Multi-Directional Impedance Control with Electromyography for Compliant Human-Robot Interaction

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Abstract-Compliant human-robot interaction is necessary for the seamless integration of robotic devices into everyday life. Surface electromyography (sEMG) provides a potential interface for compliant control due to the natural relationship between muscle activity and joint stiffness. Previous works have used sEMG to predict and control impedance along a single degree-of-freedom (DOF). However, humans interacting in unstable environments tune both the magnitude and direction of their impedance. This paper proposes a framework for multidirectional impedance control with sEMG to enhance compliant interactions. The framework allows subjects to simultaneously control both the direction of motion and primary stiffness axis of a robot, enabling stable behavior with controlled compliance to external forces. The efficacy of the approach is shown in a five day experiment with a 3-DOF virtual environment. Subjects displayed significant performance enhancements consistent with motor skill learning as they learned to follow paths and stay at desired targets while compensating for external forces. The framework is also demonstrated with compliant simultaneous and proportional control of a robot arm, suggesting the approach as a natural interface for enhancing capabilities of compliant human-robot interaction.

I. INTRODUCTION

Compliant human-robot interaction is an essential component for integrating robots into everyday life. Many daily activities require variable impedance, and humans desire the same functionality when interacting with robots [1]. Impedance control allows safe interaction with uncertain environments, enhancing both utility and viability [2].

Surface electromyography (sEMG) has been identified as a candidate for naturally controlling variable impedance. During co-contraction, surface signals detected by sEMG correlate with the stiffness of corresponding joints. Tsuj et al. [3] used this correlation in one of the first myoelectric impedance controllers. A neural network was trained to map the intensity of flexor and extensor forearm sEMG to the stiffness value of a prosthetic hand as it opened and closed. Jiang et al. [4] built off this work to grip uncertain objects with the appropriate force. Ajoudani et al. [5] applied similar impedance control, tele-impedance, to control a prosthetic hand aimed at generalizing grasping capabilities using kinematic synergies. Ha et al. [6] mapped the sEMG of quadriceps and hamstring muscles to control stiffness and set-point angle for joint impedance of a prosthetic knee. Each of these works have demonstrated the natural connection between sEMG and compliant controllers, as each controller was designed to vary uniform stiffness of a prosthetic device based on sEMG.

Studies in neurophysiology indicate that humans not only control the intensity of their joint stiffness, but also the direction [7], [8]. While interacting in unstable environments, humans adapt their muscle activity to stabilize motion relative to the direction of instability [7]. This suggests that multi-directional impedance control would provide a more natural extension to, and enhance capabilities of, humanrobot interfaces. However, due to transient changes in sEMG, conventional myoelectric interfaces have struggled to provide reliable simultaneous control of motion [9], deterring EMGbased impedance controllers from extending beyond a single degree-of-freedom (DOF) [3]–[6].

This work presents a novel control scheme for the first time offering multi-directional impedance and position control in myoelectric interfaces. Recent works have shown that motor skill learning properties equally apply to myoelectric controls [9]. Properties such as control refinement [10], retention [11], generalization [12], and transfer [13] allow users to learn simultaneous and proportional motion simply by interacting with a myoelectric interface, regardless of its initial intuitiveness [14]. The proposed scheme expands on these motor learning approaches by implementing a multi-directional impedance controller in this framework.

Before describing the contributions of this study, two definitions of stiffness are defined here:

- 1) **anisotropic**: directional (non-uniform) stiffness, such that external forces produce a displacement magnitude dependent on the direction of the force.
- 2) **isotropic**: non-directional (uniform) stiffness, such that external forces produce a displacement magnitude independent of the direction of the force.

To the best of the author's knowledge, no other work has implemented multi-directional impedance and position control for myoelectric interfaces. While Vogel et. al [15] introduced an impedance controller for a robot arm, it was position-based and induced noticeable delays. Ajoudani et. al [16] proposed an impedance controller to mimic human arm impedance, but relied on motion tracking for position. Both techniques required intensive retraining each session. In contrast, this technique demonstrates motor skill learning without requiring retraining between sessions. Using sEMG inputs from upper limb muscles, users simultaneously control both the stiffness and set-point of 3-DOFs. Users stabilize

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control in the presence of external forces in an analogous way to natural limb movements [7]. Despite having no haptic feedback, subjects learn to tune the stiffness of the object being controlled to stabilize movement along desired paths.

II. METHODS

A five-session experiment was designed for subjects to learn the multi-directional impedance control with a 3-DOF virtual myoelectric interface. Throughout each session, performance metrics verified the subjects were demonstrating characteristics of a standard motor skill-type learning [17]. Each subject learned the general controls while performing tasks without any external forces for three sessions on distinct days. Subjects returned for two additional sessions in which additional tasks were introduced requiring either anisotropic or isotropic impedance control. Finally, the method was demonstrated on a KUKA Light Weight Robot 4 (LWR 4) with a Touch Bionics iLIMB Ultra prosthetic hand while grasping objects and interacting with external forces.

A. Control Paradigm

The multi-directional impedance control algorithm is an extension of the velocity control method used in [13]. In [13], *i* incoming sEMG signals, e, are linearly mapped to c output controls, u, after accounting for a muscle activity threshold σ and output gain g:

$$\mathbf{u} = g\mathbf{W}[(\mathbf{e} - \sigma) \circ u(\mathbf{e} - \sigma)] \tag{1}$$

where \circ is an element-wise matrix multiplication, u(*) is the unit step function, and **W** is a $(c \times i)$ mapping function designed to map the entire output space using equal contributions from all inputs (see Fig. 1).

Subjects have consistently shown a capacity to learn such a mapping function regardless of its intuitiveness [18], [19]. When c < i, the mapping is surjective, introducing control redundancies. That is, the magnitude of the output, $|\mathbf{u}|$, is independent of the magnitude of the input, $|\mathbf{e}|$, because some muscle contributions may cancel out the contributions of others with respect to the resulting motion.

The proposed multi-directional impedance control uses this redundancy to generate c directional stiffness outputs k with magnitudes proportional to $|\mathbf{e}|$. Thus,

$$\mathbf{k} = g\mathbf{S}[(\mathbf{e} - \sigma) \circ u(\mathbf{e} - \sigma)] \tag{2}$$

where S = abs(W) is the element-wise absolute value of matrix W (see Fig. 2). This definition of k intuitively assigns stiffness directions for individual muscle contributions to the same axis as its corresponding motion. However, the overall stiffness direction is decoupled from motion outputs, as desired, despite both having the same input space. Thus, with anisotropic stiffness, the primary stiffness direction is not necessarily the primary motion direction. Similarly, isotropic stiffness can be achieved without requiring motion.

With both a motion and stiffness component, the impedance controller is adapted from Hogan et al. [20] with



Fig. 1. Visualization of mapping ${\bf W}$ from sEMG ${\bf e}$ to output motions ${\bf u}.$



Fig. 2. Visualization of mapping **S** from sEMG **e** to output stiffnesses **k**. the following dynamic equation:

$$\mathbf{a} = \mathbf{k} \circ [\mathbf{x} - \mathbf{x}_{\mathbf{d}}] - b\mathbf{I}^{\mathbf{c}}\mathbf{v} + \mathbf{f}_{\mathbf{ext}}$$
(3)

where \mathbf{x} and \mathbf{v} are the current position and velocity of the object, \mathbf{a} is the resulting acceleration, \mathbf{I}^{c} is the $c \times c$ identity matrix, b is a scalar (isotropic) damping term, \mathbf{f}_{ext} is external force, and \mathbf{x}_{d} is the commanded set-point:

$$\mathbf{x}_{\mathbf{d}} = \mathbf{x} + \mathbf{u}\Delta t \tag{4}$$

where Δt is the sampling rate. Inertia tensors are ignored in the virtual interface.

In this experiment, EMG inputs from four muscles (i = 4) – Biceps Brachii (BB), Triceps Brachii (TB), Flexor Carpi Ulnaris (FCU), and Extensor Carpi Ulnaris (ECU) – are mapped to three control outputs (c = 3) - x, y, and z (virtual)/hand motion (robot) – and W is arbitrarily chosen following the three criteria specified in [13] (see Fig. 1):

$$\mathbf{M} = \begin{bmatrix} -0.79 & -0.06 & 0.85 & 0.00\\ -0.52 & 0.94 & -0.42 & 0.00\\ 0.33 & 0.34 & 0.33 & -1.00 \end{bmatrix}$$
(5)

The corresponding S is then (see Fig. 2):

$$\mathbf{S} = \begin{bmatrix} 0.79 & 0.06 & 0.85 & 0.00\\ 0.52 & 0.94 & 0.42 & 0.00\\ 0.33 & 0.34 & 0.33 & 1.00 \end{bmatrix}$$
(6)

1) *EMG Processing:* The raw sEMG signals of four upper arm muscles are collected, rectified, low-pass filtered (fourthorder zero-lag Butterworth, cut-off 3Hz), and normalized with respect to the subject's maximal voluntary contraction (MVC) to generate e. These signals are then subsampled to $\frac{1}{\Delta t} = 200Hz$ for input to (4). To simulate continuous control, (3) is computed at f = 2000Hz. For stability, b = 2f, and all



Fig. 3. VR control setup including the sEMG systems and monitor.

elements of k were scaled between 0 and $\frac{b^2}{4}$ based on MVC values. This ensures the system is both stable and critically damped at its highest stiffness.

Before each session, subjects perform their MVC for each muscle to scale sEMG and set external force magnitudes during isotropic and anisotropic tasks (see Section II-C.1).

2) Robot Control: LWR 4 operates in Cartesian impedance control, effectively replacing (3) with its internal system and actual external forces. During this session, (2) and (4) were updated at 200Hz according to the specifications of the robot. In contrast, only velocity commands can be sent to the iLIMB, so all compliance interaction was reserved for LWR 4. Velocity commands were sent over Bluetooth to the iLIMB for the purpose of opening and closing all fingers, in correspondance with Control Axis 3, also at 200Hz.

B. Experimental Setup

Four wireless sEMG electrodes (Delsys Trigno Wireless) were acquired from the BB, TB, FCU, and ECU with a gain of 500, digitized with 16-bit depth at a frequency of 1926Hz and broadcast via TCP. Both the virtual reality (VR) and robot interfaces receive commands at 200Hz from a custom program using C++ and OpenGL API. The setup for interacting with both the VR and robot are shown in Fig. 3 and 10, respectively.

C. Experimental Protocol

Subjects, unaware how to control the interface, attended five sessions across a span of two weeks.

1) Tasks: Subjects completed tasks by controlling a virtual helicopter (see Fig. 4) with the control paradigm described above. The goal of each task is to move a helicopter from the center of the screen along a defined path towards a helipad near an edge of the monitor. Paths were generated using bezier curves, and points were accumulated by collecting colored particles along the path within time constraints. After the alotted time passed at a given point on the path, the particles could no longer be collected for points. The trial was complete once the helicopter remains on the helipad for one second. After each trial, the map shifted the helicopter back to the center of the screen, and a new helipad and path appeared for the next trial following a five second break.

Throughout the experiment three different task variations were introduced (see Fig. 4):



(b) Anisotropic

Fig. 4. Example tasks in VR. (a) The normal control task with no external forces. Subjects moved the helicopter as if it was velocity control. (b) Anisotropic tasks. External forces, indicated by arrows, push the helicopter into one of the corners. Subjects must follow the path while retaining high stiffness in the direction of the external force to minimize its effect. Isotropic tasks are a hybrid, starting as (a) and introducing external forces (b) in a random direction once the helicopter reaches the helipad. Subjects must increase stiffness uniformly to minimize the effect of the forces.

- 1) **Control Tasks**: No external forces applied throughout the task. The helicopter moves similar to velocity control.
- Anisotropic Tasks: Constant external forces applied throughout the task. Subjects must use anisotropic stiffness to negate the effects of the external forces while moving along the path.
- 3) **Isotropic Tasks**: No external forces until the helicopter reaches the helipad. Then forces are exerted in a random direction until the task is complete. Subjects must increase isotropic stiffness while landing to negate the effects of the external forces being exerted in an unknown direction.

External forces are applied with a magnitude proportional to 75% MVC, such that subjects must use different control strategies for anisotropic and isotropic tasks. With 75% MVC required to prevent external forces from displacing the helicopter, it would be difficult and exhausting for subjects to use isotropic stiffness to complete anisotropic tasks.

2) Sessions: The first session provided a ten minute exploration phase to help subjects learn basic movements and become familiar with the tasks, as suggested in [21]. After ten minutes, subjects completed 50 control tasks.

Subjects returned on separate days for each of sessions two and three, completing an additional 50 control tasks without the initial exploration time. With only control tasks, subjects focused on learning directional movements with both speed and precision for the first 150 tasks.

Session four introduced external forces, and subjects were asked to complete 75 trials. The tasks were distributed as 50% control tasks, 25% anisotropic tasks, and 25% isotropic

TABLE I EVALUATION METRICS

Metric	Linear Learning Fit
Completion Time (CT)	$CT(n) = \kappa_{ct} - \beta_{ct} n$
Throughput (TP)	$TP(n) = \kappa_{tp} + \beta_{tp}n$
Task Score (TS)	$TS(n) = \kappa_{ts} + \beta_{ts}n$

tasks. Subjects were able to detect anisotropic tasks before the task started, but were unaware whether the other 75% of trials were control tasks or isotropic tasks until arriving at the helipad. This encouraged subjects to land with high isotropic stiffness in every trial. Session five provided the same task distribution for 75 additional trials, a total of 300 trials over the entire experiment.

3) Robot Demonstration: One subject returned after one month to demonstrate the control method on a robotic system. External forces were exerted via an elastic band as the subject completed various tasks grasping clothespins.

D. Data Analysis

Trials were analyzed based on performance metrics from all subjects. No quantifiable data was collected for the robot demonstration, as its intent is a proof of concept for intuitive transfer to physical systems.

1) Learning Trends: Metrics used for assessing performance throughout all five sessions are provided in Table I, using first degree polynomials to fit the results with respect to trial number for control tasks.

CT is the task completion time. TP is the throughput, a measure of speed and accuracy [22]. TS is the task score, a measure of speed and precision following the indicated path. n is the overall trial number, κ is initial performance, and β shows the learning rate indicative of better performance over time.

Paths are randomly generated using cubic Bezier curves:

$$\mathbf{B}(z) = (1-z)^2 \mathbf{p_0} + 3(1-z)^2 \mathbf{p_1} + 3(1-z)^2 \mathbf{p_2} + z^3 \mathbf{p_3}$$
(7)

where \mathbf{p}_0 and \mathbf{p}_3 are the origin and helipad position, respectively, and $\mathbf{p}_{1,2}$ are random points on the screen. Particles are distributed at random offsets $\mathbf{R} + \mathbf{B}(z), \forall R_i \in \left[-\frac{r}{2}, \frac{r}{2}\right]$ through uniform samples of $t \in [0, 1]$, with r the radius of the helicopter. Particles begin to disappear sequentially along the path three seconds after the start of the trial, until the last particle disappears eight seconds after the start of the trial. This encourages the subject to balance speed and precision while reaching the target, and TS is the number of particles collected over the total number of particles.

Task difficulty is given via the Shannon Formulation [22]:

$$ID = log_2(\frac{D}{W_D} + 1) \tag{8}$$

where W_D is the constant helipad diameter and $D = \int \mathbf{B}(z)dt$ is the path distance. Then, $TP = \frac{ID}{CT}$.

2) External Force Impact: The specific impact of external forces is observed through changes in percentage of multiple muscle control PM. Although subjects could theoretically complete all tasks using only single muscle activations,



Fig. 5. VR completion times per trial across all subjects, separated by task type. Error bars represent 95% confidence intervals within each session. Asterisks directly over the bar represent significant difference compared to previous session of the same task type (Welch's t-test, p < 0.05). Asterisks between two bars indicate significant differences between task types.



Fig. 6. VR throughput per trial across all subjects, separated by task type. Asterisks and error bars are represented as in Fig. 5.



Fig. 7. VR scores per trial across all subjects, separated by task type. Asterisks and error bars are represented as in Fig. 5.

optimal performance, both with and without external forces, requires a more direct path involving simultaneous activity from multiple muscles. PM measures the percentage of time that subjects activate two or more muscles for a given trial.

III. RESULTS

Five healthy subjects (all male, age 20-28) participated in the experiment. All subjects gave informed consent as approved by the ASU IRB (Protocol: #1201007252). Subjects reported no fatigue throughout the first three sessions, but slight fatigue during sessions four and five due to the high muscle activity required to overcome external forces.

A. Learning Trends

CT, *TP* and *TS* from all control trials were fit to Table I, with parameter values presented in Table II. Each metric shows a significant learning rate ($\beta > 0, p < 0.05$) despite



Fig. 8. Example tasks from VR. Each column shows the control progression for each task type. Magenta lines represent the desired path, with green circles indicating helipad position. Blue lines represent the actual path taken by the subject, and red lines indicate the path taken after initially landing on the helipad until finally completing the task by staying there for a full second. (a, d, g) Control tasks: subjects progressed controls from primarily single muscle control, as indicated by straight lines, to simultaneous inputs to more precisely follow the paths. (b, e, h) Anisotropic tasks: external forces initially overpowered the subjects' control, but subjects learned to eliminate those effects through anisotropic stiffness while moving in the desired directions. (c, f, i) Isotropic tasks: external forces initially drove helicopters away from the target after the initial landing (red lines), but had less impact as subjects learned to control isotropic stiffness more consistently.

time off between sessions. Performance metric progression for each task is shown in Fig. 5, 6 and 7. The introduction of external forces significantly increased task difficulty, and accordingly reduced performance in session 4 compared to control tasks. However, the increased performance between session four and five show that subjects to control stiffness to stabilize control and improve performance over time, similarly to the control tasks throughout all five sessions. Figure 8 visualizes the learning process for each task type with respect to the desired and actual paths taken by subjects.

B. External Force Impact

During control tasks, subjects can use single muscle contractions to coarsely follow the path (see Fig. 8(a)). However, the optimal inputs involve multiple muscles to smoothly transition around curves. The introduction of external forces required simultaneous muscle activity to increase stiffness while traveling along the path. This coordination transferred



Fig. 9. VR percent of simultaneous muscle activations during each trial across all subjects, separated by task type. Asterisks and error bars are represented as in Fig. 5. The anisotropic and isotropic tasks in session four caused a significant increase in simultaneous muscle activations for all tasks.

to the control tasks, where subjects significantly increased the use of multiple muscle activations compared to the first three sessions (see Fig. 9). This correlates with significant performance improvements on control tasks in sessions four and five, suggesting that subjects obtained better control of the overall system while interacting with external forces.



(a) Anisotropic (b) Anisotropic (c) Isotropic (d) Isotropic Fig. 10. Example tasks from robot demonstration. (a-b) Anisotropic stiffness. (a) The subject provided high stiffness in the direction of the camera while moving to the right with low stiffness. (b) The LWR was easily moved to the left due to the low stiffness. (c-d) Isotropic stiffness. The subject provided uniform stiffness to prevent the robot from moving in any direction.

C. Robot Control

One subject returned after one month to apply controls to the robot. The subject reported the controls easy to remember, and intuitive to transfer. Example anisotropic and isotropic stiffness tasks are shown in Fig. 10. A supplementary video demonstrating the compliant control is available at: http://youtu.be/Z7A31QWQC21.

IV. CONCLUSION

This paper presents a novel framework for multidirectional impedance control using sEMG. Filtered sEMG is transformed into uncorrelated motion and stiffness vectors for simultaneous, proportional and compliant control of multiple DOFs. The controls are learned by interacting with the device as in normal motor skill learning tasks, allowing subjects to enhance performance over time. A five day experiment with a 3-DOF myoelectric interface verified performance trends consistent with motor learning, both in the presence and absence of external forces. Subjects learned to compensate for these external forces by increasing their directional stiffness while maintaining stable motion in the desired direction. This required simultaneous muscle activations for stable motion, which correlated with improved control in the absence of external forces. This compliant control was also demonstrated on a robotic system, indicating the capabilities offered by the proposed framework with respect to compliant human-robot interaction.

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