

**IMPROVING PERFORMANCE AND INTERNAL MODEL STRENGTH OF
MYOELECTRIC PROSTHESIS CONTROL STRATEGIES USING
AUGMENTED FEEDBACK**

by

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ABSTRACT

The ability to reach, grasp, and lift requires reliable control, a strong understanding of the arm properties, and some feedback to achieve quick and precise movements. These normal everyday activities present a challenge for upper limb amputees. Myoelectric battery-powered prostheses have been used as one approach to tackle this challenge. Myoelectric signals are highly variable signals produced by muscle contractions that require processing before being used to control prostheses' movements. For multiple degrees of freedom motion, myoelectric controllers are either robust but provide inadequate feedback, or noisy but provide rich feedback. Feedback affects both control and the development of internal models, which in turn affects the overall performance of the prostheses. The human brain has an internal model built for the arm, which imitates its behavior, predicts consequences of an action, and computes an action based on desired consequences. Researchers have been so far unable to decouple the feedback from the control, which has forced them to develop control strategies that might enable strong control signals, but at the expense of internal model strength.

The main objective of this work is to effectively decouple feedback from control by using augmented feedback and subsequently independently optimize both control and the internal model. In this work, a novel augmented-feedback myoelectric control strategy is introduced and assessed using psychophysical tests and commonly used performance measures. Results show that this developed controller enables more precise internal models, resulting in better performance than currently available controllers.

DEDICATION

To **Mom** and **Dad** I love you

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List of Symbols, Nomenclature or Abbreviations

LDA	Linear Discriminant Analysis
LR	Linear Regression
SVR	Support Vector Regression
ANN	Artificial Neural Network
SVM	Support Vector Machine
DOF	Degree-of-Freedom
TSR	Target Sensory Reinnervation
EMG	Electromyography
BCI	Brain Computer Interfaces
iVE	instrumented Virtual Egg
RCRF	Raw Controller with Raw Feedback
FCFF	Filtered Controller with Filtered Feedback
UNB	University of New Brunswick
SD	Standard Deviation
REB	Research Ethics Board
ICC	Intraclass Correlation Coefficient
SEM	Standard Error of the Mean
ACE	Acquisition and Control Environment
JND	Just-Noticeable-Difference
ANOVA	Analysis of Variance
FCAF	Filtered Controller with audio Augmented Feedback
HSD	Honest Significant Difference

SSSA	Scoula Superiore Sant'Anna
NF	No-augmented Feedback
AF	Audio-augmented Feedback
CI	Confidence Interval
DESC	Discrete Event-driven Sensory feedback Control

1. Introduction

Motivation

The ability to grasp and manipulate objects, sense and explore surroundings, and use gestures to support speech and express emotions requires reliable control, a strong understanding of how limbs work, and some amount of feedback to achieve quick and precise movements. Missing an upper limb dramatically impairs these normal everyday activities. Recent advancements in myoelectric prosthesis control for the upper limb include novel control approaches (Scheme and Englehart 2011; Jiang et al. 2014; Amsuess et al. 2016), sensor types (Weir et al. 2003; Dosen et al. 2010; Cipriani et al. 2014), and advanced hardware (Cipriani, Controzzi, and Carrozza 2011; Grebenstein et al. 2011; Catalano et al. 2014; Lenzi, Lipsey, and Sensinger 2016). Nevertheless, the impact of these advances in improving the overall performance of myoelectric prostheses is still limited. Noisy control signals - derived from the stochastic myoelectric signals (Clancy, Morin, and Merletti 2002) - and lack of adequate sensory feedback (Doeringer and Hogan 1995; Antfolk, D'Alonzo, Rosén, et al. 2013) are two of the central bottlenecks limiting these advances.

To tackle these limiting factors and improve performance, researchers have developed many control strategies that vary in control architecture (Roche et al. 2014; Vujaklija, Farina, and Aszmann 2016) and feedback level (Battye, Nightingale, and Whillis 1955; Wheeler et al. 2010; Saunders and Vijayakumar 2011). The most commonly used control strategies are either robust but lack adequate feedback, or noisy but provide rich feedback (Figure 1-1). This feedback is required for the development of better human understanding, known as internal models, which

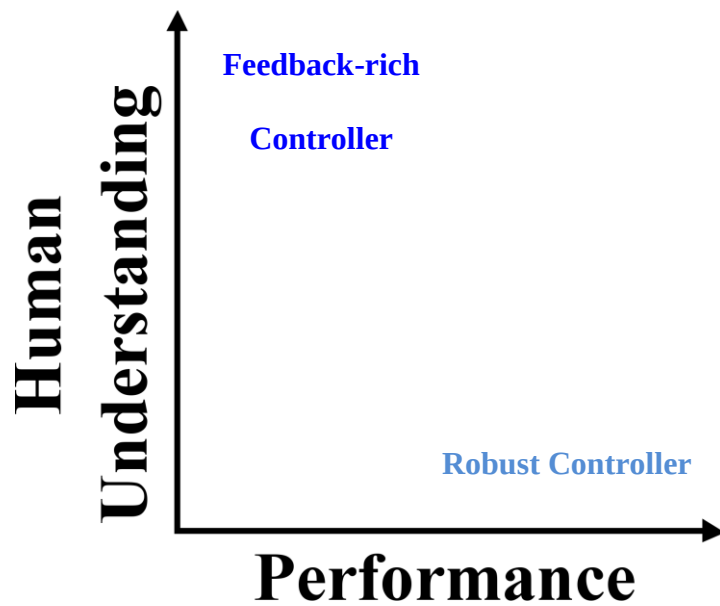


Figure 1-1. Currently available control strategies are either robust and enable better short-term performance or feedback-rich and enable better human understanding.

play an important role in improving performance (Matija et al. 2017; Lum et al. 2014). **So far, researchers were unable to optimize this tradeoff as they were unable to decouple the feedback from the control.**

In this work, augmented audio feedback is used to effectively decouple feedback from control and a new hybrid myoelectric control strategy that uses this feedback is developed. This hybrid control strategy combines control signals from the robust controller with augmented audio feedback derived from the feedback-rich controller. Both performance and internal model strength are evaluated using this control strategy for a virtual target acquisition task and also for a grasp-and-lift task using a prosthetic hand. The central hypothesis in this work is that the augmented feedback controller enables a stronger internal model, leading to better performance

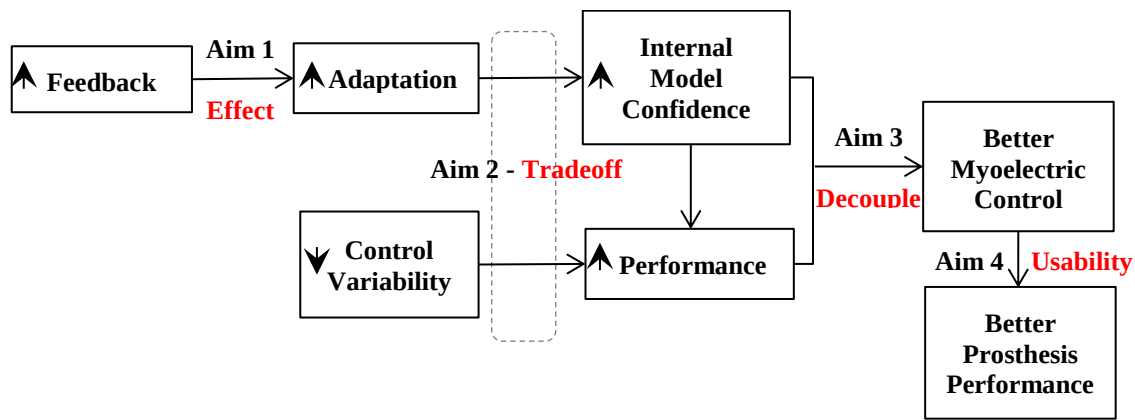


Figure 1-2. Schematic showing how the final objective of this work is accomplished and how the aims relate to each other.

than that of currently available myoelectric controllers. This hypothesis is tested using the following specific aims (and as noted in Figure 1-2):

Specific Aim 1

Investigate how different levels of feedback inherent in current myoelectric control strategies affect user adaptation.

In this study, the hypothesis was that high levels of feedback enable better user adaptation rates. 24 able-bodied subjects were asked to use two common types of myoelectric control strategies that differed in feedback level to move a cursor towards targets in a virtual target acquisition task. Results from this study showed that a myoelectric control strategy with a high level of feedback enables users to better adapt to errors.

Specific Aim 2

Investigate the tradeoff between myoelectric control strategies that provide better short-term performance at the expense of providing inadequate feedback to develop a strong internal model, and controllers that provide adequate feedback, but at the expense of noisier control signals.

The hypothesis in this aim was that high level of feedback improves internal model strength. Psychophysical tests were used to assess internal models developed by 24 able-bodied subjects when using the same myoelectric control strategies investigated in specific aim 1 for a virtual target acquisition task. Outcomes from this study revealed that feedback-rich control strategies may be used to improve internal model confidence, but less variable control signals controllers (filtered controller) enable better short-term performance.

Specific Aim 3

Investigate the effect of an augmented feedback myoelectric control strategy on internal model strength and short-term performance for a virtual target acquisition task.

To mitigate the tradeoff between controllers that enable better short-term performance and those that provide sufficient feedback to develop a strong internal model, audio-augmented feedback was used to decouple the feedback from the control. A novel control strategy was introduced by using audio to augment filtered controller feedback (Figure 1-3). Strength of the internal model developed and short-term performance were evaluated for 24 able-bodied subjects while using this novel control strategy. Results from this study confirm the hypothesis that audio-augmented feedback controller enables the development of a strong internal model and better performance.

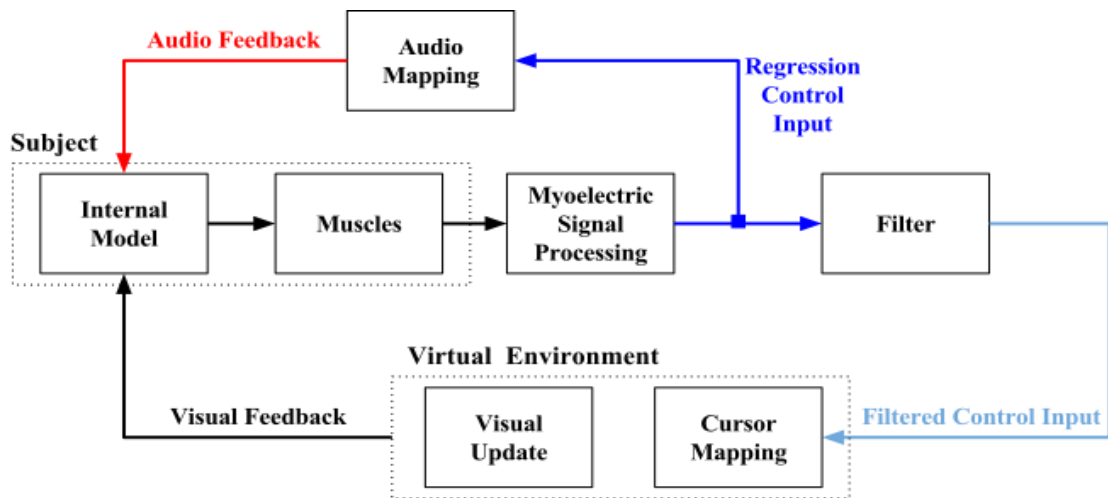


Figure 1-3. Closing the control loop using audio to augment the visual feedback.

Dark blue lines denote rich-feedback but variable control signals. Light blue lines indicate reduced feedback and less variable control signals.

Specific Aim 4

Investigate the effect of a myoelectric control strategy based on filtered control signals with augmented feedback on internal model strength and performance for a grasp-and-lift task using a prosthetic hand.

The hypothesis here was that audio-augmented feedback improves both internal model strength and short-term performance of a myoelectric prosthetic hand. Seven able-bodied subjects were asked to use an audio-augmented feedback control strategy and a regular control strategy without additional feedback to control a robotic hand for a grasp-and-lift task. Internal model strength and performance of these controllers were assessed. Results showed that benefits of using audio-augmented feedback for improving internal model strength and performance of

myoelectric controllers extend beyond a virtual target acquisition task, which is a step closer to clinical implementation.

Justification and Feasibility

Myoelectric signals are highly variable signals produced by muscle contractions that require processing before being used for controlling a prosthesis (Clancy, Morin, and Merletti 2002). Many disparate myoelectric signal feature extraction methods (Phinyomark, Limsakul, and Phukpattaranont 2009) have been used to obtain useful information from noisy myoelectric signals. Out of these methods, the time domain feature extraction method has shown well-established performance in obtaining myoelectric patterns with minimal processing overhead (Scheme and Englehart 2011). This method has allowed for the development of various control strategies that have had the potential capability to map more movements over multiple degrees of freedom than earlier control strategies.

Existing Systems

Although early implementations of prosthesis control strategies, such as the on/off control strategy enables binary opening and closing of a hand (Battye, Nightingale, and Whillis 1955) and the proportional control strategy that facilitates control of the speed of opening and closing of a hand, have been considered robust, they are limited by the number of usable independent control sites (Oskoei and Hu 2007). To overcome this limitation, researchers have used machine learning for identification of multiple patterns of movements, such as grip, flexion/extension, adduction/abduction, and pronation/supination (Oskoei and Hu 2007). Linear Discriminant Analysis (LDA) (Hargrove, Englehart, and Hudgins 2007), Linear Regression (LR) (Smith, Kuiken, and Hargrove 2016), Support Vector Regression (SVR) (Scheme et al. 2011;

Ameri et al. 2014), and Artificial Neural Networks (ANN) (Aggarwal et al. 2008) are some of the commonly used data-driven machine learning approaches used to identify myoelectric signal patterns for the purpose of control. These machine learning algorithms translate information in the myoelectric signals to either sequential or simultaneous control (Roche et al. 2014).

SVR, in particular, is based in support vector machine (SVM) theory and can be used for either classification (Castellini et al. 2009), i.e., sequential, or regression (Ameri et al. 2014), i.e., simultaneous, control tasks. In both cases, SVM/SVR has been shown to yield performance superior to that of LDA/LR (Scheme and Englehart 2011; Castellini et al. 2009; Ameri et al. 2014). When employed as a regressor, the output is a kernel-based weighted mixture of the inputs, supporting simultaneous activation of more than one DOF at a time and providing rich feedback. In addition, SVR may be employed as a classifier, while preserving the same decision space, by gating all the regressors' activations other than that of the DOF with highest level of activation; therefore selecting the single most active DOF and providing less variable control signals but at the expense of providing less feedback. SVR was used in the implementation of control strategies tested in this work due to its ability to configure control output and feedback. Figure 1-4 shows an example of control signals produced to control 2 degrees-of-freedom, such as wrist extension/flexion and abduction/adduction, for regression control and filtered control.

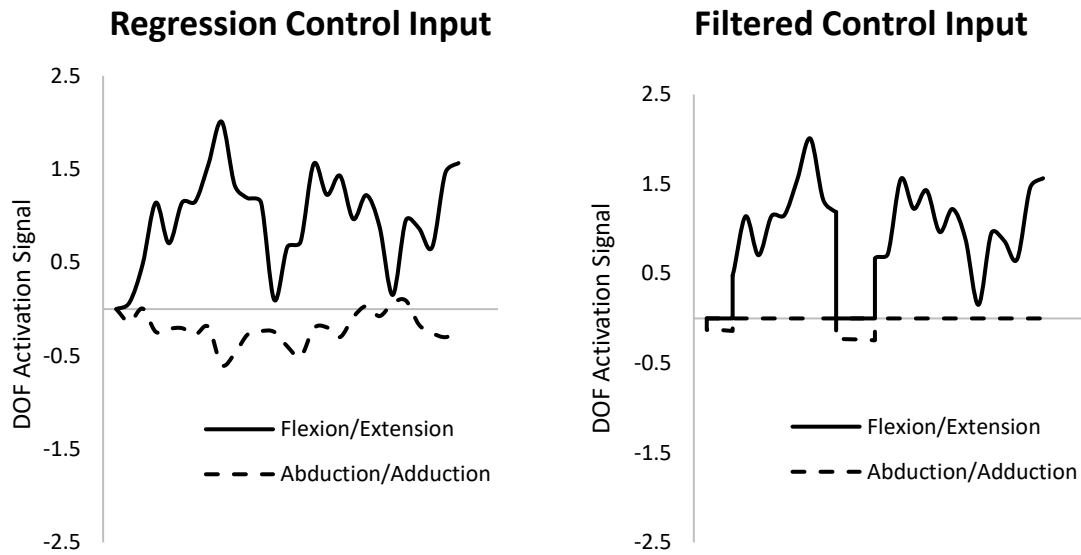


Figure 1-4. Example of control signals for wrist flexion/extension and abduction/adduction when using Regression control and Filtered control.

Feedback Options

Sensory feedback, which is the second bottleneck, has also been shown to be of importance for robust control and in improving performance (Antfolk, D’Alonzo, Controzzi, et al. 2013). When interacting with the environment, amputees lack many of the different modalities of sensory information that able-bodied persons use for guidance from their lost limb, therefore limiting their control loop and making them unable to interact with their environment effectively (Childress 1985). To close the loop between users and their prosthetic devices, researchers have proposed providing sensory information to prosthesis users using both invasive and non-invasive methods (Antfolk, D’Alonzo, Rosén, et al. 2013). The Target Sensory Reinnervation (TSR) method has the potential to provide sensory feedback to amputees that feels

like it is in the missing limb (Kuiken et al. 2004; Hebert et al. 2014), but includes risks of permanent paralysis of the target muscles and development of painful neuromas (Kuiken et al. 2007). Other invasive feedback methods, such as stimulation of sensory peripheral nerves (Raspovic et al. 2014), has the potential to elicit close-to-natural tactile sensations, however many prosthesis users prefer non-invasive feedback methods that do not require surgical intervention (Clemente et al. 2016). With this preference in mind, researchers have proposed using non-invasive sensory substitution methods to provide sensory information to prostheses users either through a sensory channel other than the one that is normally used or through the same channel but in a different modality (Antfolk, D'Alonzo, Rosén, et al. 2013). Vibro-tactile (Rombokas et al. 2013; D'Alonzo and Cipriani 2012), mechano-tactile (Antfolk, D'Alonzo, Controzzi, et al. 2013), electrotactile (Kaczmarek et al. 1991; Green et al. 2011; Gonzalez-Vargas et al. 2015), skin stretch (Wheeler et al. 2010), and auditory (Gonzalez et al. 2012) are just some of the techniques that have been developed and used to provide prosthesis users with feedback and have shown promising improvement in performance. Although some studies (Antfolk, D'Alonzo, Rosén, et al. 2013) have shown that sensory feedback improves performance, others (Antfolk, D'Alonzo, Controzzi, et al. 2013) have concluded that sensory feedback had no effect on performance. This conflict is due to an unclear understanding of how the incorporation of feedback relates to performance.

One hypothesis has been that feedback improves performance through real-time regulation. To investigate this hypothesis, researchers implemented many sensory feedback methods to directly improve control in real-time by providing information that has been lost due to amputation (Chatterjee et al. 2008; Ninu et al. 2014). Results from many studies have shown promising improvement in performance (Dosen et al. 2016; Markovic et al. 2017a), sense of

embodiment (Marasco et al. 2011), and prosthesis incorporation (Sengul, Shokur, and Bleuler 2014) when using feedback for real-time regulation; however the efficacy of the feedback methods used, such as resolution and latency, introduces a new challenge (Saunders and Vijayakumar 2011).

Feedback may not only be used in real-time regulation, but also to improve the user's understanding of the system, which may enable better long-term performance. This understanding is stored and modeled by the human brain as an internal model. There are two types of internal models (Cisek 2009): forward models and inverse models. Forward models are used to predict consequences of an action, i.e., to predict the position of the arm and the sensory feedback for a given control signal (Jordan 1996). Inverse models are used to compute an action based on desired consequences i.e., to generate control signals for a desired arm position. Researchers (Sainburg et al. 1995) have concluded that feedforward commands based on the proprioceptively updated internal model of the limb facilitate precise motion. However, it is still a challenge to fully understand how the brain uses the feedback with the internal model to enhance the performance.

In an attempt to explain this phenomenon mathematically, Wolpert et.al (Wolpert, Ghahramani, and Jordan 1995) have proposed that the brain's estimation of the next state of the arm using the internal model can be modeled by a Kalman filter. In this model, a weighted factor of the feedback is assumed to be combined with the internal model based on the uncertainty of the feedback. Johnson et.al (Johnson et al. 2017) have suggested a framework that demonstrates that the strength of the internal model is indeed affected by feedback (recently modified by Blustein and Sensinger 2017, see Appendix A). Common current myoelectric control strategies either provide adequate feedback but at the expense of more noisy control signals, such as with

regression-based control, or provide better short-term performance at the expense of providing inadequate feedback to develop a strong internal model, such as classification-based control.

Augmented feedback can be used to convey artificial proprioceptive and exteroceptive information (Markovic et al. 2017b; González and Yu 2009), which may help to develop strong internal models. In particular, researchers (Dosen et al. 2015) have proposed providing information to the user through augmented visual feedback using electromyography (EMG) biofeedback. Their results showed that users were able to exploit the augmented visual biofeedback to improve their performance for a grasping task. However, many powered prosthesis users reject their devices due to the constant visual attention and high level of concentration required to control their devices (Atkins, Heard, and Donovan 1996). Unlike visual feedback, audio requires less focus of attention (Eldridge 2006) and reduces distraction (Sigrist et al. 2013). Researchers have used audio augmented feedback in both robotic teleoperation (Apostolos et al. 1992; Liu and Meng 2005) and Brain Computer Interfaces (BCI) (Tidoni et al. 2014) and have concluded that audio augmented feedback improves performance. Therefore, this audio augmented feedback is used here in the development of a novel myoelectric control strategy that enables both better performance and a stronger internal model.

Innovation

Many researchers have thought that a logical approach to improving performance was to use feedback to directly improve control (Childress 1980; Clemente et al. 2017). Although some studies have found this approach to be effective in the absence of vision (Wheeler et al. 2010), others have found that feedback had no effect on performance (Antfolk, D'Alonzo, Rosén, et al.

2013; Johnson et al. 2014). The contradiction between these findings may be described by the use of the feedback not solely in real-time regulation, but also in internal model formation. The high fidelity of vision may make the use of augmented feedback superfluous for real-time control, but some aspects of internal model formation are difficult to learn using Cartesian feedback sources, such as vision (Berniker and Kording 2008). To overcome this difficulty, other feedback sources were explored, however not to replace vision, but rather to augment it. Augmented feedback may be used to relay information to prosthesis users - information that differs from that relayed by vision, such as level of muscle contraction and decoded myoelectric control signals - which aids users in the control of their devices.

Augmented feedback may play a very important role in affecting performance; though not as much by real-time regulation as by improving internal model regulation. Posed this way, a novel question arises: is it possible to decouple the most useful feedback for internal model formation from the most reliable control paradigm. The powerful concept of decoupling control from internal model formation is, for the first time, introduced in this work to determine the effect of the feedback on the internal model strength before incorporating feedback in the control.

Significance

The control of myoelectric powered prostheses requires constant visual attention and a high level of concentration that has led many powered prosthesis users to reject their devices (Atkins, Heard, and Donovan 1996). The applied concept of decoupling the control from the internal model formation facilitates further improvements in the control strategies. In particular, control strategies that use feedback options that reduce the need for visual attention while supplying

users with adequate feedback to develop strong internal models; therefore, increasing reliability and promoting acceptance of the prosthetic devices by powered prosthesis users.

In the absence of strong internal models, prosthesis users rely more on real-time feedback to control their devices. Despite advances in sensory feedback methods for myoelectric prosthesis control (Markovic et al. 2017a), one must question the efficacy of the feedback methods, such as their resolution and latency (Saunders and Vijayakumar 2011). A key feature of myoelectric prosthesis control is the ability to act in a feedforward manner, i.e., use internal models. Developing a strong internal model for myoelectric prosthesis control enables users to rely less on real-time feedback as they build a better understanding of the system and task.

Furthermore, the ability to assess and evaluate prosthesis users' internal model after training sessions in a clinic will serve as an indicator of how beneficial these training sessions were to the users, therefore enabling clinicians to improve training procedures. Beyond the field of myoelectric prosthesis control, evaluating human understanding through methods and tests used in this work can be generalized to a variety of health disorders ranging from stroke to spinal cord injuries, i.e., determining which treatments and procedures affect patients' learning and adaptation the most.

Summary

Prosthesis users abandon their devices for many reasons including noisy myoelectric control signals, which affects accuracy, intuitiveness, and response time, and the lack of adequate sensory feedback (Resnik, Meucci, and Lieberman-klinger 2012), which affects incorporation and embodiment. To tackle these reasons, researchers have developed various control strategies, which enable sequential or simultaneous control, and explored many sensory feedback

techniques to improve performance. However, they have not always been successful in improving performance by providing feedback, possibly because they have not looked into improving internal model strength, which in turn improves performance. To measure the internal model strength and relate it to improvements in performance, recent work has shown that internal model strength could be assessed if appropriate tools are used. Thus, exploring feedback to improve internal model strength becomes a feasible way to improve performance.

In this work, augmented-audio feedback is used to decouple the most useful feedback for internal model formation from the most reliable control paradigm and then is used in the implementation of a novel myoelectric control strategy. Strength of the internal model developed and short-term performance were evaluated for subjects while using this novel control strategy in a virtual target acquisition constrained-time task (as a proof-of-concept). To take a step closer to clinical implementation, both the internal model strength and short-term performance were evaluated for subjects while using this same control strategy to control a prosthetic hand for a grasp-and-lift task.

Thesis Structure

In each of the following chapters, one of the previously mentioned aims is presented as a self-contained article in the same order they were presented in this chapter. Chapter 2 investigates how different feedback levels inherent in myoelectric control strategies affect user adaptation. Chapter 3 follows up on the outcomes from the previous chapter and investigates the tradeoff between myoelectric control strategies that provide better short-term performance at the expense of providing inadequate feedback and control strategies that provide adequate feedback, but at

the expense of more noisy control signals. Chapter 4 investigates the potential of using audio-augmented feedback to decouple feedback from control and uses it to develop a novel myoelectric control strategy that mitigates this tradeoff and subsequently independently improves both control and the development of the internal model. Chapter 5 tests the developed control strategy in chapter 4 to verify that its benefits extend to functional activities, such as a grasp-and-lift task, when using a prosthetic device. Finally, Chapter 6 further discusses the work done in this thesis, summarizes the major contributions, and proposes future work.

Statement of Authorship

All articles presented in this thesis represent work designed and implemented by the candidate. In all articles, the candidate was integral in problem statement, hypothesis formulation and experimental design phases. The candidate performed the experimentation, completed all data analysis, and prepared manuscripts. Dr. Sensinger and Dr. Scheme provided guidance and discussion during problem statement and experimental design, and provided critical reviews for all written work. In Chapter 5, Dr. Cipriani provided input during the experimental design, Engels helped with the experimentation, and Dr. Controzzi provided input during data analysis.

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2. The Effect of Myoelectric Prosthesis Control Strategies and Feedback Level on Adaptation Rate for a Target Acquisition Task

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Abstract

The long-term performance of myoelectric prostheses is related not only to the short-term performance of the controller, but also to the user’s ability to learn and adapt to the system. Different control architectures may have inherent tradeoffs between their short-term performance and the amount of relevant feedback that informs this adaptation. In this study we focused on the ability of two common types of myoelectric control interfaces: raw control with raw feedback, such as a regression, and filtered control with filtered feedback, such as a classifier, to affect user adaptation. We evaluated trial-by-trial adaptation to self-generated errors during a multi degree-of-freedom target acquisition task by fitting a linear regression model to data collected from 24 able-bodied subjects. Subjects showed significantly higher adaptation behavior to self-generated errors when using raw control with a raw feedback strategy than when using filtered control with a

filtered feedback strategy, which suggests that control strategies with more feedback allow for higher adaptation. These results support our hypothesis that feedback-rich control strategies allow users to better understand the myoelectric control system, which may enable better long-term performance.

INTRODUCTION

Myoelectric prostheses are a common tool used to help persons with an upper limb amputation perform activities of daily living [1]. Although myoelectric signals, the amplified electrical activity corresponding to a muscle contraction, are widely considered the best available control interface for powered prostheses [2], many amputees abandon their devices out of frustration due to the lack of precision of the prosthesis' movements [3]. Noisy control signals, derived from the stochastic myoelectric signals [4], and lack of adequate sensory feedback [5], [6] are two of the central bottlenecks limiting precision.

Researchers have developed many control strategies that vary in control architecture [7], [8] and feedback level [6], [9]–[11]. Early implementations of prosthesis control strategies focused on direct control of a single degree-of-freedom (DOF). More recent efforts have explored classifiers that use pattern recognition to select the most likely degree of freedom [12], or simultaneous controllers such as regressions [13], in which multiple DOFs can be simultaneously activated. Although most studies have focused on the direct connection between the controller itself and its associated short-term performance, each controller also has an inherent amount of feedback or lack of feedback associated with it that may indirectly affect performance, particularly as subjects adapt over longer terms.

Some studies have shown that sensory feedback improves performance (*e.g.*, [14]) whereas others have concluded that sensory feedback has no effect on performance (*cf.* [6]). These conflicting results may arise because feedback may not only be used in real-time regulation, but also to improve user’s understanding of the system, which may enable better long term performance. Posed this way, a novel question arises: do commonly used controllers that have varying degrees of sensory feedback influence the ability of subjects to adapt, potentially creating a tradeoff between short-term performance and longer-term adaptation? To answer this question, we need to evaluate how the feedback inherent in various control strategies affects user’s feedforward control behavior.

In this work, we explore one aspect of quantifying user’s feedforward control behavior by evaluating trial-by-trial adaptation to self-generated error for a multi-DOF target acquisition task. We implement two control strategies to represent the two commonly used types of myoelectric controllers. The first is a regression, which is inherently feedback-rich but provides noisier control than classifiers. We term this controller a *raw controller with raw feedback (RCRF)*. We compare this controller against a controller analogous to a classifier, and which thus has cleaner signals but reduced feedback (since it only activates a single DOF at a time). We term this controller a *filtered controller with filtered feedback (FCFF)*. Our results show that users achieve greater adaptation rates when they use the feedback-rich control strategy than when they use the filtered control with a filtered feedback strategy.

METHODS

Goal-directed tasks are a useful platform to measure performance and trial-by-trial adaptation [15]. Here, a virtual target acquisition constrained-time task [16][17] is used to explore this behavior. In this task, features extracted from myoelectric signals produced from muscle contractions are mapped using the candidate control techniques to the velocity of a cursor on a computer screen.

A. Control Strategies

The majority of myoelectric control strategies are developed from control architectures that can be thought of as either classifiers, which allow for sequential control only, or regression techniques, which allow for simultaneous control. Support Vector Regression (SVR) is a nonlinear control strategy that is often used in research; runs well in real-time experiments; and has shown good performance both as a classifier for sequential control [18] and as a regression for multi-DOF simultaneous control [8], [19]. Researchers in a recent study [19] concluded that SVR-based control strategies had superior performance to other simultaneous control strategies for real-time and proportional myoelectric control of multiple degrees of freedom while providing adequate feedback. For these reasons, we chose to use SVR as a common platform to test both control strategies. This choice was made to make the two controllers as similar as possible outside of the variables we wished to test. The first control strategy allows simultaneous multi-DOF control and is known as RCRF. The second control strategy is a filtered and discretized version of the first control strategy, which only allows activation of the most activated DOF at a time and is thus analogous to a classifier. Hence, this strategy is referred to as FCFF.

B. Experimental Setup

Subjects sat to the left of a custom-built arm and wrist restraint and the chair height was adjusted for a comfortable posture. A computer screen was mounted perpendicular to the line of sight of the subject and a UNB Smart Electrode System [20] with eight bi-polar electrode pairs was placed around the subject's right forearm. The forearm was placed in the restraint, which restricted wrist movement in order to ensure isometric contractions. During the experiment, subjects were instructed to control a cursor using muscle contractions to reach a series of targets (Fig. 2-1). These targets were cross-hairs with a red circle that imploded completely two seconds after trial initiation. This study examined a block of trials in which participants tried to acquire the same target over 80 trials. When testing RCRF, subjects received visual feedback of the cursor moving simultaneously in 2 DOF corresponding to their muscles contractions. Similarly, subjects testing FCFF received visual feedback of the cursor moving, but only in 1 DOF at a time corresponding to their muscles contractions for the highest activated DOF.

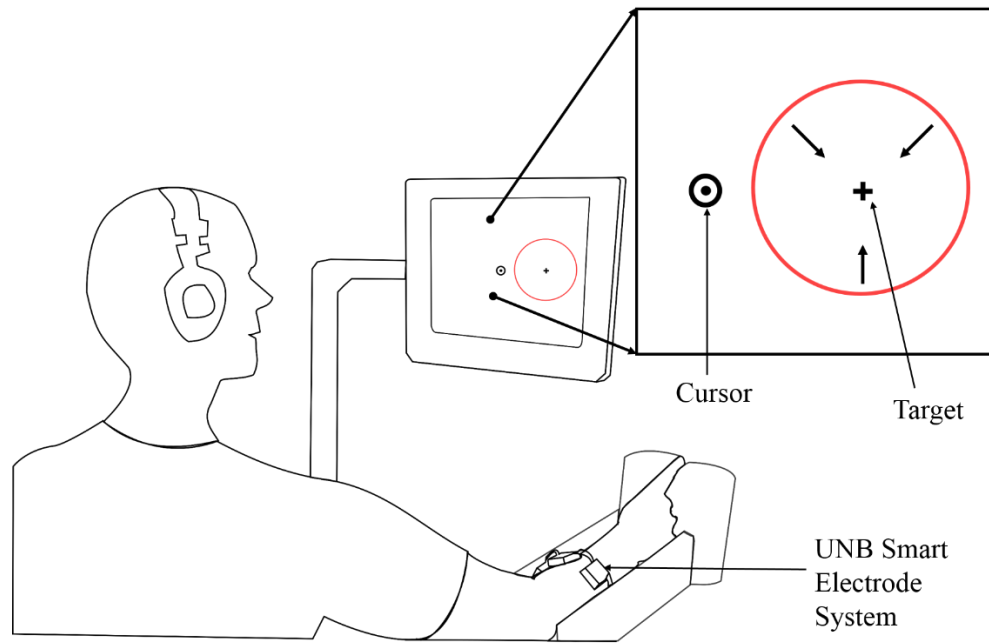


Fig. 2-1. A subject controlling a cursor on the screen to acquire a target. Subject's right arm is placed in a restrainer and myoelectric signals are extracted using the UNB Smart Electrode System placed on the subject's forearm.

C. Subjects

A total of 24 healthy subjects participated in the study (13 male and 11 female, mean and SD of age: 25.2 ± 4.9 years). All subjects were right-hand dominant and had either normal or corrected-to-normal vision. All procedures and protocols were approved by the University of New Brunswick Research Ethics Board (REB 2014-019). Informed consent was obtained from all subjects prior to participation in the experiment. 18 subjects were assigned randomly to either group 1 or group 2 (nine subjects each). Group 1 subjects tested RCRF then FCFF and group 2

subjects tested FCFF then RCRF. The remaining 6 subjects were assigned to control group 3 who tested FCFF twice.

D. Outcome Measures

In this study, we were interested in quantifying the rate at which the nervous system updates the understanding of the target acquisition task. This quantification can be achieved by measuring trial-by-trial adaptation rate. Trial-by-trial adaptation is the feedforward modification of an action from one trial to the next based on error feedback from the last trial [21]. This adaptation is accomplished by the nervous system building or modifying an understanding of a task to appropriately account for errors [22].

E. Data Analysis

We extracted the angle of departure for the first 300 - 500 msec of each trial to capture the subject's feedforward intent before they began to compensate using real-time feedback [23]. We defined the error angle as the difference between the departure angle and the optimal path angle (horizontal in this study). This error was computed for each of the 80 trials performed by the subjects. Adaptation rate for each subject was computed using the following first-order linear regression equation

$$Error_{n+1} - Error_n = \beta_1 \times Error_n + \beta_0 \quad (1)$$

where n is the trial number, β_0 is the regression constant, and β_1 is the adaptation rate.

MATLAB and the Statistics Toolbox (Release 2014a, The MathWorks, Inc., Natick, Massachusetts, United States) were used to run a two-sample t-test on the adaptation rate results for subjects in all groups. The Statistical Package for the Social Science software (IBM Corp, Released 2016, IBM SPSS Statistics for Windows, Version 24.0. Armonk, NY: IBM Corp) was

used to calculate the intraclass correlation coefficient of the adaptation rates of group 3 subjects, using a two-way mixed effects model at a 95% confidence interval.

RESULTS

To allow for development of myoelectric control strategies with better long-term performance, we needed to identify whether the level of feedback inherent in common control schemes could affect users' behavioral control. This paper addressed this need by evaluating trial-by-trial adaptation to self-generated errors when using two types of myoelectric controllers in a target acquisition task.

Subjects reaching targets using the first control strategy, RCRF, achieved an average error angle of $18.1^{\circ} (\pm 40.4^{\circ} \text{ SD})$. Similarly, subjects using FCFF reached targets with an average error angle of $-6.1^{\circ} (\pm 52.2^{\circ} \text{ SD})$. The higher standard deviation in the trial-by-trial error using FCFF can be justified by the fact that the reduced feedback in the FCFF control strategy only visually reflected error angles that were greater than 45 degrees. In contrast, the rich feedback from RCRF reflected all error that are not only self-generated errors, but also errors produced from the controller noise, which allowed subjects to continuously correct for these errors. Fig. 2-2. shows a sample data plot of trial-by-trial error for a subject using RCRF and FCFF control strategies.

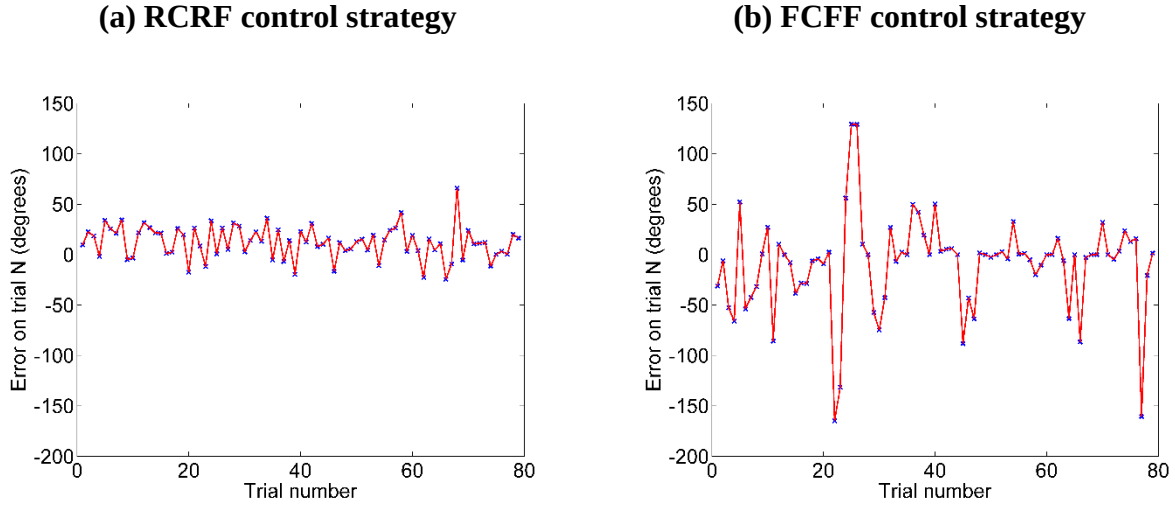


Fig. 2-2. Sample data for a single subject in group 2 showing trial-by-trial error using a) the RCRF control strategy (error fluctuating around a mean of $-12.8^\circ (\pm 16.1^\circ \text{ SD})$ and b) the FCFF control strategy (error fluctuating around a mean error of $-9.9^\circ (\pm 47.5^\circ \text{ SD})$).

For adaptation rate, a slope of -1 corresponds to perfect adaptation; a shallower slope indicates that the subject did not adapt enough; and a slope steeper than one indicates that the subject over compensated. We found that subjects in both groups 1 and 2 achieved high adaptation rates when testing RCRF, regardless of order of presentation of the controllers. In contrast, subjects in group 2 who tested FCFF exhibited low adaptation rates. To illustrate this, Fig. 2-3 shows adaptation rates computed for a subject in group 2 using RCRF ($\beta_1 = -1.36$) and FCFF ($\beta_1 = -0.35$). Overall adaptation rates across control strategies (Fig. 2-4) indicate that adaptation rates for subjects using RCRF in both groups 1 and 2 were significantly higher than adaptation rates for subjects using FCFF in group 2 (two-sample t-test, $p < 0.0001$). These results support the hypothesis that the feedback-rich control strategy allows for high adaptation.

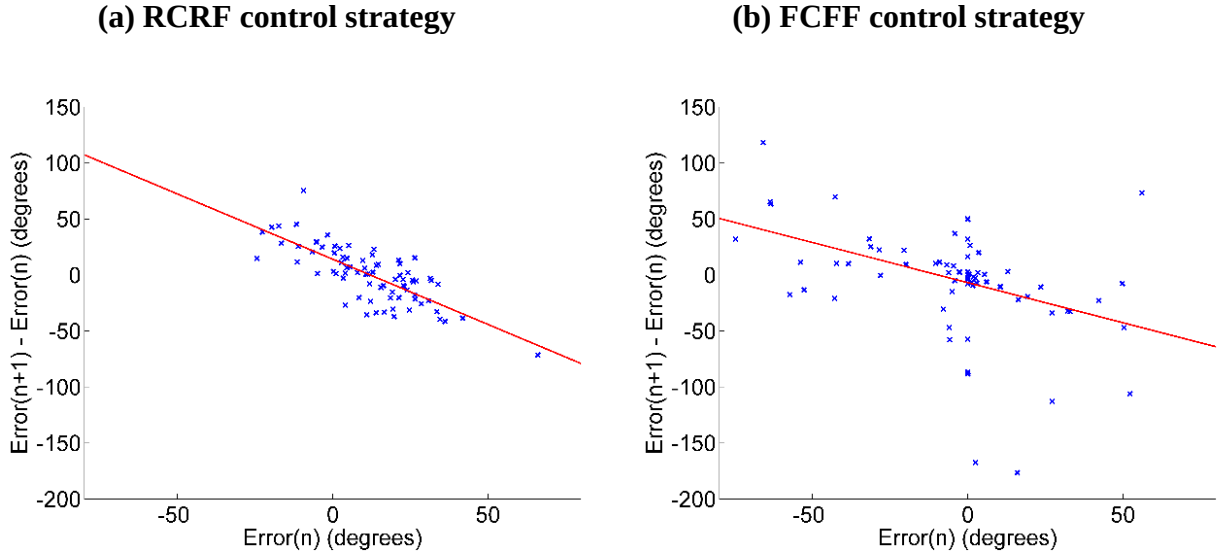


Fig. 2-3. Adaptation rate extracted using equation (1) from sample data for subject 1 in group 2 using a) RCRF control strategy ($\beta_1 = -1.36$) b) FCFF control strategy ($\beta_1 = -0.35$).

To quantify any possible learning effect, we randomly assigned equal numbers of subjects to groups 1 and 2. Group 1 subjects tested RCRF then FCFF, while group 2 subjects tested FCFF then RCRF. Subjects who used FCFF in group 1 achieved significantly higher adaptation rates than subjects in group 2 who used the same control strategy second (two-sample t-test, $p < 0.0001$). As suspected, subjects in group 1 learned how the controller worked using RCRF and used this knowledge when testing FCFF. This learning is reflected in the adaptation rate of subjects using FCFF after being exposed to RCRF (group 1), but not reflected in the adaptation rate of subjects using RCRF after using FCFF (group 2).

To ensure that the increase in adaptation rate was a result of the increased feedback level and not a repercussion of subjects going through a cognitive learning phase [24], group 3 subjects were asked to use the FCFF control strategy twice without testing the RCRF strategy. Results for subjects in this group (Fig. 2-5) showed that the effect of a re-test using FCFF on adaptation

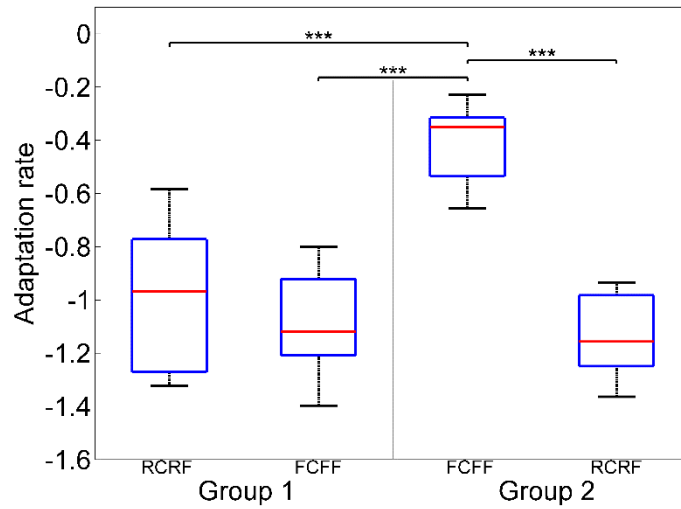


Fig. 2-4. Overall adaptation to self-generated error across control strategies tested by groups 1 and 2 subjects. Adaptation rates calculated using equation (1). Note that the greater negative values correspond to greater adaptation to self-generated errors. (*) indicates significant difference of $p < 0.001$.**

rate was not statistically significant ($p = 0.67$) with a moderate reliability (ICC = 0.74, SEM = 0.074).

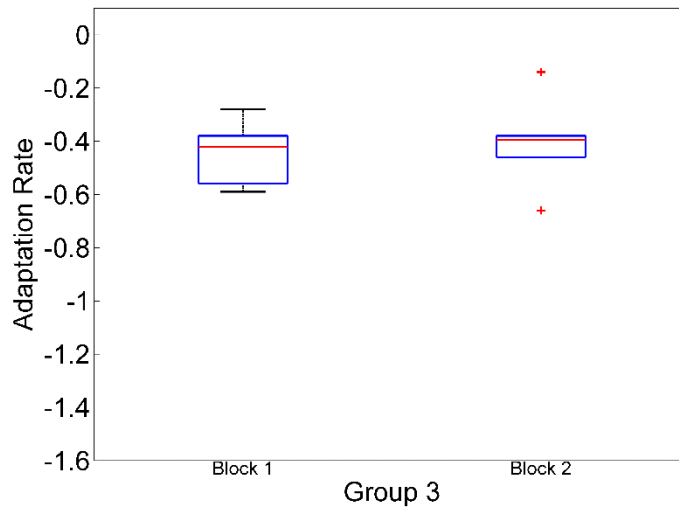


Fig 2-5. Overall adaptation to self-generated error for subjects in group 3 testing FCFF twice. Blocks 1 and 2 represent the first and the second adaptation rate tests, respectively.

DISCUSSION

Recent interest in transitioning to in-home training and use of myoelectric prosthetic devices triggered the need for developing myoelectric control strategies with better long-term performance. A key unexplored element to tackling this challenge is improving users' understanding of the myoelectric control system. To be able to improve this understanding, we first need to learn more about how it is developed. Here we measured one aspect of this understanding in the form of adaptation rate to self-generated errors. Two commonly used control strategies were tested: a feedback-rich but noisy control strategy, RCRF, and a less noisy, but reduced feedback control strategy, FCFF. Subjects were asked to acquire a single virtual

target over a block of 80 trials using each of these control strategies. The error in starting angle was recorded for each trial to evaluate the trial-by-trial adaptation rate. Upon analyzing these data, we found that subjects who used the RCRF control strategy achieved higher adaptation rates than those using the FCFF control strategy. Thus, we concluded that feedback-rich control strategies may enable better understanding of the control system than those with reduced feedback.

It was also found that users were able to retain and use relevant knowledge when using FCFF after first being exposed to the feedback-rich RCRF control strategy. On the other hand, the order of controller presentation did not have an effect on the adaptation rates when using RCRF. These results support the hypothesis that feedback-rich control strategies may allow users to adapt more appropriately and hence better understand the myoelectric control system.

One limitation of this study is that no amputee subjects were included, but we suspect that they would exhibit similar performance to the healthy subjects tested here [25], because trial-by-trial adaptation rate to self-generated errors is a measure of human behavior and understanding and not physical ability. Future work informed by this study includes, but is not limited to, identifying the amount of relevant feedback needed to effectively improve user adaptation and investigating the effect of feedback on other aspects of user's understanding *e.g.*, just-noticeable-difference, of the control system.

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3. Evaluating Internal Model Strength and Performance of Myoelectric Prosthesis Control Strategies

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Abstract

Ongoing developments in myoelectric prosthesis control have provided prosthesis users with an assortment of control strategies that vary in reliability and performance. Many studies have focused on improving performance by providing feedback to the user, but have overlooked the effect of this feedback on internal model development, which is key to improving long-term performance. In this work, the strength of internal models developed for two commonly used myoelectric control strategies: raw control with raw feedback (using a regression-based approach), and filtered control with filtered feedback (using a classifier-based approach), were evaluated using two psychometric measures: trial-by-trial adaptation and just-noticeable-difference. The performance of both strategies was also evaluated using a Schmidt's style target acquisition task. Results obtained from 24 able-bodied subjects showed that although filtered control with filtered feedback had better short-term performance in path efficiency ($p < 0.05$), raw control with raw feedback resulted in stronger internal model development ($p < 0.05$), which may lead to better long-term performance. Despite inherent noise in the control signals of the regression controller,

these findings suggest that rich feedback associated with regression control may be used to improve human understanding of the myoelectric control system.

Index Terms— Prosthetics, electromyography, support vector machines, internal model, learning, performance, muscles, control systems, mathematical model, real-time systems, testing.

I. INTRODUCTION

Decades of advancements in myoelectric signal acquisition and processing have made myoelectric controlled prostheses a promising option for upper limb amputees [1]. Nevertheless, precise real-time decoding of movement intent from highly variable myoelectric signals and adequate methods of providing feedback to users remain a challenge [2]. Myoelectric signal variability can contribute to inconsistency in prosthesis control that results in unintended prosthesis movements [3]. Many research studies have tackled this issue by exploring feature extraction methods to obtain more useful and robust information from noisy myoelectric signals [4]. Time domain and frequency domain features are some of the most referenced of these features and are commonly used in conjunction with pattern recognition algorithms implemented in myoelectric control systems [5], [6]. The current myoelectric control systems can be broadly categorized as on/off control, proportional control, classifier-based control, and regression-based control [7].

On/off control strategies are used for binary control of a device, whereas proportional control strategies facilitate control over the speed of the prosthesis movement [8]. Although these types of control strategies are considered robust and have found clinical acceptance, the controllable number of degrees-of-freedom is limited by the number of usable independent control sites [9].

Classifier-based pattern recognition approaches are able to overcome this limitation, but are only capable of classifying movements sequentially [10], [11]. This drawback has more recently been overcome through the use of regression-based myoelectric controllers [12], which enable simultaneous and independent control but at the expense of the robustness of classifier-based approaches to unintentional changes in contraction patterns.

Feedback has also been shown to be of importance for robust control and in improving performance [13]. Feedback can be used for real-time regulation of control signals, as well as in the development of the user's understanding of the system, known as their internal model [14]. Many researchers have explored the effect of feedback for real-time regulation on performance, but little work has explored its effect on internal model development (in part due to an inability to evaluate or quantify internal model strength) [15].

Quantifying this internal model enables the development of better control strategies by identifying which control strategies promote better understanding of the system and may therefore lead to better long-term performance. In a recent study [16], researchers investigated the effect of using two different myoelectric control strategies on user adaptation, which is one of the facets that can be used to estimate the strength of an internal model [17], [18]. Their results showed promising evidence that inherent feedback in myoelectric control strategies influences adaptation, which should in turn influence the user's corresponding internal model.

In our work we sought to explicitly demonstrate that influence on a person's internal models by measuring adaptation rate along with other factors, such as sensory noise and controller noise, which are necessary to calculate internal model strength. We used a recently developed psychophysical framework to assess the internal models developed using two myoelectric control strategies that differed in the feedback provided to the user during a multi degree-of-

freedom (DOF) target acquisition task. The underlying signal processing for both control strategies was done using the same pattern recognition algorithm to ensure that only the feedback effect impacted the internal model strength. The first strategy implemented feedback-rich but noisy (variable) regression-based control, which we refer to here as *raw controller with raw feedback (RCRF)*. The other control strategy was analogous to a classifier, which provided reduced (discretized) feedback but more forgiving control, and is referred to here as *filtered controller with filtered feedback (FCFF)*. The psychometric test results detailed below support the hypothesis that the feedback-rich controller enables a low sensory uncertainty and strong internal model leading to a high adaptation rate. Conversely, performance test results indicate that the filtered classification-based controller yielded better short-term path efficiency and accuracy.

II. METHODS

A. Tested Control Strategies

Many machine learning algorithms have been proposed to translate information in the myoelectric signals to either sequential or simultaneous control. Linear Discriminant Analysis (LDA) [19], Linear Regression (LR) [20], Support Vector Regression (SVR) [21], [22], and Artificial Neural Networks (ANN) [23] are some of the commonly used data-driven approaches used to identify myoelectric signal patterns for the purpose of control. SVR, in particular, is based in support vector machine (SVM) theory and can be used for either classification or regression control tasks. In both cases, SVM/SVR has been shown to yield performance superior to that of LDA/LR [4], [24], [22]. When employed as a regressor, the output is a kernel-based weighted mixture of the inputs, supporting simultaneous activation of more than one DOF at a

time. This strategy is referred to here as RCRF due to the direct relationship between inputs and both control and feedback outputs. To approximate a classification output, while preserving the same decision space, the FCFF controller was achieved by gating all RCRF activations other than that of the DOF with highest level of activation (the classifier selected only the single most active DOF).

B. Experimental Setup

Subjects sat in a comfortable chair in an upright position with their line of sight perpendicular to a computer display screen. The height of the chair was adjusted to ensure a comfortable posture and that the subjects' right arm was fully relaxed in a restrainer. This restrainer consisted of a fixed foam-padded wrist support, an adjustable foam-padded elbow support, and a foam-padded hand slot that provided resistance to hand movements while providing a comfortable setting during scheduled breaks between testing blocks. A UNB Smart Electrode System [25] was placed on the subject's right forearm (Fig. 3-1) and the real-time myoelectric signals extracted from muscles contractions were monitored using the Acquisition and Control Environment (ACE) software package [26] developed using MATLAB (Release 2007, The MathWorks, Inc., Natick, Massachusetts, United States).

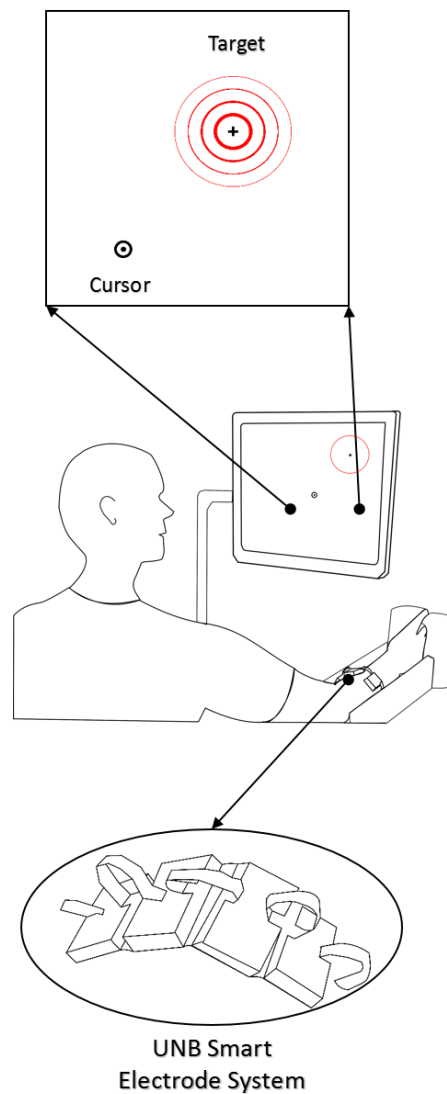


Fig. 3-1. Experimental Setup. A subject performing the target familiarization block by controlling a cursor on the screen using myoelectric signals sensed by the UNB Smart Electrode System, which is placed on the subjects forearm, to acquire a target

Using isometric muscle contractions of the wrist extension/flexion and abduction/adduction, subjects controlled a cursor on the computer screen to acquire targets in a custom program that we implemented within the ACE software package. Targets consisted of cross-hairs that appeared at randomly ordered pre-determined positions on the screen. Using a

Schmidt's style test paradigm [27], a shrinking red circle surrounded each target. This circle shrank for a pre-specified amount of time, which was determined by the testing configuration, before disappearing to indicate the end of a trial and the beginning of the next trial.

C. Subjects

Twenty-four right-handed subjects with either normal or corrected-to-normal vision (13 male and 11 female, mean and SD of age: 25 ± 5 years) provided written consent to participate in a three-hour experimental session. These subjects were recruited primarily by word-of-mouth or the University of New Brunswick (UNB) public news and notices. Participants were informed of the overall purpose of the study, but were naive to the specific purpose and outcomes of the built-in testing blocks. The University of New Brunswick Research and Ethics Board approved this study and no compensation was provided for participation.

Eighteen of those subjects were randomly assigned to either group 1 or group 2 (nine subjects each) and the remaining subjects were assigned in a follow up study to group 3. All subjects in this study completed the same testing blocks, but the order of the control strategy presentation depended on which group a subject was assigned to. Group 1 subjects tested the RCRF control strategy first and then the FCFF control strategy, leaving group 2 subjects to start with testing the FCFF control strategy and then the RCRF control strategy.

To investigate any possible learning effect due to prolonged use of the myoelectric system, group 3 subjects acted as a control group for this study, testing the FCFF control strategy twice.

D. Experiment Protocol

After obtaining consent from the subjects, they were asked, on a scale from 0 to 2, to rate their myoelectric control experience between no experience and moderate experience. Before placing

the UNB Smart Electrode System on the subject's right hand, the skin over their forearm was cleaned using an alcohol wipe. A couple of minutes were allowed for the real-time myoelectric signal amplitudes to settle below 1 micro-volt after which the controller training block started. In this training, subjects were asked to follow the position of a cursor on the screen using isometric muscle contractions of the wrist for extension/flexion DOF and adduction/abduction DOF, twice for each DOF, and their myoelectric signals were recorded. An SVR pattern recognition algorithm used time-domain features extracted from these recorded signals to form the base of the controllers used in this study. For each controller tested, subjects completed four blocks in the following order:

- 1) Control practice and target familiarization

This block consisted of three mini tasks. For the first task, subjects were asked to 'paint the screen' by controlling a brush on the computer screen and trying to cover the maximum achievable area on the screen in one minute. Afterwards, subjects were given time to learn how to use the controller by instructing them to freely control a cursor on an empty screen starting with mild contractions in one DOF at a time and then exploring the different muscle contraction combinations and their effect on the controlled cursor for two minutes. The last task consisted of three sets of 16 targets. Each target in those sets appeared at a random position from 1 of 8 predetermined positions on the screen and subjects were prompted to reach that target in 12 seconds or less. If a target was acquired in less than the indicated time, a motivational "Successful" green text appeared on the screen, the screen was cleared, and a 3 seconds count down started before another target appeared. Conversely, if the target was not acquired in the indicated time, a red "Time Out" text appeared on the screen, before beginning the countdown for the next target.

2) Adaptation rate test

Subjects were instructed to acquire a single target on the horizontal axis over a set of 80 trials. A trial started when the target appeared on the screen and ended after 2 seconds. Subjects were allowed 1 second to relax the contracted muscles between trials. If the target was acquired, the trial ended before the 2 seconds elapsed and provided the subject with a motivational “Successful” text, otherwise the trial terminated after the 2-second mark.

3) Just-noticeable-difference (JND) test

The JND is a measurement of sensory thresholds related to the estimation of specific points of the psychometric function underlying the perception of sensory stimuli [28]. In the experimental design of the JND test, the subject was forced to select between two alternative choices presented, with one of the choices having a specific stimulus added (Fig. 3-2). This method is known as two-alternative forced-choice (2AFC) task, and the stimulus used was computed using an adaptive staircase [28]. This adaptive staircase quickly converges to the JND by adapting the stimulus amplitude of each trial according to the following equation:

$$C_{(n+1)} = C_n - \frac{S}{n_{Rev}+1} \times (Z_n - \phi), \quad (1)$$

where C is the stimulus, n is the trial number, S is the step size, n_{Rev} is the number of reversals between the correct and incorrect states, Z is a binary quantity that depends on the response at the n_{th} trial as follows: Z is equal to 1 in case of success and 0 in case of failure, and ϕ is the accuracy (set to 0.84) [29]. For this block, subjects were asked to reach a single target twice in 2 seconds and then identify which of the two trials had the added stimulus. Subjects were not given feedback on their response.

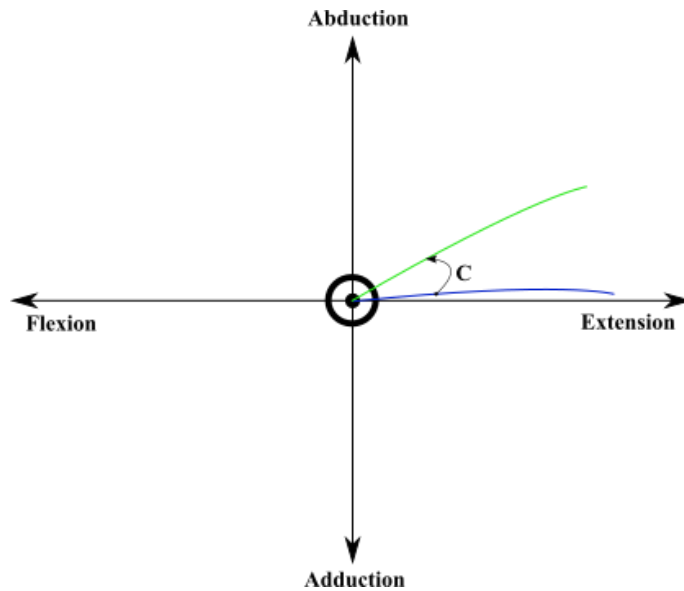


Fig. 3-2. Example of a stimulus added to control signal activating cursor movement. The blue line shows actual control signal and the green line shows the perturbed control signal

Following the (modified standard, standard) method design discussed in [30], the stimulus used was restricted to a counter-clock wise rotation of the control signal. Data collected from three subjects in a pilot study was used to obtain an estimate of the initial stimulus to be used in this study. Only the target lying on the positive x-axis was explored and the test block terminated when the number of reversals reached 23 [31].

4) Performance test

To assess the performance of each controller, subjects were asked to complete three challenging target sets. Each target set consisted of 16 targets which appeared at a random position drawn from 1 of 8 predetermined positions on the screen. For the first set of targets, subjects were instructed to acquire each target within 2 seconds. This time constraint was further reduced to 1.7 seconds for the second target set. The last challenge required subjects to acquire

Table 3-1: Summary of the test blocks

Block	Description
Control Practice	Control a cursor on an empty screen for 2 minutes
Target Familiarization	Acquire 48 targets in less than 12 seconds per target. Targets appeared at random positions on the screen
Adaptation rate test	Acquire a single target on the horizontal axis in less than 2 seconds 80 times.
JND test	Attempt to acquire a single target on the horizontal axis in less than 2 seconds twice.
Performance test	Acquire 16 targets that appeared at random positions on the screen in less than 2, 1.7, and 1.4 seconds.

targets in 1.4 seconds or less per target. A short description of the tasks required in each block is listed in Table 1.

E. Outcome Measures

The main goal of this study was to assess the developed internal model strength and the performance of two commonly used myoelectric controllers. To accomplish this goal, psychophysical experiments were conducted to evaluate various parameters that influence the development of the internal model using a novel framework (see supplementary material).

1) *Trial-by-trial adaptation*

Adaptation rate is a measure of how much the nervous system changes or modifies an internal model for a given task [32]. This rate is extracted by quantifying the rate of feedforward modification of the control signal from one trial to the next based on error feedback from the last trial [33]. Following the same procedure used to compute the adaptation rate in [34], the following equation was used to extract this rate

$$error_{n+1} - error_n = \beta_1 \times error_n + \beta_0, \quad (2)$$

where *error* is the angle formed between the horizontal axis and the initial cursor trajectory, n is the trial number, β_0 is the linear regression constant, and $-\beta_1$ is the adaptation rate.

2) *JND*

This parameter is a measure of the minimum perceivable stimulus in degrees identified by the subject when using each control strategy and was identified after the termination condition for the JND test has been satisfied. This parameter was used to quantify the amount of controller noise and sensory noise for each controller on a per subject basis [35].

3) *Internal model uncertainty P_{param}*

A novel framework was introduced to quantify uncertainties in the internal model parameters given controller noise and sensory noise parameters (see Appendix A). These uncertainties are represented in the P_{param} parameter. The lower the value of this parameter, the higher the strength of the internal model developed.

4) *Performance*

An experimental protocol was designed with which the short-term performance of the control strategies could be objectively evaluated using the following indicators.

a) *Path efficiency*

Paths taken to reach targets within a given time constraint during the performance test block were compared against the optimal paths [36] *i.e.*, path optimizing distance covered, to compute efficiency.

$$\eta_p = \left(1 - \frac{P - P^*}{P^*}\right) \times 100, \quad (3)$$

where η_p is the path efficiency in percent, P is the actual path taken, and P^* is the computed optimal path. To ensure consistency of this measure, the optimal path for the RCRF, which enables 2-DOF simultaneous control, was computed as the shortest radial path between the cursor's starting point and the final point where the cursor landed when the trial was terminated. For the FCFF, which allows for the activation of only one DOF at a time, the optimal path was computed as the Manhattan distance covered to reach the final point where the cursor landed.

b) *Accuracy*

The accuracy was defined as how closely a target is reached given the time constraint. As with the technique used to ensure consistency in assessing path efficiency, the radial error was defined as the distance between the center point of a target and the actual final point reached for RCRF tests. This error was calculated as

$$RE = \sqrt{(t_x - c_x)^2 + (t_y - c_y)^2}, \quad (4)$$

where RE is the radial error, t is the target Cartesian coordinates and c is the final cursor position in Cartesian coordinates. The distance error for the FCFF tests was computed as

$$CE = (t_x - c_x) + (t_y - c_y). \quad (5)$$

The ratio between RE and the shortest radial path from the starting point to the center of a target was used to compute the accuracy for the RCRF control strategy as

$$\eta_a = \left(1 - \frac{RE}{p^*}\right) \times 100, \quad (6)$$

and the ratio between CE and the Manhattan distance path from the starting point to the center of a target was used to compute the accuracy for the FCFF control strategy as

$$\eta_a = \left(1 - \frac{CE}{p^*}\right) \times 100, \quad (7)$$

where η_a is the accuracy in percent.

F. Data Analysis

Myoelectric signals, controller activation, and the cursor path were recorded for each trial in the test blocks. For the trial-by-trial adaptation rate, error angles were computed for the first 300–500 msec of each trial to capture the subject’s feedforward intent without incorporating feedback for real-time regulation. Only the successfully acquired target trials in the adaptation rate test

were used to assess the path efficiency. Subject responses and the stimuli used in the JND test were recorded. All error bars shown in the figures were based on the standard error of the mean (SEM) to reflect its dependency on the sample size [37].

G. Statistical Analysis

The outcome measures presented in the previous section were analyzed using two sample t-tests (equal sample size) in MATLAB and the Statistics Toolbox (Release 2014a, The MathWorks, Inc., Natick, Massachusetts, United States) to investigate the effect of controller type on each of these outcome measures. The Statistical Package for the Social Science software SPSS (IBM Corp, Released 2016, IBM SPSS Statistics for Windows, Version 24.0. Armonk, NY: IBM Corp) was used to conduct an ANOVA to investigate the effect of controller testing order on the performance and the internal model uncertainty P_{param} . Finally, an ANOVA with repeated measures was used to compute the intraclass correlation coefficient of the adaptation rates, JNDs, internal model uncertainty, and path efficiency of group 3 subjects using a two-way mixed effects model with absolute agreement at a 95% confidence interval to investigate learning effects [38]. All analyses used a significance criterion of $\alpha = 0.05$ and Leven's test in SPSS was used to investigate homogeneity in variances of the data being analyzed to ensure that parametric test assumptions were satisfied. If they were not satisfied, nonparametric Mann-Whitney U test was used.

III. RESULTS

The main goal in this study was to investigate the effect of using two commonly used myoelectric control strategies on the strength of the internal model developed for a reaching task.

The first control strategy, RCRF, represents a regression control strategy that allows for simultaneous control in more than 1 DOF at a time and is rich in feedback, but has comparably noisy control signals. The other control strategy, FCFF, has less variable control signals, but has reduced feedback and only allows for activation of only 1 DOF at a time. In this work the short-term performance and the strength of the internal model developed were assessed when using these control strategies. To further expand on this work, short-term performance in a target acquisition task was also evaluated when using both control strategies.

Adaptation rate test. From equation 2, $-\beta_1 = 1$ indicates perfect adaptation; lower values indicate lower adaptation; and a value higher than 1 indicates overcompensation. All subjects achieved high adaptation rates when using the feedback-rich RCRF control strategy, regardless of the order of presentation of the controllers (Fig. 3-3). In contrast, the order of presentation had a significant effect on the adaptation rate of subjects using FCFF after being exposed to RCRF and subjects using FCFF before being exposed to RCRF (two-sample t-test, $p < 0.001$). Upon performing t-tests on the adaptation rate data for groups 1 and 2, a significant difference was found between subjects testing RCRF in both groups 1 and 2 and subjects testing FCFF in group 2, who were not exposed to RCRF (two-sample t-test, $p < 0.001$). No significant difference was found between adaptation rate data of subjects using RCRF and subjects using FCFF after being exposed to RCRF. Exposure to the RCRF control strategy enabled subjects to adapt more when using the FCFF control strategy. This effect could be a result of either a translation of the internal model developed for RCRF to FCFF in group 1 subjects or a ramification of prolonged use of the myoelectric system, which was further investigated in more details using group 3 subjects' results.

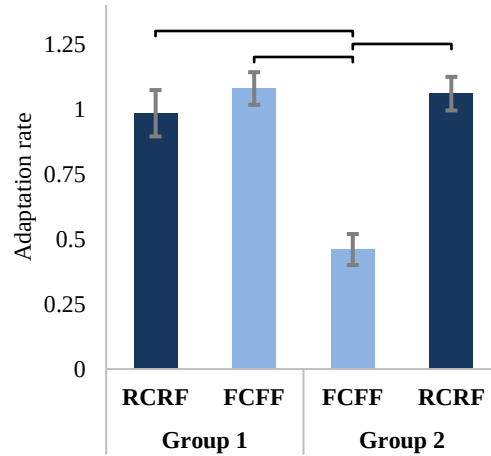


Fig. 3-3. Trial-by-trial adaptation to self-generated error results across control strategies tested by subjects in groups 1 and 2. Horizontal bars indicate significant difference.

JND test. The perception threshold for each controller was measured using the 2AFC procedure, in which an adaptive staircase was used to determine the stimulus to be added. The lower the threshold a subject was able to identify, the better ability to detect and adjust for smaller changes in the control system they had. In this test, subjects were able to identify a lower threshold when using RCRF than when using FCFF, regardless of the order of presentation (Fig. 3-4).

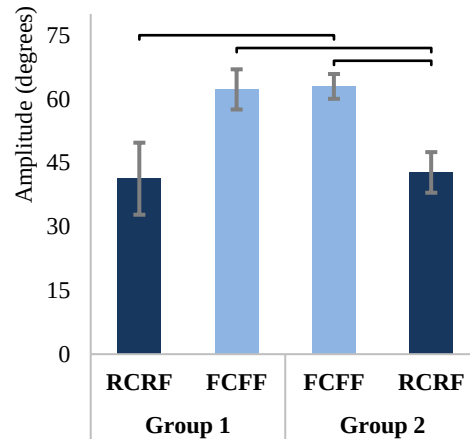


Fig. 3-4. Overall JND results across control strategies for groups 1 and 2. Subjects using the RCRF control strategy were able to obtain lower JND than subjects using FCFF control strategy. Horizontal bars indicate significant difference.

Likewise, there was no significant effect due to the order of controller presentation on JND values when using FCFF. Results show that, on average, subjects were able to identify a stimulus that was at least 15° lower when using RCRF than when using FCFF (Fig. 3-5). In fact, subjects using RCRF in group 2 had a significantly lower JND value than subjects using FCFF in both groups (two-sample t-test, $p < 0.05$). Even though subjects using RCRF in group 1 obtained lower JND values than when using FCFF in the same group, this difference was not significant (two-sample t-test, $p = 0.07$). These JND values were, however, significantly lower than the values obtained by subjects using FCFF before being exposed to RCRF (two-sample t-test, $p < 0.05$). These results indicate that RCRF may enable users to identify smaller perturbations or changes in the controller by providing them with more detailed feedback.

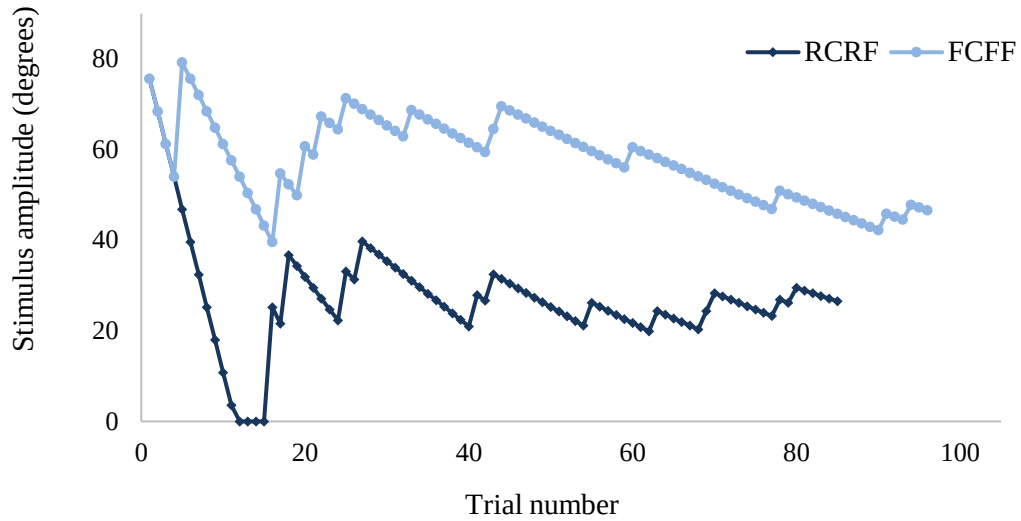


Fig. 3-5. Sample data for a subject in group 1 showing the stimulus amplitude adjusted according to an adaptive staircase with a termination condition of 23 reversals and targeting 84% detection threshold.

Internal model. Psychophysical parameters extracted from tests conducted in this study were used to quantify uncertainty in the internal model parameters developed in response to a control strategy. Quantifying this uncertainty allows for the identification of the control strategy that enables the development of a stronger internal model by indicating the one that enables lower internal model parameter uncertainty. Fig. 3-6 shows results for internal model uncertainty for the feedback-rich RCRF control strategy and the reduced feedback FCFF control strategy. These results show that subjects who used FCFF before being exposed to RCRF had significantly higher internal model uncertainty than subjects who used RCRF in group 1 (Mann-Whitney U test, $p < 0.05$) and RCRF in group 2 (Mann-Whitney U test, $p < 0.01$), which suggest that a feedback-rich control strategy may enable the formation of a stronger internal model.

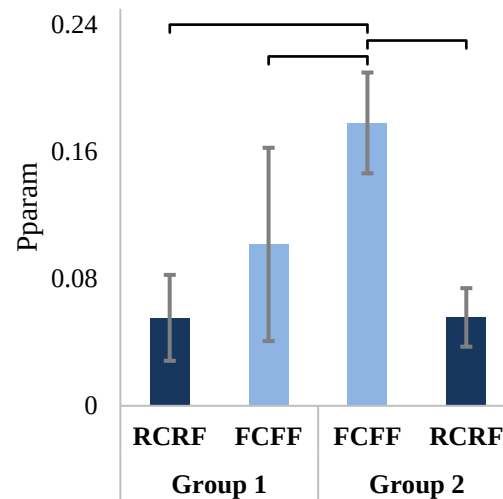


Fig. 3-6. Internal model uncertainty results across control strategies for groups 1 and 2. RCRF control strategy allows for the development of a less uncertain internal model parameters than the FCFF control strategy.

In addition, subjects who used FCFF before being exposed to RCRF had significantly higher internal model uncertainty than subjects who used FCFF in group 2 (Mann-Whitney U test, $p < 0.05$). This result suggests not only that using a RCRF control strategy aids in the development of a less uncertain internal model, but also the possibility of translation of the internal model *i.e.*, no significant difference between internal model uncertainty for subjects using FCFF after being exposed to RCRF and subjects using RCRF in both groups 1 and 2.

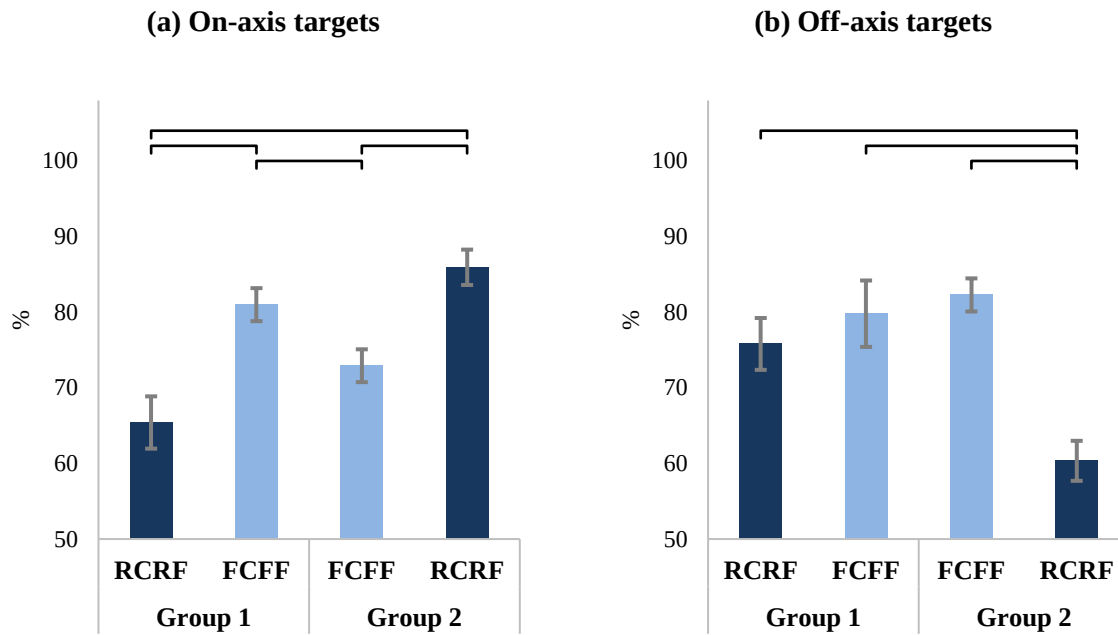


Fig. 3-7. Results for accuracy normalized by the optimal distance between the starting point and the center of a target computed for each control strategy. (a) On-axis targets accuracy results show that subjects testing RCRF in group 1 achieved the lowest accuracy, but subjects in group 2 testing the same controller achieved the highest accuracy. (b) Off-axis targets accuracy results show a significant drop in the accuracy for subjects using RCRF in group 2 and all other controllers.

Performance. The short-term performance of each control strategy was evaluated by determining how accurately and efficiently the task was achieved using endpoint accuracy and path efficiency. In the performance test, subjects were asked to acquire targets that were either on-axis, which optimally required the activation of 1 DOF, or off-axis, which optimally required the activation of 2 DOF simultaneously.

Results for the on-axis targets accuracy show that there was no significant difference between the control types, however the exposure to any controller had a significant effect on improving

accuracy of the second controller tested. A controller that was tested in the second block outperformed the controller that was tested in the first block (two-sample t-test, $p < 0.01$) (Fig. 3-7. a), regardless of controller.

Interestingly, subjects using RCRF after being exposed to FCFF had significantly lower accuracy for off-axis targets than subjects using FCFF in both groups 1 and 2 (two-sample t-test, $p < 0.01$) and subjects using RCRF before being exposed to FCFF (two-sample t-test, $p < 0.01$), which suggests that subjects were influenced by the technique they used to reach off-axis targets using the sequential FCFF control strategy and therefore didn't make use of the RCRF ability to do simultaneous movements (Fig. 3-7. b).

The second performance assessment tool used here was path efficiency (Fig. 3-8). Equation 3 was used to compute path efficiency for the control strategies tested in the performance test. On-axis targets path efficiency results show that for a simple 1 DOF task there was no significant difference between subjects who used RCRF first and FCFF first, however there was a significant increase in the path efficiency when retesting using any controller (two-sample t-test, $p < 0.01$). This observation may be a result of subjects exploring effective techniques that can be implemented using both control strategies. It is also worth noting the increase in the successfully acquired target count when retesting a controller. In particular, the successfully acquired target count when using RCRF after being exposed to FCFF was 5 times higher than the count for RCRF before being exposed to FCFF. This result suggests that there is a possible improvement in achieving 1 DOF tasks using the RCRF if the subject was exposed to a 1 DOF sequential control strategy.

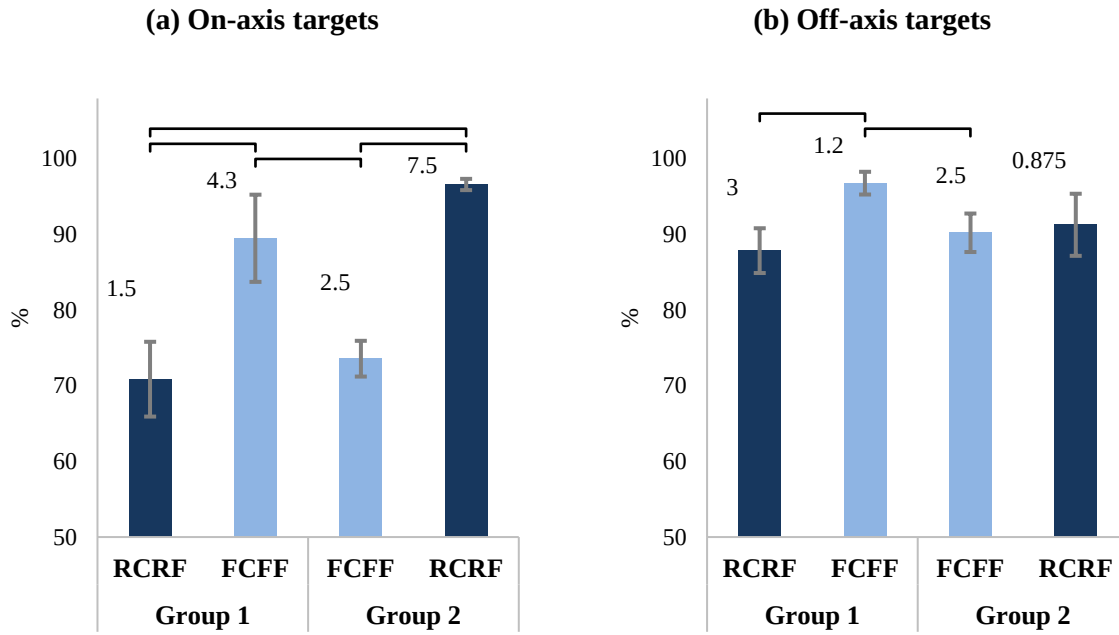


Fig. 3-8. Results for path efficiency calculated with respect to the optimal path between the starting point and the final point reached computed for each control strategy. (a) On-axis targets path efficiency results show that subjects testing RCRF in group 2 achieved the highest path efficiency and the highest success count for acquiring targets, but subjects in group 1 testing the same controller acquired the lowest success count for acquiring targets. (b) Off-axis targets path efficiency results show a significant increase in path efficiency for group 1 subjects testing FCFF after being exposed to RCRF.

For the off-axis target path efficiency, results show a significant improvement when using FCFF after being exposed to RCRF (two-sample t-test, $p < 0.05$), which may support the claim that using FCFF could be improved for a 2 DOF task if the subject was first exposed to a simultaneous control strategy like the RCRF. In addition, results show a drop in the successfully acquired target count of about 3 times when using RCRF after being exposed to FCFF.

TABLE 3-2: SUMMARY OF GROUP 3 TEST RESULTS

Outcome metric	ANOVA REPEATED MEASURE P	ICC	SEM
ADAPTATION rate	0.67	0.74	0.074
JND	0.43	0.65	10
Internal model uncertainty	0.47	0.81	0.071
Path efficiency On-axis targets	0.26	0.72	1.8
Path efficiency Off-axis targets	0.79	0.85	1.9
Accuracy On- axis targets	0.81	0.64	3.2
Accuracy Off- axis targets	0.44	0.74	5.7

Group 3 results. For this group, a test-retest experiment was conducted using only the FCFF control strategy. Table 3-2 summarizes the statistical analysis for the results obtained from this group. These results show that there was no significant difference in internal model assessment parameters or performance measures when testing FCFF twice. In fact, test results for adaptation rate, JND, and internal model uncertainty showed no significant within-subject effect of retesting FCFF with good reliability ($ICC > 0.6$). Similarly, performance measure test results for both on-axis and off-axis targets indicated no significant difference between block 1 and block 2.

IV. DISCUSSION

Research efforts in the field of myoelectric control have provided many solutions to improve control and performance. Classifiers, as represented here by FCFF, and regression control, as represented as RCRF, are two of the more commonly used emerging solutions. Despite differences in feedback and control signals, each of these control strategies has been found to overcome the limitations of conventional myocontrol [4], [9], [39], however their effect on the developed internal model strength, which affects user's adaptation and the long-term performance, had not been explored. In this study, not only the short-term performance, but also the internal model strength were assessed using psychophysical and performance tests for a multi-DOF virtual target acquisition task.

Psychophysical test results showed that RCRF enabled significantly higher adaptation to self-generated errors and the achievement of significantly lower perception threshold than FCFF. These parameters were reflected in the internal model strength, where it was also found that subjects who used RCRF developed an internal model that was significantly less uncertain (more confident) than subjects using FCFF. These results support our hypothesis that feedback-rich control strategies like RCRF enable the development of a stronger internal model than reduced-feedback control strategies like FCFF. Conversely, performance test results show that subjects had slightly better path efficiency and accuracy when using FCFF than with RCRF, which prompts a question about how much feedback is most useful for the development of a strong internal model without sacrificing the short-term performance.

The exposure to a feedback-rich control strategy enabled subjects to adapt more when using a reduced-feedback control strategy afterwards. It was found that this effect was a result of a

translation of the internal model developed by the feedback-rich controller to the reduced feedback one and not a ramification of prolonged use of the myoelectric system. Test results from group 3 subjects who tested the reduced feedback control strategy twice indicated that the prolonged use of this controller did not improve performance or internal model strength.

To be able to compare performance results of the 2 DOF simultaneous RCRF control strategy with the 1 DOF sequential FCFF control strategy, the performance metrics for each control strategy were defined differently. Manhattan distances were used to compute path efficiency and accuracy for the FCFF control strategy and radial distances were used to compute path efficiency and accuracy for the RCRF control strategy. This approach was used to reduce bias in the performance metrics.

Results from this study demonstrate that there was a significant improvement in the on-axis targets path efficiency and accuracy when using FCFF after being exposed to RCRF. Since the task of reaching on-axis targets only requires a simple activation of 1 DOF, the improvement in both accuracy and path efficiency may be a result of subjects using the understanding of how to effectively control the cursor in 1 DOF when they were exposed to the 2 DOF feedback-rich RCRF control strategy first and therefore informing their choice of the technique to be used to acquire targets when using FCFF. It should be noted that the exposure to any controller had a significant effect on improving accuracy of the second controller tested. From this, it may be surmised that previous experience, *i.e.*, effective control technique developed and used for a control strategy, may be translated from one control strategy to another.

In contrast to our findings, Hahne et al. [16] found that classifier-based control yielded worse path efficiency than regression (they reported classifier path efficiencies of 0.27 ± 0.12). We found similarly poor results during a preliminary investigation using LDA/LR approaches, and

subsequently transitioned to SVM/SVR approaches, which have been shown to have superior performance and are equally clinically viable [12], [22]. Also in contrast to [16], which employed a position control paradigm, we used a velocity control paradigm (EMG was mapped to cursor velocity rather than position) as it is less noisy and much more commonly used in clinical practice [40], [41]. These two differences likely account for the difference in performance found between the two studies. The substantially better performance seen in this work, coupled with a more clinically relevant control paradigm likely enabled us to more accurately isolate the effects of feedback as they pertain to internal model strength.

In conclusion, despite classifiers such as FCFF enabling better short-term performance, regression approaches such as RCRF enabled the development of a stronger internal model leading to better long-term performance. With this conclusion in mind, future contributions to training and use of myoelectric prosthesis devices could be enabled by allowing users to train using feedback-rich controllers to develop a strong internal model and therefore improve long-term performance when using other controllers.

V. ACKNOWLEDGMENT

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4. Myoelectric Prosthesis Control: Improving Internal Model Strength and Performance Using Augmented Feedback

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Abstract

Myoelectric prosthetic devices are commonly used to help upper limb amputees perform activities of daily living; however amputees still lack the sensory feedback required to facilitate reliable and precise control. Augmented feedback may play an important role in affecting both short-term performance, through real-time regulation, and long-term performance, through the development of stronger internal models. In this work, we investigate the potential tradeoff between controllers that enable better short-term performance and those that provide sufficient feedback to develop a strong internal model. We hypothesize that augmented feedback may be used to mitigate this tradeoff, ultimately improving both short and long-term control. We used psychometric measures to assess the internal model developed while using a filtered myoelectric controller with augmented audio feedback, imitating classification-based control but with augmented regression-based feedback. In addition, we evaluated the short-term performance using a multi degree-of-freedom constrained-time target acquisition task. Results obtained from 24 able-bodied subjects show that an augmented feedback control strategy using audio cues

enables the development of a stronger internal model than the filtered control with filtered feedback, and significantly better path efficiency than both raw and filtered control strategies. These results suggest that the use of augmented feedback control strategies may improve both short-term and long-term performance.

INTRODUCTION

Recent advances in material design, micromachining, and the understanding of human neuromuscular systems have enabled the development of lightweight prosthetic devices that can be used to help amputees perform activities of daily living. One approach to controlling these devices is to use myoelectric signals sensed from contractions of the amputee's remnant or congenitally different muscles¹. Researchers have developed many signal processing techniques², feature extraction methods³⁻⁵, and control strategies⁶ to enhance the performance of this approach. Despite these advancements in the field of myoelectric prostheses, many amputees still abandon their devices out of frustration⁷, due in part to insufficient precision in the control of prosthesis movements and a lack of adequate sensory feedback^{8,9}.

Although invasive feedback, such as stimulation of sensory peripheral nerves¹⁰, has the potential to elicit close-to-natural tactile sensations, many prosthesis users prefer non-invasive feedback methods that do not require surgical intervention¹¹. With this preference in mind, researchers have proposed using non-invasive sensory substitution methods to provide sensory information to prostheses users either through different sensory channels or using different modalities¹². Vibro-tactile¹³, mechano-tactile¹⁴, electrotactile¹⁵⁻¹⁷, skin stretch¹⁸, and auditory¹⁹ are just some of the techniques that have been developed and used to provide prosthesis users with feedback. Although some studies (e.g.,^{14,20,21}) have shown that sensory feedback improves

performance, others (c.f., ¹⁴) have concluded that sensory feedback had no effect on performance. This lack of consensus arises, at least in part, because of an unclear understanding of how the incorporation of feedback relates to performance.

The role of feedback for real-time regulation and in improving human understanding of the control system and the task being performed is still unclear. Researchers have hypothesized that this understanding is stored in the human central nervous system in the form of an internal model. This internal model holds properties of the arm, which are used to imitate its behavior ²², predict consequences of an action, and compute an action based on desired consequences ²³. Hence, this internal model affects the overall performance of a prosthesis ²⁴.

Augmented feedback can be used to convey artificial proprioceptive and exteroceptive information ^{21, 25}, which may help to develop strong internal models. In particular, researchers have used audio augmented feedback in both robotic teleoperation ^{26, 27} and Brain Computer Interfaces (BCI) ²⁸ and have concluded that audio augmented feedback improves performance. We hypothesize that audio augmented feedback may similarly improve the performance of myoelectric prosthesis control by enabling the development of stronger internal models.

In a recent study ²⁹, we assessed the performance and the strength of internal models developed by users when using two myoelectric control strategies that differed in control signals as well as level of feedback. The main aim of that study was to investigate whether the ability of users to adapt is influenced by the degree of sensory feedback inherent in different myoelectric controllers. Results from that study show that control strategies with raw control signals and high feedback level (RCRF, such as with regression-based control) enable the development of a strong internal model, but at the expense of short-term performance. In addition, we found that control

strategies with filtered control signals and reduced feedback (FCFF, such as classification-based control) enable better short-term performance, but hinder the development of internal models.

To mitigate this tradeoff, we have extended this work by decoupling the concepts of control and feedback through the use of augmented feedback. We combined the filtered control strategy that resulted in better short-term performance with audio augmented feedback from the raw control strategy that enables the development of stronger internal models. In this work, we assessed internal model strength and short-term performance for this audio augmented feedback control strategy known as Filtered Control with audio Augmented Feedback (FCAF) and compared its results to the two commonly used myoelectric control strategies, RCRF and FCFF, that we assessed previously ²⁹. Our results show that the audio augmented feedback control strategy produces better short-term performance (as assessed using path efficiency and accuracy) than the feedback-rich control strategy, while enabling the development of a stronger internal model than the reduced feedback control strategy.

RESULTS

To inform the development of myoelectric control strategies with better short- and long-term performance, we investigated whether augmented feedback could improve user's internal model strength without reducing short-term performance of the control. Short-term performance and internal model strength (as a predictor for long-term performance ³⁰) were evaluated while using a filtered control strategy that was augmented by audio feedback in a virtual target acquisition constrained-time task.

Outcome Measures

To assess human understanding and evaluate performance of the audio-augmented controller, we employed the same five parameters that were used in our previous work ²⁹:

- Adaptation rate was extracted by computing the rate of feedforward modification of the control signal from one trial to the next ^{31, 32}. The first 300 – 500 msec of each trial was used to ensure that only the subject’s feedforward intent was captured.
- The just-noticeable-difference (JND) parameter was computed from a perception threshold test as the threshold value reached after 23 reversals calculated by an adaptive staircase ³³.
- Internal model uncertainty P_{param} was calculated using controller uncertainty, JND, and adaptation rate ²⁹.
- Performance of the audio-augmented control strategy was evaluated using path efficiency, computed by comparing the path taken to reach a target to the shortest Manhattan path to that target.
- Accuracy of target acquisition was computed as the Manhattan distance between the center point of a target and the actual final point reached. The ratio between this value and the optimal Manhattan path was then used to compute normalized accuracy as a percentage.

Psychophysical tests

The adaptation rate serves as an indicator of how much humans modify their internal models when performing a task. A value of 1 indicates perfect adaptation; higher and lower values correspond to over- and under-compensation, respectively. Results for the adaptation rate test show that there was a statistically significant difference in adaptation rates to self-generated errors between the groups of subjects who used the RCRF, FCFF, and FCAF controllers, as

determined by a one-way ANOVA ($F(2, 21) = 9.17, p = 0.02$). A Tukey HSD post hoc test reveals that the adaptation rate for subjects using FCFF (0.46 ± 0.19) was significantly lower than RCRF ($0.98 \pm 0.3, p = 0.02$) and FCAF ($0.86 \pm 0.27, p = 0.021$). In addition, no significant difference was found between adaptation rate data for subjects using the RCRF and FCAF control schemes ($p = 0.65$). These results suggest that audio-augmented feedback may enable similar adaptation behavior to feedback-rich control strategies (Figure 4-1. a).

The JND parameter is a measure of the smallest measure of stimulus that a subject is able to identify when using a certain controller. The lower this parameter, the better the ability of a subject to detect changes in the controller used. Like the adaptation rate results, analysis of JND test data using one-way ANOVA revealed a significant difference between subjects using RCRF, FCFF, and FCAF ($F(2, 21) = 5.17, p = 0.008$). Upon running a Tukey HSD post hoc test on the data, we found that subjects who tested FCFF had significantly higher JND values (59 ± 16 degrees) than other subjects who tested RCRF (45 ± 20 degrees) and FCAF (47 ± 13 degrees), but no significant difference in JND data between subjects who tested RCRF or FCAF ($p = 0.92$), which suggests that feedback in both RCRF and FCAF was sufficient to allow subjects to perceive a lower sensory threshold than the reduced feedback FCFF (Figure 4-1. b).

Both adaptation rate and JND results were used to compute the internal model uncertainty for each of the tested control strategies. The lower the internal model uncertainty, the more confident a subject is in the control system used. Results showed significant difference in internal model uncertainty between the control strategies (robust Welch ANOVA ($F(2, 13) = 9.3, p = 0.003$)). Games-Howell post hoc analysis revealed a significant difference between internal model uncertainty for subjects who tested FCFF (0.14 ± 0.1) and the subjects that tested RCRF or FCAF ($0.055 \pm 0.09, p = 0.035$ and $0.041 \pm 0.034, p = 0.004$, respectively). In contrast, there

was no significant difference in the internal model uncertainty between subjects that used RCRF or FCAF ($p = 0.56$) (see Figure 4-1. c). These findings suggest that a strong internal model may be developed when using either the RCRF or FCAF control strategy, which confirms the first part of our hypothesis that audio-augmented feedback may enable the development of a stronger internal model than FCFF alone.

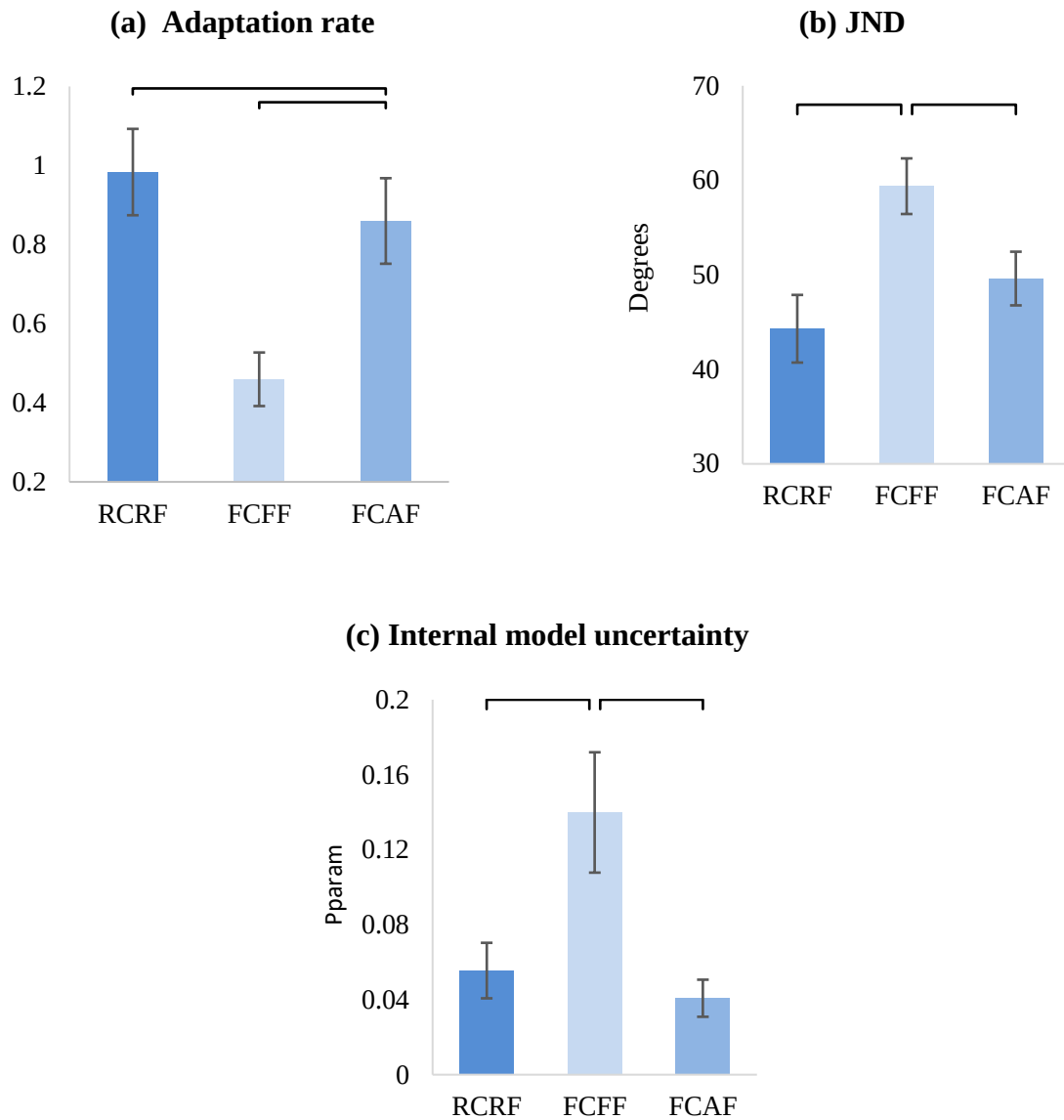


Figure 4-1. Overall psychophysical test results. (a) Results for adaptation rate across control strategies showing low adaptation rate to self-generated errors when using FCFF. (b) JND results across control strategies showing low perceivable sensory threshold when using either RCRF or FCAF. (c) Internal model uncertainty reflected by both adaptation rate and JND results showing statistically significantly less uncertain internal models developed when using RCRF and FCAF than the one developed when using FCFF.

Performance test

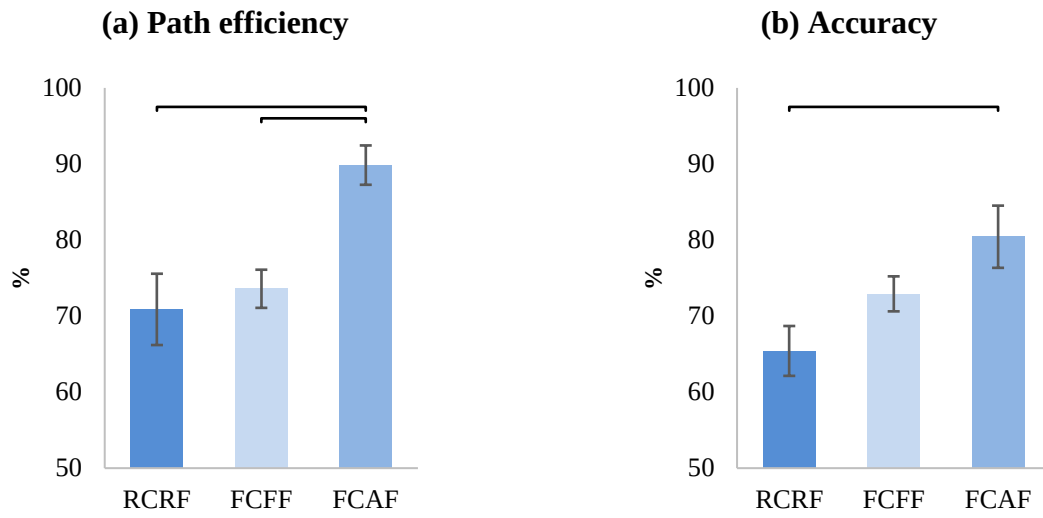
For on-axis path efficiency, there was a significant difference between control strategies as determined by a one-way ANOVA ($F(2, 21) = 5.8, p = 0.01$). Bonferroni post hoc analysis showed that subjects who tested the FCAF control strategy had significantly higher path efficiency than subjects who tested either the FCFF or RCRF strategies ($p = 0.019, p = 0.02$) (Figure 4-2. a). Analysis of the accuracy data collected from subjects using the three control strategies showed a significant difference between control strategies (one-way ANOVA ($F(2, 21) = 4.5, p = 0.024$)). Even though subjects that used FCFF achieved high accuracy for on-axis targets ($73 \pm 7\%$), it was not significantly different (Bonferroni post hoc test) from subjects using who used RCRF ($65 \pm 11\%, p = 0.36$) or FCAF ($80 \pm 11\%, p = 0.51$). Conversely, subjects who tested FCAF achieved significantly higher accuracies than those who tested RCRF ($p = 0.02$) (Figure 4-2. b). These results further support our hypothesis that augmented feedback may also enable better short-term performance. For off-axis target performance tests, the null-hypothesis was not rejected when comparing path efficiency or accuracy data between the three control strategies (one-way ANOVA ($F(2, 21) = 0.16, p = 0.86$)) (Figure 4-2. c and d).

Learning effect

We ran 28 dependent paired t-tests to investigate possible learning effects when testing with one control strategy and retesting using another one (summarized in Table 1). Unlike adaptation rate, a significant learning effect was observed for JND values of subjects who used FCFF after being exposed to FCAF, where the JND dropped from 74 ± 8.0 degrees to 43 ± 4.2 degrees ($p = 0.029$). This suggests that there may be possible enhancement in sensory perception threshold when using the FCFF control strategy after first being exposed to the feedback-rich

FCAF control strategy. Conversely, learning effect for JND values for subjects who tested FCFF after FCAF were not significantly reflected in the internal model uncertainty ($t(3) = 1.41$, $p = 0.25$), because internal model uncertainty is affected by several other parameters e.g., adaptation rate and controller noise. These results suggest that internal model uncertainty for FCFF may be improved after being first exposed to FCAF by improving sensory perception, and less so by adaptation. Interestingly, on-axis target path efficiency significantly increased when testing the FCAF control strategy after testing the feedback-rich RCRF control strategy ($t(3) = -14$, $p = 0.005$). Also, accuracy for on-axis targets when using FCFF after first being exposed to FCAF increased significantly from $84 \pm 3.7\%$ to $94 \pm 3.1\%$ ($t(3) = 23$, $p = 0.028$).

On-axis Targets



Off-axis Targets

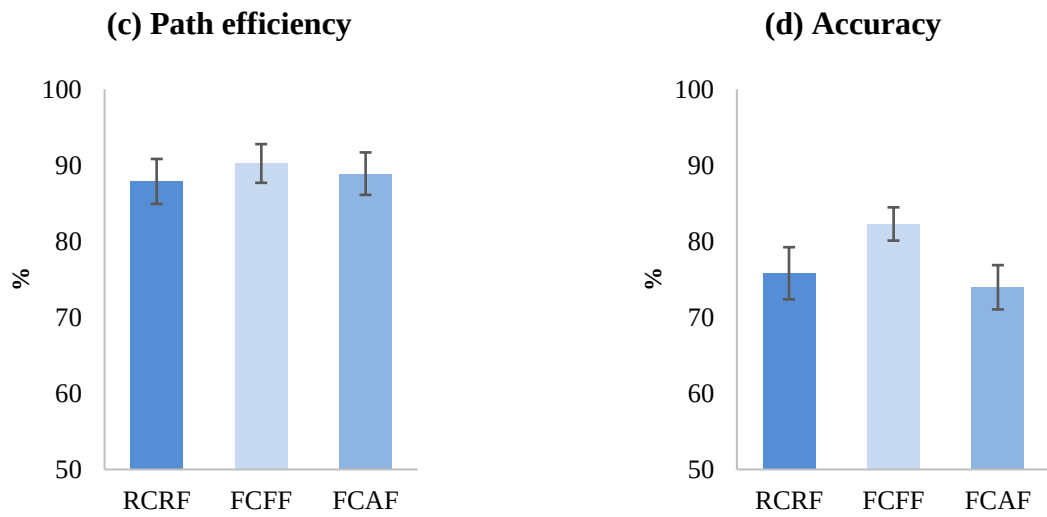


Figure 4-2. Overall performance test results. (a) and (b) show results for on-axis targets path efficiency and accuracy, respectively, across control strategies. (c) and (d) show no significant difference between control strategies tested for off-axis targets path efficiency and accuracy, respectively.

DISCUSSION

Significant progress made in the fields of signal processing, sensory substitution and pattern recognition for myoelectric prostheses has allowed for improvements in the performance of myoelectric control. It stands to reason that such improvement is partially driven by feedback ³⁴, however contradictory results about the effect of feedback on performance oppose this belief.

To address this discrepancy, a recent study ²⁹ showed that feedback may improve long-term performance by contributing to the development of stronger internal models, but without improving short-term performance. In this work, we investigated the unexplored effect of augmented feedback on short-term performance, human understanding and, ultimately, long-term performance with the hypothesis that augmented feedback may enable stronger internal model generation and better short-term performance. Our results showed that an audio-augmented feedback control strategy enables the development of a significantly stronger internal model than a classification-like filtered control with filtered feedback control strategy. This audio-augmented feedback controller also resulted in significantly better path efficiency for a one DOF task than both the raw feedback and the filtered feedback controllers.

Unlike classification-based control methods, the use of a regression-based control strategy enables the extraction of more information that may be used for augmented feedback. In this work, the concept of a hybrid control strategy that combines the robustness of classification-based control and the rich feedback of regression-based control was introduced. The concepts of feedback and control were effectively decoupled by employing classifier-like control, while providing the user with audio-augmented feedback derived from the feedback-rich regression control scheme.

Adaptation rate results showed that the controller with audio-augmented feedback enabled better adaptation behavior than FCFF while maintaining similar adaptation behavior to the feedback-rich RCRF. Hence, we may conclude that audio-augmented feedback may contain sufficient and comparable information as the RCRF, therefore enabling better understanding of the myoelectric system than FCFF. Equally as important, JND results for sensory perception showed that subjects who used either RCRF or FCAF achieved lower sensory thresholds than those who used FCFF, which again supports the conclusion that feedback inherent in FCAF was as effective as the feedback in the feedback rich RCRF control strategy, enabling the perception of lower sensory thresholds. These results combined with results from the assessment of internal model uncertainty confirm our hypothesis that audio-augmented feedback enables the development of a strong internal model, possibly leading to better long-term myoelectric control performance.

On-axis performance results showed that audio-augmented feedback helped subjects perform better with respect to path efficiency and accuracy when compared to FCFF. This finding suggests that subjects are able to integrate the audio feedback and use it for real time regulation as well as for internal model development. We also found that when subjects were first trained with FCAF and then used FCFF, they retained the internal model developed for FCAF and were able to achieve better on-axis accuracy. This observation raises a new question to be investigated in future work: how long can this stronger internal model be retained before reverting completely to a model developed by the FCFF control strategy?

Future work informed by this study could include investigating the effect of using augmented feedback with other controllers on internal model strength and short-term performance, assessing internal model strength and the long-term performance of regression-

based control strategies that use other modalities of augmented feedback (such as vibrotactile), investigating how long the human central nervous system is able to retain a strong internal model, and assessing the benefits of using augmented feedback for limb-different individuals. Some limitations to this study were: the learning effect due to prolonged exposure to the feedback-rich control strategy was not investigated, no amputees were included in this study, and only a one DOF task was used for the assessment of the internal models.

The benefits of using audio-augmented feedback for myoelectric prosthesis control, highlighted in this study, call for inclusion of audio feedback in myoelectric control training procedures. One might argue that providing audio feedback using an earpiece or headphones to prostheses users might be impractical or uncomfortable, but emerging technologies, such as those that transmit sound using bone conduction, may soon enable users to benefit from other types of similarly augmented feedback. Furthermore, it is not yet known how frequently this augmented feedback is needed. It is possible that users could occasionally enable the audio-augmented feedback to re-enforce their understanding.

METHODS

Control Strategies

In order to conduct a fair comparison between the control strategies developed here and the ones assessed in ²⁹, Support Vector Regression (SVR) was selected as the machine learning algorithm for the implementation of FCAF. The output from the SVR model for simultaneous activation of 2 degrees-of-freedom was directly mapped to RCRF, but only the highest activated DOF was used in FCFF; therefore, only allowing sequential control. Similar to FCFF, the FCAF control strategy only allowed sequential control, but used audio feedback to convey simultaneous

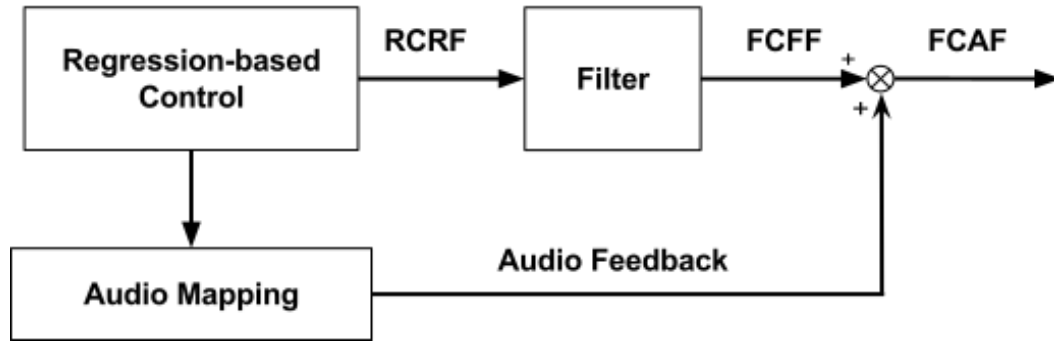


Figure 4-3. Control strategy development. RCRF is raw control with raw feedback (regression), FCFF is filtered control with filtered feedback (classifier), and FCAF is filtered control with audio-augmented feedback (classifier control with regression feedback).

control information, making this controller a hybrid between classification-based control and regression feedback (Figure 4-3).

Audio Augmented Feedback

For the FCAF control strategy, audio feedback maps the simultaneous activation of the 2 DOF motion using 4 audibly distinct frequencies i.e., one frequency per direction, (see Figure 4-4). The amplitude of the tone is directly proportional to the SVR output, requiring no knowledge of the intended task. For instance, a subject using FCAF to reach a point to the right of the cursor while activating both the right and up directions, but with a higher activation in the right direction will see the cursor moving to the right. Accompanying to that cursor movement, the subject will hear two tones simultaneously with frequencies of 500 Hz and 800 Hz with the 500 Hz tone being louder than the 800 Hz tone.

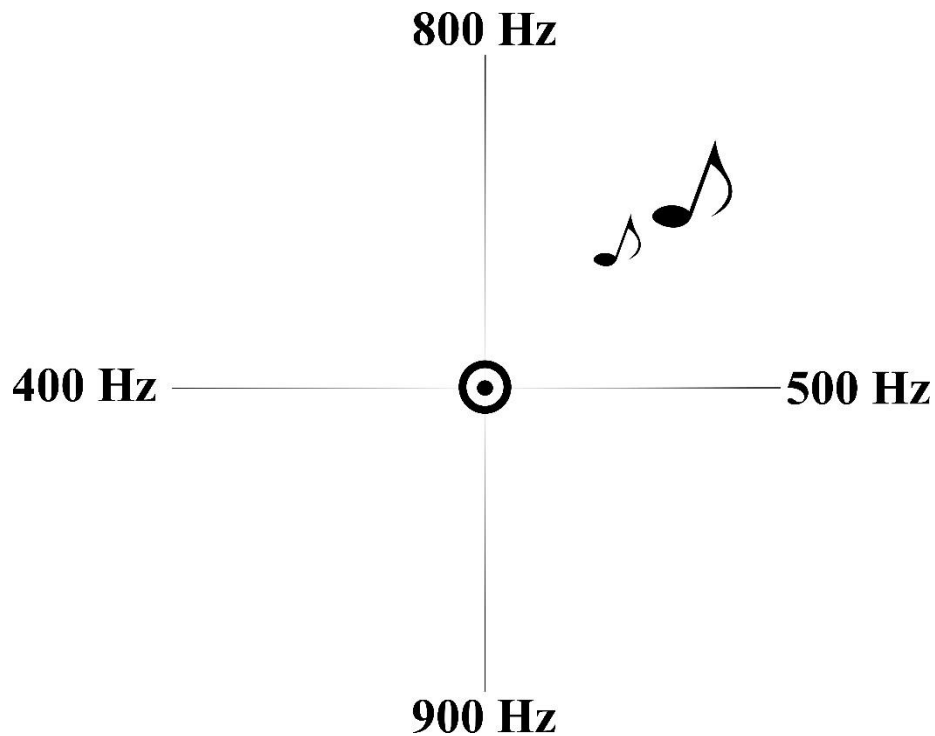


Figure 4-4. Audio map showing the frequencies assigned for each direction. The volume is directly proportional to the magnitude of the activation in each direction.

General Experimental Procedures and Protocol

Each subject sat comfortably in a chair approximately 80 cm away from a computer screen with their right arm relaxed in a restraint and used their left hand to press keys on a keyboard placed on a desk in front of them. Subjects were asked to wear a 15 mW Cobra headset with the volume set to a no more than 52.5 ± 3 dB for the whole period of the experiment, but were allowed to remove it during scheduled breaks between the testing block. During the testing blocks, subjects controlled a cursor on a computer screen using isometric muscle contractions sensed by an electrode array placed on their forearm to acquire targets (Figure 4-5).

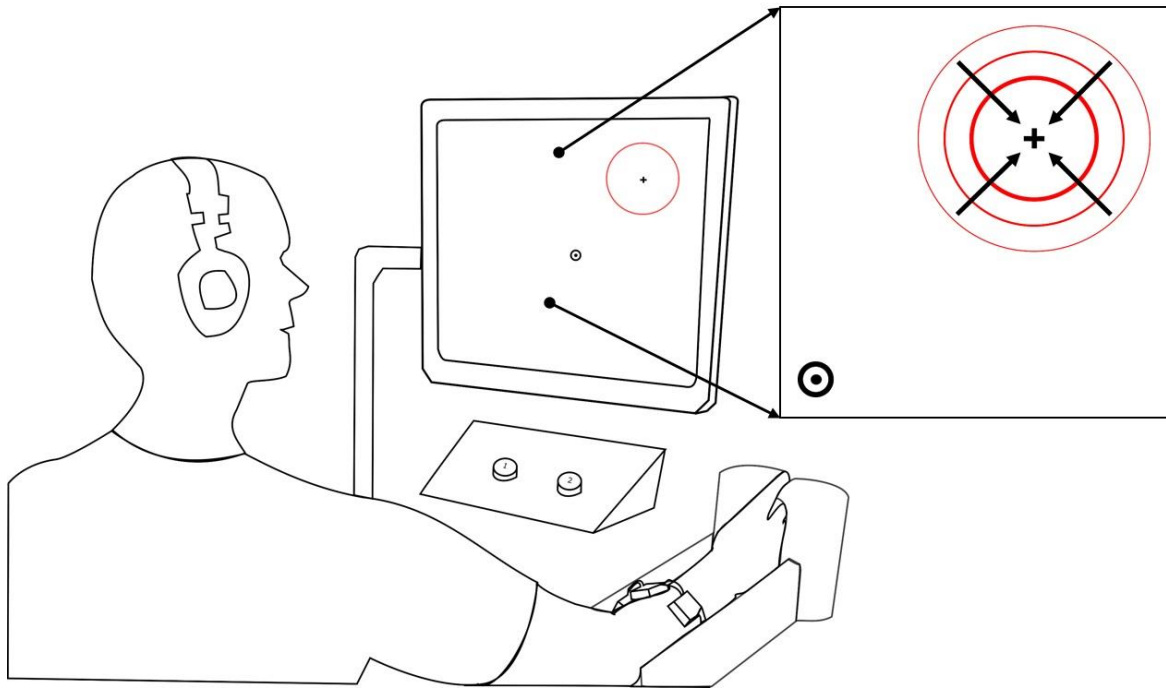


Figure 4-5. Experimental Set-up, with a subject controlling a cursor on the screen to acquire a set of targets during the training phase. Subjects were allowed to make their choice during the just-noticeable-difference test by pressing keys on a keyboard.

Targets were crosshairs surrounded by an imploding red circle. Using the same experimental protocol implemented in ²⁹, which was approved by the University of New Brunswick's Research and Ethics Board (file number 2014-019), subjects used each control strategy to complete a series of test blocks in a specific order after accomplishing a training block.

The training block consisted of three sets of targets that appeared at predetermined, but randomly ordered, positions. Each set consisted of 16 targets, which subjects were asked to acquire in less than 12 seconds, after which it would disappear and another target would appear. Before the start of each test block, subjects were given a 2 minutes break, in which they were allowed to stand, remove the headset, and stretch if needed. The first test block was used to test

the adaptation to self-generated errors. In this block, subjects were asked to repeatedly acquire a single target on the horizontal axis over a set of 80 trials.

The JND perception threshold test, the second test block, is a psychometric measure of sensory threshold for perception of a sensory stimulus. In this test, subjects were presented with two trials where one of these trials was perturbed with a stimulus. Subjects were then asked to select the trial which they thought had the added stimulus by pressing 1 for trial 1 and 2 for trial 2 on a keyboard³³. The added stimulus was calculated using an adaptive staircase with accuracy set to 0.84³⁵. Finally, the last test block was a performance test where subjects were asked to acquire targets, arranged in 2 sets of 16 targets each. For the first set of targets, subjects were tasked with acquiring each target in less than 1.7 s, whereas they were only allowed 1.4 s for each target in the second target set.

Participants

A total of twenty-four healthy right hand dominant subjects (15 male, and 9 female; mean and SD of age: 25 ± 6 years) participated in the study. All participants had either normal or corrected-to-normal vision. Informed consent was obtained from subjects before conducting the experiment according to the University of New Brunswick's Research and Ethics Board (REB 2014-019). Subjects were randomly assigned to one of 3 main groups (eight subjects each) (Figure 4-6). Group 1 subjects tested RCRF and 4 subjects from this group were randomly selected to retest using FCAF, referred to as subgroup 2. Group 2 subjects tested FCFF and 4 subjects from that group were randomly selected to retest using FCAF (subgroup 4). Finally, group 3 subjects tested FCAF and 4 subjects were selected at random to redo the experiment using RCRF (subgroup 5), while the remaining 4 subjects were asked to redo the experiment using FCFF, and were referred to as subgroup 6.

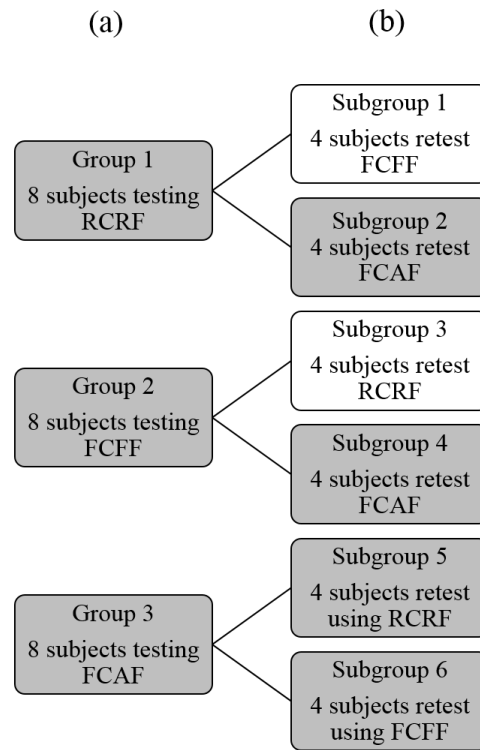


Figure 4-6. Subject assignment to testing groups. (a) 3 groups of 8 subjects each were used to assess differences in outcome measures between the three control strategies tested. (b) Subgroups of 4 subjects each (in gray) were used to investigate possible learning effects on FCAF after using RCRF and FCFF, and on both RCRF and FCFF after using FCAF.

Data from Groups 1, 2, and 3 were used to assess differences in outcome measures between the control strategies tested. Additionally, data from subgroups 2, 4, 5, and 6 were used to investigate possible learning effects between the commonly used control strategies and the audio-augmented feedback control strategy. Learning effects between the raw and filtered controllers, subgroups 1 and 3, were investigated in a previous work ²⁹.

Statistical Analysis

The Statistical Package for the Social Science software SPSS (IBM Corp, Released 2016, IBM SPSS Statistics for Windows, Version 24.0. Armonk, NY: IBM Corp) was used to run Levene's test on JND, adaptation rate, internal model uncertainty, and performance measure results to investigate homogeneity in variances of the data. If data variances were found to be homogenous, one-way ANOVAs were used to assess differences between outcome measures for the control strategies tested. If statistical significance was found, post-hoc analysis was performed using either the Bonferroni or Tukey HSD test and reported using the one with the highest confidence in the p-value ³⁶. Conversely, if data variances were found to be heterogeneous, robust Welch ANOVA was used instead, and followed by post-hoc analysis using Games-Howell test (Figure 4-7). Paired two sample t-tests were used with data collected from subjects in the subgroups (equal sample size). All analyses used a significance criterion of $\alpha=0.05$ and error bars shown in data plots were based on the standard error of the mean (SEM)

³⁷.

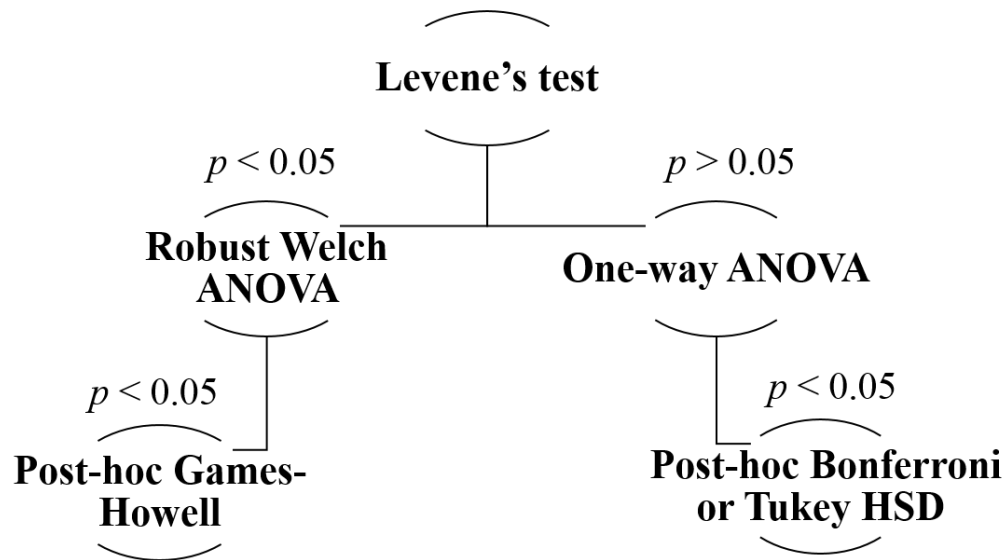


Figure 4-7. Statistical analysis decision tree followed throughout the analysis of the results in this study.

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AUTHOR CONTRIBUTIONS STATEMENT

A.S., E.S., and J.S. planned the experiments and A.S. prepared and conducted the experiments. A.S analyzed the results, and all authors reviewed the manuscript and approved the submitted version.

ADDITIONAL INFORMATION

Competing financial interests: The authors declare that they have no competing interests.

APPENDIX

<i>Outcome measure</i>	<i>Controller learning effect</i>	<i>Dependent paired t-test</i>
<i>Adaptation rate</i>	FCFF effect on FCAF	$t(3) = -2.1, p = 0.17$
	FCAF effect on RCRF	$t(3) = -1.7, p = 0.34$
	FCAF effect on FCFF	$t(3) = -0.20, p = 0.86$
	RCRF effect on FCAF	$t(3) = -0.61, p = 0.65$
<i>JND</i>	FCFF effect on FCAF	$t(3) = 0.50, p = 0.66$
	FCAF effect on RCRF	$t(3) = 3.0, p = 0.090$
	FCAF effect on FCFF	$t(3) = 5.7, p = 0.029$
	RCRF effect on FCAF	$t(3) = -1.6, p = 0.26$
<i>Internal model uncertainty</i>	FCFF effect on FCAF	$t(3) = 1.9, p = 0.20$
	FCAF effect on RCRF	$t(3) = -0.0070, p = 1$
	FCAF effect on FCFF	$t(3) = 1.4, p = 0.25$
	RCRF effect on FCAF	$t(3) = 0.38, p = 0.73$
<i>On-axis target path efficiency</i>	FCFF effect on FCAF	$t(3) = 2.2, p = 0.30$
	FCAF effect on RCRF	$t(3) = -3.0, p = 0.10$
	FCAF effect on FCFF	$t(3) = -1.45, p = 0.38$
	RCRF effect on FCAF	$t(3) = -14, p = 0.005$
<i>On-axis target accuracy</i>	FCFF effect on FCAF	$t(3) = 0.03, p = 0.98$
	FCAF effect on RCRF	$t(3) = -1.7, p = 0.23$
	FCAF effect on FCFF	$t(3) = 23, p = 0.028$
	RCRF effect on FCAF	$t(3) = -0.96, p = 0.44$
<i>Off-axis target path efficiency</i>	FCFF effect on FCAF	$t(3) = 0.61, p = 0.61$
	FCAF effect on RCRF	$t(3) = -1.7, p = 0.24$
	FCAF effect on FCFF	$t(3) = 0.74, p = 0.54$
	RCRF effect on FCAF	$t(3) = 0.61, p = 0.61$
<i>Off-axis target accuracy</i>	FCFF effect on FCAF	$t(3) = -1.5, p = 0.27$
	FCAF effect on RCRF	$t(3) = 0.95, p = 0.44$
	FCAF effect on FCFF	$t(3) = 2.5, p = 0.13$
	RCRF effect on FCAF	$t(3) = -2.8, p = 0.11$

Table 4-1. Statistical analysis using dependent t-test for subgroups 2, 4, 5, and 6 to investigate possible learning effect.

5. Improving Internal Model Strength and Performance of Prosthetic Hands Using Augmented Feedback

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INTRODUCTION

The apparently simple and seamless way adult humans use their hands to grasp and manipulate objects is in fact the result of (up to ten) years of training, during childhood, and of a sophisticated blend of feedforward and feedback control mechanisms (Johansson and Cole 1992). The function of such an elegant system may be corrupted when neurological injuries interrupt the connections between the central nervous system (CNS) and the periphery, as in the case of upper limb amputation. In this case, myoelectric prostheses provide a solution to replace such hand function by partially restoring the feedforward control mechanism. This mechanism is affected by two key factors. The first factor is the control system, which affects the robustness of control signals driving the prosthesis' motors. The second factor is the human understanding of the system, which is modeled by the CNS and is known as the internal model (Kawato 1999).

For a representative motor task, such as grasp-and-lift, the brain refines and updates the internal model using multi-modal sensory feedback (tactile, visual, and auditory) during and after the movement (Imamizu et al. 2000). Unlike unimpaired individuals, myoelectric prosthesis users have to rely more on visual feedback due to the lack of adequate sensory feedback from

their devices (Atkins, Heard, and Donovan 1996). This deficiency contributes to the inability of users to fully adjust their internal model, which affects overall performance (Lum et al. 2014).

To address this deficiency, researchers have provided augmented sensory information using invasive and non-invasive methods (Antfolk, D'Alonzo, Rosén, et al. 2013; Childress 1980). Several of the invasive methods show promise, including Target Sensory Reinnervation (TSR) and stimulation of sensory peripheral nerves (Kuiken et al. 2004; Hebert et al. 2014; Tan et al. 2014; Davis et al. 2016; Delgado-Martínez et al. 2017). However, many prosthesis users prefer non-invasive methods that do not require surgical intervention (Cordella et al. 2016; Engdahl et al. 2015).

Other researchers have evaluated many non-invasive sensory substitution methods to provide sensory information either through a sensory channel other than the one that is normally used or through the same channel but in a different modality (Antfolk, D'Alonzo, Rosén, et al. 2013). Vibro-tactile (Rombokas et al. 2013; D'Alonzo and Cipriani 2012), mechano-tactile (Antfolk, D'Alonzo, Controzzi, et al. 2013), electrotactile (Kaczmarek et al. 1991; Green et al. 2011; Gonzalez-Vargas et al. 2015), skin stretch (Wheeler et al. 2010), and auditory (Gonzalez et al. 2012) are just some of the techniques that have been developed and tested to provide prosthesis users with supplementary feedback. In the presence of vision, some studies have showed that augmented sensory feedback had little to no effect on performance (Cipriani et al. 2008). Conversely, others have demonstrated the efficacy of using augmented sensory feedback in enhancing motor control (Antfolk, D'Alonzo, Rosén, et al. 2013). This conflict arises because it is unclear how this augmented feedback affects internal model development and performance.

One hypothesis is that feedback improves performance through real-time regulation (Chatterjee et al. 2008; Ninu et al. 2014; Raspopovic et al. 2014). Results from many studies

show promising improvement in performance (Dosen et al. 2016; Markovic et al. 2017), sense of embodiment (Marasco et al. 2011), and prosthesis incorporation (Sengul, Shokur, and Bleuler 2014) when using feedback for real-time regulation; however the efficacy of the feedback methods used, such as resolution and latency, introduces a new challenge (Zafar and Van Doren 2000). To overcome this challenge, Dosen et.al (Dosen et al. 2015) proposed providing electromyography (EMG) biofeedback to the user through visual feedback, which amputees rely on the most (Atkins, Heard, and Donovan 1996). Their results show that users are able to exploit the augmented visual biofeedback to improve their performance for a grasping task. In a follow-up study, Schweisfurth et.al (Schweisfurth et al. 2016) implemented the EMG biofeedback using a multichannel electrotactile interface to transmit discrete levels of myoelectric signals to users. They compared this feedback approach to classic force feedback and found that the electrotactile EMG biofeedback allows for predictive control and improves performance. However, it is unclear whether this improvement is driven by the use of this feedback for real-time regulation or by the adjustments made to the internal model.

Our group has recently suggested a framework that demonstrates that the strength of the internal model is indeed affected by feedback (Johnson et al. 2017). In the field of myoelectric prosthesis control, we used this framework to assess the strength of the internal model developed when using different myoelectric control strategies. In a previous study (Shehata, Scheme, and Sensinger 2017a), we noted that various types of control strategies, in the very act of filtering biological signals, provide inherently different levels of feedback to the user. Whereas most researchers focus on the impact of those filters on the direct performance of the prosthesis, we demonstrated that it also affects the ability of the person to form an internal model. In that study, we assessed the internal model strength and performance when using two common myoelectric

control strategies (Hahne, Markovic, and Farina 2017; Shehata, Scheme, and Sensinger 2017c) that differed in the inherent feedback provided to the user, namely: (a) regression-based control or (b) classification-based control. We showed that the variability in regression controllers provided valuable and rich information to improve the internal model, even though it resulted in increased variability in the control signals. In contrast, the inherent filter in classification-based control, which limited this variability and thus improved the smoothness of movements, also prevented the formation of a strong internal model. In other words, continuous feedback-rich control strategies, may be used to improve internal model strength, but classification-based controllers, enable better immediate performance.

In an effort to incorporate the benefits of both control strategies, we enabled the information inherent in the variability of the regression controller to be used by the subject without affecting movement performance by relaying that variability through an augmented sensory feedback source (Shehata, Scheme, and Sensinger 2017b). In that study, we implemented a novel myoelectric control strategy with audio-augmented feedback for a virtual target acquisition task. We demonstrated that audio-augmented feedback enables the development of a strong internal model and better performance.

Here, we extended our previous work and narrowed the gap between research and clinical usability in a prosthesis. The main goal of this work was to verify that the ability to decouple internal model strength and motion variability using the audio-augmented feedback extended to real-world use, where the inherent mechanical variability and dynamics in the mechanisms and the user-socket interfaces may contribute to a more complicated interplay between internal model formation and motion variability. To accomplish this goal, we compared internal model strength and performance of a myoelectric control strategy with and without audio-augmented

feedback for a grasp-and-lift task using a multi-degree of freedom prosthetic hand (Cipriani, Controzzi, and Carrozza 2011). We extracted parameters that affect the internal model strength using psychophysical tests and used an instrumented Virtual Egg to assess the performance (Shehata, Scheme, and Sensinger 2017a; Controzzi et al. 2017). Our results show that audio-augmented feedback may be used to decouple internal model formation and motion variability resulting in improved internal model strength and improved performance for myoelectric prosthetic devices.

METHODS

Control Strategy

Classifier-based myoelectric control is considered as one of the advanced strategies of myocontrol (Hahne, Markovic, and Farina 2017). This control strategy may be implemented using various pattern recognition algorithms (Hargrove, Englehart, and Hudgins 2007; Tenore et al. 2007). In recent studies, we used Support Vector Regression (SVR) algorithm, which has been proven to enable better performance than other algorithms, to implement a classifier-based myoelectric control strategy (Shehata, Scheme, and Sensinger 2017a; Shehata, Scheme, and Sensinger 2017b). This algorithm provided regression-based control signals that simultaneously activated more than 1 DOF at a time, which were gated to only allow the activation of 1 DOF at a time. Here, we used these gated, i.e., classifier-based control, signals to activate either hand open/close or thumb adduction/abduction of a prosthetic hand.

Building on the classifier-based control, we implemented a novel control strategy, namely Audio-augmented Feedback (AF) control strategy, which is able to decouple internal model formation from control variability. We relayed information in the regression-based control

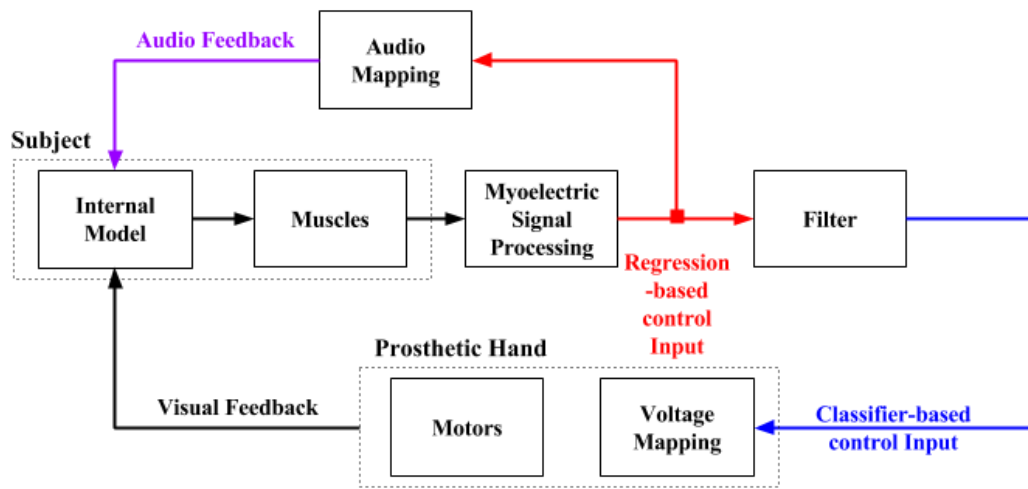


Figure 5-1. Closing the control loop using audio to augment the visual feedback.

Dark blue lines represent the classifier-based control signals. Red lines represent the regression-based control signals and the purple lines represent the audio feedback.

signals through continuous auditory cues to augment the feedback from the classifier-based myoelectric control (Figure 5-1).

In earlier work, we demonstrated that audio-augmented feedback improves internal model strength and the performance for myoelectric prosthesis control in a virtual target acquisition task (Shehata, Scheme, and Sensinger 2017b). We argued that these improvements may extend, but still have to be demonstrated, beyond a virtual target acquisition task. In this study, we tested the classifier-based control with and without audio-augmented feedback for a grasp-and-lift task when using a prosthetic hand.

Audio-augmented Feedback

Constant visual attention and high level of concentration caused by visual feedback may lead powered prosthesis users to reject their devices (Atkins, Heard, and Donovan 1996). Unlike visual feedback, audio requires no focus of attention and reduces distraction (Sigrist et al. 2013; Eldridge 2006). Audio feedback has been used in various and proven to enable better performance (Apostolos et al. 1992; Liu and Meng 2005; González and Yu 2009).

Consequently, we used audio feedback to map simultaneous activation of hand open/close and thumb adduction/abduction with four frequencies: 400 Hz, 500 Hz, 800 Hz, and 900 Hz, i.e., one frequency per class. The amplitude of a tone was directly proportional to the control output, which was mapped to the velocity of the thumb or fingers. For instance, a subject contracting muscles to close the hand, but accidentally mildly contracting muscles for abduction of the thumb would see the hand closing and hear two different tones simultaneously associated with hand close and thumb abduction; one loud (400 Hz) and one soft (800 Hz). Using this method, we ensured similar audio mapping to that used in our previous study (Shehata, Scheme, and Sensinger 2017b).

Hardware

The prosthetic hand used for this experiment was a right-handed version of the IH2 Azzurra Hand (Prensilia, Italy). This hand has 11 degrees of freedom (two for each finger and three for the thumb) and five degrees of actuation (DoA). Four of these DoAs are used to independently flex/extend the thumb, index, middle and ring/little as a pair, and the remaining one is used to abduct/adduct the thumb (opposition). The size and the weight of the artificial hand are comparable with the human hand (Cipriani, Controzzi, and Carrozza 2011). In this

study, the prosthetic hand open/close and the thumb abduction/adduction were the only two degrees-of-freedom activated. For the first DOF, we mapped user's wrist flexion/extension to the prosthetic hand flexion/extension of the index and middle fingers as well as the thumb, i.e., hand close/open. For the second DOF, we mapped user's wrist abduction/adduction to the abduction/adduction of the thumb of the prosthetic hand

We assessed the capability of the sensory feedback provided to the subjects in improving their sensorimotor control of the prosthetic hand using a sensorized test object known as the instrumented Virtual Egg (iVE). The iVE is a rigid plastic test-object ($57 \times 57 \times 57$ mm³; approximately 180 grams) equipped with two strain gauge-based force sensors (Strain Measurement Devices, model S215 – 12 pounds-force; each located at one of two parallel grasping sides), able to measure grasp force exerted on the object. An additional sensor on the base of the test object measures lift force of the test-object when it is resting on the table (Strain Measurement Devices, model S215 – 2 pounds-force). Further, if the subject generated a grasp force larger than a preset threshold (approximately 3.1 N), the instrumented object virtually broke; this event was signaled to the subject through a colored light on the iVE (Controzzi et al. 2017).

Participants

Seven healthy subjects (4 male, and 3 female; mean and SD of age: 24 ± 5.6 years) participated in this study. All participants had either normal or corrected-to-normal vision, were right-handed, and none had earlier experience with myoelectric pattern recognition control. Informed consent according to the University of New Brunswick Research and Ethics Board and to Scuola Superiore Sant'Anna was obtained from subjects before conducting the experiment

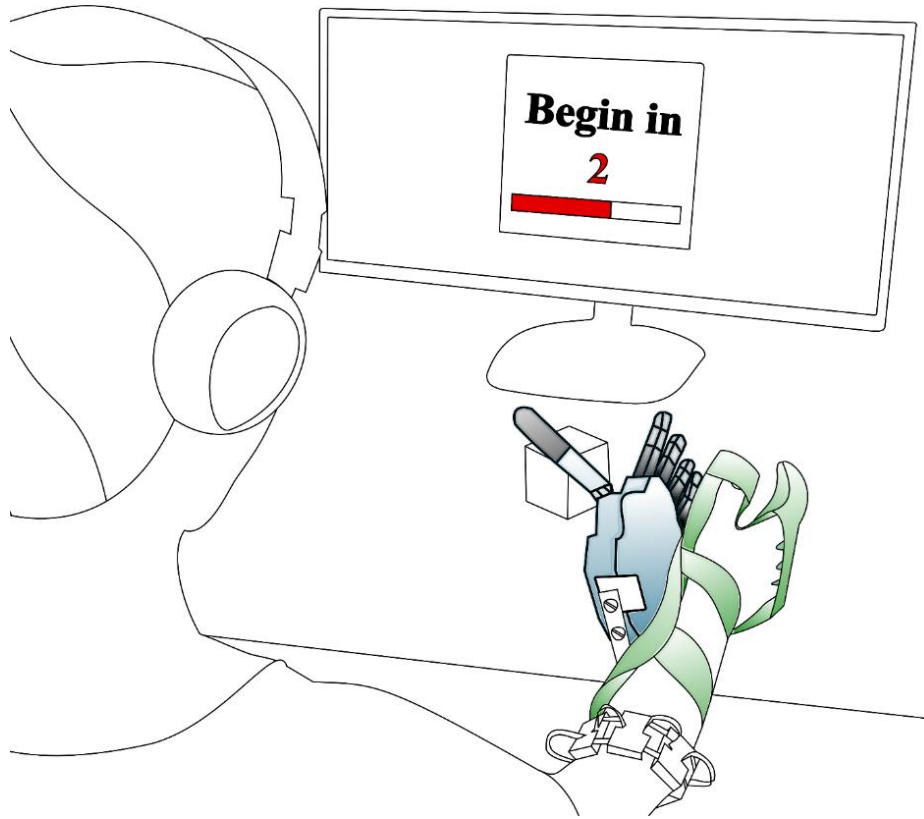


Figure 5-2. Subject controlling a prosthetic hand to grasp-and-lift an instrumented virtual egg without breaking it. The prosthetic hand is controlled using the subject's myoelectric signals sensed by an electrode array placed on their forearm.

(UNB REB 2014-019). These subjects tested the classifier-based control without augmented feedback (NF) and then retested with the audio-augmented feedback (AF).

General Experimental Procedures and Protocol

Each subject sat comfortably in front of a computer screen with their right arm relaxed in a bypass prosthesis with medial rotation (Wilson, Blustein, and Sensinger 2017). Subjects

were asked to wear a 1000mW Sony (MDRZX100) headphone with the volume set to a maximum of 52.5 ± 3 dB for the whole period of the experiment, but were allowed to remove it during scheduled breaks between testing blocks (Shehata, Scheme, and Sensinger 2017b). During these testing blocks, subjects controlled the IH2 Azzurra hand using isometric muscle contractions sensed by an electrode array placed on their forearm to grasp-and-lift the iVE (see Figure 5-2) (Wilson et al. 2011). A couple of minutes were allowed for the sensed myoelectric signals to settle and a notch filter at 50, 150, 250 and 350 Hz was used. Movements of the prosthetic hand were limited to allow flexion/extension of index and middle fingers and thumb and adduction/abduction of the thumb. The iVE was set to change its color from green to red if the grasping force exceeded a predetermined force, thus simulating an egg breaking (known as fragile mode). Subjects used each feedback method to complete a series of test blocks in a specific order after accomplishing a training and familiarization block.

The training and familiarization block consisted of 40 grasp-and-lift trials. Subjects were given verbal instructions to grasp-and-lift the iVE without breaking it in less than seven seconds after which a “Time out” text appeared on the computer screen and the prosthetic hand returned to a predetermined start pose (Figure 5-3). The training and familiarization starting pose was hand fully opened and thumb adducted (Figure 5-3. a). During the first 25 trials, subjects were prompted to see the feedback when the iVE broke (fragile mode), but were not given this feedback for the following 15 trials (rigid mode) to keep subjects engaged with the task and not lose interest quickly during the adaptation test block. Subjects were allowed to proceed to test blocks when they achieved at least 75% successful grasp-and-lift of the iVE.

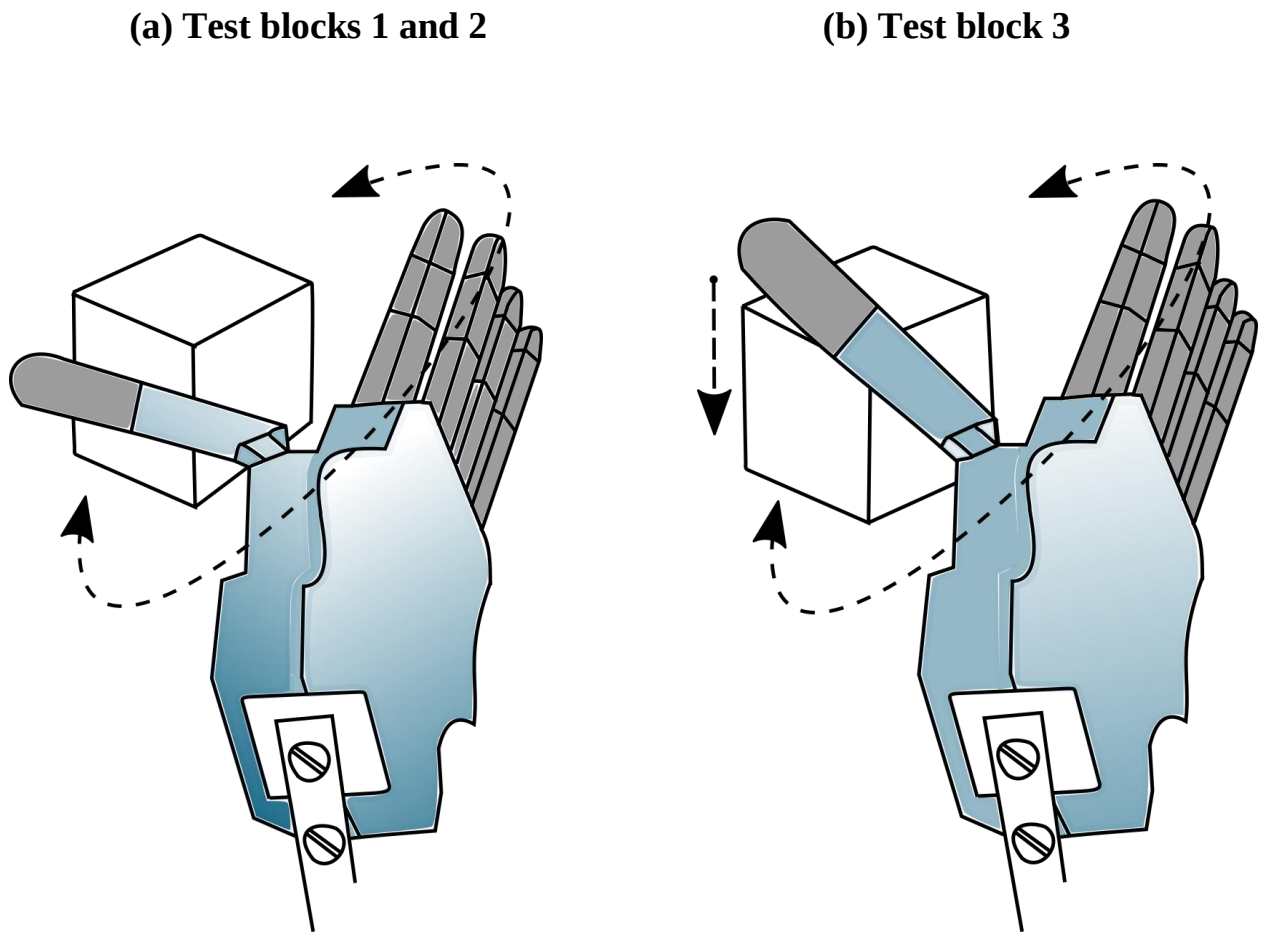


Figure 5-3. Hand starting pose. (a) Starting pose for the training and familiarization, adaptation and JND blocks. Subjects had to only activate the thumb and fingers flexion to grasp the object carefully without breaking it. (b) Fingers and thumb are extended and the thumb is abducted. This pose was used for the performance test in which subjects had to adduct the thumb and then close the hand to grasp the object and transfer it from one side of a barrier to the other.

Before the start of each test block, subjects were given a two minutes break, in which they were allowed to stand, remove the headset, unstrap the bypass, and stretch if needed but the electrode array was not removed for the whole duration of the experiment. The first test block

tested the adaptation to self-generated error. In this block, subjects were asked to grasp-and-lift the iVE over a set of 40 trials in less than five seconds per trial. Adaptation rate was computed as how much subjects adjusted their grasp trajectory from one trial to the next based on error observed between their trajectory and activating only the hand close/open DOF, i.e., optimal trajectory (Bastian 2008). The prosthetic hand starting pose for this test and the following perception threshold test was similar to that of the training and familiarization block where subjects had to only activate the hand close/open DOF to achieve this task efficiently.

Perception threshold is a psychometric measure of sensory threshold for perception of a sensory stimulus, which was measured in the second test block. In this test, subjects performed two lift trials (fragile mode). In one of the two trials, a specific stimulus was added causing the hand to behave differently. The subjects were then asked to identify the changed trial by pressing the “1” or “2” key (for trial one or two) on a keyboard placed in front of them. The magnitude of the added stimulus was calculated using an adaptive staircase as rotation in the control space in degrees with target probability set to 0.84 (Faes et al. 2007; Ernst and Banks 2002). For instance, if a subject was generating control signals for thumb abduction, a 90 degrees rotation in the control signal would switch activations from thumb abduction to hand close. Each trial lasted for four seconds and subjects were encouraged to take breaks whenever they needed. The final noticeable stimulus reached was recorded when number of reversals for this staircase reached 23 (Shehata, Scheme, and Sensinger 2017a).

Finally, the last test block was a performance test where subjects were given 20 trials to move the iVE (fragile mode) from one side of a barrier (H: 14.5 cm x W: 25 cm, similar to the Box and Blocks test (Mathiowetz et al. 1985)) to the other in less than 10 seconds per trial. The starting pose of the hand was adjusted to evaluate subject’s performance for a 2-DOF task in

TABLE 5-1 SUMMARY OF THE EXPERIMENTAL PROTOCOL

Task	DESCRIPTION
Control Practice	Control the prosthetic hand for two minutes – a combination of close/open the prosthetic hand and abduct/adduct the thumb.
Training and Familiarization	25 trials of grasp-and-lift of the iVE with the breaking feedback and 15 grasp-and-lift trials without the breaking feedback. Each trial lasted for seven seconds.
Adaptation rate test	A total of 40 grasp-and-lift trials. Each trial lasted for five seconds.
JND test	Grasp-and-lift the iVE in less than four seconds and identify the trial with the added stimulus in a set of two trials, repeat this task until convergence of an adaptive staircase.
Performance test	Transfer the iVE from one side of a barrier to the other 20 times in less than 10 seconds per transfer.

which subjects had to activate the thumb adduction\abduction DOF to lower the thumb and then activate the hand close\open DOF to grasp the iVE properly then lift it to the other side of the barrier (Figure 5-3. b). Table 5-1 summarizes the experimental protocol used in this study.

Outcome Measures

Internal Model Parameters

Similar to our previous research (Shehata, Scheme, and Sensinger 2017a; Shehata, Scheme, and Sensinger 2017b), we assessed human understanding of the myoelectric control strategies for a grasp-and-lift task using the following psychometric measures:

- Adaptation is a measure of feedforward modification of the control signal from one trial to the next (Johnson et al. 2017). For each trial in the adaptation rate test, control signal activations in both DOFs, i.e., open/close hand and adduction/abduction of thumb, were

recorded. To capture subject's feedforward intent, the first 500 msec of the recorded activations for each trial were analyzed. The target control signal was activation of the closing of the prosthetic hand only. Other activations were considered as self-generated errors and subjects were instructed to minimize those activations. The following equation was used to compute this adaptation rate.

$$error_{n+1} - error_n = \beta_1 \times error_n + \beta_0, \quad (1)$$

where *error* is the angle formed between the closing of the hand activation trajectory, i.e., target, and the actual hand activation trajectory, *n* is the trial number, β_0 is the linear regression constant, and $-\beta_1$ is the adaptation rate.

- Just-noticeable-difference (JND) is a measure of the minimum perceivable stimulus in degrees identified by the subject when using each feedback method (Faes et al. 2007). This parameter is extracted from the Perception threshold test block.
- Internal model uncertainty P_{param} is a measure of the confidence of a user in their developed internal model for a control strategy with a certain feedback method.

Performance Parameters

- Number of successful transfers of the instrumented object from one side of a barrier to the other without breaking it (fragile mode).
- Time taken by subjects to successfully transfer the instrumented object from one side of a barrier to the other without breaking it (fragile mode).
- Number of submovements per trial. This parameter is calculated as the number of zero-crossing pairs of the third derivative of the grasp force profile per trial (Fishbach et al. 2007).

Statistical Analysis

The Statistical Package for the Social Science software SPSS (IBM Corp, Released 2017, IBM SPSS Statistics for Windows, Version 25.0. Armonk, NY: IBM Corp) was used to run Levene's test on JND, adaptation rate, internal model uncertainty, and performance measure results to investigate homogeneity in variances of the data. If data variances were found to be homogenous, we ran two-sample paired t-tests to assess differences between these outcome measures at a significance criterion of $\alpha = 0.05$ for the two feedbacks tested. If data variances were found to be nonhomogeneous, a Wilcoxon signed-rank test was conducted. The confidence interval was calculated using the standard deviation (95% CI = mean $\pm$ 1.97 $\times$ SD).

RESULTS

To confirm that benefits of using audio-augmented feedback for improving internal model strength of myoelectric controllers extend beyond a virtual target acquisition task (Shehata, Scheme, and Sensinger 2017b), we assessed the internal model developed when using this audio-augmented controller and the no-augmented feedback controller to control a prosthetic hand for a grasp-and-lift task. In addition, short-term performance when using both controllers was evaluated.

Internal Model Assessment

Two psychophysical experiments were employed to evaluate parameters that are used to assess internal model strength (Shehata, Scheme, and Sensinger 2017a). The first experiment tested the trial-by-trial adaptation to self-generated errors. The outcome from that test indicated how much the internal model was modified from one trial to the next based on error feedback.

A unity value indicated perfect adaptation, i.e., internal model modified to perfectly compensate for errors. Results for this test showed that there was a statistically significant difference between subjects using NF and AF control strategies (two paired-samples t-test ($t(6) = -4.6$, $p = 0.004$)). Subjects using AF control strategy had significantly higher adaptation rate (1.2 ± 0.25) than subjects using the NF control strategy (0.75 ± 0.15) (Figure 5-4. a). These results align with previous study results (Shehata, Scheme, and Sensinger 2017b) and confirm that audio-augmented feedback enables high adaptation behavior for a grasp-and-lift task using a prosthetic hand.

The second experiment was the perception threshold test. The outcome measure from this test identified the smallest perturbation in the control signal a user could perceive when using a controller. A lower threshold indicated better user ability to perceive small perturbations in the control strategy used. A paired samples t-test revealed a significant difference in the JND data between subjects using NF control strategy and AF control strategy ($t(6) = 3.4$, $p = 0.014$) (Figure 5-4. b). Audio-augmented feedback control strategy enabled a significantly lower perception threshold (44.6 ± 10 degrees) than the NF controller (58.5 ± 12.5 degrees). These results suggest that audio-augmented feedback may improve the user's ability to perceive low sensory threshold.

The parameters from these two tests were used in the assessment of internal models developed for each of the tested feedback conditions. We also measured internal model uncertainty, which reflected the confidence of a user in the internal model developed. A low internal model uncertainty indicated high confidence in the internal model developed. A related samples Wilcoxon signed-rank test showed a statistically significant reduction in the internal model uncertainty for subjects using AF control strategy (0.22 ± 0.11) compared to subjects

using NF control strategy (1.8 ± 0.6) ($p = 0.018$) (Figure 5-4. c). These results confirm our hypothesis that audio-augmented feedback controllers enable a strong internal model for a grasp-and-lift task using a prosthetic hand.

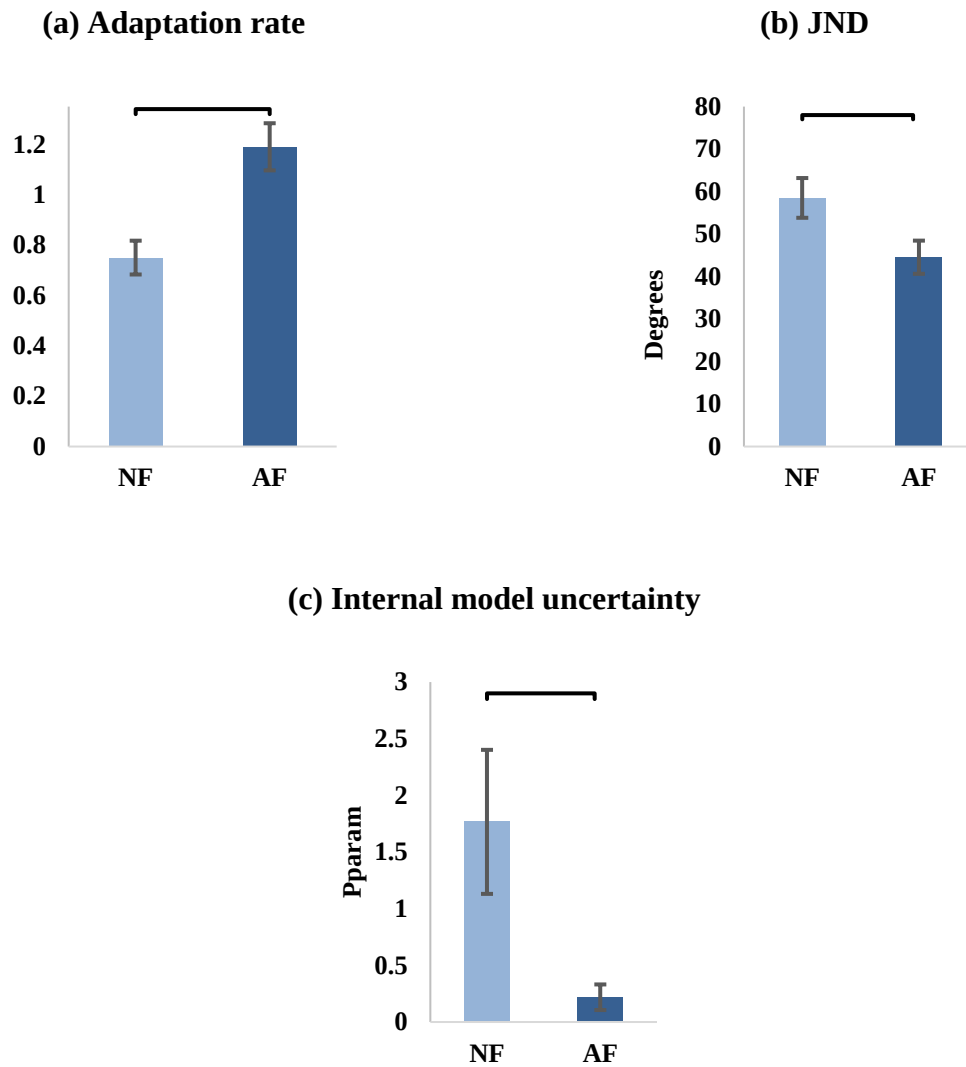


Figure 5-4. Psychophysical test results. (a) Adaptation rate results showing audio-augmented feedback control strategy enabling higher adaptation to self-generated error than the no-augmented feedback control strategy. (b) Perception threshold test results showing low JND value when using the audio-augmented controller. (c) Internal model uncertainty (P_{param}) results showing significant reduction in the internal model uncertainty when using the audio-augmented feedback control strategy. Horizontal bars lines indicate statistical significant difference.

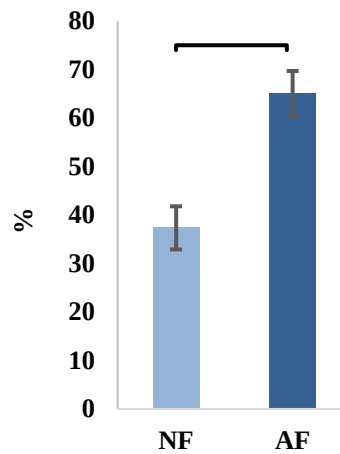


Figure 5-5. Successful transfer rate of the iVE without breaking it from one side of a barrier to the other. Subjects using the audio-augmented feedback control strategy had 1.74 times higher successful transfers than when using the no-augmented feedback control strategy.

Performance test

We used the number of successful transfers of the iVE from one side of the barrier to the other as an indicator to assess performance for the two feedback conditions tested here (test block 3). Figure 5-5 shows that the percentage of successful transfers when using AF control strategy ($65 \pm 12 \%$) was significantly higher (two paired-sample t-test, $t(6) = -2.87$, $p = 0.028$) than when using NF control strategy ($37.34 \pm 19 \%$). This result suggest that augmented feedback improves short-term performance of myoelectric control strategies. It is worth noting that the time taken for subjects to accomplish this task using AF control strategy (8.3 ± 0.74 s) was not significantly different than when using the NF control strategy (8.4 ± 0.65 s) (see Figure 5-6).

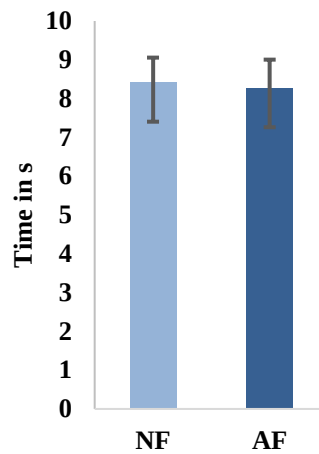


Figure 5-6. Completion time for successful transfers. Subjects using the no-augmented feedback controller had similar completion time to subjects using the audio-augmented controller

To further investigate how augmented feedback improves short-term performance, we analyzed grasp force profiles for successful grasp-and-lift trials during the adaptation test. Data was recorded from only five subjects as the iVE failed to record data for the other two subjects due to a communication error.

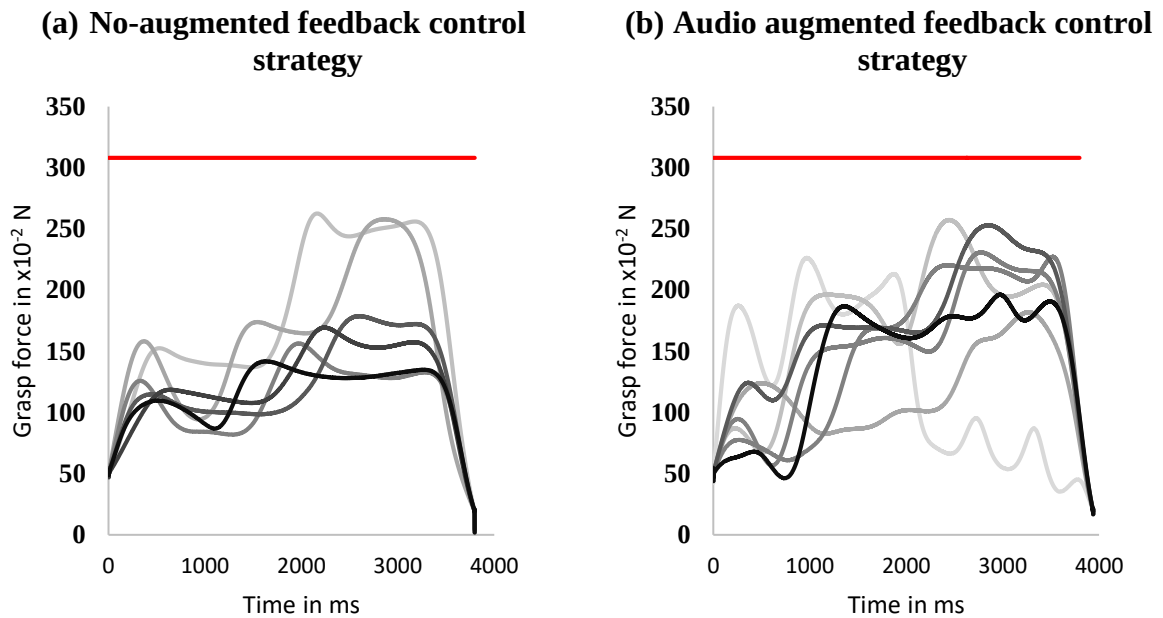


Figure 5-7. Sample successful grasp-and-lift trials for a single subject during adaptation rate test using (a) the no-audio-augmented feedback control strategy (moderate grasp force changes per trial) and (b) the audio-augmented feedback control strategy (high grasp force changes per trial). The red line in both plots shows the preset breaking force. A progression of trials ranging from the beginning of the task (light gray) to the end of the task (black)

Figure 5-7 shows a progression of trials ranging from the beginning of the task (light gray) to the end of the task (black). When using the NF control strategy, subjects changed their grasping force during the grasp-and-lift task, though not as much as when using AF control strategy. This effect may be quantified using submovement analysis of the grasp force profile (Doeringer and Hogan 1998; Kositsky and Barto 2001; Dipietro et al. 2009). The number of submovements served as an indicator of use of feedback for real-time regulation of the grasping force. The higher this number, the greater the use of feedback in real-time regulation. Results

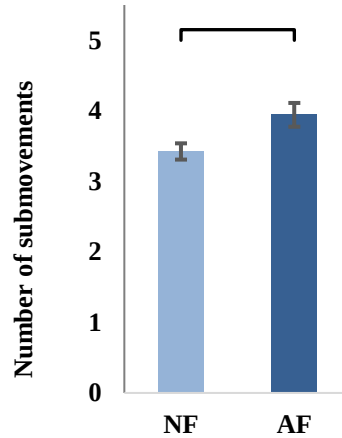


Figure 5-8. Submovements computed from the grasp forces of successful trials from the adaptation rate test for a sample of five subjects.

show that subjects using AF control strategy had a significantly higher number of submovements (3.94 ± 0.12) than subjects using NF control strategy (3.255 ± 0.17) as determined by a two-sample independent t-test ($(t(90) = -3.17)$, $p = 0.002$) (see Figure 5-8). These results suggest that audio-augmented feedback enables better short-term performance through enabling the development of stronger internal model.

DISCUSSION

Many research studies have focused on improving performance of myoelectric prosthesis control by providing feedback to the user, but only few studies have investigated the effect of this feedback on the internal model, which is key to improving long-term performance (Strbac et al. 2017). Due to an inability to assess internal model strength, this effect remained unquantified. For the first time, we used a recently developed psychophysical framework to assess the developed internal model strength when using different myoelectric prosthesis

controllers (Shehata, Scheme, and Sensinger 2017a). In a recent study (Shehata, Scheme, and Sensinger 2017b), we developed a myoelectric prosthesis control strategy that showed promising results for improving both the performance and the internal model strength by using augmented audio feedback for a virtual target acquisition task. To bridge the gap between research and clinical usability in prostheses, we assessed short-term performance and the internal model strength for this myoelectric control strategy when controlling a prosthetic hand. Our results in this study confirmed the hypothesis that audio-augmented feedback enables the development of strong internal model and better short-term performance when controlling a prosthetic hand for a grasp-and-lift task.

Internal model strength is affected by the quality and the quantity of feedback provided to users (Shehata, Scheme, and Sensinger 2017a). An indicator of this model strength is the adaptation rate. For the two control strategies tested here, we found that the audio-augmented feedback control strategy enabled high adaptation rate, which indicates that feedback information provided by audio is being incorporated by the users in their internal models. One of the parameters that affects internal model strength is the sensory uncertainty. Subjects that used the audio-augmented controller were able to achieve lower JND values than when they used the no-augmented feedback controller, which indicates that audio feedback provides useful information for the users that aids them in acquiring more confidence in their sensory feedback, in turn leading to a stronger internal model. The higher confidence in the internal model developed when using the audio-augmented controller indicates an improvement in the user's understanding of the controller used, and suggests improvement in the long-term performance (Shehata, Scheme, and Sensinger 2017a).

To avoid translation of strong internal models developed for controllers that provide adequate feedback to controllers that do not, all subjects in this study tested the no-augmented feedback controller first and redid the test using the augmented audio feedback controller. However, it is possible that the reduction in internal model uncertainty for the audio-augmented controller is a repercussion of prolonged exposure to the control strategy and the experiment. This possibility has been addressed in our previous studies (Shehata, Scheme, and Sensinger 2017a; Shehata, Scheme, and Sensinger 2017c) where we asked subjects to test and retest the same control strategy (no-augmented feedback) and concluded that there was no improvement in adaptation rate, JND, internal model strength, or the performance (good reliability, ICC > 0.6). Consequently, we argue that any improvement in those parameters is due to the control strategy used and not due to prolonged exposure.

To ensure that continuous audio feedback was not a distraction to the user and in turn did not compromise short-term performance, we assessed the short-term performance when using this control strategy by computing the success rate of transferring an instrumented object from one side of a barrier to the other side without breaking the object. Performance results show a significant increase in success rate when subjects used the audio-augmented controller over the no-augmented feedback controller, however both controllers had similar completion time. This improvement may not only be credited to the stronger internal model developed by users, but also because users may be using audio feedback for real-time regulation. To further investigate this improvement, we used submovement analysis to look at the grasp force profiles. This analysis revealed that subjects using the audio-augmented controller adjusted their grasping forces more frequently than when they used the no-augmented feedback controller, which suggests that augmented audio feedback may be used for developing internal models with high

confidence in feedback leading to use of this feedback for real-time regulation. Hence, augmented audio feedback improves both short-term performance through real-time regulation and long-term performance through development of strong internal models.

In this study, we conducted the psychophysical tests on one DOF, i.e., closing the hand to grasp-and-lift an object, to avoid fatigue and loss of motivation. However, we designed the performance test for a two-DOF task where subjects had to activate both DOFs, i.e., hand close/open and thumb adduction/abduction, to ensure that subjects are able to fully control the device to achieve a task and to acquire performance results that may be compared to previous studies (Shehata, Scheme, and Sensinger 2017a; Shehata, Scheme, and Sensinger 2017b; Hahne, Markovic, and Farina 2017). During the performance test, we noticed that lifting the bypass weight affected users' ability to open the hand after grasping the object, which affected the performance for both control strategies equally. This weight effect may be avoided in future experiments by using a tool balancer (Wilson, Blustein, and Sensinger 2017).

Some subjects reported that continuous audio feedback may be a distraction, however our results show that even though subjects may not be fully focused on integrating this feedback, they unconsciously integrate it into their internal models. With this in mind, a new question arises: would task specific discrete audio feedback, i.e., discrete beeps on grasp and release of an object akin to the Discrete Event-driven Sensory feedback Control (DESC) principle (Johansson and Cole 1992; Clemente et al. 2016), be less irritating while potentially enabling similar integration? This question will be addressed in future research.

In this study, we used a newly developed instrumented object that has not been used in any study before. This device was able to record grasp forces for most subjects, however due to communication issues and untested functionalities for prolonged use (three hours per session)

data from two subjects were not properly recorded. Future versions of this device will have secure protocol for transferring data and cyclic redundancy check on single or multiple packets implemented.

Although audio-augmented feedback showed promising results, we still need to identify the minimum quantity of feedback that is useful for developing strong internal models and the quality of feedback that enables real-time regulation. Future work informed by this study includes: exploring a combination of other augmented feedback that might enable an even stronger internal model, exploring the effect of augmenting other feedback modalities on the internal model strength, investigating the effect of audio-augmented feedback control strategy for a more complex task on the internal model strength and the performance, and finally investigating the users' ability to retain an internal model that has been developed when using the audio-augmented feedback control strategy.

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6. Conclusion

Researchers have developed many signal processing techniques, feature extraction methods, sensor types and control strategies to enhance the performance of myoelectric controllers. Despite these advancements in the field of myoelectric prostheses, many amputees still abandon their devices out of frustration, due in part to insufficient precision in the control of prosthesis movements and a lack of adequate sensory feedback. To increase reliability and promote acceptance of the prosthetic devices by powered prosthesis users, these issues must be addressed.

The aim of this work was to improve the performance of myoelectric prosthesis controllers by investigating the potential tradeoff between controllers that enable better short-term performance and those that provide sufficient feedback to develop a strong internal model. To achieve this aim, the concepts of feedback and control were effectively decoupled by employing classifier-like control, while providing the user with audio-augmented feedback derived from the feedback-rich regression control scheme. This novel hybrid control strategy combined the robustness of classification-based control and the rich feedback of regression-based control, thereby enabling a stronger internal model and hence better performance.

Contributions

The research conducted throughout this work has resulted in a significant contribution to the field of myoelectric prosthesis control. The novel contribution of this research is the decoupling of the concepts of feedback and control using a simple yet effective solution and the use of a psychophysical framework for the first time to assess internal model strength. The outcomes of this work can be described as follows:

- Comparing two control strategies that were never compared before due to differences in their implementation. The first control strategy was a classifier-based controller, which used machine learning algorithms, such as LDA, that separated DOF into classes, i.e., open hand, close hand, and no motion. The second control strategy was a regression-based controller, which used machine learning algorithms, such as LR, that allowed continuous control over a DOF, i.e., open/close of the hand. In this work, the underlying signal processing for both control strategies was done using the same pattern recognition algorithm to ensure fairness of comparisons. Similar implementation may be used for further investigations and comparisons.
- Decoupling feedback from control and exploring methods to mitigate the tradeoff between reliable control and rich feedback.
- Using psychophysical tests for the first time to evaluate the internal model strength in the field of myoelectric prosthesis control strategies.
- Developing a novel hybrid myoelectric control strategy that enables better performance than current myoelectric controllers.
- Implementing the novel controller for a prosthetic hand and pushing research findings one step closer to clinical implementation.

Findings

The Effect of Feedback on User's Adaptation

A key unexplored element to improving myoelectric control performance is improving the user's understanding of the myoelectric control system. To be able to improve this

understanding, parameters that affect its development must be studied. One of these parameters is adaptation rate to self-generated errors.

Control strategies that represent the two commonly used types of myoelectric prosthesis controllers were implemented. The first strategy implemented feedback-rich but noisy (variable) regression-based control. The other control strategy was analogous to a classifier, which provided reduced (discretized) feedback but more forgiving control. Despite differences in feedback and control signals, each of these control strategies has been found to overcome some of the limitations of conventional myocontrol (Zecca et al. 2002; Parker, Englehart, and Hudgins 2006; Oskoei and Hu 2007; Scheme and Englehart 2011). To test these controllers, subjects were asked to use each controller to control a cursor on a computer screen to acquire 80 virtual targets. Subjects showed significantly higher adaptation behavior to self-generated errors when using the feedback-rich control strategy than when using the reduced feedback control strategy ($p < 0.05$), which suggests that control strategies with more feedback allow for higher adaptation. This finding encouraged deeper investigation of how these control strategies, which differed in both control signals and feedback level, affect other aspects of human understanding and ultimately overall performance.

The Effect of Myoelectric Controllers on Internal Model Strength and Performance

Human understanding is stored and modeled by the brain as an internal model. A recently developed psychophysical framework was used to assess internal models developed when using the same myoelectric control strategies discussed in the previous section during a multi degree-of-freedom (DOF) virtual target acquisition task. The performance of both strategies was also evaluated using a time-constrained target acquisition task.

Subjects were able to identify significantly smaller perturbations in their control when using a feedback-rich controller than when using reduced the feedback controller. This result combined with the higher adaptation rate enabled by the feedback-rich controller led to the development of a stronger internal model than the one developed when using the reduced feedback controller. Conversely, performance test results indicated that the reduced feedback classification-based controller yielded better path efficiency and accuracy.

Improving Internal Model Strength and Performance Using Augmented Feedback

To mitigate the tradeoff between controllers that enable high adaptation but poor performance and controllers that enable good performance but low adaptation, a novel hybrid control strategy was introduced by relaying feedback from the rich-feedback controller using audio to augment the classification-based controller. As in previous tests, subjects used this controller to acquire targets in a virtual target acquisition task and both internal model strength and performance were assessed. Results showed that subjects using the audio-augmented feedback controller showed similar adaptation behavior to those using the feedback-rich controller and significantly higher adaptation behavior to self-generated errors than those using the reduced feedback controller. Similar to those using the feedback-rich controller, subjects using the audio-augmented controller were able to identify significantly smaller perturbations in their control system than when using the reduced feedback controller. Consequently, combining high adaptation rate with low sensory perception threshold enabled by audio-augmented feedback controller resulted in internal model strength comparable to the one developed when using the feedback-rich controller and stronger than the one developed for the reduced feedback controller (Figure 6-1).

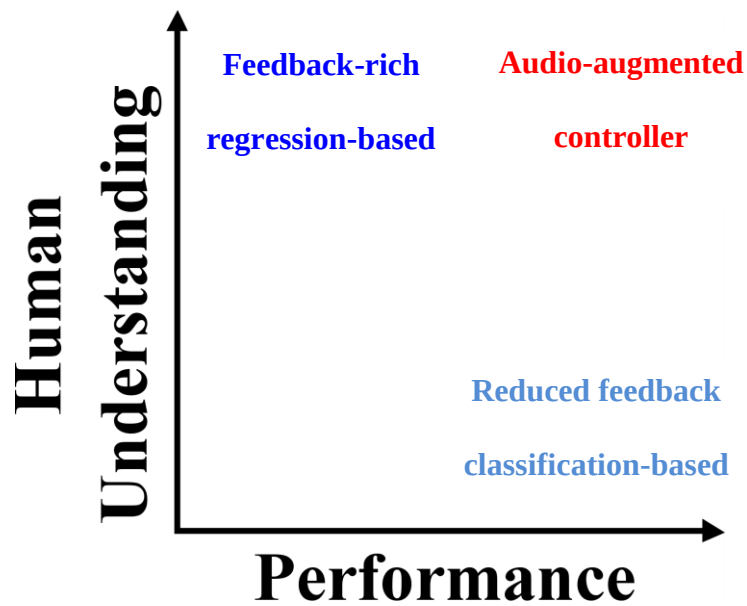


Figure 6-1. Augmented-audio controller enabling stronger internal model than reduced feedback classification-based controller and better performance than feedback-rich regression-based control strategy.

Since the novel audio-augmented controller was a classification-based controller, the same performance metrics used for the reduced feedback classification-based controller were used to assess its performance. It is worth noting that the audio-augmented feedback controller enabled significantly better path efficiency than both the reduced feedback classification-based controller and the feedback-rich controller. In addition, the accuracy for the audio-augmented controller was trending higher than both of the other controllers. This result confirms the hypothesis that the strong internal model developed when using audio-augmented feedback controller may enable better performance.

Bridging the Gap between Research and Clinical Practice

To confirm that the benefits of using audio-augmented feedback for improving internal model strength of myoelectric controllers extend beyond a virtual target acquisition task, internal model strength and performance were assessed when using this audio-augmented controller to control a prosthetic hand for a grasp-and-lift task. Results were compared to those obtained with the reduced feedback classification-based controller, which confirmed the hypothesis that the audio-augmented feedback controller enables stronger internal model strength and better performance than the reduced feedback controller.

Internal Model Translation

An unexpected effect was observed when subjects were exposed to a feedback-rich control strategy prior to testing the reduced feedback control strategy. This effect was that subjects were able to adapt more when using a reduced-feedback control strategy after first being exposed to feedback-rich control (Chapter 3). It was found that this effect was a result of a translation of the internal model developed by the feedback-rich controller to the reduced feedback one and not a ramification of prolonged use of the myoelectric system. A similar effect was seen when subjects were exposed to the audio-augmented feedback control strategy prior to the reduced feedback controller.

The observed improvement in the internal model developed for the reduced feedback controller after the exposure to the audio-feedback controller calls for the inclusion of audio feedback in myoelectric control training procedures. As such, audio-augmented feedback may be useful during the training phase of prostheses users to develop strong internal models.

Afterwards, users may continue benefiting from that developed strong internal model while using any other control strategy of their preference.

Limitations

For this work, no amputee subjects were included, but it is suspected that they would exhibit similar trends in internal model formation to the able-bodied subjects tested, because psychophysical metrics are measures of human behavior and understanding and not physical ability (Shehata et al. 2017; Johnson et al. 2017; Metzger et al. 2010); however, absolute performance may vary depending on level of amputation (Lum et al. 2014).

The learning effect due to prolonged exposure to the feedback-rich control strategy was not investigated; therefore, no conclusions could be drawn about possible performance improvement for the feedback-rich control strategy, but definitive conclusions were made for short-term performance for all controllers tested in this work. Results from a recent study (Strbac et al. 2017) have shown significant improvement in long-term performance over a period of five days of testing for amputees and suggested that this improvement may be credited to a strong internal model. Consequently, the assessment of internal model strength presented in this work may serve as an indicator of long-term performance while reducing the duration of experiments (five sessions for five days to a one three-hour session).

To acquire reliable psychometric measures, experiments conducted throughout this work were relatively long (three hours per session), which made subjects less motivated (Mathiowetz et al. 1985) and easily bored; that may have had an effect on performance. Since the order of controller testing was randomized for all experiments, except for the last one, this effect was

accounted for (Kirk 1982). A more engaging experiment, such as using games, may increase subject's intrinsic motivation and perseverance (Prahm et al. 2017).

Although the performance measures in this work were determined for multi-DOF tasks, the psychophysical tests conducted here only tested one DOF. These results should generalize across DOF for non-complex tasks, such as virtual target acquisition and grasp-and-lift; however, for more complex tasks these tests must extend to more than one DOF.

Lifting the bypass weight in the grasp-and-lift experiment using the prosthetic hand affected users' ability to open the hand after grasping the object, which affected the performance of the different control strategies. Although this issue affected the tested control strategies equally, it may have been avoided using a tool balancer (Wilson, Blustein, and Sensinger 2017).

Future Work

The contributions of the work presented in this thesis can have a great impact not only on the field of myoelectric prosthesis control, but also on the broader fields of assistive devices for rehabilitation, human machine interfaces, and computational motor control. The following are suggestions for future work informed by this research:

- Exploring a combination of other augmented feedback that might enable an even stronger internal model.
- Exploring the effect of augmenting other feedback modalities, such as continuous audio and discrete vibrotactile or continuous audio and discrete electrostimulus, on the internal model strength.
- Investigating the effect of audio-augmented feedback control strategy for a more complex task on the internal model strength and the performance.

- Investigating users' ability to retain an internal model that has been developed when using a given control strategy
- Identifying the minimum quantity and quality of relevant feedback needed to effectively improve user understanding and hence improve performance with least computational power.
- Development of new training procedures to use augmented feedback to improve internal model and then investigate the effect of this internal model on long-term performance.
- Investigating the effect of using augmented feedback with other controllers than the classifier-based, such as conventional myoelectric controllers, on internal model strength and short-term performance.
- Assessing internal model strength and the long-term performance of regression-based control strategies that use other modalities of augmented feedback, such as vibrotactile.
- Assessing the benefits of using augmented feedback for limb-different individuals.
- Last but not least, using bone conduction technology to relay audio feedback to amputees and investigate benefits of using augmented-audio feedback controller for them.

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Appendix A: A Framework to Estimate System Uncertainties Using a Hierarchical Kalman Filter Model

This framework is developed by **Daniel H. Blustein** and **Jonathon W. Sensinger**. In this thesis, this framework is used to estimate myoelectric control system uncertainties to evaluate internal model strength.

Model overview: The model is based off that presented by Johnson et.al 2017. It consists of two Kalman filters (Kalman, 1960): the first is a state estimation model that iteratively updates the system's state estimates over the course of the simulated movement. The second Kalman filter is a parameter estimation model which generates and updates parameter estimates after each simulated movement.

The state estimation model first **predicts the state and covariance**:

$$\hat{x}'_n = \hat{A}x_{n-1} + \hat{B}u \quad (1)$$

$$P'_n = \hat{A}P_{n-1}\hat{A}^T + Q \quad (2)$$

These and the following variables are summarized here:

Table I. State Estimation Variables	
x	state
$\hat{x}$	estimated state using estimated parameters (' indicates prediction or prior)
A, B	system dynamics
$\hat{A}, \hat{B}$	estimated system dynamics, composed of estimated parameters: $\hat{A}, \hat{B} = f(params)$
u	control signal
P	state estimate uncertainty
Q	process noise
z	sensory feedback information
H	observation matrix
R	measurement noise
K_s	Kalman gain of state estimation

The model then **performs the movement**:

$$x_n = Ax_{n-1} + Bu + \varepsilon, \quad p(\varepsilon) \sim N(0, Q) \quad (3)$$

The **movement is observed**:

$$z_n = Hx + v, \quad p(v) \sim N(0, R) \quad (4)$$

Then the **state prediction is corrected**:

$$K_s = P'_n H^T (H P'_n H^T + R)^{-1} \quad (5)$$

$$\hat{x}_n = \hat{x}'_n + K_s (z_n - H \hat{x}'_n) \quad (6)$$

$$P_n = P'_n (I - K_s H) \quad (7)$$

The parameter estimation model utilizes the following variables:

Table II. Parameter Estimation Variables	
$params$	parameters
P_{param}	propagated uncertainty of parameters
Q_{param}	uncertainty of parameters
R_{param}	Uncertainty of sensory information used to update parameters. $R_{param} = P$
K_{param}	Kalman gain
H_{param}	mapping of parameters to states
A_{param}	forgetting factor

The

model first **updates the parameter uncertainty** based on the preceding movement:

$$Q_{param} = \frac{error^T * error}{P_{param} + R_{param}} \quad (8)$$

Then a **forgetting factor**, which models the effect of time of no use (set to 1, i.e., ignored), **and the parameter uncertainty** are incorporated:

$$params = A_{param}params \quad (9)$$

$$P_{param} = A_{param}P_{param}A_{param}^T \quad (10)$$

The **parameters and uncertainty** are then updated:

$$P_{param} = P_{param}(I - K_{param}H_{param}) + Q_{param} \quad (11)$$

$$K_{param} = \frac{P_{param}H_{param}^T}{(H_{param}P_{param}H_{param}^T + R_{param})} \quad (12)$$

$$params = params + K_{param}(\hat{x} - \hat{x}') \quad (13)$$

Parameter estimation framework

Model parameters are estimated given movement data collected from a person. The parameters of interest are:

- R = sensory uncertainty
- Q = controller uncertainty
- P_{prm} = internal model uncertainty

Movements to a target are completed without any exteroceptive feedback. From these movement results, we estimate controller uncertainty as:

$$Q = \sigma^2 = \frac{\sum(x_n - x')^2}{n} \quad (14)$$

where x_n is the movement endpoint, x' is the movement target and σ^2 is the movement variance attributed to the controller ($R = 0$ for this experiment).

A second movement task is used to determine the just noticeable difference (JND) of a perturbation of the control signal using an adaptive staircase (Faes et. al 2007). The JND can be converted to a measure of system variance (Ernst & Banks 2002) as:

$$Q + R = \sigma^2 = \frac{JND^2}{2} \quad (15)$$

where the system variance (σ^2) is equivalent to the total system noise which include sensory noise (R) and control noise (Q). Given equations 14 and 15, a value for R can be determined algebraically.

For a task with simple dynamics, only one state (x) and one parameter (gain), and endpoint feedback,

$$K_s = \frac{Q}{Q+R} \quad (16)$$

where K_s is the Kalman gain of the state estimator. We use an error-minimization optimization method to estimate K_{param} , the Kalman gain of the parameter estimation model (this method is described in Blustein et al. 2017, currently under review). The estimated endpoint ($\hat{x}$) is required, which we measure with a post-movement indication or can be set equal to x when K_s approaches 1. We estimate internal model uncertainty by rearranging equation 12 as

$$P_{param} = \frac{K_{param} R_{param}}{H_{param}^T - H_{param}^T K_{param} H_{param}} \quad (17)$$

where R_{param} is calculated as

$$R_{param} = P = Q - \frac{Q^2}{Q+R} \quad (18)$$

and H_{param} can be calculated for this system as

$$H_{param} = u = \frac{x_n}{G_n} \quad (19)$$

or set to equal 1 to represent a 1:1 sensitivity mapping of states and parameters. Using this approach sensory uncertainty (R), controller uncertainty (Q), and internal model uncertainty (P_{pm}) can be estimated for a behaving human.

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Research Experience

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April 2014 - September 2013	Website Administrator Developed and managed faculty of Engineering and Material Science website at the The German University in Cairo
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- A. Shehata**, E. Scheme and J. Sensinger. 2017. The Effect of Myoelectric Prosthesis Control Strategies and Feedback Level on Adaptation Rate for a Target Acquisition Task', IEEE 15th International Conference on Rehabilitation Robotics. London, UK.^O
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