“Harnessing Motor Unit Activity: From Lab to Clinic”

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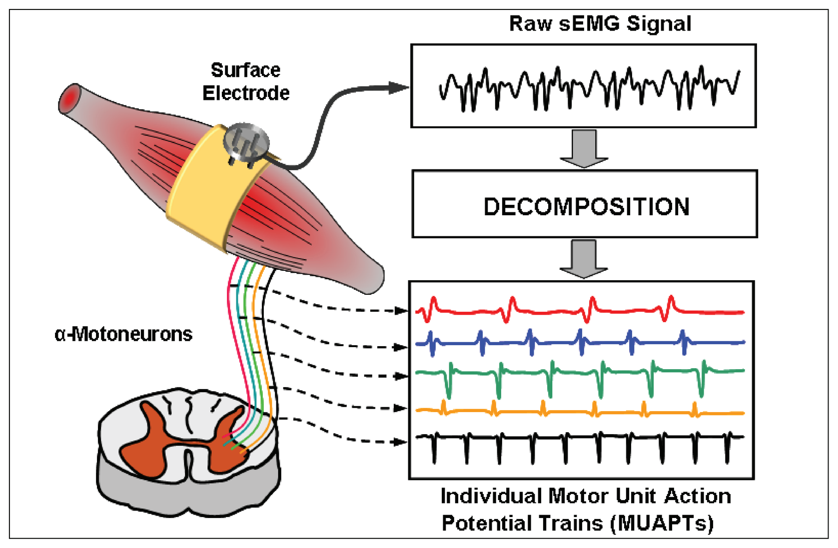
Goal: To develop an automatic and non-invasive system to accurately and quickly decompose surface electromyographic (sEMG) signals into their constituent motor unit action potentials (MUAPTs). This will enable a wider range of studies to investigate the workings of the healthy and diseased neuromuscular system.

Project 1: Develop Technology for Decomposition of sEMG Signals

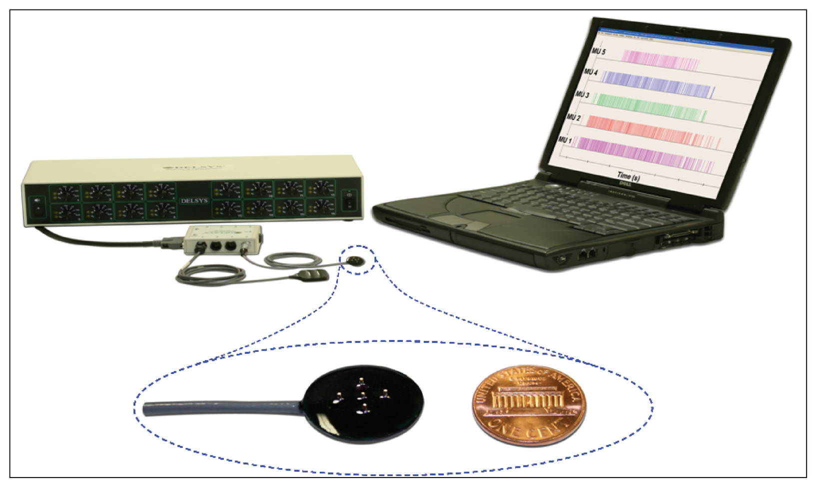
Aim: to develop a) a non-invasive sensor system for acquiring decomposable sEMG signals, and b) software algorithms to accurately decompose the sEMG signals into individual MUAPTs.

sEMG Decomposition



Data collected from the sEMG sensor is decomposed into individual Motor Unit Action Potential Trains (MUAPTs). Decomposition makes it possible to obtain the firings of many of the motor units which are activated during a contraction. The motor unit trains represent the information controlled by the CNS and PNS to activate the motor units. Their measurement can reveal normal motor control strategies as well as neuromuscular disorders.

sEMG Precision Decomposition System Device



A Precision Decomposition system used in the laboratory or at the bedside to acquire and decompose sEMG signals detected from a 5-pin array sensor (inset) that is placed on the skin over the muscle of interest. The system provides appropriate conditioning and troubleshooting for attaining high-fidelity recordings. The interactive software provides a means to create and store protocols and feedback displays to subject and operator.

sEMG Decomposition Challenges

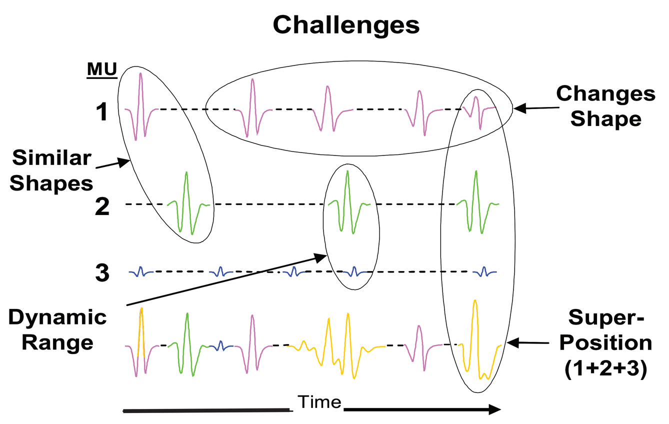
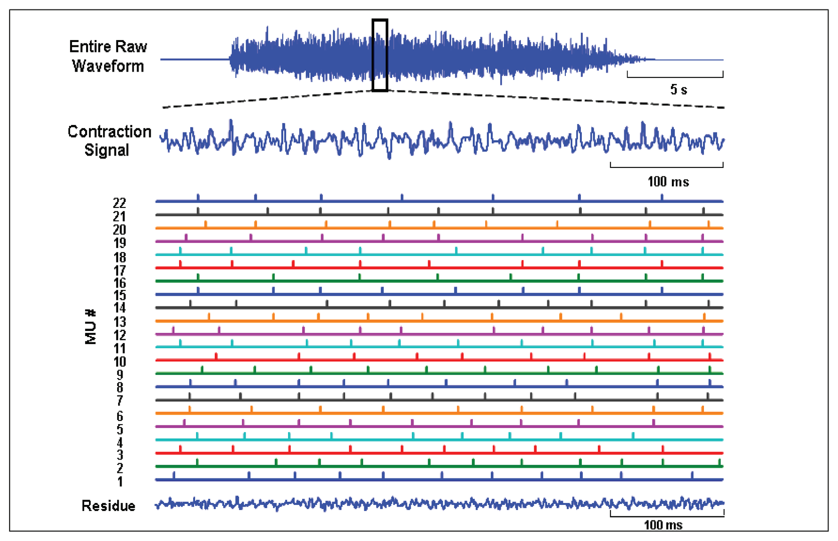


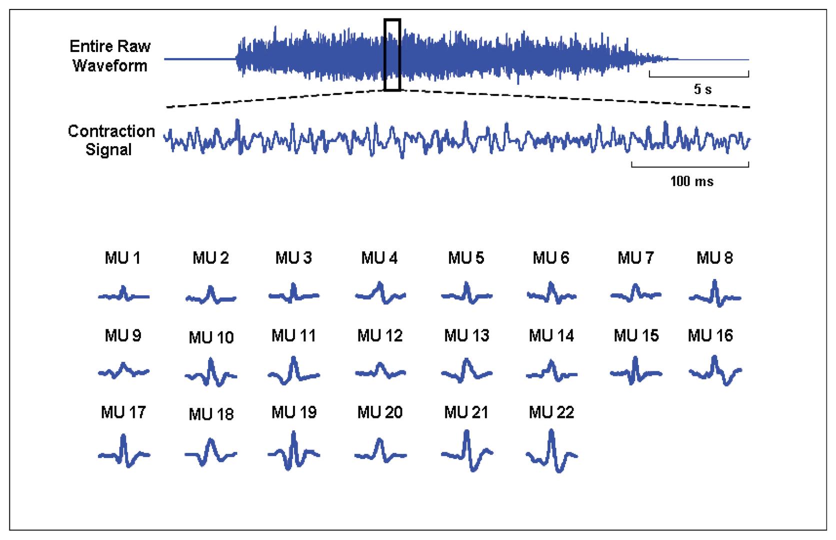
Illustration of four categories of challenges that arise in the decomposition of sEMG signals: similar MUAP shapes, changes in MUAP shape, large dynamic range in MUAP amplitudes, and superposition of MUAP’s.
Decomposition Algorithms process the data using classifiers designed to resolve these complexities and automatically produce a Decomposition. The classifiers are controlled and tuned utilizing an AI architecture constructed around a knowledge-based blackboard specifically designed to manage algorithms that evolve in complexity, and develop a knowledge base that becomes more comprehensive as the descriptors of the signal to be analyzed increase. An example of a Decomposition Result is shown in the figure below.

De Luca CJ, Adam A, Wotiz R, Gilmore LD, and Nawab SH, “Decomposition of surface EMG signals”, *J. Neurophysiology*, **96: 1646-1657, 2006.**

Decomposition Result



Bar plot of 22 motor unit firings decomposed from the sEMG signal. Top figure represents 1 channel of the sEMG signal from a 25 s isometric constant-force contraction from the FDI muscle. The second figure is an expanded view of a signal epoch within the black box. The raster below is the bar plot of the motor unit firings in the epoch. The residue signal at the bottom is that signal which remains when all the identified MUAPs have been removed.

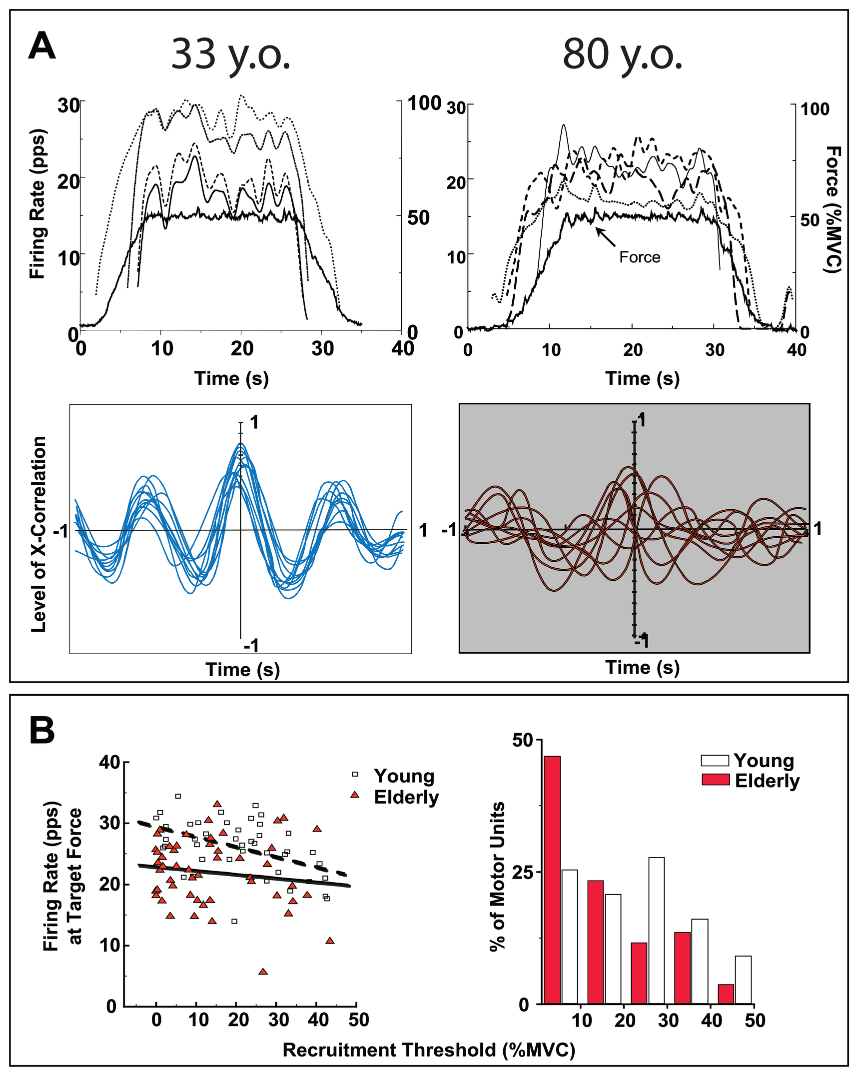


These are the motor unit action potentials from one channel of the sEMG decomposition shown in the figure on the left. The MUs are numbered in the order of recruitment. Motor unit #1 (MU1) is the first to be recruited, and MU22 is the last recruited. Note that the amplitude of the action potentials generally increases as the recruitment progresses; a behavior consistent with Henneman’s Size Principle.

Project 2: Clinical Application of the Decomposition Technology

Application: to delineate the age-related progression in the deterioration of motor unit control (Left) and identify the effects of Parkinson’s disease on MU control (Right)

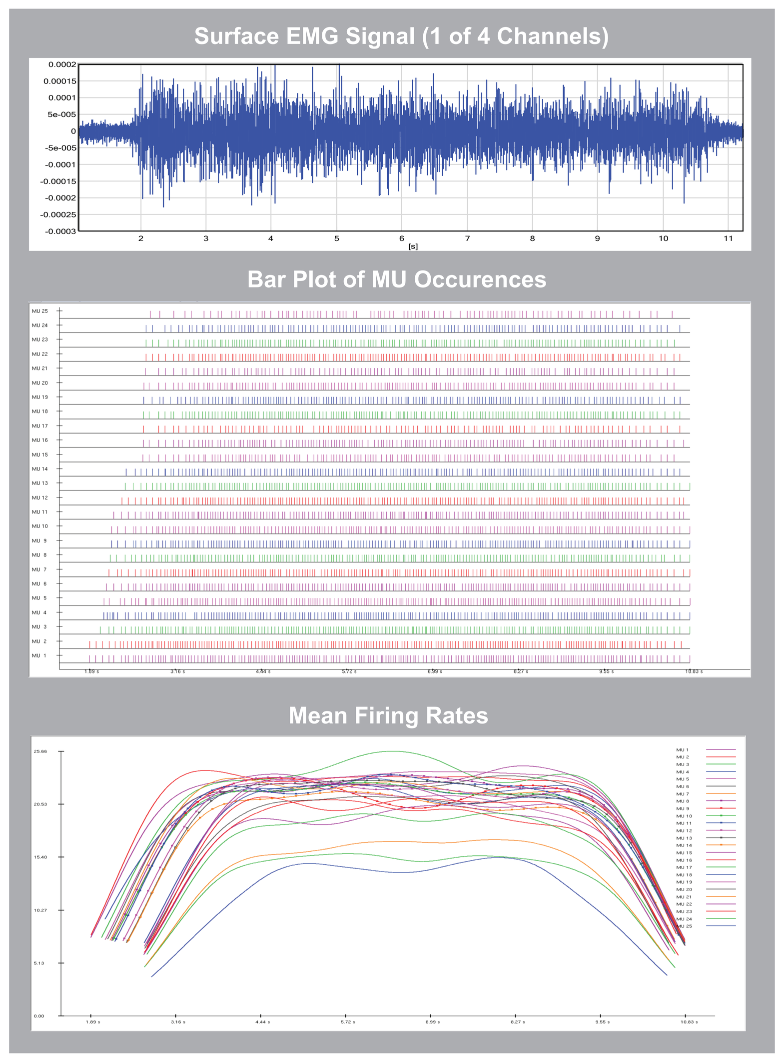
Effects of Age on MU Control



Example of altered motor unit firing behavior in the elderly from FDI data. The plots in A compare mean firing rates and cross-correlation values between MU pairs for a 33 yo “control” subject (Left) and a 80 yo subject (Right). The plots in B demonstrate that MUs in the elderly have higher mean firing rates when first recruited than the younger adults.The goal is to acquire a data base (10-85+ yo) to delineate the influence of age on MU control.

Erim Z, et al. “Effects of Aging on MU Control properties”, *J Neurophys* 82, 1999

Parkinson’s Disease and MU Control

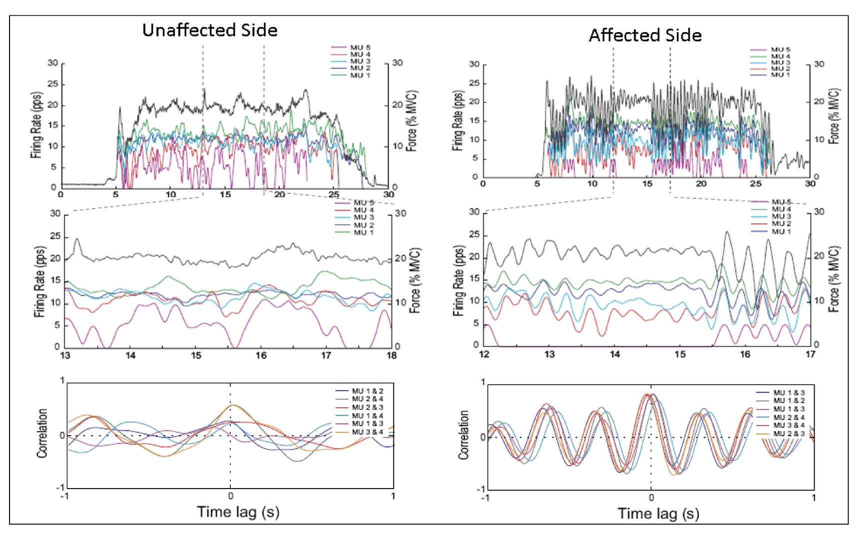


Decomposition results from a 66 y.o. subject with Parkinson’s disease and motor fluctuations. The EMG data (Upper) were recorded from the TA muscle during ankle Dystonia. The bar plot (Middle) identifies the firing occurences of 25 MUs. The mean firing rates of the MUs are smoothed (3s Hanning window) and plotted as a function of contraction duration (Lower). These are preliminary results; however, the nested behavior of the firing rates appear consistent with normal MU control.

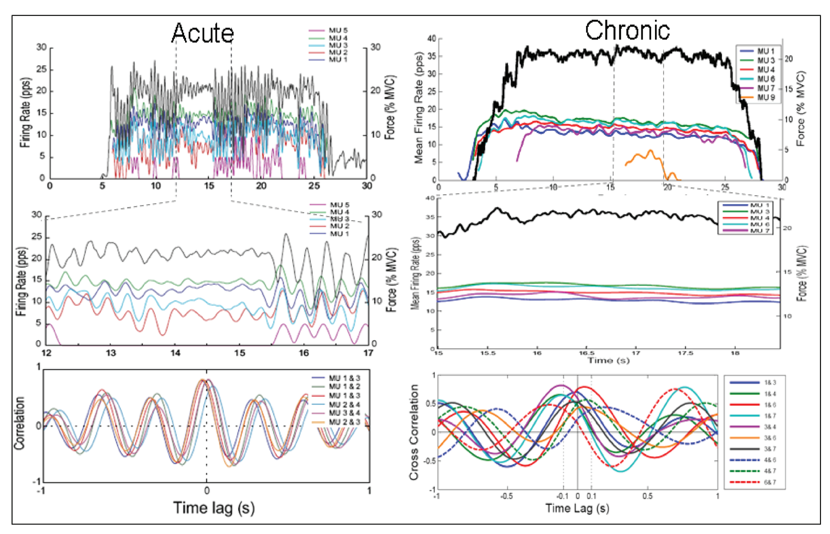
Application: investigate the efects of acute and chronic cerebellar stroke on the control properties of motor units and their relationship to muscle force production.

Cerebellar Stroke

Acute: Unaffected vs. Affected Side



Acute vs. Chronic



Samples of decomposed data from the FDI muscle during 20% MVC force trajectories (bold lines) from a patient with acute cerebellar stroke (Left). Differences in mean fiing rates and force (upper and middle plots) as well as the cross-correlation between MU pairs (lower plots) can be seen for the unaffected and affected side. Data from the affected side of this acute subject are compared to a chronic cerebellar patient (Right), indicating that modifications in regulating force are accompanied by MU control adaptations.

Sauvage C, Manto M, Adam A, Roark R, Jissendi P, and De Luca CJ, “Ordered motor unit firing behavior in acute cerebellar stroke”, ***J. Neurophysiology*** **96: 2769-2774, 2006.**

Acknowledgement

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