CTRL-Labs: Hand Activity Estimation and Real-time Control from Neuromuscular Signals

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Abstract
CTRL-Labs has developed algorithms for determination of hand movements and forces and real-time control from neuromuscular signals. This technology enables users to create their own control schemes at run-time — dynamically mapping neuromuscular activity to continuous (real-valued) and discrete (categorical/integer-valued) machine-input signals. To demonstrate the potential of this approach to enable novel interactions, we have built three example applications. One displays an ongoing visualization of the current posture/rotation of the hand and each finger as determined from neuromuscular signals. The other two showcase dynamic mapping of neuromuscular signals to continuous and discrete input controls for a two-player competitive target acquisition game and a single-player space shooter game.

Author Keywords
Neuromuscular Signals; Real-time Control; Hand Tracking; Hand Gestures; Electromyography (EMG).

ACM Classification Keywords
H.5.2 [Human-centered computing]: Interaction devices.

Introduction
One of the primary drawbacks for many hand gesture recognition systems is that users must be directly within the

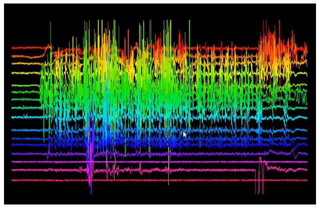

Figure 1: Multi-channel surface EMG signals used by our algorithms to determine hand state and map neuromuscular signals to discrete and continuous input.

field of view of cameras and sensors—which ultimately constrains the scenarios where these systems are useful [4, 9]. Some emerging alternative approaches for hand gesture recognition are the use of surface electromyography (EMG) and mechanomyography (MMG) since they are non-invasive and can be worn directly on the body [7, 5].

MMG uses vibrational information generated from tendons and muscles [5]. On the other hand, surface EMG–a consumer-ready form of clinical electromyography [8]–uses surface electrodes on the skin to measure electrical potentials produced by muscles in response to motor nerves [7]. Previous research has shown that just 10 electrodes is enough to detect four different types of grasps and the amount of force applied with accuracy around 75% [2]. Similarly, through use of as few as 32 electrodes, Tenore et al. [12] demonstrated that it is possible to detect flexion and extension movements with 90% accuracy for each finger. More dense configurations of electrodes, such as an array of 192, can detect a much wider variety and number of gestures with similar levels of accuracy as well [1].

However, while recent research has successfully applied surface EMG to detect hand gestures [1, 2, 12], the potential applications of such technology still remains largely unexplored. In this demonstration, we present new results by applying machine learning algorithms to:

1. Determine forces & joint angles of the wrist/fingers.
2. Quickly and dynamically map neuromuscular activity to continuous (real-valued) and discrete (categorical or integer-valued) input signals during runtime.

To showcase some of the more fundamental capabilities of our software, we have built three demonstration applications that 1) visualize wrist and finger angles/movements; and 2) control games mapping neuromuscular activity to continuous and discrete control signals, using arbitrary movement-based or motionless control schemes that can be trained from scratch within seconds. The non-invasive nature and mass-market potential of surface EMG and the dynamic input mapping features of our software make this system suitable for many application areas including smart-watch and mobile device interaction, prosthesis control, and text generation and editing [6, 10, 11].

Description of the System

Commercial systems for obtaining surface EMG signals exist [3, 8]. We acquire 16 channels of surface EMG signals from forearm muscles that control the hand and wrist. Data is sent wirelessly to our software back-end, which applies various machine learning algorithms to determine forces and joint angles of the wrist and fingers. Additionally, the system allows the user to perform runtime training of arbitrary real-time control mappings from their neuromuscular activity to continuous (real-valued) and discrete (categorical or integer-valued). We can use the results of these dynamic mappings for a variety of applications.

Applications and Demonstrations

To showcase the potential of our software, we highlight its main capabilities through three demonstration applications that illustrate how it can support fundamental interactions that are necessary for the creation of new tools for specific needs and applications.

Hand State: Detecting Hand Pose and Orientation

The Hand State demonstration provides users with real-time tracking and visualization of the configuration and

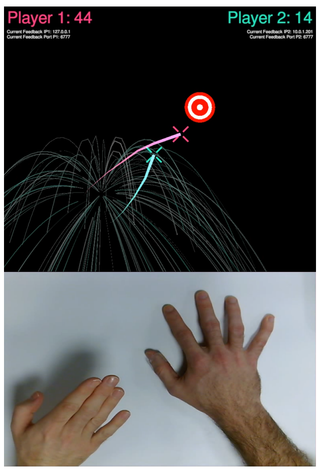

Figure 3: Target Acquisition. Two players compete to hit the most targets. During game play, players train mappings from their neuromuscular activity to continuous input signals that move a cursor along the x and y axes.

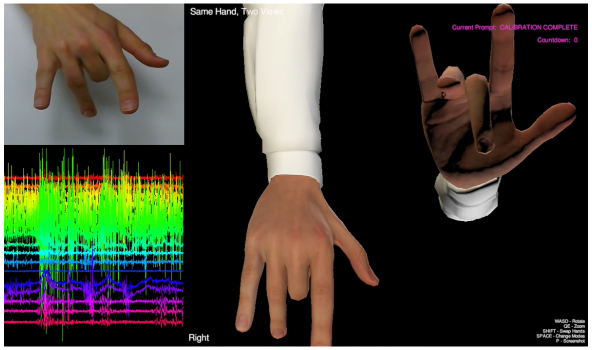

Figure 2: Hand State. The virtual hand renders in real-time the wrist and finger movements determined from the neuromuscular signals.

forces of the hand, including joint angles for the wrist and each finger (see Figure 2). More specifically, as a user moves their hand and fingers, the virtual hand and fingers will move and rotate to match the estimated position of their hand. A live demonstration with a user wearing non-invasive surface EMG sensors will be shown to visitors. The demonstrator will make a variety of hand movements while showing visualizations of the neuromuscular signals acquired by the sensors (Figure 1) and the system's predicted hand state (Figure 2).

Target Acquisition: Two Dimensions of Continuous Input
The Target Acquisition demonstration is a two-player competitive game where attendees race to hit a target (see Figure 3). During play, players train a mapping from their neuromuscular signals to control a cursor's velocity along the x and y axes. The players use these control mappings to race against each other to be the first to get their cursor over a target. Once a target has been "hit" by one of the cursors, the corresponding player gets a point and the target randomly respawns to a new location on the screen.

Figure 4: Space Shooter. Players use custom neuromuscular mappings to control a ship that can rotate, thrust, fire bullets to destroy incoming objects, and raise a shield.

The first player to a set number of points wins.

Space Shooter: Simultaneous Continuous/Discrete Input
This demonstration allows visitors to train a control scheme for playing a space shooter game (see Figure 4). During a pre-game training phase, players train mappings for both continuous input—to control rotation and thrust of the ship—and discrete input—to fire bullets and shield the ship from incoming objects. Notably, when compared to many existing games of this genre (e.g., Space Invaders, Asteroids, etc.), the typical control scheme is reduced from two hands to one. Additionally, the continuous (real-valued) control of thrust and rotation gives players more nuanced control than the discrete button presses for movement in many of these games. Players will destroy as many objects as possible to gain points before their ship is hit.

Conclusion
CTRL-Labs software enables use of neuromuscular signals for a variety of novel applications and interaction paradigms. These basic demonstrations illustrate a sophisticated system that can track individual finger position, rotation, and force exertion, as well as dynamically map neuromuscular

activity to discrete and continuous input signals. Through interaction with our three demonstration applications, we aim to give attendees a first hand experience with neuromuscular signals as a tool for dynamic control, and provide inspiration for using neuromuscular interfaces in potential application areas such as mobile device interaction, prosthesis control, and text entry.

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