# A WEARABLE SONOMYOGRAPHY SYSTEM FOR PROSTHESIS CONTROL

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## ABSTRACT

Sonomyography (SMG) is a promising alternative to electromyography (EMG) for extracting control signals from functional muscle activity in real time. SMG uses ultrasound imaging to non-invasively record superficial and deep muscle activity, making it possible to differentiate the independent contributions of individual muscles during functional movements. Previous challenges surrounding the miniaturization of ultrasound instrumentation have prevented exploration of SMG as a feasible modality for prosthesis control. In this paper, we describe our work developing a 4-channel wearable ultrasound system capable of tracking in vivo muscle interfaces using frequency-modulated continuous wave imaging.

## CLASSIFYING GRASPS USING SONOMYOGRAPHY

Surface EMG remains the primary method for sensing muscle activity to actuate a prosthetic hand. However, EMG suffers from poor amplitude resolution, a low signal-to-noise ratio, and is subject to crosstalk from adjacent muscles [1], [2]. These barriers can make it difficult to derive a rich set of control signals for intuitively controlling multiple degrees-of-freedom within a multiarticulate prosthetic hand. SMG is an alternative sensing modality that uses ultrasound imaging of muscle contractions to spatially resolve individual muscle activities with sub-millimeter precision. Because SMG enables spatiotemporal characterization of both superficial and deep muscle activity and is not subject to intermuscular crosstalk, SMG makes it possible to differentiate the independent contributions of individual muscles during voluntary movement. Control signals for driving a prosthetic hand can thus be extracted from the ultrasound signals using machine learning models (Fig. 1).

Similar to EMG control, SMG control employs a supervised learning framework that uses classification algorithms to compare features of ultrasound signals to training data. Ultrasound images of forearm muscle tissue have enough unique spatiotemporal information for classification algorithms to differentiate between various hand grasps. Our benchtop testing has revealed that SMG can identify five individual digit movements in able-bodied individuals with 97% cross-validation accuracy [3] and fifteen complex hand grasps with 91% cross-validation accuracy (Fig. 2) [4]. We also found that, with minimal training required, SMG can identify five grasps for individuals with upper limb loss with 96% cross-validation accuracy [5], [6]. These results indicate that SMG is a feasible means to classify hand grasps from muscle tissue for prosthesis control.

We investigated grasp classification using a sparse set of ultrasound scanlines to understand the minimum hardware requirements for a wearable ultrasound system [7]. We recorded ultrasound images from the forearms of five able-bodied subjects performing five grasps (power grasp, pinch, index point, key grasp, wrist pronation) using a 128-element linear array transducer. We then selected different subsets of scanlines to quantify the extent to which classification accuracy was affected. Even with a subset of only four scanlines, classification accuracy was virtually unchanged (94 ± 6% for 128 scanlines, 94 ± 5% for 4 scanlines). This demonstrates the feasibility of using a small number of single-element transducers rather than a full array, which simplifies the instrumentation that would need to be incorporated into a prosthesis socket. We thus chose to implement a wearable SMG system using only 4 individual transducers.

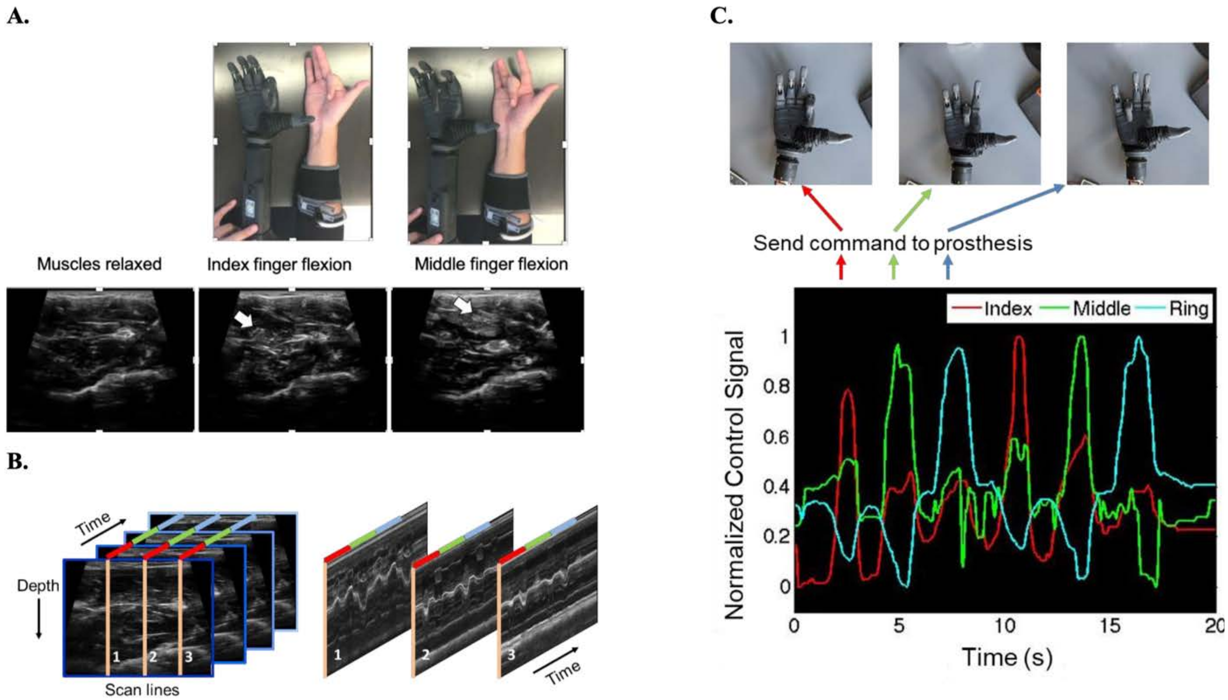


Figure 1. Schematic showing our approach to prosthesis control with SMG. (A) Muscle deformation over time is tracked with an ultrasound transducer placed on the forearm. The figure shows an able-bodied subject performing index finger flexion and middle finger flexion. The corresponding ultrasound images show different muscle compartments deforming for each movement. (B) M-mode ultrasound images (depth over time) show deformation of different muscle compartments over time corresponding to individual finger movements (red, green, blue segments). (C) Control signals are extracted based on the muscle deformation associated with individual finger movements (red, green, blue traces) and are then mapped to movement of a prosthetic hand.

## DEVELOPMENT OF A WEARABLE ULTRASOUND SYSTEM

We have developed a 4-channel wearable SMG system for controlling a prosthetic hand (Fig. 2). Our implementation employs frequency-modulated continuous wave imaging instead of traditional pulse-echo approaches, which enables miniaturization of ultrasound parts using low-voltage commodity hardware and allows low-frequency processing speeds. A key feature of frequency-modulated continuous wave imaging is the use of a linear chirp signal to encode the depth of ultrasound reflections as a range of frequencies, which bypasses the need to transmit short-duration high amplitude pulses to create a depth-resolved map of the received reflections. We anticipate that our implementation of low-power ultrasound imaging will serve as the foundation for future prosthesis controlled by SMG.

Our ultrasound system consists of an AD5930 chirp generator, four single element ultrasound transducers, a power regulation subsystem, hardware for four-channel signal processing, and an external NI-6210 DAQ. The transducers are formed as single element PZT crystals with a 4.25 MHz center frequency and sized to be 7 mm in diameter and 0.5 mm thick. The PZT crystals are dampened with a silicone backing layer and mounted in a 3D-printed bracket that can be secured to a forearm with an elastic strap. The power subsystem is designed to take a 7.4 V battery input and provide ±5 V for the signal processing hardware. The signal processing hardware for each channel consists of a radio frequency (RF) amplifier, a demodulator, an audio frequency (AF) amplifier, and a low-pass filter. Because the depth is encoded as frequency, we low-pass filter the signal at 100 KHz to limit the imaging depth to 15 cm. The DAQ samples the output of the AF amplifier at 250 kS/s, and controlled with Matlab for the classification algorithms.

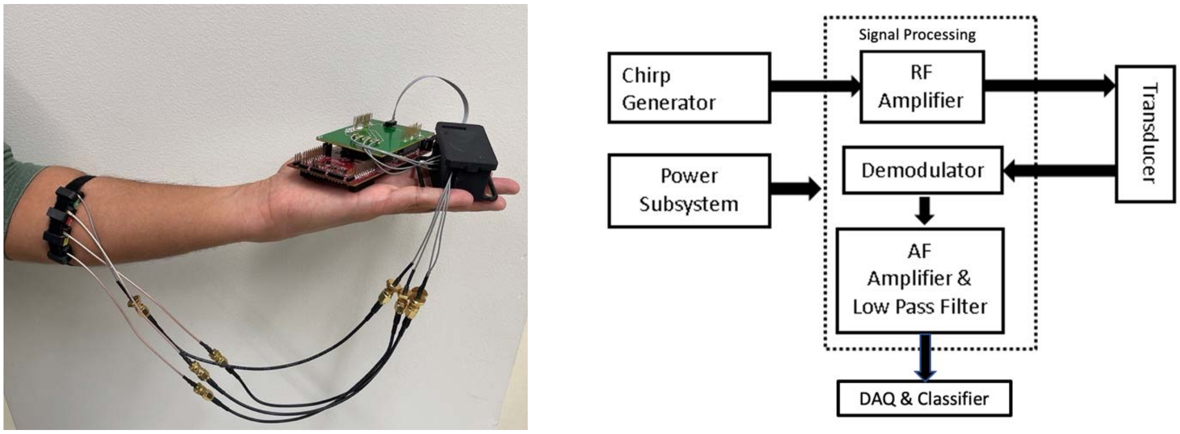


Figure 2. *Left:* The prototype of our 4-channel wearable ultrasound system. *Right:* System diagram of the hardware components.

We have also made some progress extending our wearable system to include an embedded processor capable of executing machine learning classification algorithms in real-time. We recently implemented a Linear Discriminant Analysis algorithm on the embedded processor and found it could predict a user's hand grasp with > 90% accuracy during benchtop testing, which is comparable to the classification accuracy obtained when analyzing the ultrasound signals using MATLAB (Fig. 3).

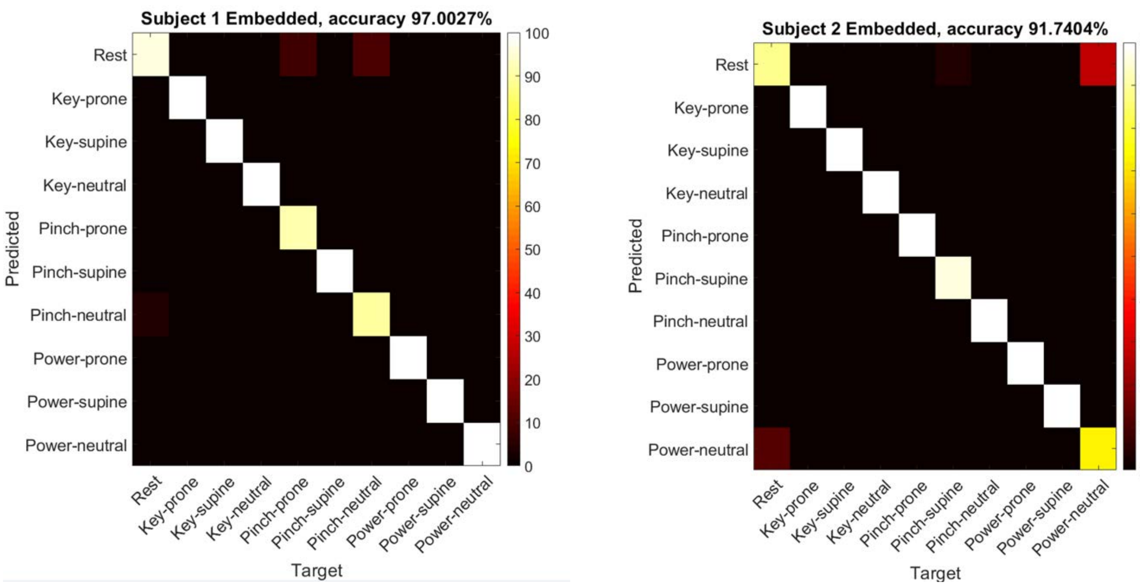


Figure 3. Offline grasp classification accuracy obtained using an embedded processor when testing two able-bodied subjects.

## DISCUSSION

We believe SMG demonstrates numerous advantages over EMG, making it a promising modality for restoring dexterous movement to individuals using upper limb prostheses. One of the primary benefits of SMG is that muscle activity can be sensed with high spatial specificity, even in deep-seated muscle compartments. As a result, crosstalk from muscles that are not associated with the intended movement is effectively suppressed. It is also noteworthy that full-resolution ultrasound imaging is not required to achieve robust classification. Classification accuracies are not affected even when a subset of only four ultrasound scanlines are used. Single-element transducers may be used instead of a full array, reducing the instrumentation required for implementing SMG control in standalone prostheses. Our testing has found that learning to use SMG requires minimal training. In fact, transradial amputees were able to achieve 96% classification accuracy for 5 grasps after only a few minutes of training time [5].

Our wearable SMG system can reliably record m-mode ultrasound imaging signals which can be used to classify hand grasps. Our future work focuses on implementing a wearable SMG system into an upper limb prosthesis to perform hand grasp classification in real-time. We have made considerable progress towards miniaturizing the front-end signal processing components, as well as implementing the grasp classification algorithms within an embedded system so that classification and control can be performed untethered to a computer. We are also working on packaging all the hardware components to fit within a socket alongside the hardware to drive a multiarticulate prosthetic hand. Our goal is to develop a complete SMG prosthesis control system for users to test within their own homes [8].

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