve a good classification performance.

IV. DISCUSSIONS

This model is appropriate for use in many applications, because it was constructed with published physiological data. Realistically however, the articulations of different muscles and muscle groups are synergistic, involving multiple agonists. As a preliminary interface for research on neuromuscular process, only the fascicles innervating prime mover muscles for each contraction were modeled to simplify the study. The authors expected that this will satisfy the fundamental fascicular innervation pattern, and the main observations will hold.

With respect to the duration of each motion, results showed 2 seconds for each motion is adequate and it is therefore recommended to save computing and training time. The degree of nerve fiber activation which is associated with information content is a primary factor in classification performance. Although the results suggest that a strong contraction should be used to activate more brachial fibers for abundant information, this is not always possible or convenient, and certainly limits the versatility of the methods.

As discussed in this work, the feature set and the analysis window size also influence the classification performance. It was shown that an analysis window length of 0.08 seconds offers a good compromise between accuracy and response time. The classification performance between alternative feature sets, SC and TD did not show large differences, however, they will be investigated in the future, according to their implemention, reliability and optimizations (such as threshold selection and noise immunity) .

V. SUMMARY

A novel peripheral nerve model is developed, incorporating stochastic neural innervation processes to offer a useful interface for investigations on functional neuromuscular excitations and applications and preparations before human experiments.

The work assessed the accuracy with some parameters in data acquisition and recognition. The results suggest that sufficient neural information from viable active nerve fibers in a recording is the critical factor in classification decision making. The information abundance is associated with the active fiber numbers and motion duration. Signal analysis parameters (analysis window size, feature set) will affect performance as well. The choices of feature set, SC or TD, both showed distinctive performance in classification. A relatively short analysis window (0.08 seconds) is possible while maintaining good performance.

This model has provided preliminary analysis for peripheral nerve interface-based neural control of upper limb prostheses. Refinement of this model may allow an optimal observation in anticipation of implantation in human subjects in the near future. Other intrinsic factors will be further investigated, including the sensitivity to noise and the compatibility of recording tools.

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