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Efficient Human Control of Robots Using Simultaneous My electric Interfaces

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Abstract-

Myoelectric controlled interfaces became common in several areas like advanced prostheses, exoskeletons, and robot teleopration. Myoelectric management has seen decades as a possible interface between human and machines. Myoelectric management is full of potential to considerably amendment human–robot interaction as a result of the power to non-invasively live human motion intent. Myoelectric management has stressed intuitive controls that mimic human intentions. Moreover, these controls have restricted accuracy and practicality, which ends in user-specific decoders with upper-bound constraints on performance. The mapping functions between myoelectric activity and management actions for a task, shows that human subjects area unit able to management a synthetic system with increasing potency by simply learning the way to management it. The tactic is tested exploitation two completely different management tasks and four different abstract mappings of higher limb myoelectric signals to manage actions for those tasks. However, current management schemes have struggled to attain the sturdy performance that's necessary to be used in industrial applications. As demands in myoelectric management trend toward synchronous multifunctional management, multi-muscle co ordinations, or synergies, play larger roles within the success of the management theme. The natural emergence of a replacement muscle natural action house as subjects determine the system dynamics of a myoelectric interface. These synergies correlate with long learning, increasing performance over consecutive days. this suggests that new muscle synergies area unit developed and refined relative to the mapping employed by the management task, suggesting that peak performance could also be achieved by learning a continuing, discretional mapping perform instead of dynamic subject- or task-specific functions. The tactic could be the neural management of any device or robot, while not limitations for human-related counterparts. The power to boost, retain, and generalize management, while not having to recalibrate or retrain the system, supports management schemes promoting natural action development, not essentially user-specific decoders trained on a set of existing synergies, for economical myoelectric interfaces designed for long use.

Keywords--Myoelectric control; Muscle synergies; Electromyography; Motor learning; Human-robot interaction; Real-time systems

1. INTRODUCTION

Myoelectric controlled interfaces have become a major exploration in recent years due to their applications in advanced prostheses, exoskeletons, and robot teleoperation. Myoelectric control, with potential to manipulate multiple degrees-of-freedom (DoFs) simultaneously via muscle activity, offers a convenient interface between humans and machines. With control inputs noninvasively representing nearby motor unit action potentials (MUAPs) through surface electromyography (sEMG), myoelectric control research has been primarily driven by the potential to create prostheses and orthoses which intuitively respond to users' intentions. However, despite a constant exploration focus and increasing desire for enhanced myoelectric control applications, exploration advances have struggled to translate to clinical and commercial applications. Although user's

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desire simultaneous, multifunctional control of prostheses, they often reject myoelectric prostheses in favor of more robust body powered ones. Advances in electroencephalographic (EEG) and electromyographic (EMG) signal detection and processing have given researchers reliable and noninvasive access to brain and muscle activity. This technology offers promise to help amputees regain independence, humans to perform tasks beyond their physical capabilities and robotic devices and machines to be teleoperated with precision. The control scheme is learned by subjects as they interact with a virtual reality (VR) interface over two days. Throughout the two sessions, subjects display motor learning trends controlling fewer DoFs with targeted muscles. The lack of reliable simultaneous control schemes is one of the major reasons for a gap between research and commercial applications.

The main challenge in myoelectric controlled interfaces lies in decoding neural signals to commands capable of operating the desired application. Many decoding algorithms have been developed using machine learning techniques, but these currently suffer from subject specificity and require intense training phases before any real-time application is feasible. A few other approaches have implemented simple decoders meant to be intuitive for users to control simple commands, but these intuitive mappings suffer from task specificity and assume that intuitive commands translate to maximal performance for a given task. In both cases, the decoders are designed to maximize the initial performance of the user, which does not take advantage of a human's natural ability to form inverse models of space, optimize control strategies and learn new muscle synergies while completing precise physical tasks. Thus, these approaches do not necessarily provide a foundation for maximal performance over time. The two concepts that will be frequently used are:

1) Control task: Task to be executed by the subject using the myoelectric interface, implying both the device to be controlled (e.g., a robot hand) as well as its possible functions (e.g., open/close fingers etc.);
2) Mapping function: Mathematical function that maps myoelectric activity to control actions for the task, e.g., a function that will translate myoelectric signals to opening the fingers of a robot hand.

Simultaneous myoelectric control, in which multiple DOFs can be controlled at the same time via sEMG inputs, requires identification of complex interactions between multiple muscles, commonly referred to as muscle synergies. Specific to myoelectric control and as used, muscle synergies are defined by these complex muscle activation patterns, which are executed by users as high-level control inputs, regardless of any neurological origin. Myoelectric control has focused on accurately decoding user muscle activity into intuitive and desired limb motions. This approach trains decoders to adapt to a specific, supposed constant, motor system to produce desired output. Intuitive control is often translated as a requirement for high system accuracy (i.e. realistic predictions of user kinematics). However, despite a decade of trained decoders consistently reporting accuracies and correlations above 90% in offline analysis, they have not necessarily translated to enhancements in commercial applications. Linear combinations of synergies are capable of describing complex force and motion patterns in reduced dimensions. Control schemes associating synergies with control outputs can generally be grouped into two approaches: pattern recognition and motor learning.

Pattern recognition-based controls decode muscle activity into intuitive control outputs by training a model on a dataset associating sEMG-related inputs with desired outputs, shown in Fig.1. The models are trained via pattern recognition techniques to mimic intent based on existing synergies.

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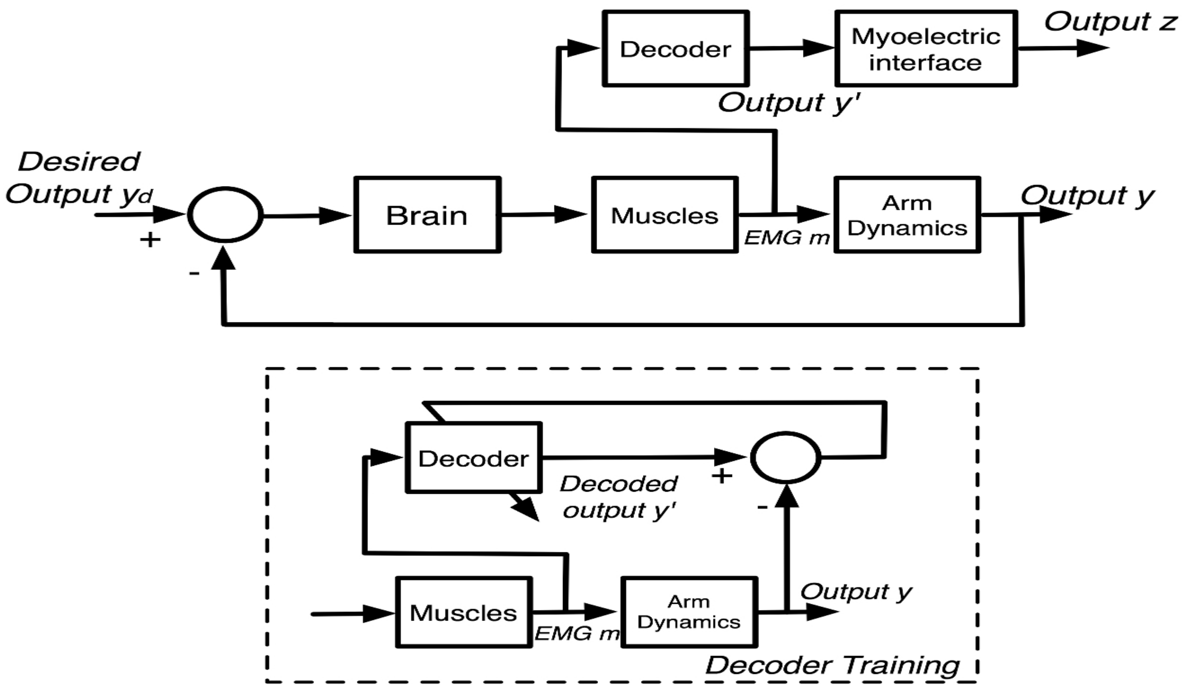

Fig.1 General Model of myoelectric interface with trained decoders

Motor learning-based controls train a motor system to develop and refine synergies associated with system dynamics of a specific mapping function relating sEMG inputs with control outputs, shown in Fig.2. The user learns the system dynamics via feedback while interacting with the control interface.

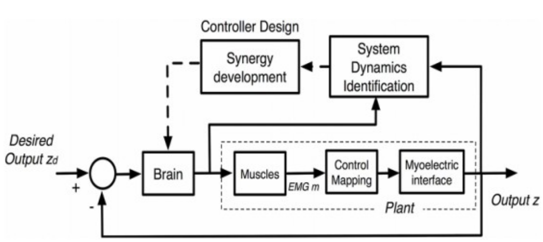

Fig.2 General Model of myoelectric interface using motor learning

2. MUSCLE SYNERGIES VIA SEMG

Muscle synergies are thought of the underlying coordination principles utilized in myoelectric management, and are represented via multiple metrics. Muscle synergies are studied extensively in neuroscience as a possible basis for neural management. The hypothesis that the human motor system directly initiates movement through versatile combos of muscle synergies. Direct action metrics specifically valuate electromyogram activation patterns. Different strategies interpret these patterns as task and biomechanical constraints instead of direct synergies. In spite of medical specialty origin, muscle synergies ar authoritative in myoelectric management schemes thanks to sEMG inputs directly coding muscle activation temporal order, form and intensity. The imperfect ability to systematically live muscle activations with sEMG has been well determined. Factors like muscle depth and thickness, innervations zones, quality of skin contact, skin electrical resistance, temporal order and intensity of muscle contractions, and cross-talk from close muscles all add variability to sEMG recordings. Once recording from multiple muscles to extract synergies, several of those complications ar exaggerated. Additionally to ancient considerations for hardiness thanks to transient changes in sEMG signals management schemes implementing coinciding multifunctional management need further thought with reference to conductor placement, potential cross-talk, amplitude cancellation, and therefore the range and choice of muscles.

2.1 CONDUCTOR PLACEMENT

Electrode placement influences signal-to-noise (SNR) and amplitude thanks to the abstraction

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variability of muscle activity. Once targeting specific muscles, ideal placement is near the muscle belly removed from innervations zones. However, external forces and dynamic postures shift electrodes relative to underlying muscles throughout use. Consistent placement between sessions, each completely at intervals and comparatively between subjects, makes these effects decreased. giant electrodes and/or multiple recording sites per muscle may scale back the consequences and extract sturdy signals while not requiring ideal placement.

2.2 Amplitude cancellation

Amplitude cancellation will increase at higher activation levels, underestimating the sEMG activity up to five hundredth at peak contraction. Normalizing signals via most voluntary contraction (MVC) reduces this result, however usually causes overestimation at intermediate activations. However, amplitude cancellation has very little result on onset detection, usually conserving muscle activation temporal order and form of sEMG patterns to cause lowest impact on detected synergies.

2.3 Cross-talk

Cross-talk contributes to exaggerated muscle synergies and excess variability once acting tasks. Though the consequences will be reduced, characteristic cross-talk could add helpful data from tiny or deep muscles that can't be recorded directly. Freelance part analysis (ICA) and spatio-temporal filters ar capable of extracting individual muscle activities from sEMG signals to separate cross-talk similarly as any interference from different electrophysiological signals.

2.4 Muscle choice of selection

Muscle selection additionally directly impacts management via muscle Synergies. Smaller sets of muscles usually overestimate explained variance, forming incomplete action sets and threatening preciseness controls. Increasing the quantity of muscles, choosing dominant muscles from a master set of synergies, or approximating dominant muscles with major muscles will every facilitate maximize preciseness.

Extracting additional data through multiple sEMG sites assists with every of the on top of challenges to effectively characterize natural synergistic muscle behavior. This data will usually be represented by linear combos of muscle synergies that kind advanced mappings between the action and its result on a limb. Thus, feature extraction from incoming signals is important to supply descriptive synergistic inputs to an impact theme portraying these mappings.

3. METHODS

3.1 Experimental Setup

Wireless surface EMG electrodes were placed on four upper limb muscles of a human subject. A multifunction data acquisition card (DAQ) (USB-6343X, National Instruments) acquires and digitizes the signals for input to a custom application running on a personal computer (PC). The EMG signals are processed in real time and converted to control variables for a given task via a mapping function, and the effect is displayed to the subject for online closed-loop visual feedback. The program is written in C++ using OpenGL API for the graphical display.

3.2 Control Tasks

Two distinct tasks provide different visual feedback for the Subject as shown in Fig. 3

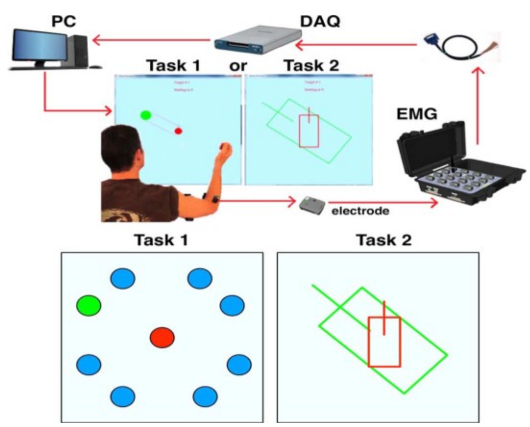

Fig.3 an EMG system, DAQ, and visual interface (top). The two tasks the subjects control using EMG signals (bottom).

The goal of each task is to transition a virtual object from its initial state to one of eight target states as quickly as possible. Task 1 is a standard center to reach out task, where the subject needs to control the center (red) circle and move it on top of one of eight possible target (green) circles as fast as possible. The eight target locations (blue circles) are symmetrically distributed around the four quadrants

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of the circle with respect to an origin at the center of the screen, and each quadrant represents a target area.

Task 2 consists of two rectangular objects, with a straight line bisecting one edge of each object to provide orientation, as shown inFig.3.Thegoalof the task is to control the red object by resizing and orienting it to match the stationary green one. Similarly to Task 1, there are eight possible combinations of size-orientation for the green object. Each combination maps along the control axe equivalently to the target locations in Task 1. Those eight targets are similarly grouped to four target areas equivalent to the four quadrants of a circle.

3.3 Mapping Functions

EMG signals are acquired at 1 kHz from four right arm muscles: Biceps Brachii (BB), Triceps Brachii (TB), Flexor Carpi Radialis (FCR) and Extensor Carpi Ulnaris (ECU). The raw EMG signals are pre-processed with full-wave rectification and a low pass filter (2nd order Butterworth, cut-off 8Hz) to remove high frequency noise and obtain a linear envelope of the signal. The processed signal is then transformed through the mapping function to produce the output command.

The muscle synergies were quickly developed between both antagonistic and biomechanically independent muscles, and that habitual synergies between biomechanically dependent muscles are difficult to alter, these four muscles were specifically chosen as two pairs of antagonistic muscles (BB/TB and FCR/ECU) which are biomechanically independent in order to enhance the potential for new synergies. The signals are sampled at 1 kHz frequency by the DAQ. The raw EMG signals undergo a preprocessing stage that is commonly used in the field of electromyography in order to compute the linear envelope of the signal. The linear envelope performs full-wave rectification of the raw signals and then passes them through a low pass filter (second-order Butterworth, cutoff frequency of 8 Hz). The smoothed signal provides a reliable input signal to the mapping function for each trial.

A mapping function is a 2 X 4 matrix Wi, relating a 4 X 1 vector e of filtered EMG to a 2 X 1 vector U of control outputs:

$$U = W_i e,\ i \in \{1,2,3,4\}$$

Each of the mapping functions transforms the EMG amplitude to control variables in a unique way that can be represented visually as vectors in the 2-D control space. The control axes correspond to the velocity of the moving circle along the (horizontal) and (vertical) direction in the case of Task 1. For Task 2, the two control axes correspond to the angular velocity and change in size of the rectangle. An activation threshold of 0.02 mV was set for each of the muscles, so as to make sure that there is no control output when the subject is resting. The control outputs are represented visually in 2D control space, with control axes corresponding to the x (horizontal) and y (vertical) velocities of the moving circle in the case of Task 1. For Task 2, the two control axes correspond to the angular velocity and change in size of the rectangle. An activation threshold of 0.02mV is set for each muscle to nullify any control output at rest.

It should be noted that the subject’s arm is not constrained, and muscular volume contraction (MVC) is not used to normalize the EMG signals, which differs from most other relevant studies. Instead of using position control with respect to MVC, subjects are free to move their arm into any configuration to fully explore each mapping and minimize the effect of potential biomechanical constraints in a given configuration. It is hypothesized that with this freedom in forming the inverse model, subjects can learn to respond and adjust appropriately to an unnormalized output when performing velocity control. Also by ignoring MVC, trends in performance over multiple days are inclusive of the performance-diminishing impact of intrasubject variability caused by sensor.

3.4 Trials

A single subject consists of a semi-random arrangement of trials performed over a period. The trials are arranged so that the tasks alternate and mapping functions are not repeated until every other mapping has been seen in between, with an additional constraint that no mapping is seen twice on the same day as an attempt to minimize the feeling of familiarity for each trial. Each trial consists of a combination of task and mapping that are unknown to the subject before the trial begins. The subject is assigned to repeatedly transition a virtual object (red in Fig. 3) from a beginning state to one of eight target states (green in Fig. 3) as quickly as possible. Targets appear in a quasi-random order across trials, such that each cycle of eight targets is randomly arranged.

4. DATA ANALYSIS

Learning and retention phases collected trial data from the EMG inputs, helicopter path, and completion time. These components are analyzed to see the effects of learning the system dynamics with regards to efficient control, synergy development, and performance retention and generalization after the learning phase is completed. All subjects considered Task 1 to be easier than Task 2 and found some mapping functions easier than others. However, none were aware that both tasks required the same input responses, though some noticed that a few of the trials required similar muscle activity to move the virtual objects. Quantitative evaluation of learning and performance is done in three steps.

1. Confirm that learning occurred in the trials for each target area.
2. Quantify the effectiveness of prior learning transfer to subsequent trials.
3. Evaluate the overall performance of subjects when presented with each mapping function.

4.1 LEARNING

The foremost step is to identify how well subjects learn to perform the given task successfully. The general trend of learning is expected to follow an exponential decay, where initially the time required to successfully perform any task is high and it decreases exponentially towards a final steady-state value. For that reason, the data from each trial is fit to an exponential curve and the time constant of the curve gives the learning rate.The higher the time constant, the more the learning rate.

4.2 LEARNING TRANSFER

The next main aspect is to compare how well learning is transferred across mapping functions for each control task and across control tasks for each mapping function. This is to identify whether the subject is learning to interact with each individual control task better irrespective of the different mapping functions, or whether the subject is learning to understand the controls of each individual mapping function irrespective of the control tasks.

4.3 OVERALL PERFORMANCE

Due to the significance of consistent mapping functions on learning transfer, overall performance evaluation is quantified with a performance score incorporating learning transfer, learning rate, and end performance specifically for each mapping function. Each of these three quantities are deemed important components for evaluating how well users can interact with a given mapping function. Then, this score can be compared with initial performance, or intuitiveness of a mapping function.

5. CONCLUSION

Robust simultaneous multifunctional myoelectric interface control is a necessary achievement for commercial applications in prostheses, orthoses, and robotic control. Muscle synergies play a crucial role in these control schemes due to the inherent necessity to extract temporal activation patterns between multiple muscles. These controls have struggled in real-time control due to the high variability of sEMG signals. When designing a new control scheme, the selection of muscles and placement of sEMG electrodes is an essential component determining the potential success of the scheme. Synergy features can produce robust activation signals used for input to a linear decoder to output complex but intuitive control variables. The decoder can be designed using pattern recognition or motor learning-based control schemes depending on the desired control outputs and interactions from the user. Performance is determined to be more dependent on familiarity with a given mapping function than familiarity with a given control task, indicating that subjects can learn new control tasks so long as they know how to explore the task space. Motor learning schemes have so far proven more robust to degradation, but require a potentially no intuitive learning phase. Although a lot of advances are needed for robust commercial applications, myoelectric controls remain a technique with potential to significantly change human–robot interaction.

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