Beyond Surface Electromyography: Novel Measures of Muscle Activation for High-Degree-of-Freedom Assistive Device Control*

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***Abstract*— To enable intuitive end-user control of high-degree-of-freedom exoskeletons and other assistive devices, we propose two novel measures of muscle activation for use as control signals: vibration, as measured via acoustic myography, and deformation, as measured via ultrasound. When used alongside or instead of traditional surface electromyography signals, these measures offer significant insight into musculoskeletal dynamics and the potential for enhanced device control capabilities.**

I. Introduction & Objectives

From assistive exoskeletons to teleoperated robot arms, a wide array of sophisticated, high-degree-of-freedom (DoF) devices have the mechanical potential to replicate human dexterity. At the same time, intuitive control of the full range of these devices' potential behaviors — i.e., independent manipulation of each DoF — remains an open problem due to the high cognitive load on the human user. Generally, this load is resolved by extracting biological control signals that the user naturally modulates; this is most often accomplished via surface electromyography (sEMG), a measure of electrical depolarization during muscle activation.

Although sEMG is ubiquitous in the field of biosignal-driven assistive devices, the signal is noisy, spatially aggregate, sensitive to sensor placement, and doesn't measure many downstream physiological factors that impact the final muscle output force [1]. As a result, most sEMG-controlled devices are capable of modulating only a single DoF (e.g., grasp closure) or classifying a finite number of discrete behaviors (e.g., grasp types). To address these limitations, we explore two alternative measures of activation that can be directly related to muscle force: muscle *vibration* (as measured via acoustic myography, or AMG) and muscle *deformation* (as measured via ultrasound). Because both are measures of mechanical phenomena — unlike the neurological signals measured by sEMG — we can construct dynamics-informed control systems without building an input-output model relating neurological intent to muscle force. AMG, like sEMG, provides a waveform signal, but boasts a significantly higher signal-to-noise ratio and less sensitivity to electrode location [2]; ultrasound requires comparatively complex image processing and uses sensors that are bulkier and less readily wearable, but it generates a spatially localized signal to permit independent analysis of individual muscles. We therefore investigate both activation signals to build a more complete and versatile understanding of macro-scale muscle physics relevant to assistive device control.

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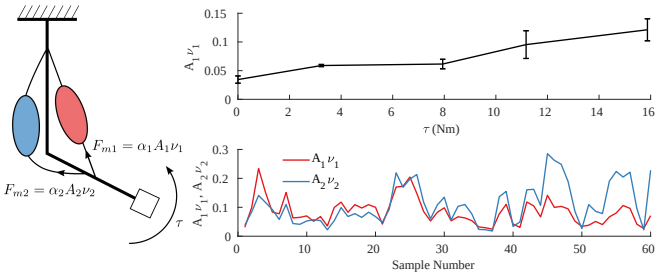

Fig. 1. Preliminary acoustic myography data of the biceps and triceps brachii show substantial correlation with muscle output force. *Left*: Simplified sagittal model of the elbow used in data analysis. *Right, top*: $A_1\nu_1$ of the biceps is highly correlated with output torque τ ($r = 0.9, p < 10^{-6}$). *Right, bottom*: Example $A_1\nu_1$ and $A_2\nu_2$ trajectories (of the biceps and triceps, respectively) during random isometric elbow stiffness modulation, showing significant correlation between the two data series ($r = 0.6, p < 10^{-7}$), consistent with maintaining constant output torque.

II. Aggregate Muscle Force via Vibration

The manner by which the electrical potential changes measured by sEMG are translated into muscle output force is poorly understood; as a result, it remains difficult to use the sEMG signal for control in both physics-based and black box frameworks, and most available systems use either simple differential control schemes or machine learning approaches with ad hoc signal features. In contrast, the muscle vibration measured by acoustic myography (AMG) is thought to directly reflect the dual mechanisms by which muscle force is generated: increased numbers of recruited fibers (reflected in signal amplitude) and increased firing of each motor unit (reflected in signal frequency) [2]. This relationship has been explored in analyses of muscle efficiency over the course of sports training and rehabilitation [2], but it has not yet been leveraged in real-time scenarios such as device control.

To investigate the feasibility of AMG-driven, physics-based control schemes — and to illustrate the advantage of physics-based systems — we consider the simplified model of human elbow flexion shown in Fig. 1, in which the forces F_{m1} of the (biceps-like) agonist and F_{m2} of the (triceps-like) antagonist are modeled as proportional to the product of AMG amplitude and frequency ($A_1\nu_1$ and $A_2\nu_2$, respectively). The forearm is modeled as a point mass centered at its distal end. The task of gravity compensation — i.e., holding the forearm still in the presence of gravity — can be accomplished using a continuous range of agonist and antagonist force values, and during the unstructured motion of daily life, these forces are often modulated to vary elbow stiffness. All human joints are similarly over-actuated, and if we wish to design controllers that mimic the full range of human capability, we must be able to model and understand this phenomenon. Differential control schemes, by their very

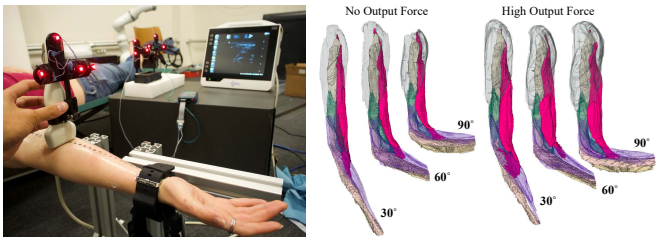

Fig. 2. Muscle deformation, as measured via ultrasound, shows promise as a highly localized measure of muscle force. *Left*: Experimental setup enabling the collection of volumetric arm models via ultrasound and motion capture. *Right*: Preliminary volumetric data of the biceps brachii (magenta) and surrounding muscles show measurable deformation due to changes in both elbow angle and load.

structure, are not capable of modeling this over-actuation.

While even the simplified model above is difficult to validate in vivo, we performed a preliminary proof-of-concept analysis [3] by collecting AMG data from the biceps and triceps brachii of a single subject under static conditions to validate the following two hypotheses: (1) under relaxed conditions (i.e., minimal elbow stiffening), $A_1\nu_1$ correlates positively with output torque τ; and (2) for a given τ, under varying elbow stiffness, $A_1\nu_1$ correlates positively with $A_2\nu_2$ to maintain a constant output torque. Collected data supported both hypotheses, as shown in Fig. 1, suggesting that the $A\nu$ quantity is well-correlated with muscle force.

Given this promising initial data, we are currently working to investigate both the temporal and spatial resolution of the AMG signal, fit and validate parameters α_1 and α_2 to our preliminary model to enable force inference, and expand the resultant models to complex multi-muscle systems.

III. Localized Muscle Force via Deformation

Perhaps the most significant limitation of the sEMG (and AMG) signal is its spatially aggregate nature: it is largely impossible to disambiguate the signals of individual surface muscles, and deep muscles cannot be observed at all. We thus propose muscle deformation as an alternative measure of activation, which can be measured in a highly localized manner via ultrasound.

While ultrasound has been used in device control via deep learning classification methods [4], there does not yet exist a model directly relating deformation to activation (or, more precisely, to muscle output force). In addition, while muscle deformation occurs during force exertion [5], it also occurs during passive changes in kinematic configuration, when the changing relative positions of the attachment points cause muscles and tendons to stretch and slide.

In a preliminary study [6] to understand the relationship between muscle deformation and output force in the presence of purely kinematic deformation, we generated a factorial set of volumetric arm scans under multiple loading conditions and elbow angles from each of three subjects. Each scan was collected using an expert-manipulated ultrasound probe in conjunction with motion capture, which allowed each ultrasound image to be localized in space. We then manually segmented the biceps brachii (along with other elbow flexors and surrounding tissue structures) of a single subject to generate the first-ever data set permitting separable analysis of force- and configuration-associated muscle deformation. This data set can be accessed at `hart.berkeley.edu`.

In addition to data set generation, our preliminary analyses confirmed that both load and configuration changes cause muscle deformation that is readily observable via ultrasound, as shown in Fig. 2. We also showed that the location of maximal change in biceps cross-sectional area under loading is relatively robust to shifts in elbow angle, suggesting that a well-placed stationary ultrasound probe could generate muscle force measurements that are robust to configuration. We are now working to develop and validate low-dimensional deformation models and to speed up the tissue segmentation process using both semi-automated image registration [7] and fully-automated neural networks [8].

IV. Conclusion & Future Directions

Underlying our exploration of novel muscle activation measures is the idea that *better system identification of musculoskeletal dynamics will lead to more capable assistive device control schemes*. While some contend that black box models of human intent are sufficient for control signal extraction — and, indeed, many of the most capable current devices rely on such models — we argue that grounding observed activation signals in biological mechanisms will enhance not only physics-based control schemes, but black box models as well. An AMG study, for example, could illuminate the trade-off between increased motor unit firing rate and fiber recruitment, allowing for better interpretation (and thus neural network feature design) of the corresponding sEMG signal. Similarly, deformation analysis could inform the choice of sensor location during ultrasound-based gesture classification. Ultimately, we aim to use these technologies to enhance our understanding of the human musculoskeletal system and its own internal control strategies, allowing for the design of more capable assistive device control schemes.

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