Using Rank Order Filters to Decompose the Electromyogram

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Abstract

This research effort applies nonlinear filters to model generated muscle and nerve signals and compares the results to determine correlation. A class of nonlinear filters, Rank Order filters (ROF), has been used to examine a variety of biological signals, and has shown to be faster and more accurate than traditional muscle signal processing techniques. Using accepted parameters, the authors use a signal representing the nerve signal to generate the muscle signal. Then, using these nonlinear filters on the generated signal, the authors attempt to recover the original (nerve) signal. Three test sets of data are generated that range from simple (no noise) to fairly complex (noisy and varied amplitude). A ROF family, window size 25, was applied to the rectified generated electromyographic signals. The filters tested were the upper half of the window, that is, 13 to 24, for each of the signals. Comparisons of these results, normalized, with the normalized values utilized to generate the electromyographic signals are presented.

Introduction

Electromyographic (EMG) signals are the detectable result of the central nervous system (CNS) controlling muscle activation. In normal muscle function, the CNS controls contraction by asynchronously contracting small numbers of cells in the muscle. The EMG, as an electrical signal, can be detected using both surface and needle or finewire electrodes. No method exists that accurately determines the number of neurons based on EMG processing.

The implication that the EMG is related to the electroneurogram (ENG) (the electrical signal measured at the nerve) is intuitive, but values (either theoretical or experimental) correlating them were not found in an extensive literature search. Once established, this relationship would vary based on the muscle involved as each muscle has a range of neurons controlling it. However, it could provide a reference value if it is assumed that the ENG, as measured, is proportional to the "intent" of the CNS.

This relationship, if known, would provide a solid argument for the decomposition of the EMG as a valid indicator of the desired intent of the CNS. The focus of this research is the validation of a positive relationship between the ENG, as represented by the firing curve, and the EMG. The technique used in this effort is Rank Order filters, which have been previously applied by these authors to the EMG, but not the ENG, and hence, not correlated.

The Motor Unit Action Potential and the EMG

The signal measured at the surface of the skin is a composite of all of the signals from all active motor units filtered through skin, muscle and other body fluids. The motor unit action potential can have many shapes as a result of the geometry of the data collection, recruitment of a variety of motor units, and the volume conduction within each individual person.

The EMG is the detectable electrical signal that results from muscle recruitment being passed through a low pass filter (skin and connective tissue) [1]. Hence, the EMG is the detection of the ion flow from many muscle fibers contracting. The chemical process, which is recorded as the EMG, originates at the cellular level and is the summation of many cells firing as the muscle contracts. The shape of the EMG is affected by the dispersion of the muscle cells of each motor unit throughout the muscle. Each motor unit, composed of many muscle cells, generates its own signal, called the motor unit (MU) action potential (MUAP), which is influenced by the dispersion of the individual muscle cells in the muscle, the amount of contraction by other motor units, and the amount of fat, skin and bone in the vicinity. The EMG is the summation of all the motor units firing at any one time.

As there may be thousands of muscle cells firing at any one time, the surface EMG may be considered as a zero-mean Gaussian process $s(t) \in N(0, \sigma_s)$, modulated by muscle activity, plus independent zero-mean Gaussian additive noise $n(t) \in N(0, \sigma_n)$. The important factors in these assumptions are zero-mean (since electrically neutral) and Gaussian (due to asynchronous firing), plus the Gaussian noise.

Rank Order Filters

Rank Order (RO) filters are a subclass of Order Statistic (OS) filters, which have been shown to be useful for robust signal smoothing. In addition, the RO filters do a better job of simultaneously preserving edges (they shift an edge) and smoothing noise than linear filters. The OS filters can be optimized for i.i.d noise peculiar to the chosen signal. The median filter, a RO filter, sequences the data values low to high, and outputs the *N+1* data value for a window size of *n=2N+1* and preserves edges exactly. The median is an OS filter which has optimal breakpoint of 50% (resistance to impulsive noise –

random neuronal firings) and ignores large baseline shifts (muscle artifacts). The RO filter shown in the images of this study is a 20^{th} of 25, that is r=20. The 20^{th} value of the window size 25 is chosen for the output of the filter. Rank Order filters eliminate rising impulses of width less than $2N+2-r$ or falling impulses less than r points [2]. All RO filters with r greater than 13 were evaluated, and r=20 produced the best results. Rank Order filters have no effect on areas having constant value within a half window length at the end of the signal. Additionally, they will move edges forward or backwards determined by the r selected. If $r > N + 1$, the edge will advance (move left). This same property will affect the length of the constant regions, by either shrinking or expanding them. The movement of the edges can be rectified after filtering, as the movement is small and of known value.

Generation of Artificial EMG

In order to provide unbiased data to test this filtering technique, "simulated test sets" of EMG data were generated using MATLAB© to replicate what should be collected with cup electrodes on the skin surface of an experimental subject. These test sets are designed to be the equivalent of sending a known signal through an unknown filter to validate the filter. Generation of these test sets utilized a variety of MUAP shapes along with a range of speeds to simulate the nerve conduction velocity that changes with neuron diameter and the variety of amplitudes possible with a unique MUAP.

The Hodgkin-Huxley equation, knowledge about that number of neurons in a particular nerve, and the desired geometry of the data collection electrodes were all utilized in the design of the test set with some assumptions made about motor unit recruitment. Seven different MUAP waveforms were utilized, as well as a Gaussian range of nerve velocities. One hundred motor units were modeled, with a "firing curve" as the basis for when each MU fired. This firing curve is the number of MUs firing at any one time, and hence is the basis to which our results are compared against. In this firing curve, along with individual MU firings, four contractions are generated, utilizing all MUs and using known natural recruitment methodologies. The firing curve is divided into different contractions, and different types of contractions. The first 1000 points are individual MUAPs firing. The first contraction (1000-4500) and second contraction (5000-10000) utilize a natural recruitment scheme, increasing the number of MUAPs firing and increasing the number of neurons firing, with a fast increase. The third (11000-23000) and fourth (25000-40000) use the same schema, but with a slow increase. Three test data sets are generated – the first had constant amplitude MUAPs, no noise, and is termed the Constant Amplitude EMG (CEMG). The second test data set varies the MUAP amplitude, has no noise, and is termed the Amplitude varied EMG (AEMG). The most difficult data set varies the MUAP amplitude, has 10% Gaussian white noise, and is termed the Noise EMG (NEMG). All use the same firing curve to generate the EMG signal. The outputs are shown in Figure 1.

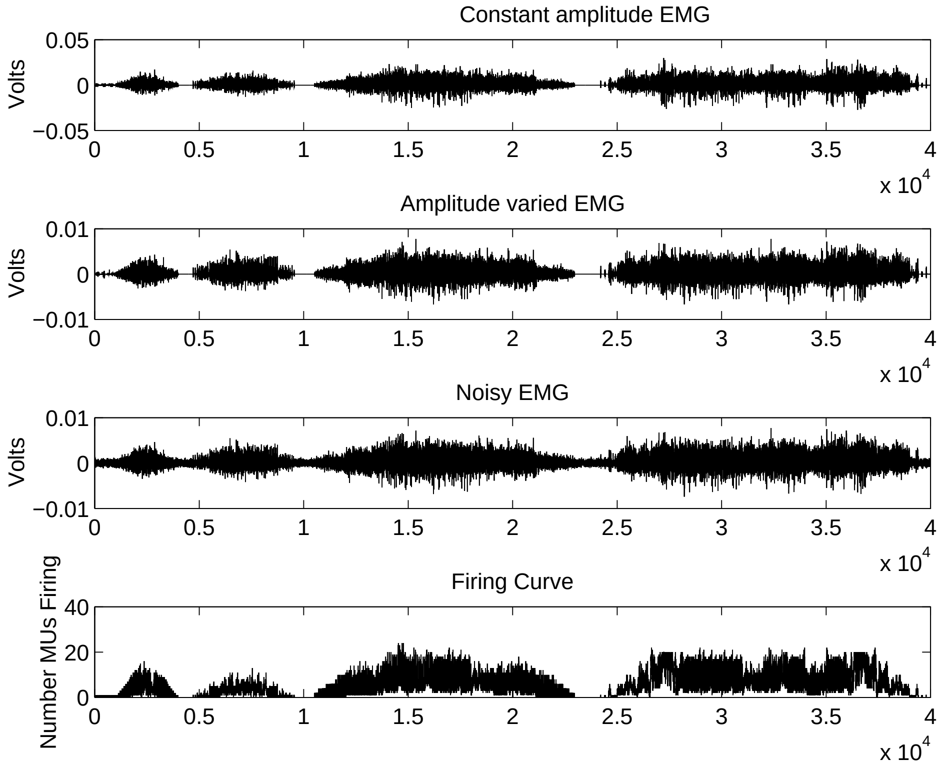

Figure 1. Generated EMGs and Firing Curve

Signal Processing

Using MATLAB, a variety of RO filters were applied to all three generated signals. A window size of 25 was determined based on the design parameters of the EMG signal generation, primarily sampling rate (of less importance is the morphology of the MUAP waveforms). For a larger (faster) sampling rate, with the parameters designed here, a larger window size would be appropriate. The lower r-values in a RO filter will tend to be more sensitive to the noise in a signal, whereas the larger r-values will ignore any signals of size $r–1$ or less. A larger window size will, obviously, provide a larger selection of r.

The upper half of the window size was applied to these signals in order to compare the results. Rank Order filters tend to shift edges based on the r-value, and this was verified in this research effort. The median filter does not shift the edges, but r-values above the median (> 13 in this case), will move the edge earlier in time by r–13. The RO filters were applied to the rectified values of the generated EMGs.

Results

In addition to the phase shift from the filter, the morphology of the motor unit action potential causes some time lag between the firing curve and the generated signal. This phase lag is small, and the two tend to cancel each other out. The firing curve is divided into different contractions, each a different type of contraction for a total of five different regions. All RO filters with $r < 20$ lost the individual MUAP firing as can be seen in Figure 2. The filters were not sensitive enough until $r \geq 20$ as shown in Figure 3. The remaining regions faired better. The tracking in the first contraction, as seen in Figures 2 and 3, was much closer. The large single spikes were lost, but the envelope was well tracked. As can be seen in Figures 4 and 5, (fast contraction) the ideal situation with constant amplitude EMG and no noise produced the closest tracking. In Figures 6-9, there is not much significant difference between the clean and the other EMG signals except during the quiet time between contractions. Even in the most challenging case (NEMG), the recovered firing curve is more accurate than one using current techniques [3].

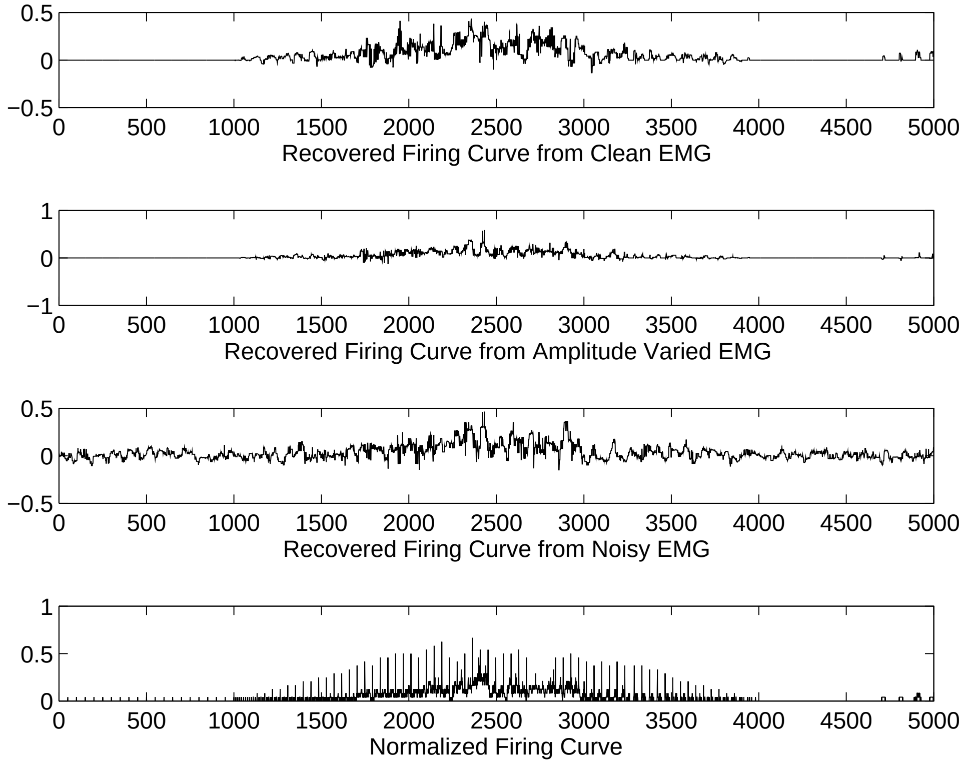

Figure 2. First 5000 points using a median ROF.

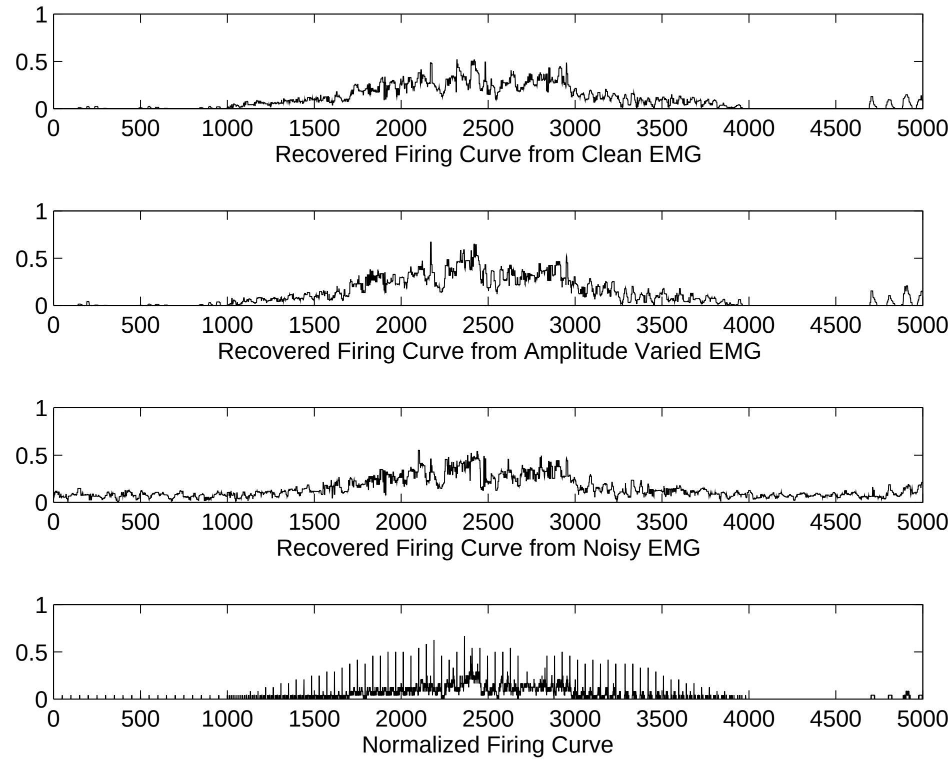

Figure 3. First 5000 points using a 20 of 25 ROF.

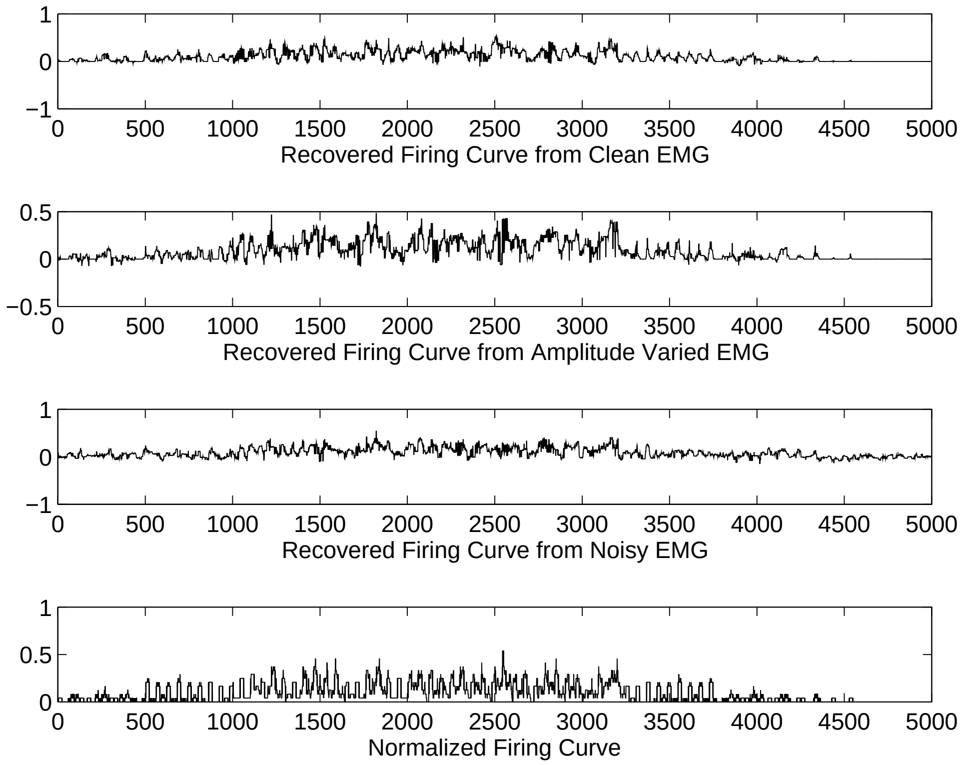

Figure 4. Second contraction using a median ROF.

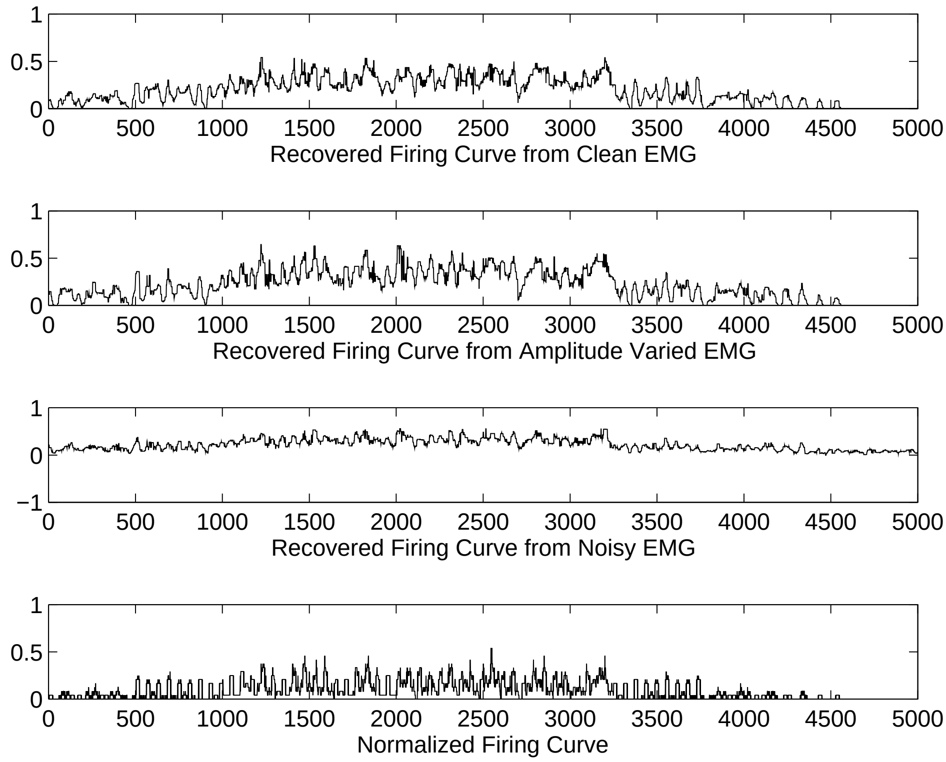

Figure 5. Second contraction using a 20 of 25 ROF.

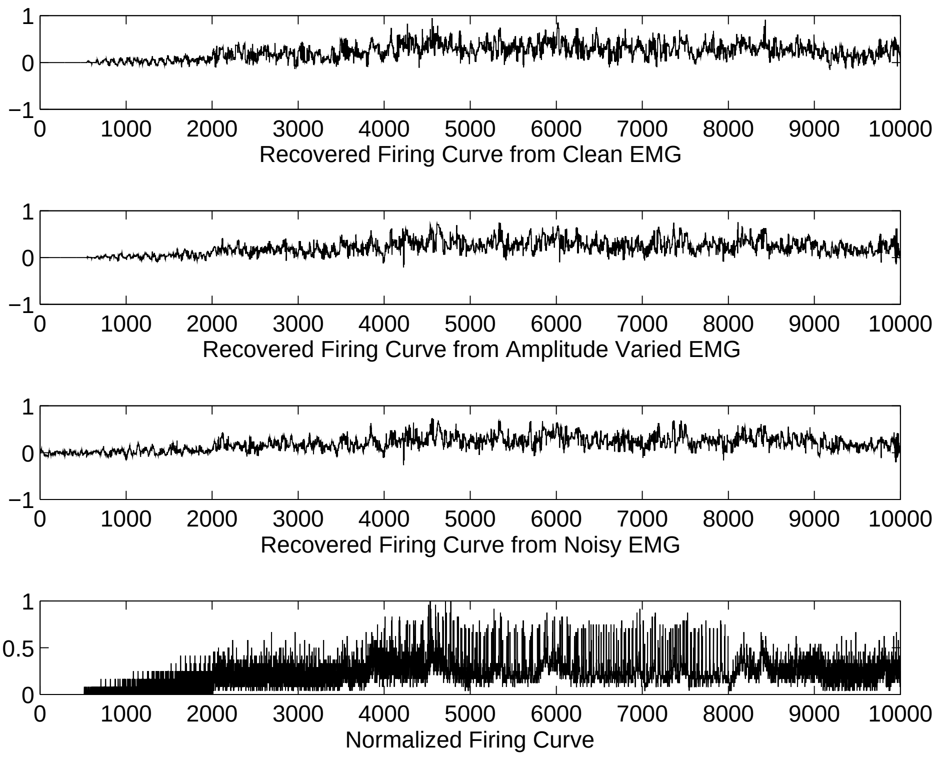

Figure 6. Third contraction using a median ROF.

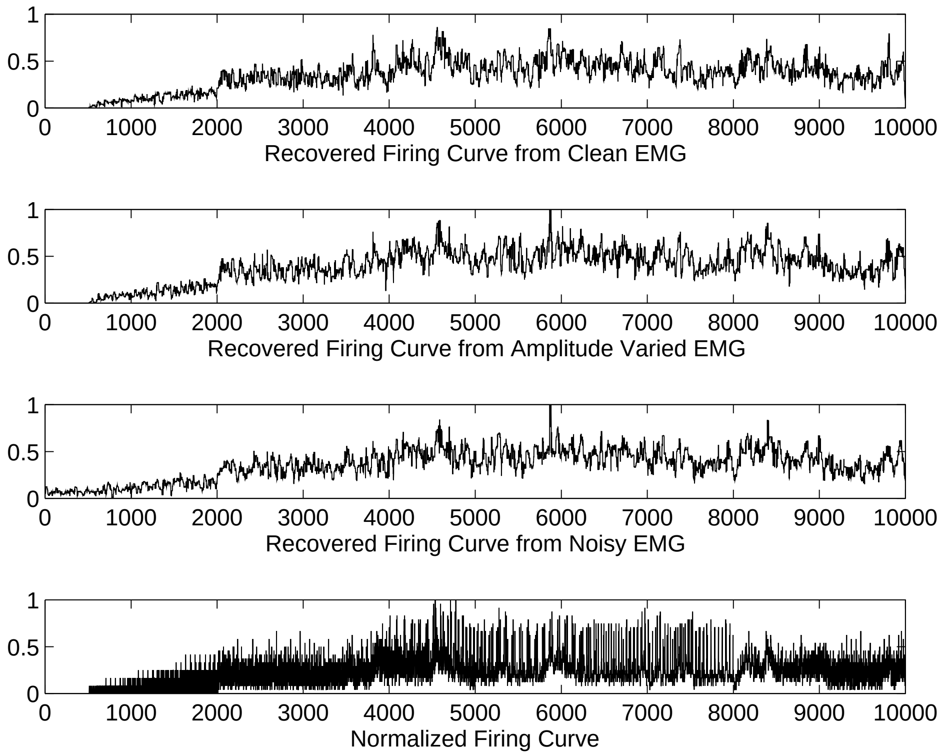

Figure 7. Third contraction using a 20 of 25 ROF.

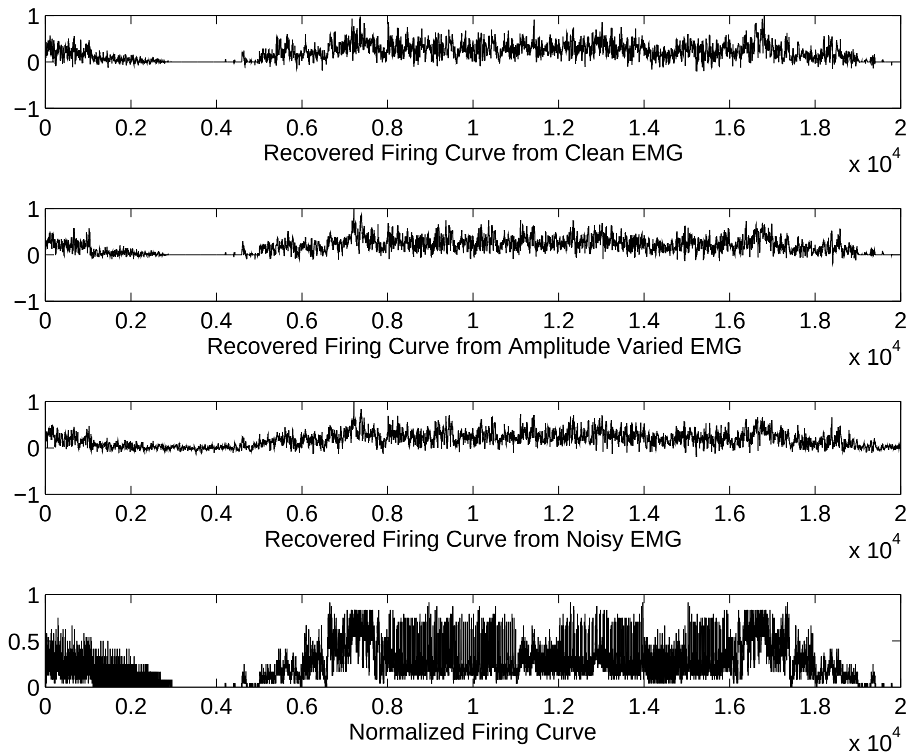

Figure 8. Fourth contraction using a median ROF.

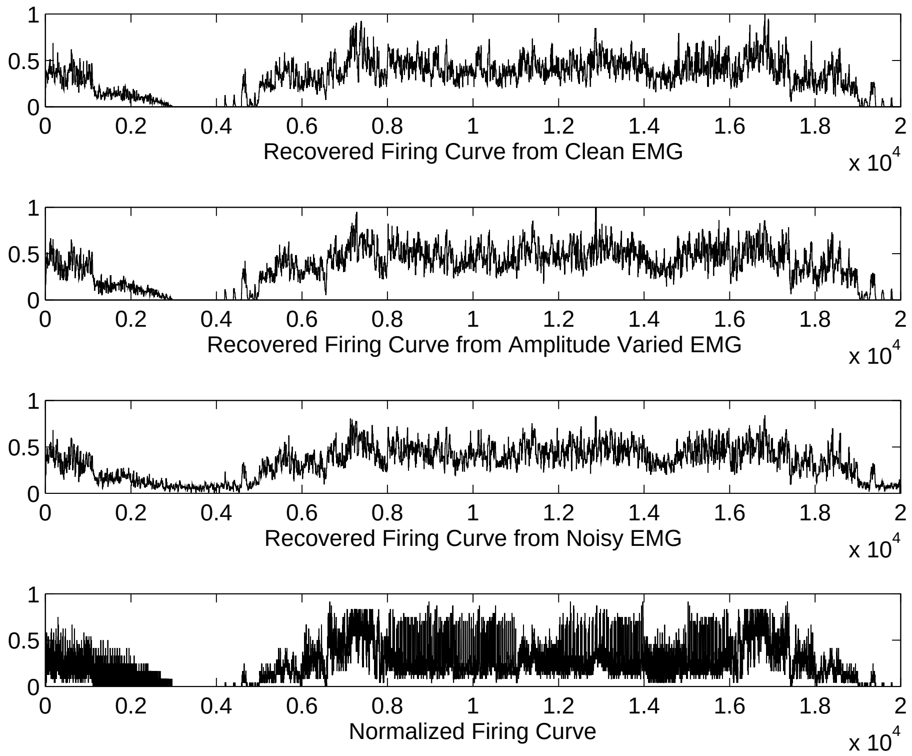

Figure 9. Fourth contraction using a 20 of 25 ROF.

References:

[1] JV Basmajian and CJ DeLuca, "Muscles Alive: The Functions Revealed by Electromyography". Williams & Wilkins, 5^{th} edition, 1985.

[2] TA Node and NC Gallagher Jr, "Median Filters: Some Modifications and their Properties". *IEEE Transactions on Acoustics, Speech, and Signal Processing*, ASSP-30: 739-746, Oct 1982.

[3] DJ Roberson, CB Schrader and HG Longbotham, "Adaptive Robust Detection of Below Lesion, Noninvasive Electromyographic Signals for Muscle Control". *Proceedings of the 32^{nd} Conference on Decision and Control*, San Antonio, TX, pages 2525-2526, 1993.