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Sonomyography shows feasibility as a tool to quantify joint movement at the muscle level

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Abstract— **Several methods have been used to quantify human movement at different levels, from coordinated multi joint movements to those taking place at the single muscle level. These methods are developed either in order to allow us to interact with computers and machines, or to use such technologies for aiding rehabilitation among those with mobility impairments or movement disorders. Human machine interfaces typically rely on some existing human movement ability and measure it using motion tracking or inertial measurement units, while the rehabilitation applications may require us to measure human motor intent. Surface or implanted electrodes, electromyography, electroencephalography, and brain computer interfaces are beneficial in this regard, but have their own shortcomings. We have previously shown feasibility of using ultrasound imaging (Sonomyography) to infer human motor intent and allow users to control external biomechatronic devices such as prosthetics. Here, we asked users to freely move their hand in three different movement patterns, measuring their actual joint angles and passively computing their Sonomyographic output signal. We found a high correlation between these two signals, demonstrating that the Sonomyography signal is not only user-controlled and stable, but it is closely linked with the user's actual movement level. These results could help design wearable rehabilitation or human computer interaction devices based on Sonomyography to decode human motor intent.**

I. Introduction

Human machine interfaces have permeated several aspects of our lives. They have been on an incremental journey right since the inception of the graphical user interface [1]–[3]. It has opened up entirely new ways for us to interact with machines, especially computers. Although user interfaces have been around for some time [4]–[6], advances in recent decades have enhanced our ability to acquire clean biosignals capturing human motor intent, reducing the need to physically press buttons or move a pointer. Several biosignal extraction methods such as surface or implanted electrodes [7], [8] brain computer interfaces [9]–[11], surface electromyography [12]–[15], Electroencephalography [16], and Functional Near-Infrared Spectroscopy (fNIRS) [17], [18], have found applications in human rehabilitation and human computer interaction. These techniques also allow us to enable human enhancement, which is "an attempt to temporarily or permanently overcome the current limitations of the human body through natural or artificial means" [19].

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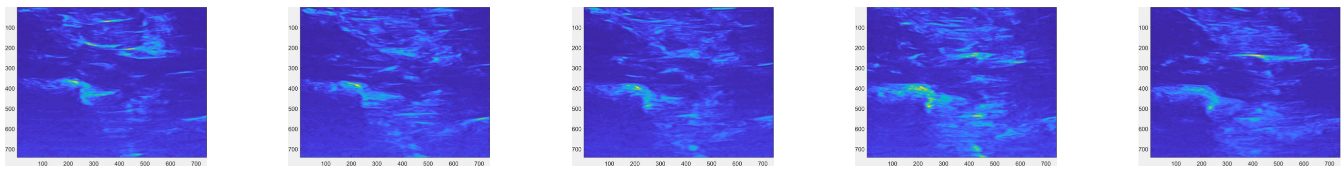
However, these methods have their own limitations. For example, surface electromyography (sEMG) has low signal-to-noise characteristics, random fluctuations in the sEMG signal [20], [21], and low specificity between individual muscles because of cross talk [22], [23]. Recently, subcutaneously implanted electrodes [24], [25] have emerged as an alternative but these methods are highly invasive. A non-invasive method to acquire clean biosignals easily, that can be used in real-time to decode human motor intent, and be used as an input to a reliable human machine interface is a critical unmet need.

One emerging biosignal that provides access to human motor intent non-invasively is ultrasound imaging [26]–[30]. Ultrasound imaging provides a non-invasive sensing modality that can spatially resolve individual muscles, including those deep inside the tissue, and detect dynamic activity within different functional compartments in real-time. In fact, ultrasound imaging has been shown to be useful for detecting individual finger positions [31], [32], along with other complex muscle deformation patterns [33]. Prior work from our laboratory has shown that real-time ultrasound imaging of forearm muscle deformations during volitional motor activity can be used for real-time classification of multiple degrees of freedom in able-bodied individuals [32], [34]–[36] and individuals with transradial amputation [30], [37]. Ultrasound techniques offer a reliable way to measure muscle deformation, as opposed to electrical signals from deep lying musculature. Some of the problems associated with other types of control are overcome by using ultrasound, since it gives direct access to muscle movements deep below the skin. Recently, we have proposed a proportional position control paradigm using ultrasound sensing (Sonomyography) [26], and shown feasibility in able-bodied subjects and prosthetic users. Users were able to control the height of virtual cursor on a screen using Sonomyography in the presence of visual feedback [26], [35] with very high accuracy, and that this accuracy drops slightly when users are not given any visual feedback of the target [35] thereby having to rely solely on their sense of proprioception.

In this work we wanted to investigate whether Sonomyography was tracking the user's joint angles in real-time. Subjects performed three motions - wrist flexion-extension, power grasp (hand open/close), and wrist adduction/abduction, with their hand inside an opaque box. We passively collected cross-sectional ultrasound images of their forearm and tracked their joint angles (and computed motion completion levels). Subjects could not see their own hand and were asked to freely move from a fully extended state to a

(a) MCL = 100% (b) MCL = 75% (c) MCL = 50% (d) MCL = 25% (e) MCL = 0%

Fig. 1: (a-e) Representative hand postures attained by the subject while going from full extension to full flexion (MCL = motion completion level).



(a) MCL = 100% (b) MCL = 75% (c) MCL = 50% (d) MCL = 25% (e) MCL = 0%

Fig. 2: (a-e) Cross-sectional ultrasound images captured from a subject's forearm while their hand was at postures given Fig. 1a-1e respectively.

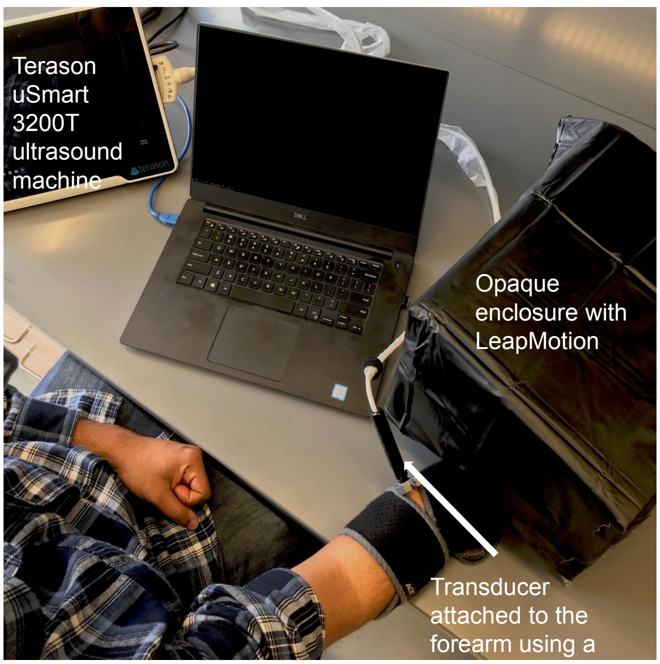


Fig. 3: Photo of the experimental setup used for collecting data. The ultrasound probe was strapped onto the subjects' forearm and they placed their arm inside an opaque enclosure. The image sequence generated by the ultrasound machine was fed into a desktop computer, which calculated a proportional signal as per the method described in our previous work [26].

fully flexed state of each motion. Our hypothesis was that the proportional signal we generated from the corresponding ultrasound cross-sectional images would reliably track the joint angles measured at any given time instant.

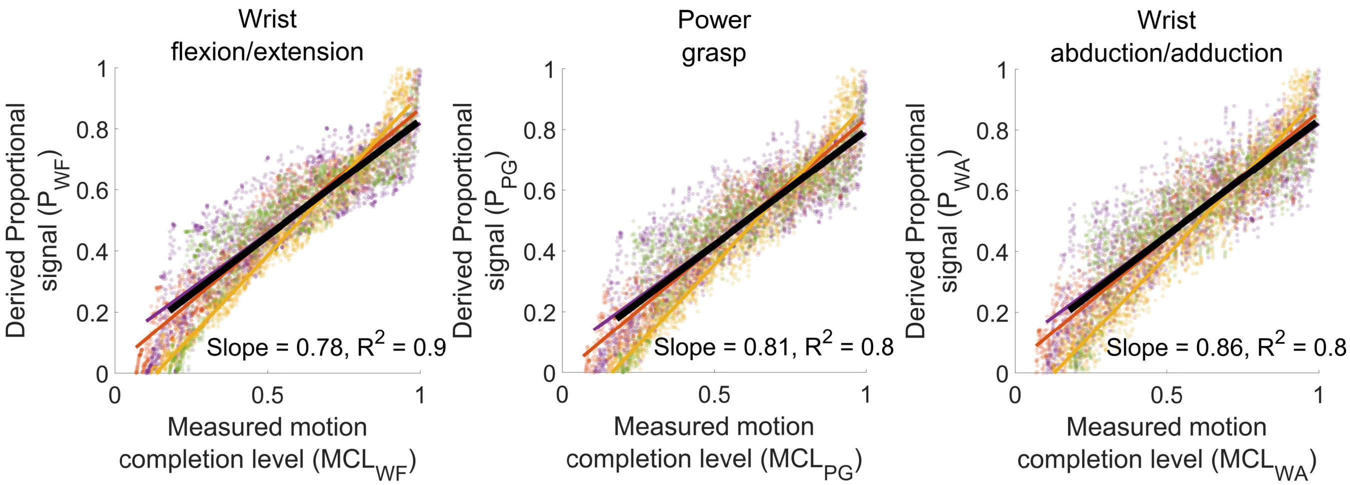
II. Experiment

A. Participants

A total of 4 able bodied individuals (mean age: 22 ± 2 years) were recruited for the experiment. All participants provided written informed consent to take part in the experiments. All of the participants reported being right-hand dominant. All experiments in this work were approved by the George Mason University Institutional Review Board.

B. Setup and Procedure

Participants were asked to sit upright with their elbow below their shoulder and the forearm comfortably secured to a platform on the armrest of the chair (see Fig. 3). Participants were instrumented with a clinical ultrasound system (Terason uSmart 3200T) connected to a low-profile, high frequency, linear, 16HL7 transducer. The imaging depth was set to 4 cm and the gain was set to 60. The transducer was manually positioned on the volar aspect of the dominant forearm in order to access the deep and superficial flexor muscles of the forearm. The transducer was secured in a custom designed probe holder and held in place with a stretchable cuff. In order to ensure that participants were not relying on their visual sense to perform each task, their hand was placed in an opaque enclosure to prevent direct observation of the wrist and hand movements. A USB-based video grabber (DVI2USB 3.0, Epiphan Systems, Inc.) was used to transfer ultrasound image sequences in real time to a PC (Dell XPS 15 9560). The acquired image frames were processed in MATLAB (The MathWorks, Inc.) using custom-developed algorithms as given in our previous work [26]. A Leap Motion Controller (Leap Motion, Inc.) was attached to the inner top surface of the opaque box such that it could see the full hand. The leap motion device measured the completion level for each motion using custom-developed MATLAB scripts.



(a) (b) (c)

Fig. 4: Proportional signal derived from sonomyography as a function of motion completion level for all the tested hand motions, from LeapMotion tracking. The black line represents the linear fit for all the subjects, while the other colored lines represent individual subjects, and the colored dots represent the data for each subject separately. For all the motions, as the motion completion level increased, the signal derived from sonomyography increased proportionally, as per equation 1, equation 2, and equation 3 respectively.

The participants performed 5 trials of 3 motions each. For wrist flexion/extension, they were asked to start by having their wrist completely extended, then flex it as much as possible, and then return to the fully extended pose. For power grasp (hand open/close), they were asked to start with their hand in the fully open hand posture, then close their hand, and then open. For wrist adduction/abduction, they were asked to start with the wrist fully adducted, move it to a fully abducted state, and then return to a fully adducted state. As they did this, the ultrasound setup used custom developed algorithms to predict a motion completion level for each motion, and the leap motion measured the actual joint angles. This data was then analyzed post-hoc using MATLAB. The participants had no visual feedback of their own hand or any other visual aids. The ultrasound cross-sectional images and the motion tracking frames were both captured passively as the participant simply moved their hand using their sense of proprioception. The subjects were asked to move their hand smoothly through the range of each motion without performing any jerky movements.

Representative hand postures for wrist flexion/extension (Fig. 1a-1e) with their corresponding cross-sectional ultrasound frames (Fig. 2a-2e) give examples of the collected data. Each time point produced one ultrasound frame and hence one predicted motion completion level, and one measured motion completion level from LeapMotion tracking.

III. Results

The proportional signal generated by our algorithm using ultrasound images (eg. Fig. 2a-2e) increased as the motion completion level (eg. Fig. 1a-1e) increased for all the motions in the experiment. One ultrasound image is used to compute the motion completion level at each time instant. Hence, each ultrasound image becomes one point in Fig. 4a, Fig. 4b, or Fig. 4c.

Hand motion	Average error	Standard deviation
Wrist Flexion/extension	7.18	10.56
Power grasp	10.09	10.91
Wrist adduction/abduction	6.82	11.34

TABLE I: Mean and standard deviation of the error between derived proportional signal (using sonomyography) and the actual motion completion level, represented as a percentage of range of motion.

The proportional signal generated by our algorithm using ultrasound images (eg. Fig. 2a-2e) increased as the wrist traveled though its range of motion from fully flexed through fully extended (termed the motion completion level). One ultrasound image is used to compute the motion completion level at each time instant, leading to ultrasound image becomes one point in Fig. 4a, Fig. 4b, or Fig. 4c.

For all three motions (wrist flexion/extension, power grasp, and wrist adduction/abduction), we investigated the relationship between the generated proportional signal (P_{WF},P_{PG}, and P_{WA}), and measured motion completion level (MCL_{WF},MCL_{PG}, and MCL_{WA}). Fitting the proportional signal for each motion as a function of its measured motion completion level with a linear function (equation 1, equation 2, and equation 3) indicated a positive effect of motion completion level on the computed proportional signal (see Fig. 4a, Fig. 4b, and Fig. 4c). These results show that sonomyography closely tracked actual motion completion level for multiple motions reliably (R^2 values for the three motions were 0.86, 0.84, and 0.82 respectively).

$$P(MCL_{WF}) = 0.87MCL_{WF} + 0.014 \tag{1}$$

$$P(MCL_{PG}) = 0.86MCL_{PG} - 0.015 \tag{2}$$

$$P(MCL_{WA}) = 0.87MCL_{WA} + 0.016 \tag{3}$$

IV. Discussion

The Sonomyographic signal linearly tracked the actual motion completion level for wrist flexion/extension ($R^2 = 0.86$), power grasp ($R^2 = 0.84$), and wrist adduction/abduction ($R^2 = 0.82$). These results show that Sonomyography is capable of being used as a human machine interface that tracks the motion completion level for multiple hand gestures.

Sonomyography enables position control, as opposed to velocity control (for eg., found in many commercially available prosthetic devices). In velocity control, the user controls the velocity of movement of the end effector as opposed to its position. In position control however, the control signal directly corresponds with the desired position of the end-effector. Position control of an end-effector based on a control signal derived from deep-lying musculature may find applications in several areas of motor control where the user needs to have direct position control over a biomechatronic device. Prior work from our group has shown that sonomyography can be used to extract a position based biosignal from able-bodied subjects as well as prosthetic users [32], [35], [37], and to control prosthetic devices [26], [34]. Even though it is a position signal, it would be interesting to see how the signal could be affected by the velocity of muscle flexion. We intend to study this in a future study.

Lower-level muscles contain muscle spindles that get stretched during isotonic contractions. These muscle spindles stretch proportional to the expected movement of the end-effector [38]–[40]. Sonomyography measures deformation in deep-lying musculature, that contains these muscle spindles. This allows Sonomyography to be closely linked to the extent of muscle flexion in the forearm (where the ultrasound transducer is placed), and hence to the expected movement of the effector. We believe that Sonomyography shows promise to be a movement quantification technique that can be used across a variety of applications. Currently, this work has focused on imaging forearm muscles to decode motor intent [26], [32], [34], [37], but we can expand to other muscle groups in the future. In this study we investigated how well wrist motions were tracked by sonomyography independently, but future work could expand this investigation by including combined movements.

V. Conclusion

Sonomyography offers a non-invasive method to extract a biosignal that is aligned with muscle activation. We have previously shown that users can control a virtual cursor using Sonomyography. In this work, we showed that the underlying control signal extracted by Sonomyography is closely linked with the user's intended motion completion level. We passively measured the users' motion completion level and recorded cross-sectional ultrasound frames simultaneously. We used these ultrasound frames to compute the Sonomyographic proportional signal and showed that the computed signal tracked actual motion completion closely. Current results could inform the design of wearable ultrasound devices that could eventually help us develop rehabilitation tools or general human machine interfaces that use signals from underlying musculature to control biomechatronic devices.

Future work will aim to fine tune the Sonomyography function for each individual using iterative or machine learning approaches. We have found that a simple function [26] is enough to achieve the current level of usability.

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