Slip Prediction for Upper-Limb Prosthetics

by

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

Amputees have greatly benefitted from improved prosthetic technologies, increasing dexterity, degrees of freedom, and attachment to the body, however sensory feedback has made comparatively little improvement. Osseointegration has been shown to produce a transcutaneous pathway to allow for long term stable invasive electrical stimulation [1], [2]. The need for useful prosthetic feedback has been pre-existing, however now there is the capability for prosthetics to begin recreating lost sensations through neural stimulation. This thesis investigates the ability to create a slip prediction system, in a currently existing and widely used commercially available prosthetic hand. This slip prediction system is designed to alert the user before slip begins to occur to maximize potential usefulness. Two methods of stimulation are compared to a no-stimulation baseline in execution of a task designed to induce slip. Improvements are indicated through a reduction in number of slips, and improved understanding of grip capabilities, shown by prosthetic movement planning within grasp limits. One stimulation condition delivers a single rapid stimulation "spike" as slip becomes more likely. The other stimulation condition delivers a continuous stimulation, with amplitude proportional to slip likelihood. The predictor is shown to have a prediction accuracy of 69% when used with feedback. Slips across all four participants were shown to be reduced by stimulation, as 53 slips occurred using no stim, 37 slips occurred using the spike feedback, and 31 slips occurred using the amplitude feedback; however this decrease was not shown to be statistically significant. This indicates that the neural stimulation slip prediction delivered in this thesis, provided additional and actionable information even when the participant could see, hear, and freely move the prosthesis.

Acknowledgements

A large thanks and acknowledgement is unquestionably directed at my supervising professor Ning Jiang, who has been serving in an advisory capacity for the past four years, since my undergrad capstone project. Beyond just time, Prof. Jiang was pivotal in my ability to undertake a Master's degree. Through every step of my MASc, I have been shown guidance but also flexibility to direct my work where it seems most apt, provided there is scientific literature to support that direction. Such guidance was especially evident when I was not only notified of, but provided recommendation for a research opportunity in Sweden, which would have delayed and lengthened my MASc, but provided unique learning and professional development experiences.

My graduate experience would not be the same without the opportunities, people, and experiences found in the Centre for Bionics and Pain Research in Gothenburg Sweden, headed by Prof. Max Ortiz-Catalan. The arm-team which quickly became the Cybathlon-team, was welcoming, educational, and provided me with the opportunities to design and execute developments of my own volition, appropriately providing assistance when it was needed. As a systems design engineering grad trending toward electrical engineering, it was an enriching opportunity to work so closely within a bleeding-edge electrical lab with such a close focus on participant satisfaction. I am incredibly grateful to all of the CBPR I have had the pleasure of working with and have grown to know over the past year. Particular appreciation goes out to our Cybathlon athletes Tonney and Magnus. As well as Jan, whose tireless efforts to pull me out to do something fun were greatly appreciated, and won't soon be forgotten.

There are additional faces at Waterloo which deserve thanks, from the eBL: Aravind Ravi, Ben Lampert, Nargess Heydari, Paul Wolfe, who have all helped over the course of my masters, and have been friendly faces through it. I would also like to thank Prof. Clark Dickerson, who has extended assistance, and professional development experiences at every opportunity.

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1. Background

1.1 Amputation

Amputation of a major limb is a life altering event for amputees, with potential of instantly reduced independence in activities of daily life. Amputation impacts amputees in different ways, depending on the nature of the amputation. Unlike lower-limb amputation where decreases in ambulation may be the cause of diminished independence and capability, upper-limb amputations cause diminished independence through decreases in object manipulation capability. This is primarily caused by the loss of the hand, and can be exacerbated by loss of the elbow, or shoulder articulation. The natural human hand is very effectively constructed in its capability to provide strong but dextrous movements. Beyond pure mechanics, the natural hand provides a broad range of feedback to its user on the properties of external objects, and the nature of current grasps. There have been many developments in creating increasingly functional prosthetic hands, in terms of both mechanical and sensory capabilities. However due to the difficulty in providing long-term stable, rich sensory feedback, wide-ranging biomimetic sensory suites in prosthetic hands are not currently in high demand, or commercially available.

1.2 Osseointegration

Osseointegration describes the interaction between bone, and implant (typically Titanium) in which the bone has formed around the implant, and is long-term stable [3]. This process has a nearly sixty-year history, and has been shown effective in a wide range of applications [3], [4]. Osseointegration is effective for bone anchoring, but also allows for creating a safe transcutaneous structure. The biocompatibility of titanium with the bone and skin has allowed surgeons to create strong connections to the skeleton, previously deemed impossible [5]. Developed through the 1960s for facial and dental implants, the technique has been applied to many other fields such as hearing aids, cosmetic prosthetics, and both internal and external joint repair prosthesis [2], [4]–[6].

Attaching the prosthesis directly to the bone provides many benefits to upper and lower limb prosthetics over their traditional counterparts. Typical prosthetics have a socket-stump mating, which can cause a host of problems, including but not limited to discomfort, poor fit, pressure sores, and load transfer issues. Osseointegration mitigates these by creating a synthetic bone for the prosthesis to attach to, mimicking the natural skeleton [7]. The skeletal biomimicry has been found to relieve many inherent interfacing issues of current limb-prosthetics such as discomfort, weight and limited movement [7]. As such, osseointegration is particularly promising for major limb replacement through prosthetics. One such example is the OPRA (Integrum AB, Sweden) system which features a titanium fixture screwed into long-bone at the site of amputation, with a titanium abutment passing through skin at the end of the stump [2], [8] seen in Figure 1. This abutment is used for affixing prosthetic limbs rigidly and directly to the bone, and has been shown to be long term stable [2], [7]–[9].

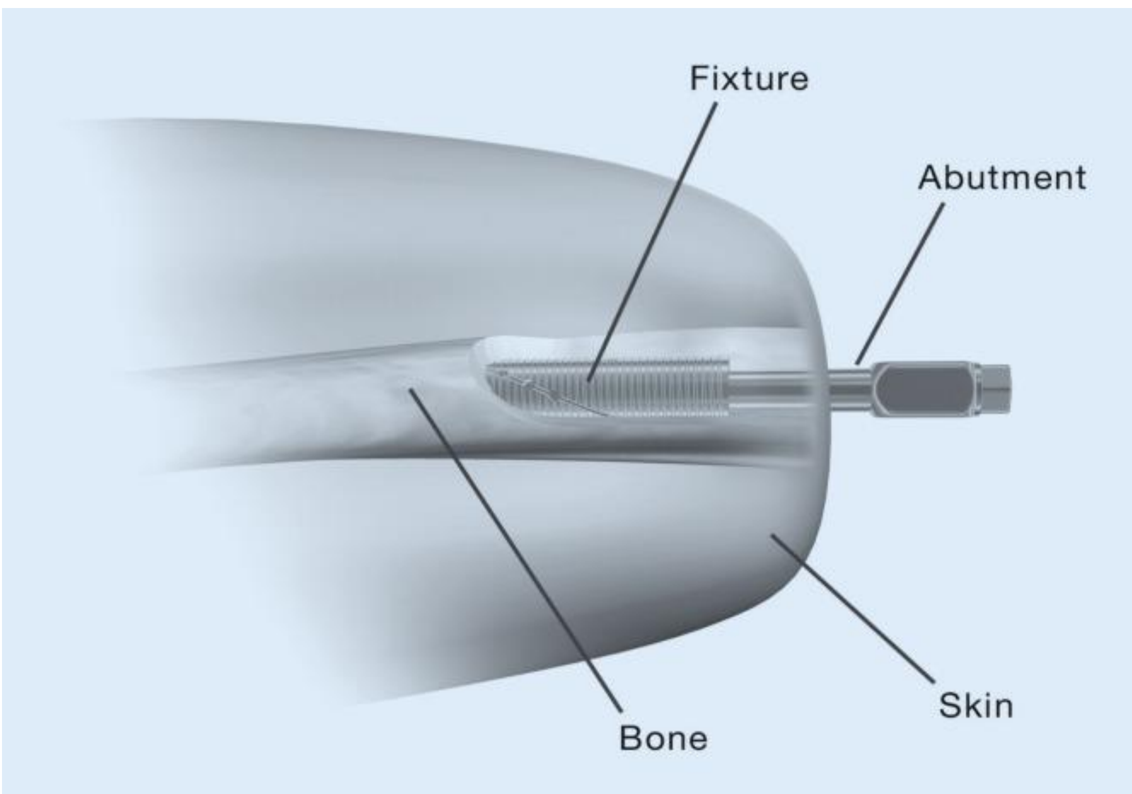

Figure 1 Cut-through view of the OPRA system embedded in long bone, from [9].

More recently, long term stable transcutaneous pathway was established by passing wires across the skin barrier using the osseointegration [2]. These wires are capable of translating electrical information across the skin such as muscle activation recording, or nerve stimulation. By eliminating the skin-electrode interface, these long term stable invasive recordings are significantly richer and more stable signals than surface recordings. Recently, neural stimulation delivered to the residual nerves through the osseointegrated pathway, has shown to be a stable and effective method of recreating the missing tactile sensations of the amputated hand [1], [2]. Osseointegration is an impressive and promising prosthetic development, which moves the field closer to recreating the natural limb through its connection, control and sensory capabilities.

1.3 Myoelectric Control

Electromyography (EMG) is the recording of detectible electric pulses released as a result of muscle activation [10], [11]. Muscle fibers conduct and generate electricity, simultaneously with mechanical contraction. This electrical activity varies in amplitude and frequency as the nervous system changes desired muscular force [10]. EMG for control applications is typically recorded as the spatial and temporal summation of electrical impulses in the receptive field of each electrode. Increasingly discerning/fine electrodes improve specificity of recording over the spatial domain. EMG acquisition requires recording of electrical activation from the active sites, and recording of a predetermined grounding site in which relevant signals would not be present. The value of the EMG is taken as the difference in activities between these two sites.

Due to the inherent position-dependant quality of the EMG, it is imperative that the recording electrodes are placed as close to the sources of the information as possible. This explains the advantages of invasive recordings over surface EMG. While maintaining effective signal to noise ratios is always important, EMG signals for rudimentary control are robust enough for daily-use application, even when recorded from the surface. There are many more EMG processing considerations and elements to consider in designing an EMG acquisition system/controller, however these are out of scope of this work.

EMG control is becoming more common in upper limb prosthetics, which in theory would allow more naturalistic control of prosthetic capabilities [11]. Despite the benefits of implanted electrodes, the discomfort of skin-penetrating wires, the propensity for transcutaneous implants to become infected over time, and the donning/doffing process the prosthesis, has resulted in most, if not all, EMG-enabled commercial prosthetics using surface EMG recording for control. Invasive EMG prosthetic control remains a developing space as prosthetics become more technically adept to make use of the richer data, and solutions to the issues surrounding transcutaneous electrodes become available.

1.4 Neurostimulation

As EMG recordings are understood as reading information from the body, electrical stimulation is understood as writing information to the body. Electrical stimulation comes in many forms, with many targets, such as muscles or nerves. Neurostimulaiton refers to the stimulation of the nervous system for any reason, which may be to promote activation, or generate new stimuli all together. It has been shown that electrical nerve stimulation delivered across the skin, or invasively is capable of creating tactile sensations in an amputee's missing limb [12], [13]. Due to underlying complexities in natural nerve encodings, it remains impossible to create perfectly biomimetic sensations through artificial nerve stimulation. It is however possible to create reliably differentiated sensations through varying stimulation pulse frequency, amplitude, and pulse width [12]. Electrical stimulation contains a vast number of different parameters, however the neurostimulation relevant to this thesis is constrained to charge balanced pulses. Balancing charges ensures the net flow of electrons at the site of stimulation remains neutral, protecting the nerve. The waveform used in this work to achieve balanced charge begins with a strong but short polarization, followed by a longer but weaker depolarization, seen in Figure 2.

The most rudimentary sensation which can easily be delivered from prosthetic hand to amputee is a magnitude of applied force detected by the sensor on the prosthetic. This is relatively easy mechanically and computationally, to both implement in the prosthetic, and

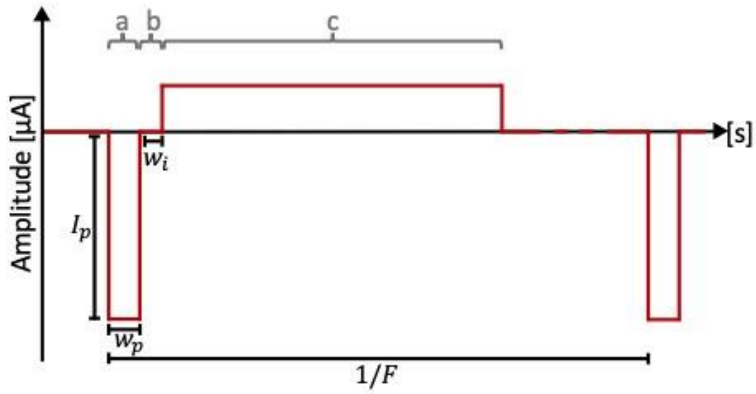

Figure 2 Neurostimulation wave form, consisting of (a) stimulation pulse, (b) interphase interval, and (c) charge recovery pulse. The stimulation pulse is 10 times stronger than the recovery pulse, however the recovery pulse is 10 times longer to maintain charge.

calculate the feedback response as linearly proportional to the force sensor [1], [14]. However, the natural hand provides significantly richer modalities of sensation sensations, which through convolution in the mind are understood as texture, pliability, and grasp stability. For example, understanding the quality of a grasp requires normal and shear forces, as well as proprioception – senses that are not provided by current prosthetics, nor are easy to create through neurostimulation. This causes users to make assumptions about the applied forces of their prosthesis based on visual and auditory feedback, and guesses at the frictive and compliance qualities of the target object. A major bottleneck for sensory feedback remains at the human-machine-interface, which must have a wide electrical and neural bandwidth at low latency, and remain long term stable outside of laboratory settings. For prosthetics to develop to the point where they are equal to human hands, major breakthroughs are required in sensory synthesis and feedback.

The sensorized hands on the market today are scarce and have limited sensory capability. In instrumented prosthetics, sensors typically feed into closed-loop control strategies which do not directly provide sensory information to the wearer. Sensorized prosthetics with a closed-loop control methodology, often provide corrective movements to the hand such as tightening grasp, when a slip is detected. One such hand which performs this way is the Ottobock Sensorhand (Ottobock, Germany), and it has been observed through amputee interaction that this function is not popular. The resulting nonvolitional prosthetic movements were reported as disconcerting and reduced feelings of embodiment. It was additionally reported that the participants would take time after each power-on of the prosthesis to switch off this behaviour. This indicates there is a need to provide the wearer with quality of grip feedback in an informative manner such that they can chose to execute volitional movements of their own accord.

1.5 Regression

Sensory synthesis is completed naturally in the brain to develop abstract understandings such as quality of grip, due to the narrow bandwidth of sensory neurostimulation, the synthesis must occur digitally pre-stimulation. Regression is the mathematical principal of determining the likelihood between different labels, based on input data of a known type. There are many different types of regression, but only linear regression between two classes, is relevant for this study. A key factor of regression is the continuous output of likelihood, compared to classification, which holds similar mathematical principals, however results in a discrete/binary output. The continuous output can be more useful in some cases, as it allows for greater understanding of the underlying prediction, and confidence of prediction.

$$X = b + \sum_{i=1}^{d} \beta_i \left[{(x_i - \mu_i)}/{\sigma_i} \right] \tag{1}$$

Equation (1) is the math underpinning the linear regressor as described above. The output X is the sum of linear data transformations on the input vector x of length d, and a scalar bias of b. The vectors β, μ, and σ are all of length d, and are the trained values responsible for encoding different classes of x. Equation (1) shows the math used in assessing the inputs using a known model, and does not show the machine intelligence mechanism used to generate the model values. The model values which scale the inputs are determined through support vector machine (SVM) training, in which a hyper-plane is mathematically determined in d-dimensional space to separate the two labels for prediction [15]. The X output value represents the distance from this plane. SVM performs well when there are underlying geometric relations between the input data, and is less prone to overfitting compared to similarly complex machine learning approaches, such as logistic regression. SVM training is a powerful tool which is applied to much more than just regression. The underlying math and processes behind SVM training, as well as assessing higher dimensional SVM regression (e.g. quadratic) are beyond the scope of this work.

Patterns and connections not observed by humans may be leveraged by machine learning. This plays a key role in sensor synthesis, which is the means of determining information from a series of sensors, which is greater than the sum of their individual parts. By providing a full suite of sensors as input to the regressor, synthesized findings can emerge from patterns in the sensor data.

1.6 Modern Upper-Limb Prosthetics

The Cybathlon is the Olympics of the powered prosthetic world, with events for many different types of prosthetics. It occurs every four years and many of the best research teams in the world participate. The purpose of the Cybathlon is to promote development in prosthetic technologies through competition. Prosthetics are growing more technically capable and are incorporating more mechanics and electronics as the field grows. EMG controlled prostheses are becoming common consumer grade devices, and multi-articulated prosthesis are allowing for a variety of different biomimetic grip patterns, even with very rudimentary EMG control [16]. Despite these improvements, the first place victors of every Cybathlon upper-limb prosthesis race has used body-powered prosthetic hands [17]. This type of prosthesis is unpowered, and is actuated using a tension table system, which closes the hand on slight shoulder movement [16].

The Cybathlon competitions are an indicator that, while developments in powered prosthetics have come a long way, there is still a demonstrated need for improvement in capability and usability of electronic prostheses. One such area of improvement is the use of sensory information in control, which has been identified as one of the four major limitations of the current state-of-the-art in prosthetic control [10]. There are many prosthetics, both commercially available and experimental, with integrated sensors, as well as developed and validated sensorized components such as individual fingers[18]. These sensors are often used for internal calculations of grip dynamics in the hand, effecting prosthetic movement outside of the direct control of the wearer [18].

1.6.1 e-OPRA System

A new bio-interface for prosthetics has been recently been developed using the aforementioned technologies. The e-OPRA (Integrum AB, Sweden) system is the electrified version of the OPRA system, and is made so through a secondary surgery after osseointegration to add implanted electrodes into the residual muscles, and onto the transected nerves [1], [2]. The implanted muscle electrodes allow for very clear and reliable EMG recording which has proven to be stable, and in some participants, allows for natural feeling movement control for the prosthetic [1], [2]. Cuff electrodes attached to the residual transected nerves provide neural stimulation, and have been shown to create reliable localized sensations of varied intensity [1], [2]. This is achieved through transcutaneous communication made possible through the osseointegration conduit. A TM4C123GH6PM microcontroller (Texas Instruments, USA) external to the body records, processes and acts upon input from the muscles, as well as calculates and executes electrical stimulation of the nerves [1], [2]. The arm and hand hardware is independent of the microcontroller, and can be replaced with any commercially available or experimental prosthetic. The microcontroller performs computations for the system, and is capable of noise cancelling, multi-input pattern matching, machine learning calculations, and all required digital signal processing. Due to these functions, the e-OPRA is the most appropriate test platform for deploying new prosthetic neural stimulation algorithms.

As the e-OPRA is still an experimental implant system, the pool of users remains a small group of participants with regular oversight, and years of documented system use. The e-OPRA system is integrated into the lives of its users in both a physical and cognitive sense. As a result of these factors, all four current transhumeral-amputee users of the system are very comfortable with the control, and have a deep understanding of their prosthetic system from a user perspective.

1.6.2 Slip Sensing

Slip detection is a developing field in smart robotics. As human-robot interaction becomes increasingly common, the requirements for robots to understand more about their surroundings will increase [18]. It is also a growing field in upper limb prosthetic development [18], as sensory and computational power becomes more spatially dense, prosthetic hands are capable of housing more of each. Even if prosthetics developed to the point in which they were mechanically equivalent to a human hand, they would not have the same level of performance without tactile, somatosensory, and proprioceptive feedback. The lack of sensory information delivered to prosthetic users causes difficulty in reacting to surprise grasping events, such as slip or deformation [19]. There is a clear benefit to providing amputees with knowledge of slip from the prosthesis, however the ways in which it has been attempted in the past are insufficient and inapplicable to daily life. Several current prominent methodologies for detecting slip include:

- Frequency analysis: recording and classifying the stick-slip relationship of an object sliding over the pertinent sensors such as force sensors, or microphones. This is done through Fourier transforms [14], [20] or wavelet pattern matching [21], [22] to detect known signal properties.
- Piezoelectricity: reading the charge generated by the micro-vibrations of slip from a piezoelectric material. Slip information can be extracted from this signal through spectral/power analysis [23], [24].
- Force comparison: comparing magnitudes of multiaxial force sensors to understand the ratio of grip force to perpendicular forces which may cause slip [25], [26]. This method assumes there is a ratio of perpendicular to transverse forces which at which a slip will be induced due to inferred friction coefficients [18].
- Force differentiation: extracting meaningful information from sharp changes in force [27], [28] or pressure sensors [29], as understood through their time derivative. Underlying mechanisms causing derivative spikes vary across sensors and implementations.

Common repeated shortcomings emerged through previously published slip mitigation work. Present in every paper reviewed except [30], was the detection of slip only once it had begun, and improvements were presented as decreasing the time to detect slip from onset. However detecting slip in progress is less useful than providing the amputee user with an understanding of the grip dynamics before slip occurs, if the goal is to prevent slip all together. Low contact force ($\leq 7N$) was reported in [13], [14], [18], [19], [21], [22], [25], [26], [28], [29], [30]–[33], which reduces the usefulness of the system as slip could easily be mitigated by increasing the grip force of the prosthetic. Only [19] showed validation of detection with high forces ($\geq 20N$). Once slip was detected, many studies proposed automatically modulating prosthetic grip (tested: [23], [27], [36], [37], stated intention to test: [22], [29], [34]), which would remove the control from the amputee and reduce agency of the prosthetic user, and can reduce feelings of ownership over the arm. Much of the work was focused on developing new prosthetic sensors ([21], [23], [25], [29], [32], [33], [35]), finger tips ([14], [19], [22], [24], [27], [28], [31], [34], [37]), or entire new hands ([20], [36]). This may be effective as a slip detection methodology, however it dramatically decreases the impact of the work, as it would be difficult to rapidly deploy the new technology to global amputees.

The aforementioned works typically did not include amputees in the validation of their designs, and thus cannot be analysed for application to daily life. Works such as these completely leave the amputee out of the loop, and validate their slip detection using robot-object, or robot-robot interaction, seen in [14], [19], [30]–[33], [35], [37], [20]–[25], [27], [28]. Only [13] included a singular (blindfolded) amputee in the loop, with neurostimulation feedback, performing a variety of tasks designed to induce slip. A particular interest of this thesis was addressing the gap in literature regarding the impact of a pre-slip notification. To provide an actionable metric of stability to the participant before slip occurs, such that the slip could be avoided rather than minimized.

1.7 Objectives of Thesis Research

The goal of this study was to implement a slip prediction algorithm on a commercially available sensorized hand and assess impact on movement planning. Slip prediction models were formulated for this hand using both heuristic hand-specific, and generalized prosthetic-independent methodologies. These were undertaken in order to quickly produce a proof of concept, and to maximize rapid application to other hands, respectively. Additionally, a user-in-the-loop test setup to determine the efficacy of slip prediction was developed and validated. This test is also used to demonstrate the impact of slip prediction feedback on amputee movement planning.

In the work presented in this thesis, four amputees received slip predictions through varied neurostimulation conditions to determine the efficacy of slip prediction, using a commercially available prosthetic. A novel experiment is used for validation, which aims to be representative of life outside of the laboratory. The experiment protocol was designed specifically to achieve this by keeping the sight, hearing, and movement of the participants uninhibited, and by using grip forces more than 20N greater than in any of the surveyed work in the literature (with the exception of [19]).

2. Methodology

2.1 Subjects

Four subjects with trans-humeral amputations participated in this study, all subjects were users of the e-OPRA osseointegrated prosthesis system. All subjects have used an osseointegrated prostheses for a range of 7±2 years, and have received nerve cuff stimulation during at-home use for 5±3 years. However the exact duration of stimulation is determined through personal preference, as not every prosthetic hand is sensorized. Each participant owns at least two different prosthetic hands; the exact amount of at-home stimulation received is determined by personal preferences of the frequency of different hand use. There is no participant mandate for at-home sensorized hand use.

Participant 1 is a right-handed 48-year-old man who had desmoid fibromatosis in his right forearm [2]. In 2003, he required a transhumeral amputation, after which he used a socket prosthesis with surface EMG control. The socket attachment was replaced by an osseointegrated prosthetic implant in 2009, also with surface electrodes used to control the prosthesis. In January 2013, when he was 41 years old, he underwent implantation of electrodes for control, and later stimulation [2].

Participant 2 is a left-handed man, who underwent a transhumeral amputation of the left arm. Due to ethical constraints, additional details of participant 2 cannot be presented.

Participant 3 is a right-handed 45-year-old man who had traumatic loss of his right arm in 1997 during work accident [2]. He had worn an electric prosthesis with a socket attachment controlled through surface EMG for 5 years but eventually abandoned it. In 2014, he received osseointegration for skeletal attachment of the prosthesis which was controlled through surface EMG. In January 2017, when he was 42 years old, he underwent nerve transfers and received an implant with the neuromusculoskeletal interface [2]. P3 is the only participant who has stimulation disabled for daily life, as he reported it became intertwined with phantom sensations.

Participant 4 is a right-handed 47-year-old man who lost his left arm as a result of high-voltage electrocution in 2011 [2]. He initially used an electrically driven prosthesis that was attached to his body with a socket and was controlled using surface EMG. In 2014, he received osseointegration to allow attachment of a prosthesis. In January 2017, he underwent implantation of the electrode interface [2].

2.1.1 Recruitment

All four participants were recruited from within the ongoing e-OPRA research from the Centre for Bionics and Pain Research (CBPR). Due to the longitudinal nature of the CBPR study, additional tests are slotted into the overarching study plan as appropriate/needed. All e-OPRA participants come to the center a few times per year as needed for experiments such as these, and to retune the arm control and neurostimulation settings. Preliminary findings, and additional information on the long-term e-OPRA study can be found in [2].

This slip notification study was presented to the potential participants during their regular visits to the laboratory, participation was voluntary; each were asked if they would like to participate after being able to read information letter and ask questions to the research team. This experiment was performed with the full host of current participants with e-OPRA systems.

2.1.2 Subject Prosthesis Details

Each participant sees a prosthetist from their home region of Sweden. The prosthetist is trained in prosthetic arm maintenance, and orienting the prosthesis in a natural way which matches the intact arm. Different prosthetists have manufactured alignment components for each of the amputees, which serves as fine tuning of the osseointegration. The prosthetic hand of each participant was changed during this study, however the alignment component was kept in place as that is what each participant was most used to. Full prosthetic system shown in Figure 3.

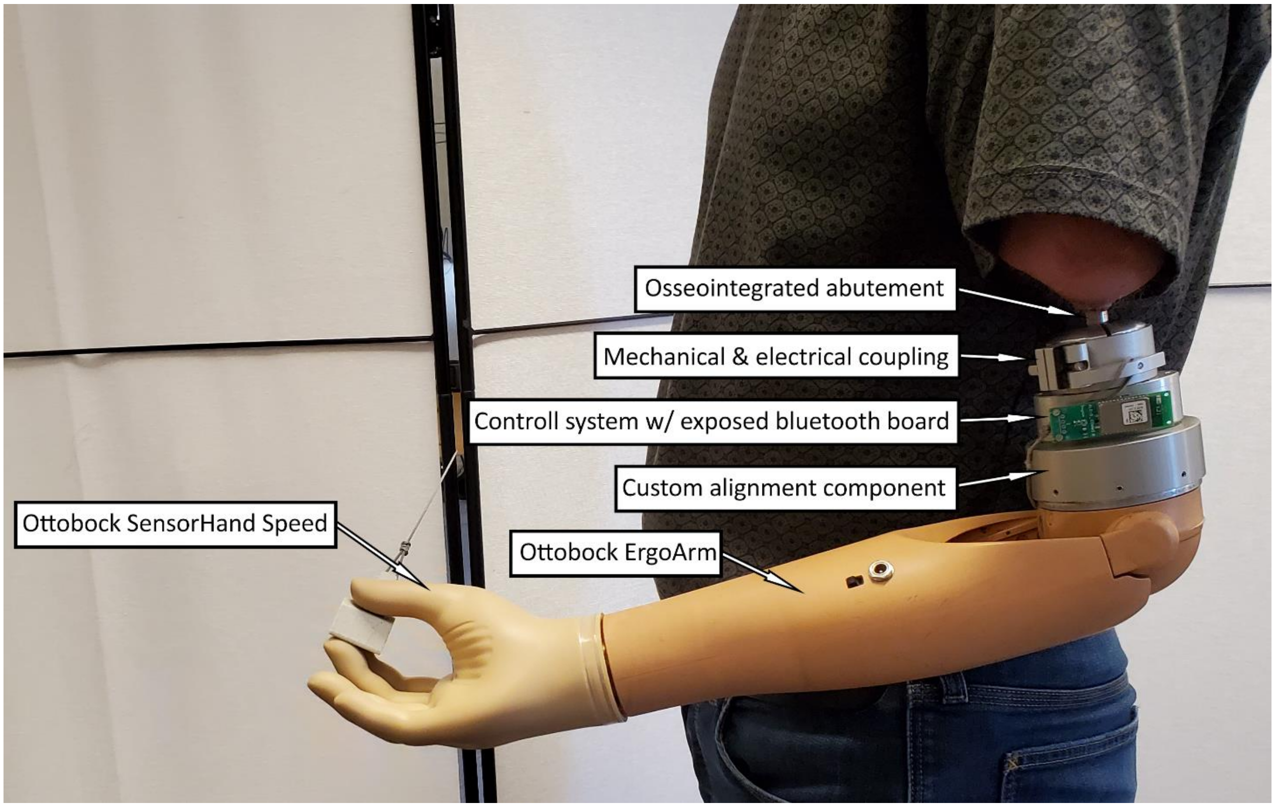

Figure 3 Main components of the prosthetic system used by the participants.

Each participant used an Ottobock SensorHand Speed right hand, and their own Ottobock ErgoArm elbow to run the experiments. To maintain consistency between participants and trials, the same Ottobock SensorHand Speed was used with each participant. Customization to the participant's prosthetic hardware was as follows: reprogramming the limb controller into the trial mode, or replacing it with a controller with the trial code on it, changing their hand to the study SensorHand Speed, and tightening the Ergo Arm passive rotation screw to limit internal/external rotation at the elbow joint. Each participant used the prosthetic elbow they came to the lab with, as it was the proper length for their natural proportions, and plays little role in the function of the experiment.

New neurostimulation feedback settings were determined for each participant at the start of their visit. Stimulation parameters which could create a clear and immediately noticeable pulse sensation, a noticeable but weak sustained sensation, and a strong but non-painful sustained sensation, respectively, were determined for each participant. Participant stimulation settings are shown in Table 1. The EMG thresholds for the maximal muscle contraction level the subject would exert during the experiment (GUI shown in Figure 4) were set far lower than the maximal voluntary contraction (MVC) level. This is to minimize participant exertion, by lowering the required myoelectric response (and muscular activation) required to move the hand. Fine prosthetic movements were not required for this study.

Table 1 Stimulation settings for each participant, determined to be noticeable but non-painful at the start of each experiment session.

Feedback	*Setting*	*Participant 1*	*Participant 2*	*Participant 3*	*Participant 4*
Spike Stimulation	Amplitude [uA]	130	450	620	700
	Frequency [Hz]	100	30	100	100
	Pulse Width [us]	100	200	350	250
Amplitude Stimulation	Amplitude, Low [uA]	120	300	450	800
	Amplitude, High [uA]	140	450	650	500
	Frequency [Hz]	30	30	30	30
	Pulse Width [us]	100	200	350	250

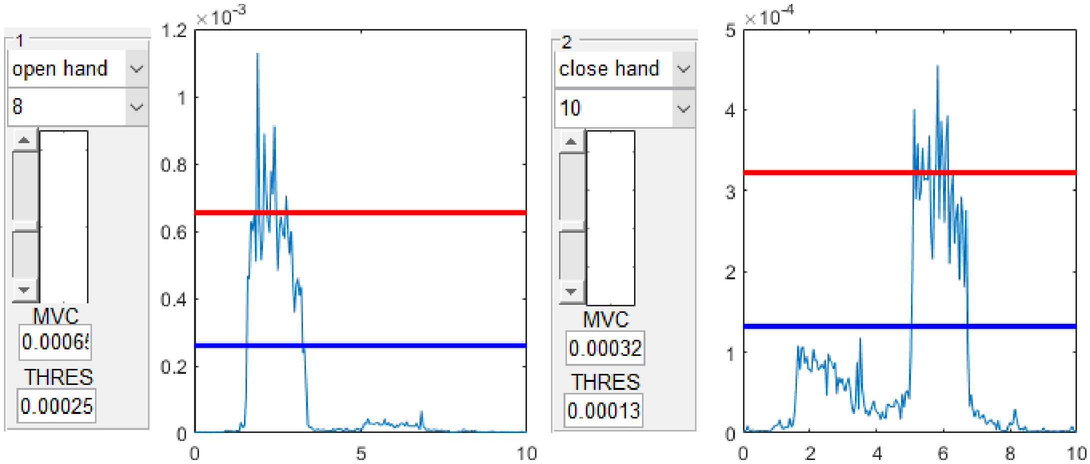

Figure 4 Screenshot of the EMG threshold setting GUI, showing absolute value of EMG in Volts over a 10 second recording; the red line represents set maximum muscle contraction, the blue line represents set minimum activation threshold. Fine prosthetic control was not needed in this experiment, thus maximum contraction was set below maximal voluntary contraction to reduce participant effort.

2.2 Ethics

This study received approval from both Office of Research Ethics at the University of Waterloo (ID#42485), and the Swedish Ethical Review Authority (DNR2020-04600). All subjects provided informed consent before starting the study. The protocol of the study was completed according to the guidelines of the Declaration of Helsinki.

In November 2020, approval from Office of Research Ethics at the University of Waterloo to run a participant-facing study was contingent on Coronavirus precautions. Risk mitigation precautions mandated by Chalmers University and University of Waterloo, were undertaken as the safest union of both sets. Hand sanitizer was readily available, personnel were reduced to the necessary minimum, masks were distributed and changed within 4-hours of use, experiment equipment was cleaned between participants, and all participants kept in contact with a physical therapist for regular health and wellness screenings before and after visits.

2.3 Equipment

2.3.1 Prostheses

The prosthetic end-effector used for all training and experiments was a SensorHand Speed hand (Ottobock Healthcare GmbH, Duderstadt, Germany). This particular hand is sensorized through three sensors located in the thumb, and one in the joint of the thumb. The thumb housed one force sensor normal to the pad of the thumb, and two parallel and oppositely directed shear sensors. The sensor in the base of the thumb recorded torque, and was calibrated such that it returned values of the linear force applied at the thumb. All participants were familiar with the operation of the hand and have used it in daily life since receiving their osseointegrated prosthesis. View of the SensorHand Speed skeleton, with the associated sensory receptive fields can be seen in Figure 5.

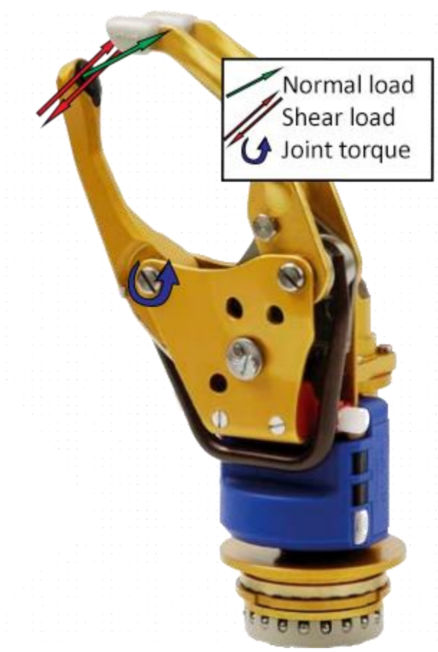

Figure 5 View of the Ottobock SensorHand Speed system without silicone cover, integrated sensory suite illustrated.

2.3.2 Grasped Objects

Two objects of known dimension were required for the experiment to be run, one to create the regressor data-set, and one used by the participant in pulling trials, called the training block, and the trial totem, respectively. The training block, shown in Figure 6 a), was 3D printed in PLA filament with an untreated surface. The trial totem, shown in Figure 6 b), was also printed with PLA, but the contact surfaces were smoothed with 120 grit sandpaper. The training block was 18mm high, and 80mm long to allow multiple slips while maintaining control of the object. The contact area of the experimental totem was also 18mm high, however was made narrower to promote the block slipping completely from the hand. The widths for the top and bottom of the target area were designed to narrowly match the widths of the contact areas of the prosthesis' silicon glove, shown in Figure 6 c). The cord was connected to the totem by an elongated neck, which was designed to discourage pronation/supination of the wrist, by increasing the torque resulting from pulling the totem out of alignment. During the experiment, the totem was connected to an exercise elastic to provide dynamic resistance. Two elastics were used, a lighter 328N/m yellow band, and a stronger 657N/m black band (determined through average of 3, 10cm pulls).

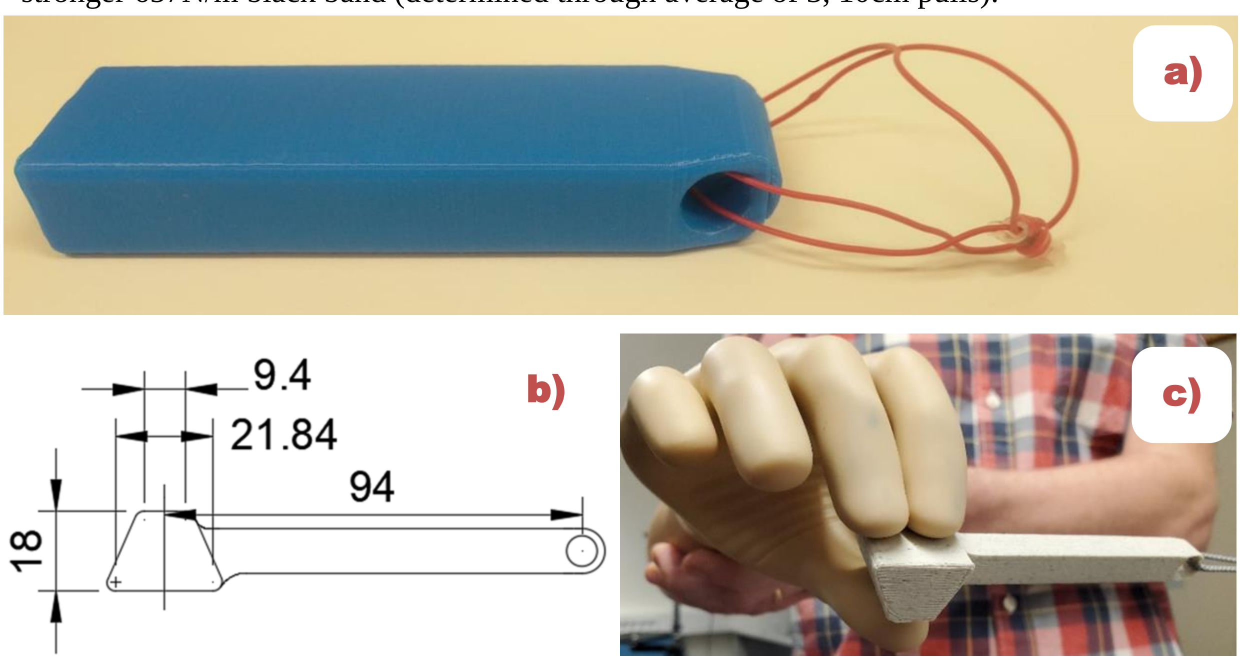

Figure 6 a) Training block, b) trial totem detail, c) view of the trial totem grasped by the prosthetic before a pull attempt.

2.4 Proof of Concept

2.4.1 Slip Forces Testing

The relationship between the grip strength, and force-to-slip needed to be characterized in order to effectively understand chance of slip. A protocol was devised and run to find the forces at which slip would occur in the prosthesis. The set-up of the investigation was as follows: the trial totem was attached to a force gauge using an exercise elastic, the training block was gripped by the prosthesis at a predetermined grip force, and the prosthesis would be slowly pulled away from the force gauge by the researcher to induce a slip. Pulls were concluded once the prosthesis lost control of the totem. Maximum achieved force, elastic type, and grip strength were recorded for each trial; 40 trials were completed for each combination of grip strength and elastic type, 160 trials in total, no randomization was undertaken.

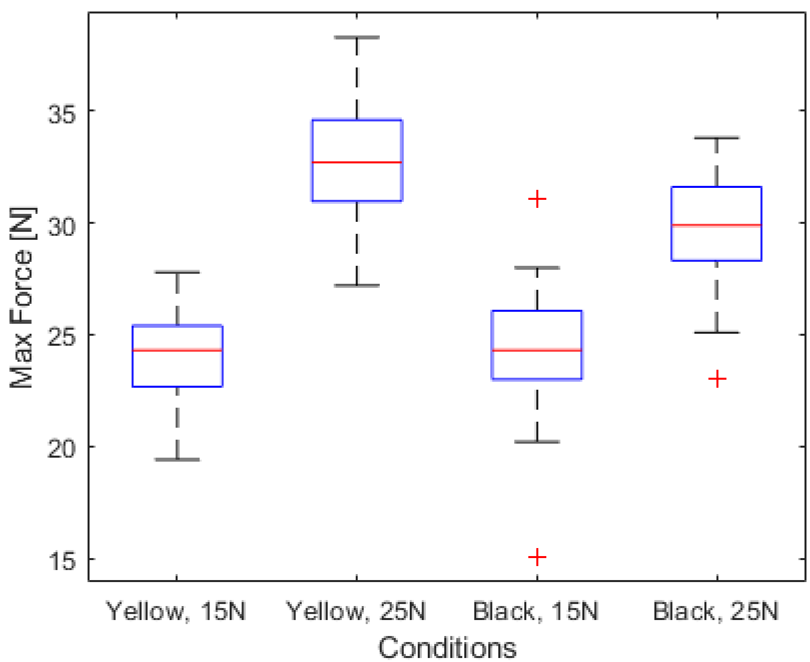

Figure 7 Maximum force results of pulling the test block until visible slip was observed, sorted by elastic and grip strengths used.

The average maximum force observed in low grip trials was 24.21N, and the average high grip observed was 31.22N, greater stratification can be seen in Figure 7. The force is very consistent between elastics in the low strength grip, however in the high strength grip a 3.00N difference in maximum forces was observed, the light elastic resulting in the highest average forces. While the data showed a 7.00N average difference between 15N, and 25N grips, the range of each grouping was large enough to create overlap between grip strengths.

This investigation was valuable as it changed the direction of experimental design. It was expected that slip would occur at a near constant force for each different grip strength. The variance in slip forces is likely due to slight changes in pull attempt speed, and by inconsistencies between grasps, both of which would also occur in participant-trials.

2.4.2 Bespoke Slip Prediction System

The proof-of-concept version of slip prediction was custom-built to prove an understanding of slip was possible to ascertain with the existing sensor array. This version also served to improve the understanding of what characterizes the slip event in the sensor domain. A series of gates each representing an observed characteristic of slip were programmed, and when each condition was met, the system reported a slip. The gates were determined heuristically, and were codified as follows:

1. The torque sensor is reporting at least 5N; below this threshold shear sensors could not always detect shear, rendering their values unreliable.

2. XOR shear sensor is reporting 0 shear; due to glove stretch mechanics, upon firm grasping the shear sensors would typically report two shear values in opposite directions, shear only present in one direction indicated a significant bias of force applied to one direction.

3. The ratio of the normal force sensor and the torque sensor is less than 2 and greater than 0; it is expected that normal force at the finger tips and applied force at the joint are roughly proportional, however dynamics of the silicone glove altered this.

4. The differentiated and smoothed (5-sample moving average) normal sensor response has been negative for the last four samples (83.3Hz), and one of the similarly differentiated and smoothed shear sensor responses is greater than -0.4; due to glove movement, as slip begins to occur the normal sensor reports decreasing values and the shear sensor reports approximately even or increasing values.

The performance of these handpicked features was very closely tied to the mechanics of the silicon glove sliding over the sensor. This system featured elements of both friction-cone and force differentiation methods of slip detection.

The bespoke slip system was deemed to have acceptable performance as a benchtop slip detection algorithm. Major shortcomings were that it was not easily tunable, and was comprised of hand-picked thresholds specific to the SensorHand. This prediction system was thus limited in widespread applicability as a generalizable solution, and would drastically increase the time to create such a predictor for future hands. The inability to tune the detector resulted in reliable detection of slips once they had already begun to occur, rather than predict slips before they began. A new creation method for a slip-prediction system was implemented, and was easily applied to a variety of different hands, and was tunable to different slip prediction confidences.

2.5 Software Developments

2.5.1 Predictor

The proposed predictor creation methodology used machine learning to perform sensory synthesis with the available data, in order to create a new sense of slip prediction. Design constraints dictated that the finished model should be as computationally simple as possible, and should be independent of the mechanics of the prosthetic. Both of these constraints would allow the proposed predictor to be replicated on a wider set of prosthetics and controllers. A trade-off presented itself between these design constraints: linear SVM regression was unable to reliably predict slip, and quadratic SVM regression was deemed too complex to easily import to all future firmware platforms, with limited memory.

Linear regression trained through SVM was deemed appropriately complex to easily import to all future firmware platforms, thus the data need to be linearized. The output of the two parallel, uniaxial shear sensors were combined through the absolute magnitude of their subtraction, to synthesize a generalized net magnitude of shear. The negative implications of this were minimal, as directionality was not intended to ever be delivered to the participant; and combining two opposing sensors into one is logical from a computational perspective. The output of the individual collinear shear sensors can be observed Figure 8, to provide an example of their relationship to shear forces. To improve richness of data based on findings from the proof-of-concept model, the first derivative of each input was calculated and also used in regression.

2.5.2 Data Recording and Training

All sensory data were transmitted from the hand into MATLAB, and labels of ‘stable’ and ‘unstable/slipping’ were manually applied in real time through keyboard input. The default label was ‘stable’ and ‘unstable/slipping’ was applied at the instant of slip initiation. The label would apply to the previous three data points, but not the current one, all data collected without a label were discarded. The training block was connected to an elastic and grasped using the SensorHand mounted into a prosthetic arm. Slips were created by manually pulling the arm against the elastic clamped to a benchtop.

The following data collection protocol was performed to generate the regressor training set. Labels were applied to pulling tasks, at grasp forces of 15N, 20N, 25N, 30N, pulling

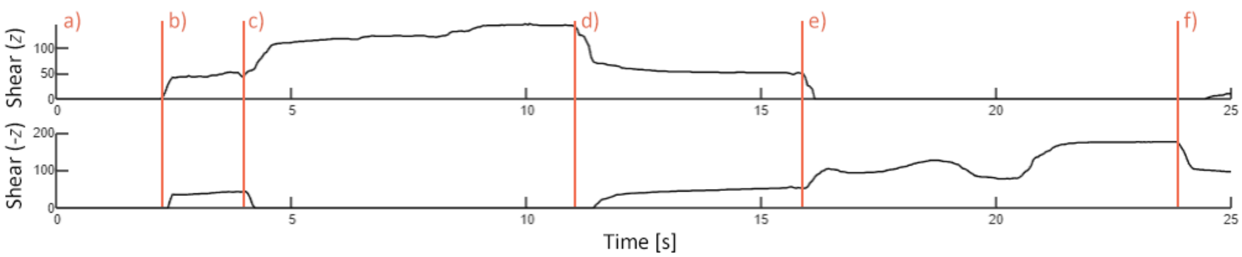

Figure 8 Response from the collinear but opposing shear sensors showing activation in both directions when no net shear is applied. a) Before grip, b) grip initiated, c) object pulled to right of hand, d) object returned to neutral grip, e) object pulled to left of hand, f) object returning to neutral grip.

from the left and right side of the hand, twice each. A fully labelled pull task consisted of applying a label at each of the following stages: grab object, apply a small amount of shear, increase shear, perform two slips, hold position after second slip, decrease shear, decrease shear to very low level. Outside of the described protocol, ten 'stable' labels were applied to the prosthesis sitting motionless with the hand empty and open.

Linear SVM training was completed using the MATLAB Statistics and Machine Learning Toolbox, using equal weightings for 'slip' and 'unstable/slipping' labels. The model was initially validated through online classification running in MATLAB, using values streamed from the prosthesis. The SVM generated regression values were then encoded on the embedded prosthetic control unit for experimental use.

2.5.3 Experimental Control Scheme

During the experiment, grip strength in each attempt was dictated by a randomized protocol, and blinded from the participant. This required a new form of control scheme which could accept a maximum grip force from the researcher for each attempt. Existing control of the prosthesis was force-modulation, proportional to EMG activity. It was not possible to simply enter limits into the controller, as the grip would routinely overshoot before sensory feedback could stop the motion. The hand provided feedback at a rate of 15ms (~67Hz), and the inertia of the hand often caused grip overshoot. This was exacerbated by intense nonlinearities in hand speed as a function of current position, and in maximum hand closing force as a function of both speed and input signal. To illustrate: the already closed hand receiving a close 50% signal may reach 30N, however a fully open hand snapping closed on a block with the same 50% signal may reach 70N.

The control scheme used for the experiment to reach the target force was developed as a binary-input, quasi-proportional controller. It was binary controlled as EMG input from open or close channels were on, or off, with no interest in magnitude of signal. This was done in an effort to reduce the physical strain on the participants, as this way the muscle activations did not need to be very strong. Upon EMG close intention, the controller would send a small close signal to the prosthetic which would gradually increase in strength over the duration of

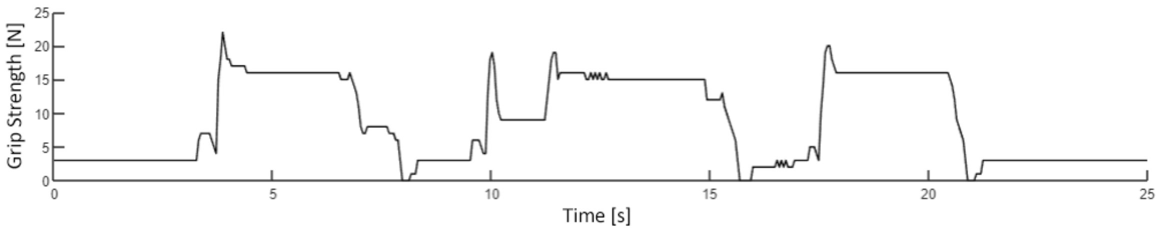

Figure 9 Grip force across three 15N ±10% grasps, showing effect of the overshoot and correction.

the EMG close intention. Participants were instructed to continuously maintain the close intention, and the controller would automatically increase closing force, and perform overshoot correction. Recorded normal force in three consecutive grasps is shown in Figure 9 to illustrate the overshoot correction. During force overshoot, while the close-hand intention was still performed by the participant, the prosthetic close hand signal was reset to its base value, and a similar gradual increase would occur in the open-hand signal. Opening strength would increase until the force decreased to the target range, or below the target, in which case closing would recommence. When target grip was reached for five consecutive sensory messages, all movement in the prosthesis was disabled until the user performed an open-hand action. This was to prevent against accidental prosthetic movement during the attempt, where forces often reported outside of the target window. Code of the aforementioned control system can be seen in Appendix A.

2.6 Experimental Design

2.6.1 Task Protocol

The experiment was designed to test the impact of the slip prediction and notification system, by creating scenarios in which the participant could not be sure of the nature of their grasp of the target object. This was achieved through the experiment-mode prosthetic controller, in which maximum force at the finger tips was controlled by the researcher. Forces were limited to either 15N or 25N, each with ±10% accuracy. Maximum grip force of 25N was deemed appropriate for the number of trials performed, as to not exhaust the participant. To induce slip, participants were instructed to pull the trial totem as far as they could without slipping,

Figure 10 View of experimental set-up from perspective of researcher (above), and participant (below). The opaque divider blinds participant to which elastic is in use, and force results from each trial.

against increasing resistance from one of two potential elastic bands. A force gauge was mounted to the bench top at the other side of the elastic, recording maximum force for the trial. Factors which may give away information on the stability of grasp where blinded from the participant. This experimental set-up can be seen in Figure 10 from the perspective of both the participant and the researcher. Grip force was sent to the controller over Bluetooth, and the elastics and force gauge were behind an opaque barrier. Maximum grip strength, and bands were blinded from the participants, and followed a randomized order unique per participant. In the case of consecutive trials without change, the action of changing a band or entering a new force were mimicked by the researchers. Two bands, and two grip strengths, each with 10 attempts resulted in 40 total attempts, with a randomized order.

Three slip notification schemes were deployed to analyze the effect on amputee movement execution, *no stimulation (no stim)*, was used as a baseline of performance. *Spike stimulation*, delivered a single quick and strong pulse when the regressor reported an imminent slip prediction of 0.4. *Amplitude modulation stimulation*, began continuous stimulation when the regressor reported 0.1 slip prediction and proportionally increased stimulation amplitude with prediction regression, reaching maximum stimulation amplitude at 0.9 slip prediction. Slip regression of 0.4 was heuristically determined during model validation to be used in the spike stimulation condition, as this value was reached after significant load was applied to the target object, and was reliably before slip. Each feedback condition was performed sequentially in unique orders per participant, resulting in 120 total pull attempts per participant.

The number of feedback conditions is greater than the number of participants in the study. As such, not every combination order of the feedback conditions could be attempted, one condition was performed twice in each slot of 1st, 2nd, 3rd. This was sub-optimal, however was deemed necessary to minimize learning-effects and stimulation condition effects from interacting. The orders of tests for each participant are shown in Table 2. The complete ordered list of condition and feedback orders can be found in Appendix B.

After readying the prosthetic for the experiment, the participants were given unlimited and undirected time to familiarize themselves with the new deterministic-force control and stimulation. This undirected time was repeated at the start of every new stimulation condition so that the participants could familiarize to and learn when the stimulation occurs. During these periods the hand was set to reach 20N (± 10%), and the participants could pull at the totem with both elastics connected to it, to prevent familiarization with the grasp force conditions. Due to the highly discretized nature of the experiment, participants were instructed that they could take rests whenever wanted, rests were additionally taken between

Table 2 Order of each stimulation condition tested for each participant.

	P1	*P2*	*P3*	*P4*
1st	No Stim	No Stim	Spike	Amplitude
2nd	Spike	Amplitude	No Stim	Spike
3rd	Amplitude	Spike	Amplitude	No Stim

stimulation conditions. After all attempts were completed, a short casual interview was run while their prosthetic was returned to its pre-experiment settings.

2.6.2 Interview

Following the completion of every stimulation condition, a semi-structured interview was performed, ending with an open dialogue on the system in question. While all participants' primary language was Swedish, all were capable enough in English for the interview to proceed without intervention from bilingual researchers. The format of the interview was shaped by the following questions:

1. What was your strategy to prevent the object from slipping?
2. How much did you rely on the algorithm feedback?
3. Did the feedback feel surprising? Or did you receive it when it was expected?
4. Do you think the feedback came too soon? Too late?
5. Did you feel in-control of the block, or did it surprise you?

No formal codifying of responses was performed. These questions were performed to understand the interests the individual participants have in using a system such as this in their daily life. This information is useful for shaping future development, and assessing future participant recruitment in longer-term slip prediction studies.

3. Results

3.1 Slip Prediction Model Generation

3.1.1 Benchtop Model Validation

The first objective of this work was validating the prosthetic-independent methodology for creating a slip prediction model which could be applied to multiple different hands. The finalized model was created using a linear SVM and hand data which were linearized before entering the model, further details in Section 2.5.

$$X = b + \sum_{i=1}^{6} \beta_i \left[{(x_i - \mu_i)}/{\sigma_i} \right] \tag{2}$$

Table 3 Regression values generated through SVM training, rounded to two decimals for brevity.

$\boldsymbol{x = \{Torque, Torque', Normal, Normal', Shear, Shear'\}}$
$\boldsymbol{\beta/\sigma = \{-0.025, 0.0059, -0.0045, -0.0064, 0.012, 0.0005\}}$
$\boldsymbol{\mu = \{17.39, -0.06, 102.51, -0.27, 85.62, 0.00\}}$
$\boldsymbol{b = 0.18}$

The SVM regression calculation is shown again for convenience as equation (2), using the values found in Table 3, presented to illustrate general importance of each system input. Positive shear is highly correlated with slip, and joint torque is negatively correlated with slip. Additionally, slip is increasingly likely as the first derivative of the normal force decreases, which indicates an increase in the likelihood of slip, as the normal force decreases. These findings align with the bespoke proof of concept system of hand-picked slip signifiers. When analyzing the relative weights of the coefficients, it is important to note torque sensor values appeared in the (13, 27) range, while the normal and synthesized shear sensors common range is (0, 200). This partly explains the relatively larger torque-coefficient magnitude when compared to the normal and shear, as the normal and shear coefficients were found in relation to much higher sensory inputs.

The resulting slip prediction model displayed near complete slip prediction capability under ideal conditions: target object of similar thickness to training object, and tension applied perpendicular to the thumb. Figure 11 shows regression of slip prediction under ideal circumstances after object grab, induced slip to the right, and then induced slip to the left. If the tension was not applied directly perpendicular to the thumb, collinear with the shear sensors, the accuracy of the model would sharply drop off. The shear sensors only detect shear along one axis, their response is proportional to the cosine of the angle between the string tension and shear sensor. This was an issue during participant trials which resulted in the calculated prediction to be too low.

3.1.2 Participant Model Validation

It was found that the participants were able to move the prosthesis in order to generate a prediction of slip much more effectively with the presence of stimulation feedback. The no-

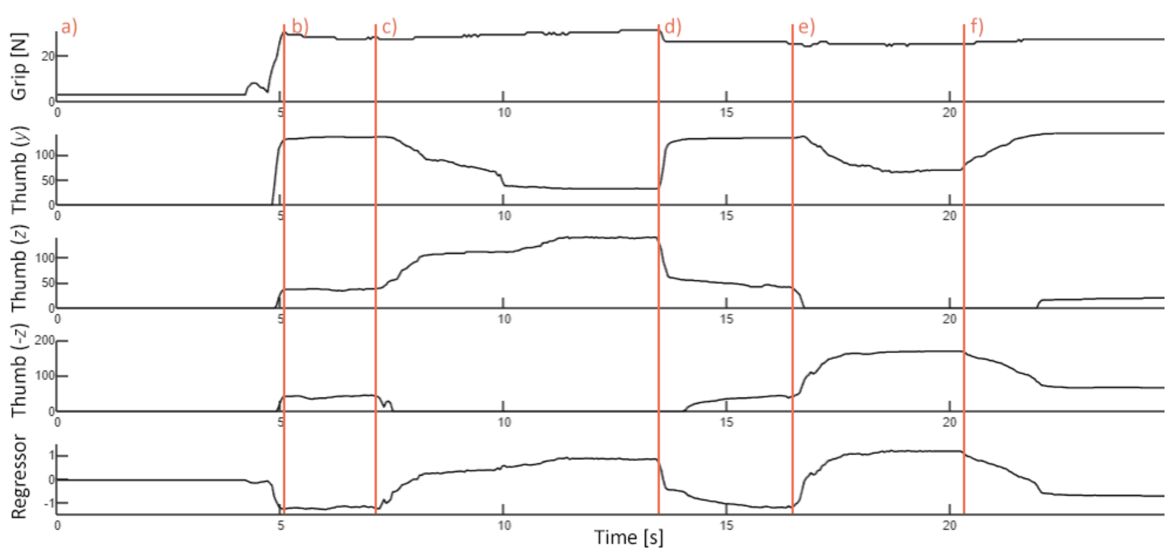

Figure 11 Visual example of the relation between each sensor value and regressor output across grasp and pull movements. a) Grasping object, b) neutral grasp, c) pulling object to the right, d) returning to neutral grasp, e) pulling object to the left, f) returning to neutral grasp.

stim condition attempts had 65 (41%) total slip predictions, and both the spike and amplitude stimulation conditions each had 111 (69%) total predictions. A learning effect was also visible in number of predictions: 51% predictions in each participants' first condition, 58% second, and 61% third. These percentages were calculated after the duplicated stimulation condition per order was averaged together, to reduce interference between order and condition. The stimulation condition can be seen to have an impact in addition to that of order, on participants' ability to generate accurate predictions.

The experiment was designed to create instances of slip/near-slip, it is reasonable to assume that each attempt should have generated a slip prediction. This indicates the model had an accuracy of 69% during conditions with stimulation, which is the state most relevant to daily life, and 60% overall (287 predictions for 480 attempts). Actual totem slips were predicted before they occurred with a 67% accuracy.

Figure 12 shows two attempts from different participants, at 15N grasp force, and amplitude feedback; the stimulation was delivered, and pulling ended before slip occurred; max force for this trial was 20.1N and 11.3N respectively. The high grip force spike near the start of the trial is an artifact of the deterministic-force controller, which often overshoots, and then corrects itself.

There was an observed failure of the system to predict slips during trials where the target object was misaligned in the grasp. Misalignment within the grasp was made common due to the design of the totem to just fit the fingers of the prosthetic. These failures of prediction took the form of a clear local maxima of prediction (Figure 13, occurring between 0.5-2 second marks), however remaining below the threshold for prediction.

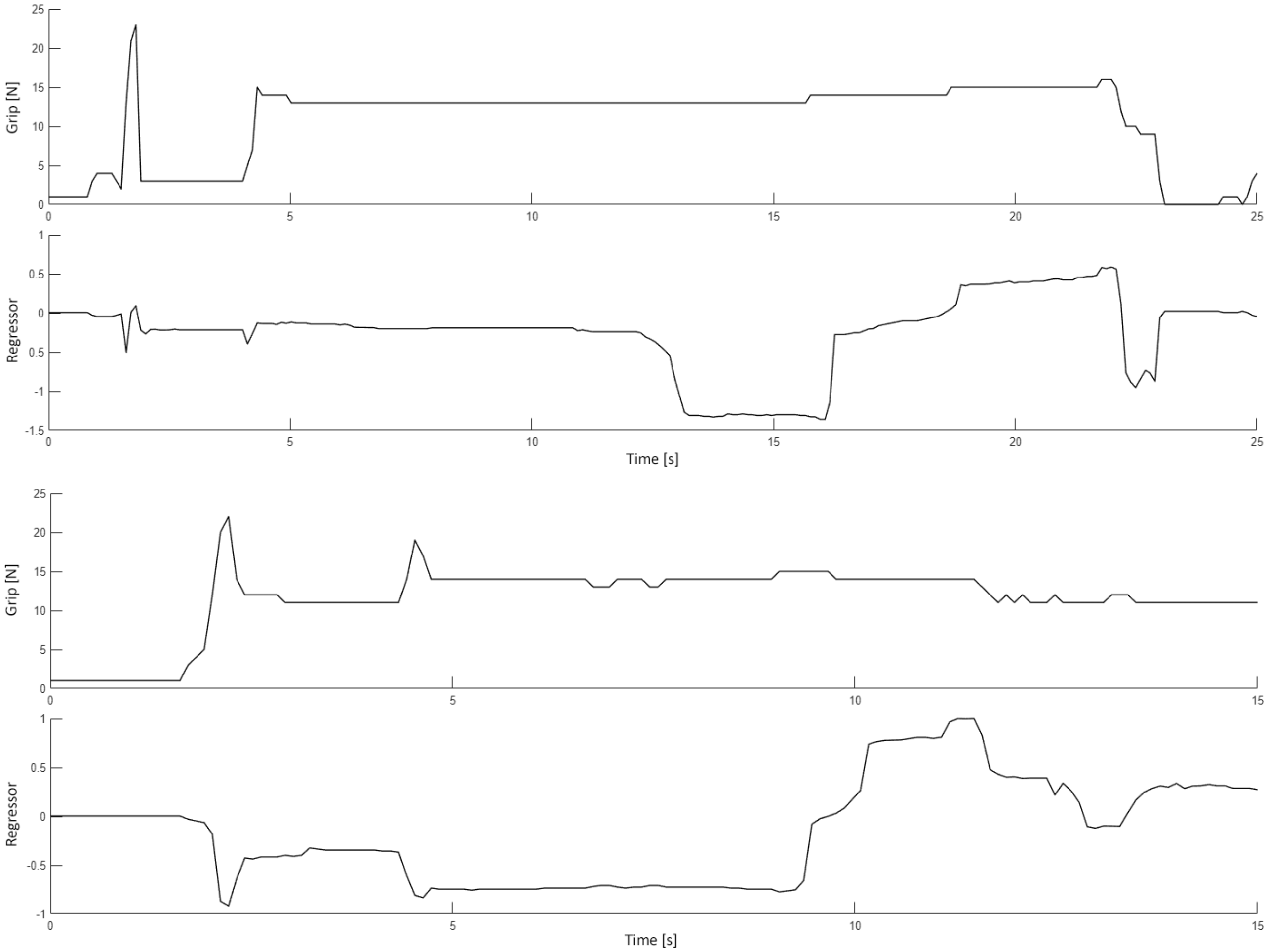

Figure 12 Two examples of grip and regressor output from two attempts from different participants which ended in a self-declared maximum pull force, using amplitude stim, at 15N grip.

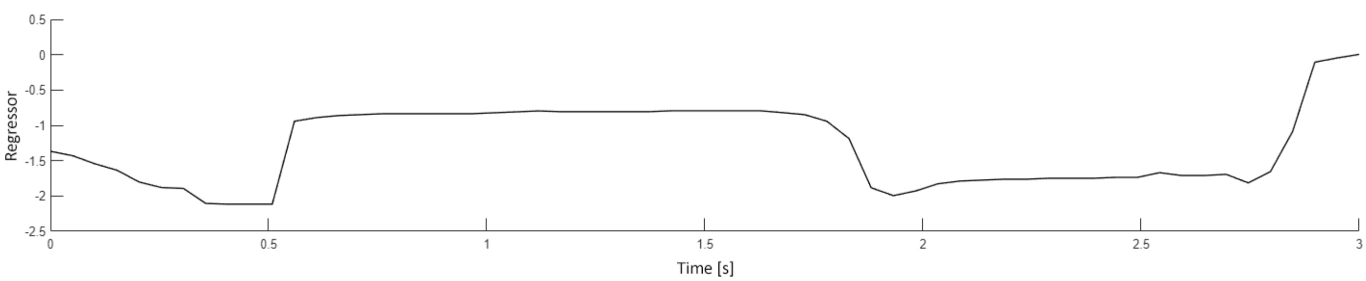

Figure 13 Regressor output of a pull attempt with the totem misaligned in grasp, local maxima of slip prediction is clearly visible from 0.5-2 seconds, however it is all below activation threshold.

3.2 Impact of Slip Prediction on Amputee Movement

3.2.1 Impact on Slip Occurrence

Across all participants and conditions, there were 121 (25%) slips, as broken down over stimulation conditions: 53 (44%) occurred during no-stim, 37 (31%) occurred during spike, and 31 (26%) occurred during amplitude stimulation. A Kruskal-Wallis test was performed, across all condition factor levels. The test was applied using MATLAB's '*kruskalwallis'* function with the assumption that the levels were independent from each other. No condition was found to have a statistically significant differing impact on number of slips, groupings shown in Figure 14. Of the 287 total predictions, 222 (77%) predictions of slip occurred during a stimulation enabled condition, of those only 49 (22%) proceeded to slip, full breakdown shown in Table 4.

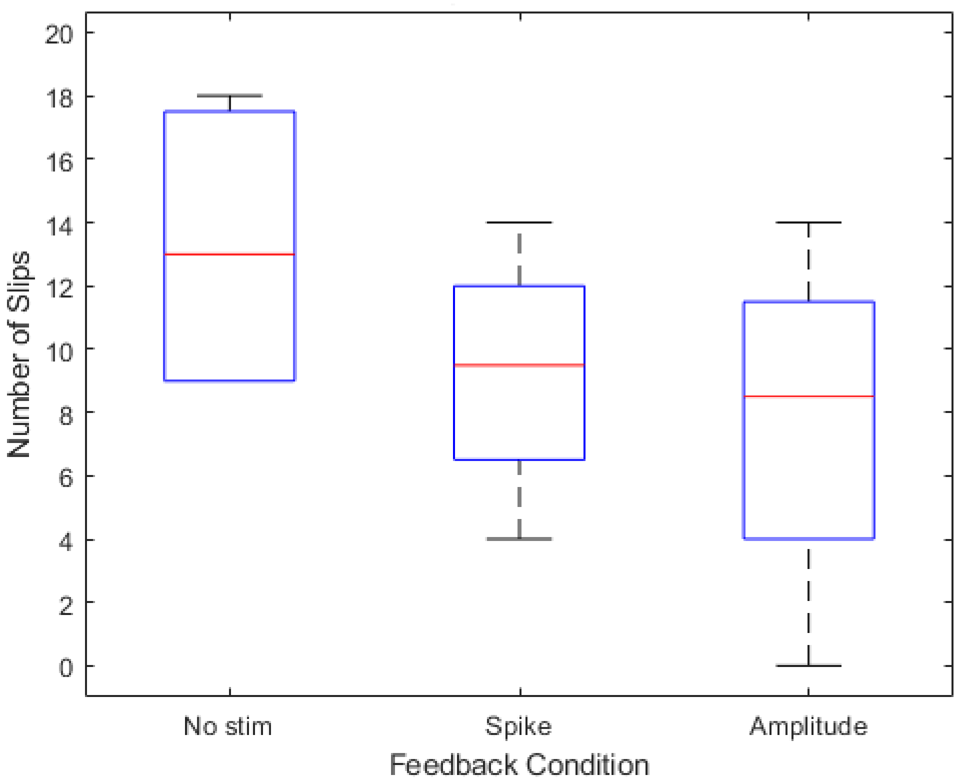

Figure 14 Slip sums across all participants by feedback condition.

Table 4 Summations of slips and predictions by stimulation condition.

Stim Result	*Predicted & slipped*	*Unpredicted & slipped*	*Predicted & non-slipped*	*No prediction & non-slipped*	*Slipped total*	*Predicted total*
No Stim	32	21	33	74	53	65
Spike	27	10	84	39	37	111
Amplitude	22	9	89	40	31	111

A learning effect related to slip mitigation was discovered in the data: 51 (42%) slips occurred in the first condition, 40 (33%) in the second, and 30 (25%) in the last. Slips by participant, condition, and order are presented in Figure 15. Averaging the number of slips of the duplicated feedback condition in each order placement leads to: 39.5 no-stim slips, 25.5 spike, and 22.5 amplitude; and by order: 37.5 first, 28.5 second, and 21.5 third. Clear condition and learning effects have been found, however potential entanglement does not significantly lessen their meaning.

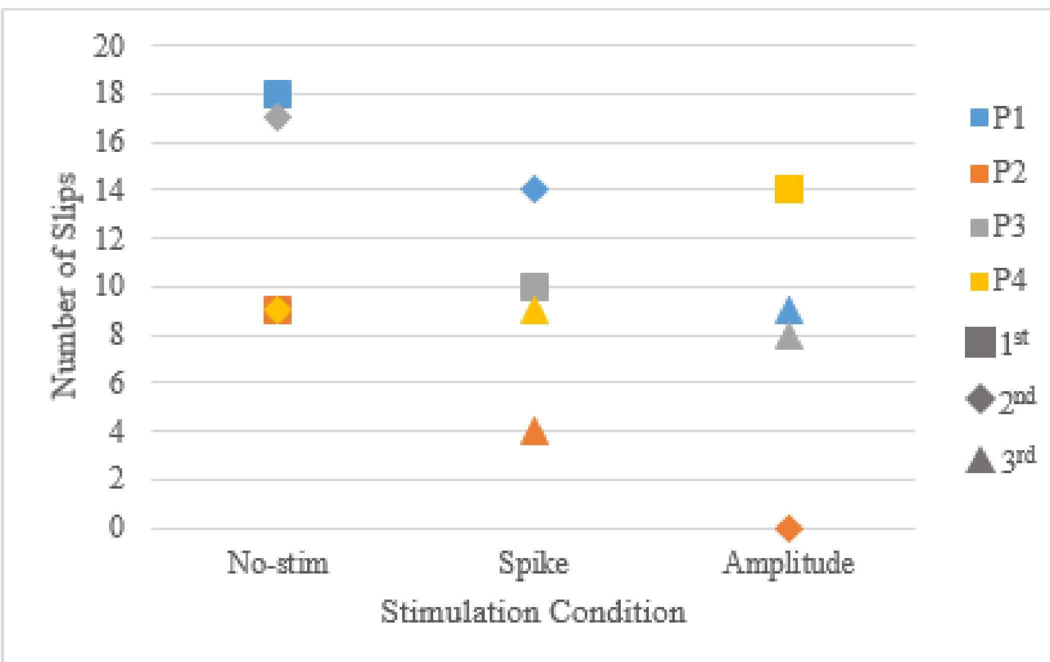

Figure 15 Number of slips in each condition, per order (shape) and participant (colour).

3.2.2 Impact on Force Achieved

Student's t-tests were applied using the MATLAB '*ttest2*' under the assumption of unequal variances, between forces by feedback condition, and between grips within feedback condition. No significant change in average forces was observed with feedback compared to without shown in Figure 16 (left), regardless of slip outcome. Significant differences were found in force between the low and high strength grips in all stimulation conditions, shown in Figure 16 (right). The median difference in achieved forces between the two grip strengths were 3.0N in no stim, 5.9N in spike, and 7.0N in amplitude. Differences between low-grip and high-grip data were found to be affected by stimulation condition. Stimulation was shown to improve separability of the force outcomes between grips through: increased distance between the average forces of each grip, and reduced force variance within each grip, shown in Table 5. Distinction between low and high grip forces in motion planning is used as a proxy for the effectiveness of grip stability translation to the participant.

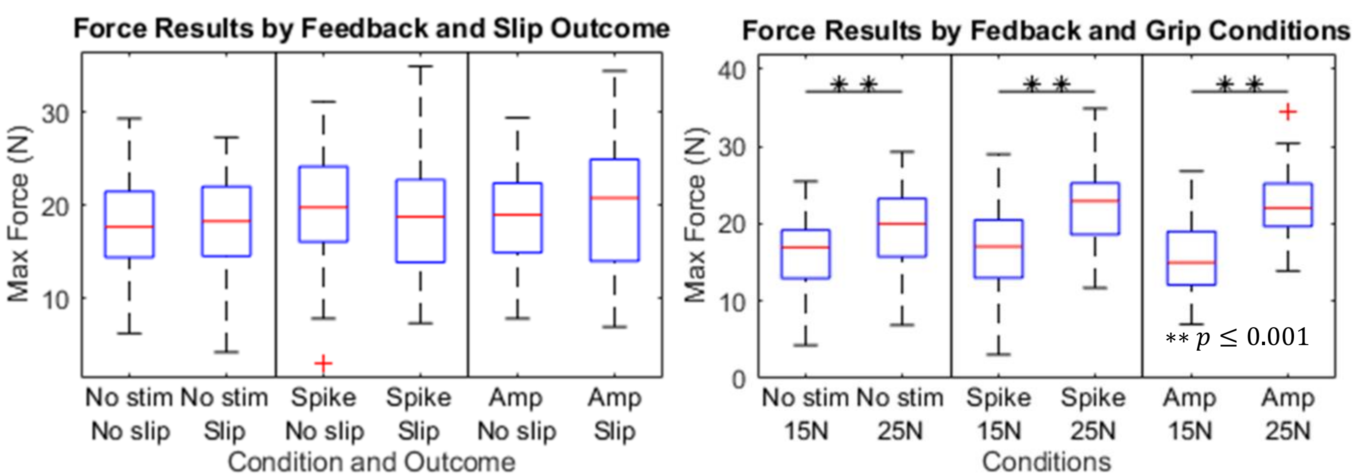

Figure 16 Maximum force per attempt between feedback condition and success (left), and feedback condition and grip force (right).

Table 5 Impact of feedback conditions on movement planning, shown by maximum force achieved.

	Difference in Group Average Force Between Grip Conditions [N]			Average Variance of Within Each Grip Condition [N]		
	No-stim	Spike	Amp	No-stim	Spike	Amp
Participant 1	6.185	6.415	6.530	19.332	9.995	17.857
Participant 2	3.880	9.000	4.445	8.398	8.540	7.736
Participant 3	0.465	5.115	10.200	13.400	17.617	7.995
Participant 4	3.160	1.450	5.160	8.807	10.238	13.088
Average	3.423	5.495	6.584	12.484	11.597	11.669
Improvement		60.56%	92.37%		7.10%	6.53%

Student's t-tests were applied to the successful pull attempts to assess the significance of the separation between grip conditions. The tests were applied with MATLAB's '*ttest2*' function, significance is shown in Figure 17 showing confidences of $p > 0.05$, $p \leq 0.05$, and $p \leq 0.001$. Each amplitude stimulation condition showed some degree of significance, P4's spike condition showed no significance, and P1 and P3's no stim condition showed no significance. Comparisons of between-subject differences in force groupings was not performed due to different pull-force baselines. This shows that even when the participant can see, hear, and freely move the prosthesis, the neural stimulation feedback conditions provide additional and actionable information with effects on motion planning.

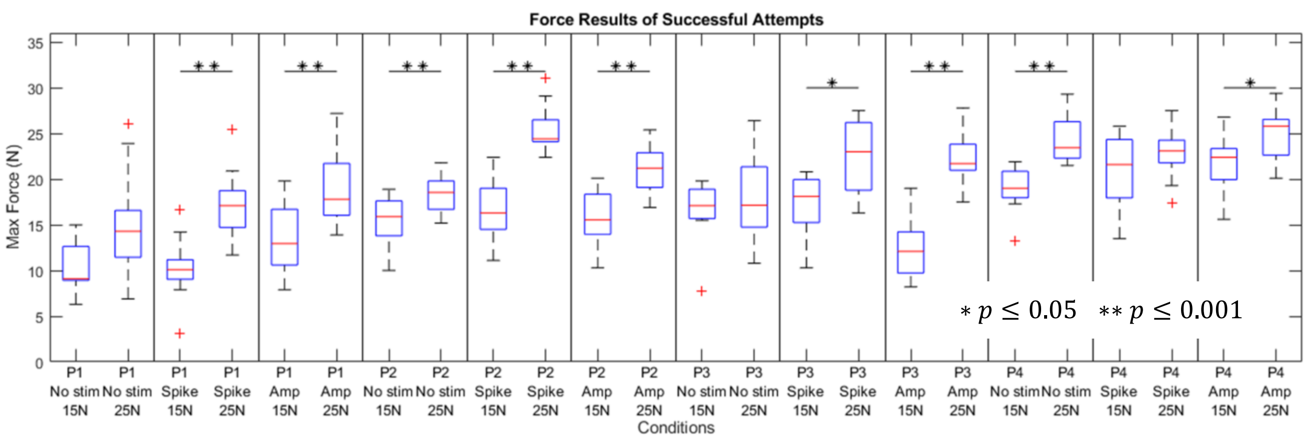

Figure 17 Achieved forces of the successful attempts, shown by each participant-feedback-grip condition.

Qualitative Results

3.2.3 Interview Results

Each experiment session ended with a semi-structured open and candid conversation regarding the participants' thoughts on the prediction system and feedback modalities. Self-reported reliance levels of different senses (Table 6) are very telling, however they do not provide a full picture, and no relation could be found from their reported strategy and their performance measured by slips or max force.

Table 6 Self-reported reliance on feedback, vision, or mechanical senses from each participant, results given on an increasing 0 to 10 scale.

Sense [0-10]	*P1*	*P2*	*P3*	*P4*
Prediction Feedback	7	5	1	2
Vision	4	9-10	8	9
Muscle/Bone Forces	3	8	4	5

Responses to "What was your strategy to prevent the object from slipping?" from each participant were:

1. "Directly when I feel the highest [stimulation], a little bit with the eye."-P1
2. "Mostly visual… It's so new."-P2
3. "Look at the object."-P3
4. "Feel, observe, and hear [in that order], feel is from sensory feedback. In 30% of the tests I didn't feel anything, but maybe I did. I received the feedback before I saw any [slips], the feedback is quite quick when I feel it. If I could feel the sensory feedback in every round I think I would never slip."-P4.

Responses to "Did the feedback feel surprising? Or did you receive it when it was expected?" were:

1. “When I expected it, but sometimes you must find the direction.”-P1
2. “It was not surprising.”-P2
3. “No, because then it would not have slipped. I cannot say that because I did not feel it.”-P3
4. “I think I received it when I should have”-P4

Responses to “Do you think the feedback came too soon? Too late?” were:

1. "No I think it is in the right time.” –P1
2. “[I wish] it came sooner.” –P2
3. "Too late, because I did not feel it.” –P3
4. “If the meaning was to not drop objects it was correct, but I can push the object a little bit further each time after feeling the feedback before it slips.” –P4

Responses to “Did you feel in-control of the block, or did it surprise you?” were:

1. "I feel in control.” –P1
2. “No, I think I had some control.” –P2
3. "Sometimes it surprised me, I mean if I did the- I could use quite a lot of force and it did not slip, and then the next run it might be slipping directly. I don’t know if it was the changing of the rubber band or what it was.” –P3
4. “No I felt in control.” –P4

In conversation after the predetermined questions, only P3 and P4 had additional comments on the experiment or system. P3 stated his disdain for the force control system, and emphasized that there would be no level of sensory feedback quality that would justify changing his control to this style from speed control. The lack of direct control over the position and speed of the prosthetic caused by the force controller was very disturbing, and had requested breaks through the experiment to deal with that discomfort. P4 stated “This is the only part of the whole sensory feedback [obscenity] that I think there may be some value in, not how hard you are holding." Indicating his preference toward this experimental system over what was being was currently deployed to his prosthesis out of the lab. A week after the study, in unrelated communication with the lab, P4 again stated their interest in continued work in this direction and their desire to use such feedback at home. These are very strong indicators that there is a need by prosthetic users to be provided richer information about the nature of their grasps in daily life.

3.2.4 **Participant Perspectives**

3.2.4.1 Participant 1

Participant 1 reported the range of stimulation to be from 1 to 5 out of 10 across the whole amplitude stimulation spectrum; the spike stimulation pulse was also reported at 5 out of 10. P1 stated reliance on the stimulation system, saying they decided when to stop pulling "Directly when I feel the highest [stimulation] a little bit with the eye." P1 also made comment on having a difficult time keeping the tension in the right direction, saying that he would pull the block and then rotate the hand under tension to check more than one direction. P1 performed the last two conditions on the following day of the first due to time constraints. P1 also rotated the prosthetic hand in its mount half of a rotation after attempt 19, and returned it to original positioning on attempt 43.

3.2.4.2 Participant 2

P2 was optimistic about using such a system, but reported that he did not have enough experience with it yet to rely on it, and mostly relied on vision. P2 also reported the stimulation was not surprising when it occurred, but that he wished it came earlier. The difference between P2's no-stim first condition and amplitude second condition was striking, with 9 slips in no-stim, and 0 slips in the amplitude. The observed strategy was ending the attempt as soon as the stimulation first occurred. Despite this conservative approach, the maximum forces recorded were comparable to the other conditions and participants.

3.2.4.3 Participant 3

P3 is the only participant who does not use sensory feedback from the prosthesis on a daily basis, citing inconsistent sensations, and confusion between stimulation and strong phantom sensations. Due to the confusion between stimulation and phantom sensations, it was not possible to establish reliable numeric scores for each sensation intensity. P3 was very explicit in his feedback that he entirely relied on vision. Through the trials he would often say of his own volition, or after being asked, that he was unsure if he was receiving any stimulation. However, the performance of P3 is in line with the rest of the participants and indicates improvement in performance in relation to richness of feedback, seen across his conditions: 1st – spike: 10 slips, 2nd – no stim: 17 slips, 3rd – amplitude: 8 slips. After the second condition P3 was frustrated at the force-control scheme, and requested to spread his participation out over two days, and returned 5 days later for the last condition.

It is clear that P3 was very well blinded to the grip strength of the hand, and reported so himself in the interview: “I could use quite a lot of force and it did not slip, and then the next run it might be slipping directly. I don’t know if it was the changing of the rubber band or what it was.” He was the only participant where the median pull force for no stim low grip strength was greater than the high grip strength, by 0.8N. Contrasting this, grip condition force differences were found of 4.6N for spike, and 9.45N for amplitude stimulations. This is possibly an indication that a subconscious success of the prediction’s neural stimulation was observed.

3.2.4.4 Participant 4

P4 reported amplitude stimulation sensations between 3 and 7 out of 10, and spike stimulation at 7 out of ten. He was the most interested in the development of this functionality for the prosthesis, stating unprompted “This is the only part of the whole sensory feedback [obscenity] that I think there may be some value in, not how hard you are holding.” P4’s self-declared results from the questionnaire immediately contradict each other, first stating 2/10 reliance on the predictor, then “Feel, observe, and hear [in that order], feel is from sensory feedback.” Behavior and comments from P4 indicated a greater interest in attempting to learn how the system worked rather than prevent slips, eventually describing the stimulation timing with “If the meaning was to not drop objects it was correct, but I can push the object a little bit further each time after feeling the feedback before it slips.” After pull 70, he began pushing the prosthesis with his hip to assist his tiring shoulder, which impacted the angle of the prosthesis, decreasing number of predicted slips. P4 indicated during the interview, and weeks later during an unrelated follow-up that he would be interested in trying this system out of the lab.

4. Discussion

4.1 Summary of Key Findings

From experimental results, we have established the following:

I. The linear SVM prediction system detected 69% of near-slip events when used by a participant with stimulation enabled.

II. The decrease in number of slips from 53 during no stim, to 37 during spike, and 31 during amplitude stimulation was not statistically significant.

III. There is a 60.56%, and 92.37% increase in separations of force outcomes between grip strengths in spike and amplitude stimulations over no stim.

IV. There is a 7.10% and 6.53% decrease in average variance of force groupings in spike and amplitude stimulations over no stim.

V. The differences in force results between grip conditions are significant in all participants using amplitude, three out of four using spike, and two out of four using no stim feedback.

4.2 Predictor and Prosthesis

The performance of the slip prediction model was limited by the highly specific pulling angle, due to the uniaxial shear sensor. Even with the very narrow receptive field, slips were predicted and behaviour was observed to have changed as a result. This is very promising to future slip prediction work, as future prosthetics with a wider array of sensors may easily address this issue.

The range of forces tested in this study (13N, 27N) has been underrepresented in previous work in this field. Most prior work tested slip detection at forces under 7N, which is much lower than the potential grip force of prosthetic hands on the market today. Maximum grip forced used (25N) was confirmed to be an appropriate grip strength for the number of repetitions; all participants took breaks between conditions, but few breaks within condition.

Additionally, due to the repeated lateral rotation nature of the experiment, participants often helped push the prosthetic against the elastic with their hip. Testing larger forces is not feasible with the shoulder lateral rotation used here.

4.3 Impact of Slip Prediction

The repeated pattern observed across the results is that the largest difference in performance measures exists between with-feedback and without-feedback; with-feedback showing improved performance outcomes. This is seen in number of slip predictions, number of slips, and statistical significance in the differences between grip levels. A similar trend also shows that within feedback, amplitude feedback tends to surpass spike feedback by a smaller margin. This is observable in the aforementioned outcomes, as well as in average grouping distance. Force groupings at each grip level contradict this trend, however by less than a single percentage point.

This may be attributed to the richness of data provided by a continuous multi-level sensation rather than a binary notification which occurs once. It is likely that if additional feedback modalities were tested, the performance would also be proportional to the richness of information delivered to the participant. There remains much work to be done in the field of peripheral nervous system stimulation, in providing richer and more biomimetic sensations.

Despite the trend showing amplitude outperforming spike stimulation, results indicate that individual participants demonstrated different relationships to each form of feedback. For example, P2 produced a force grouping spread of 9N in spike, compared to 4.44N in amplitude; and P1 showed average variance of 9.99N in spike, compared to 17.86N in amplitude feedback. This indicates potential value in providing users with options as to how they receive stimulation for optimal use.

Without feedback grip levels showed a 3.0N grouping average separation, indicating that through blinding participants still had baseline insights into the strength/stability of the grip. The baseline understanding of grip capability was likely founded on auditory feedback, observing micro-movements pre-slip, or feeling minute changes though osseovibration. These sensations are present in activities of daily life thus their inclusion was critical, as blinding or acoustically isolating participants would likely result in an overstated impact of slip stimulation. Stimulation increased the grouping separation by 2.9N (96.67%) and 4.0N (120%) beyond baseline, for spike and amplitude conditions respectively. It is reasonable to infer the increases in spread indicate greater understanding of which grip condition was used, and thus greater understanding of grip stability. This indicates the central thrusts of the experiment were valid, and that even with vision and hearing unaffected, the slip predictor provided an increased sense of grip stability, which led to improved task performance outcomes.

4.4 Limitations

During the experiment, the raw unmodified output of the regression equation determined when stimulation would occur. The raw output proved advantageous over binary output for richer information, however the trial results have shown more work is needed to improve the quality of the outcome. This is most apparent in the no-prediction results where the predictor reaches a local maximum over the pull that is still too low for classification, as shown in **Error! Reference source not found.**. This issue was observed when predicting slip with objects poorly grasped, and when pull force was sufficiently out of alignment with the shear sensors. Future tests should rectify this, by implementing post processing of the regression output to select for local maximums of a certain prominence, rather than pre-determined hardcoded values such as 0.1, 0.4, and 0.9. This may assist in accurate prediction in objects of different size and shape than what was used in the experiment.

The narrow perceptive field of slip direction was a major drawback in the resultant design. The shear reaction force reported to the model was too low when the object was pulled at a deviation from its primary axis. Furthermore, heavy objects in daily life which may be prone to slip, would likely be held hanging from the hand of a straight arm. In this position, slips due to gravity would be directly perpendicular to the ideal angle of perception with the current hardware setup. A sensor array with a set of perpendicular shear sensors could be used for vector addition to handle these perceptive gaps.

Object thickness played a large role in predictor accuracy. Objects thicker than the training block had significantly lower slip predictor outcomes. This may be solved by a diversified training set, a prosthetic hand in which the sensor-object angle of incidence was not affected by hand aperture, or a prosthetic which could transmit finger position. These investigations were deemed out of scope as this was intended as a pilot study into applied slip prediction.

Due to the exploratory nature of this study, additional target materials and shapes were not analyzed. The pre-slip nature of this detection system mitigates much of this risk, it is assumed that any materials with an equal or higher coefficient of static friction will have similar prediction outcomes. Theoretically there should exist a material with such a low friction coefficient that at 15N or 25N grip force, the shear sensors do not register enough reaction to predict the slip potential. The objects used in training and in experiment were smooth PLA, thus it is likely that most objects will satisfy the friction requirements. The silicone cosmetic prosthetic glove, is a secondary synthetic skin sometimes worn over the prosthetic to increase the aesthetic biomimicry of the prosthesis, may also effect prediction accuracy. These gloves are thin, and designed to fit snugly over the prosthetic. It is possible that using cosmetic gloves may distort the sensory patterns to such a degree that the predictor is no longer functional. This may be rectified by treating the prosthetic hand with a cosmetic glove applied as a new prosthesis entirely, and training a with-glove specific predictor.

This is the first work to show the impact of hand-prosthetic slip notification on more than one participant. Large improvement was shown in reduction of slips, however with four participants results could not indicate statistical significance. Longer tests, or tests outside of the lab setting may be what is required to validate efficacy in slip mitigation in a more powerful way.

4.5 Future Developments

Both the quantitative efficacy and qualitative user feedback results, indicate that there is justification in further development of slip prediction for use in daily life. Results of this study show promise for both present and future of prosthetics. Similar slip prediction systems could easily be applied to existing SensorHand Speed prostheses, and promote the inclusion of similar sensory suites in prosthetics currently in development. As both spike and amplitude stimulations were shown to improve slip prevention, it is assumed alternative notification mechanisms would be viable for prosthesis without direct electrical neural stimulation capabilities, such as a vibrotactile response. Prosthetic designs in the future may apply similar prediction techniques, using a wider array of sensors, multiaxial load sensors would be of a particular interest to increase the perceptive field of slip detection. Improvements to the sensory suite, as well as biomimetic neurostimulation may provide the user with richer slip information, such as direction.

There is more work to be done before this system may enter daily use. The most fundamental addition before this slip system could tested out of the lab, is the ability for the user to turn this feedback off. The ability to disengage the slip prediction system is the minimum required work for a long-term test that maintains complete prosthetic functionality and participant autonomy. Logging instances of slip, such that prosthetic control could be analyzed after the event would be required to analyse at-home use. Custom stimulation thresholds should be developed to the specifications of the participants. Affecting when the stimulation begins, or the stimulation-predictor response curve may promote comfort, ease of use, and study protocol compliance.

Long term developments to take this methodology of slip prediction beyond experimental use would reapply the practices of this work on a wider range of variables. Additional training conditions should be tested, including differing object materials and geometries. Proving efficacy with more prosthetic hands as they become available will give an indication that this methodology is indifferent to the changes in hardware which are sure to come over time. Advancing that notion further, the breadth of sensor arrays which these training methods remain functional is unknown. It is possible that as sensor arrays become more complex or specialized, the density of data required for linear prediction of slip is lost.

A significant inhibiting factor in creating broader datasets for machine learning is the human-hours associated with performing and labelling the tasks [18]. The result of such inhibition presented as the limited materials tested in this experiment. A solution must be found which does not significantly increase researcher labour. Automating the hand-object interaction using a robotic arm would drastically reduce human time to create a complete data-set. The use of automated robotic validation is currently widely used in the slip detection field for testing the detection system [14], [19], [20]–[25], [27], [28], [30]–[34] . That methodology should be applied to autonomously generating intrinsically labelled data sets for training.

The 3N difference in average pull forces between grasps in the no-stim condition, indicates that participants were able to gain some information on the stability of grasp through unintended means. Micro-slips detected though osseovibration, or sight are likely contributing to this. A more intelligent totem capable of detecting when slips occur should be developed. This may improve clarity of results as it would eliminate the ability for micro-slips to go undetected by researchers.

5.Conclusions

The objectives of this work were as follows:

1. Evaluate the performance of a prosthetic-independent method for developing a slip prediction system using computationally simple machine intelligence, and a commercially available sensorized hand.
2. Evaluate the impact a neural stimulation notification of slip probability, has on avoiding grasp slips in an upper limb prosthetic.
3. Characterize the changes in motion planning that knowledge of slip probability has, in long-term prosthetic users performing pulling tasks.

The performance of the predictor was highly correlated to the nature in which it was applied by the user. The predictor's efficacy was shown to be dependent on the height of the object grasped, as well as the angle at which shear was applied. This is likely due to the entire training regime only being performed with a single object, and the uniaxial design of the shear sensors. Accuracy of the model was greatest (69%) when it was used with feedback, which reinforced correct pull directions in the participants.

Experimental results show breakdown of slip as 44% no-stim, 37% spike stim, 26% amplitude stim. This shows improved task performance with model feedback delivered over neural stimulation. The factor levels could not be evenly balanced over the orderings, impact beyond effect of order was shown. Performance between participants varied between spike and amplitude stim as the most effective feedback for slip mitigation. This supports the idea that in application of a slip prevention system, the feedback style should be customized to the user's liking.

The results of the force data indicate participants were able to gather greater information about the abilities of a grasp with an uncertain friction force. A 61% and 92% improvement were seen in average grip grouping force separation over no stimulation, in spike and amplitude feedback respectively. Statistically significant differences were found between high grip and low grip forces in two participants using no stimulation, three participants using spike stim, and four participants using amplitude stim.

Bibliography

[1] E. Mastinu, P. Doguet, Y. Botquin, B. Hakansson, and M. Ortiz-Catalan, “Embedded System for Prosthetic Control Using Implanted Neuromuscular Interfaces Accessed Via an Osseointegrated Implant,” *IEEE Trans. Biomed. Circuits Syst.*, vol. 11, no. 4, pp. 867–877, Aug. 2017, doi: 10.1109/TBCAS.2017.2694710.

[2] M. Ortiz-Catalan, E. Mastinu, P. Sassu, O. Aszmann, and R. Brånemark, “Self-Contained Neuromusculoskeletal Arm Prostheses,” *N. Engl. J. Med.*, vol. 382, no. 18, pp. 1732–1738, Apr. 2020, doi: 10.1056/nejmoa1917537.

[3] R. Adell, “A 15-year study of osseointegrated implants in the treatment of the edentulous jaw,” *International Journal of Oral Surgery*, vol. 10, no. 6. Churchill Livingstone, pp. 387–416, Jan. 01, 1981, doi: 10.1016/S0300-9785(81)80077-4.

[4] G. Lundborg and P. I. Brånemark, “Anchorage of wrist joint prostheses to bone using the osseointegration principle,” *J. Hand Surg. Eur. Vol.*, vol. 22, no. 1, pp. 84–89, Feb. 1997, doi: 10.1016/S0266-7681(97)80026-5.

[5] A. Tjellström, J. Lindström, O. Hallén, T. Albrektsson, and P. I. Brånemark, “Direct bone anchorage of external hearing aids,” *J. Biomed. Eng.*, vol. 5, no. 1, pp. 59–63, Jan. 1983, doi: 10.1016/0141-5425(83)90080-8.

[6] B. J. Benscoter, J. J. Jaber, M. L. Kircher, S. J. Marzo, and J. P. Leonetti, “Osseointegrated implant applications in cosmetic and functional skull base rehabilitation,” *Skull Base*, vol. 21, no. 5. Thieme Medical Publishers, pp. 303–308, 2011, doi: 10.1055/s-0031-1284211.

[7] A. Thesleff, R. Brånemark, B. Håkansson, and M. Ortiz-Catalan, “Biomechanical Characterisation of Bone-anchored Implant Systems for Amputation Limb Prostheses: A Systematic Review,” *Annals of Biomedical Engineering*, vol. 46, no. 3. Springer New York LLC, pp. 377–391, Mar. 01, 2018, doi: 10.1007/s10439-017-1976-4.

[8] A. L. Overmann and J. A. Forsberg, “The state of the art of osseointegration for limb prosthesis,” *Biomedical Engineering Letters*, vol. 10, no. 1. Springer Verlag, pp. 5–16, Feb. 01, 2020, doi: 10.1007/s13534-019-00133-9.

[9] Y. Li and R. Brånemark, “Osseointegrierte Prothesen zur Rehabilitation nach Amputation: Das wegweisende schwedische Modell,” *Unfallchirurg*, vol. 120, no. 4, pp. 285–292, Apr. 2017, doi: 10.1007/s00113-017-0331-4.

[10] N. Jiang, S. Dosen, K.-R. Muller, and D. Farina, “Myoelectric Control of Artificial Limbs—Is There a Need to Change Focus? [In the Spotlight],” *IEEE Signal Process. Mag.*, vol. 29, no. 5, pp. 152–150, Sep. 2012, doi: 10.1109/MSP.2012.2203480.

[11] D. Farina *et al.*, “The extraction of neural information from the surface EMG for the control of upper-limb prostheses: Emerging avenues and challenges,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 22, no. 4, pp. 797–809, 2014, doi: 10.1109/TNSRE.2014.2305111.

[12] M. Ortiz-Catalan, E. Mastinu, R. Brånemark, and B. Håkansson, “Direct neural sensory feedback and control via osseointegration,” 2017, Accessed: Mar. 22, 2021. [Online]. Available: https://www.researchgate.net/profile/Max_Ortiz-Catalan/publication/317176837_Direct_Neural_Sensory_Feedback_and_Control_via_

Osseointegration/links/5929d2e50f7e9b9979a68e50/Direct-Neural-Sensory-Feedback-and-Control-via-Osseointegration.pdf.
[13] L. Zollo *et al.*, “Restoring tactile sensations via neural interfaces for real-time force-and-slippage closed-loop control of bionic hands,” *Sci. Robot.*, vol. 4, no. 27, Feb. 2019, doi: 10.1126/scirobotics.aau9924.
[14] R. Fernandez, I. Payo, A. S. Vazquez, and J. Becedas, “Micro-vibration-based slip detection in tactile force sensors,” *Sensors (Switzerland)*, vol. 14, no. 1, pp. 709–730, Jan. 2014, doi: 10.3390/s140100709.
[15] M. A. Oskoei and H. Hu, “Support vector machine-based classification scheme for myoelectric control applied to upper limb,” *IEEE Trans. Biomed. Eng.*, vol. 55, no. 8, pp. 1956–1965, Aug. 2008, doi: 10.1109/TBME.2008.919734.
[16] J. T. Belter, J. L. Segil, A. M. Dollar, and R. F. Weir, “Mechanical design and performance specifications of anthropomorphic prosthetic hands: A review,” *J. Rehabil. Res. Dev.*, vol. 50, no. 5, pp. 599–618, 2013, doi: 10.1682/JRRD.2011.10.0188.
[17] “CYBATHLON | CYBATHLON ETH Zürich.” 2020, Accessed: Mar. 24, 2021. [Online]. Available: https://cybathlon.ethz.ch/en.
[18] R. A. Romeo and L. Zollo, “Methods and Sensors for Slip Detection in Robotics: A Survey,” *IEEE Access*, vol. 8. Institute of Electrical and Electronics Engineers Inc., pp. 73027–73050, 2020, doi: 10.1109/ACCESS.2020.2987849.
[19] C. Gentile, F. Cordella, C. R. Rodrigues, and L. Zollo, “Touch-and-slippage detection algorithm for prosthetic hands,” *Mechatronics*, vol. 70, p. 102402, Oct. 2020, doi: 10.1016/j.mechatronics.2020.102402.
[20] D. Gö ger, N. Gorges, and H. Wörn, “Tactile sensing for an anthropomorphic robotic hand: Hardware and signal processing,” in *Proceedings - IEEE International Conference on Robotics and Automation*, 2009, pp. 895–901, doi: 10.1109/ROBOT.2009.5152650.
[21] K. Xi, Y. Wang, D. Mei, G. Liang, and Z. Chen, “A flexible tactile sensor array based on pressure conductive rubber for three-axis force and slip detection,” in *IEEE/ASME International Conference on Advanced Intelligent Mechatronics, AIM*, Aug. 2015, vol. 2015-August, pp. 476–481, doi: 10.1109/AIM.2015.7222579.
[22] R. A. Romeo *et al.*, “Identification of slippage on naturalistic surfaces via wavelet transform of tactile signals,” *IEEE Sens. J.*, vol. 19, no. 4, pp. 1260–1268, Feb. 2019, doi: 10.1109/JSEN.2018.2881831.
[23] A. Mingrino, A. Bucci, R. Magni, and P. Dario, “Slippage control in hand prostheses by sensing grasping forces and sliding motion,” in *IEEE/RSJ/GI International Conference on Intelligent Robots and Systems*, 1994, vol. 3, pp. 1803–1809, doi: 10.1109/iros.1994.407614.
[24] D. P. J. Cotton, P. H. Chappell, A. Cranny, N. M. White, and S. P. Beeby, “A novel thick-film piezoelectric slip sensor for a prosthetic hand,” *IEEE Sens. J.*, vol. 7, no. 5, pp. 752–761, May 2007, doi: 10.1109/JSEN.2007.894912.
[25] M. R. Tremblay and M. R. Cutkosky, “Estimating friction using incident slip sensing during a manipulation task,” in *Proceedings - IEEE International Conference on*

Robotics and Automation, 1993, vol. 1, pp. 429–434, doi: 10.1109/robot.1993.292018.
[26] R. Bayrleithner and K. Komoriya, "Static friction coefficient determination by force sensing and its application," in *IEEE/RSJ/GI International Conference on Intelligent Robots and Systems*, 1994, vol. 3, pp. 1639–1646, doi: 10.1109/iros.1994.407637.
[27] Z. Su *et al.*, "Force estimation and slip detection/classification for grip control using a biomimetic tactile sensor," in *IEEE-RAS International Conference on Humanoid Robots*, Dec. 2015, vol. 2015-December, pp. 297–303, doi: 10.1109/HUMANOIDS.2015.7363558.
[28] F. Cordella *et al.*, "A force-and-slippage control strategy for a poliarticulated prosthetic hand," in *Proceedings - IEEE International Conference on Robotics and Automation*, Jun. 2016, vol. 2016-June, pp. 3524–3529, doi: 10.1109/ICRA.2016.7487533.
[29] L. Osborn, N. V. Thakor, and R. Kaliki, "Utilizing tactile feedback for biomimetic grasping control in upper limb prostheses," 2013, doi: 10.1109/ICSENS.2013.6688445.
[30] M. Aboseria, F. Clemente, L. F. Engels, and C. Cipriani, "Discrete Vibro-Tactile Feedback Prevents Object Slippage in Hand Prostheses More Intuitively Than Other Modalities," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 26, no. 8, pp. 1577–1584, Aug. 2018, doi: 10.1109/TNSRE.2018.2851617.
[31] M. A. Abd, M. Al-Saidi, M. Lin, G. Liddle, K. Mondal, and E. D. Engeberg, "Surface Feature Recognition and Grasped Object Slip Prevention With a Liquid Metal Tactile Sensor for a Prosthetic Hand," Oct. 2020, pp. 1174–1179, doi: 10.1109/biorob49111.2020.9224294.
[32] A. Nakagawa-Silva, N. V. Thakor, J. J. Cabibihan, and A. B. Soares, "A Bio-Inspired Slip Detection and Reflex-Like Suppression Method for Robotic Manipulators," *IEEE Sens. J.*, vol. 19, no. 24, pp. 12443–12453, Dec. 2019, doi: 10.1109/JSEN.2019.2939506.
[33] B. Yang, X. Duan, and H. Deng, "A simple method for slip detection of prosthetic hand," in *2015 IEEE International Conference on Information and Automation, ICIA 2015 - In conjunction with 2015 IEEE International Conference on Automation and Logistics*, Sep. 2015, pp. 2159–2164, doi: 10.1109/ICInfA.2015.7279645.
[34] L. Osborn, W. W. Lee, R. Kaliki, and N. Thakor, "Tactile feedback in upper limb prosthetic devices using flexible textile force sensors," in *Proceedings of the IEEE RAS and EMBS International Conference on Biomedical Robotics and Biomechatronics*, Sep. 2014, pp. 114–119, doi: 10.1109/biorob.2014.6913762.
[35] P. Fang, L. Tian, Y. Zheng, J. Huang, and G. Li, "Using thin-film piezoelectret to detect tactile and slip signals for restoring sensation of prosthetic hands," in *2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC 2014*, Nov. 2014, pp. 2565–2568, doi: 10.1109/EMBC.2014.6944146.
[36] L. Roberts, G. Singhal, and R. Kaliki, "Slip detection and grip adjustment using optical tracking in prosthetic hands," in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, 2011, pp. 2929–2932, doi: 10.1109/IEMBS.2011.6090806.

[37] R. Barone *et al.*, “Multilevel control of an anthropomorphic prosthetic hand for grasp and slip prevention,” *Adv. Mech. Eng.*, vol. 8, no. 9, p. 168781401666508, Sep. 2016, doi: 10.1177/1687814016665082.

Appendices

Appendix A: Experimental Control Scheme

```
if(slipDetExperiment){      //During experiment:
    if(*outIdx&OPENHAND){           //OPENHAND detected
        slipDetCloseForce = 5;          //reset to minimum close force
        slipDetCounter = 5;             //remove lock on Close, Reset counter
        slipDetSolidGrasp = 0;          //no grasp occurring
    }else if(*outIdx&CLOSEHAND){    //CLOSEHAND detected
        if(slipDetCounter != 0){
            slipDetSolidGrasp = 0;      //stable grasp not occurring
            if(slipDetGrasp ==2){       //Too high force
                slipDetOpenForce += 1;      //increase opening force
                strength[0] = slipDetOpenForce;
                *outIdx = OPENHAND;         //send OPEN command to correct for over-grip
                slipDetCloseForce = 3;      //reset Close force
                slipDetCounter = 5;         //reset stability counter

            }else if(slipDetGrasp ==1){ //Correct force
                strength[0] = 0;            //don't allow the hand to close any further
                slipDetCloseForce = 3;      //reset Close force
                slipDetCounter--;           //count down to solid grasp

            }else if(slipDetGrasp ==0){ //Too low force
                slipDetCloseForce += 1;     //increase close force each loop
                strength[0] = slipDetCloseForce;
                slipDetOpenForce = 3;       //reset Open force
                slipDetCounter = 5;         //reset counter
            }
        }else{                          //When solid grasp achieved, disable CLOSEHAND
            strength[0] = 0;            //don't allow the hand to close any further
            slipDetCloseForce = 5;      //reset Close force
            slipDetSolidGrasp = 1;      //stable grasp occurring
        }
    }
}
```

Appendix B: Full Order of Conditions

P1	Band	Grip	Force[N]	Slip?	Predict?
No Stim	Light	25	22.1	1	1
No Stim	Heavy	25	23.8	1	1
No Stim	Heavy	25	26.1	0	1
No Stim	Light	25	22.9	0	0
No Stim	Light	25	21.2	1	1
No Stim	Light	15	15.7	1	1
No Stim	Light	15	15	0	1
No Stim	Light	15	14.2	1	1
No Stim	Light	25	18.9	1	1
No Stim	Heavy	25	17.5	1	1
No Stim	Heavy	25	23.9	0	1
No Stim	Heavy	15	11.2	1	1
No Stim	Heavy	15	8.9	1	1
No Stim	Heavy	15	9.9	1	1
No Stim	Light	15	8.7	1	1
No Stim	Heavy	15	9.5	1	1
No Stim	Light	15	14.7	1	1
No Stim	Light	15	9	0	0
No Stim	Heavy	25	9.4	0	0
No Stim	Heavy	25	6.9	0	0
No Stim	Light	25	16.2	0	0
No Stim	Heavy	15	6.3	0	0
No Stim	Light	25	15.4	0	0
No Stim	Light	25	16.7	0	0
No Stim	Heavy	25	11.2	0	0
No Stim	Light	25	15.2	0	1
No Stim	Heavy	15	8.9	0	0
No Stim	Heavy	25	13.9	0	0
No Stim	Heavy	15	9.1	0	0
No Stim	Light	15	4.3	1	0
No Stim	Heavy	15	8.6	1	0
No Stim	Light	15	8.6	1	0
No Stim	Light	15	12.5	0	1
No Stim	Heavy	25	9.8	0	0
No Stim	Heavy	25	12.4	0	0
No Stim	Light	25	12.2	0	0
No Stim	Heavy	15	9	1	1
No Stim	Heavy	15	12.7	0	0
No Stim	Light	25	14.3	0	0
No Stim	Light	15	9.5	1	1
Spike	Heavy	25	14.8	1	1
Spike	Light	15	10.1	0	1
Spike	Light	15	7.4	1	1
Spike	Light	15	7.9	0	1
Spike	Heavy	15	12.1	1	1
Spike	Light	25	17.9	0	1
Spike	Heavy	15	9.1	1	1

P2	Band	Grip	Force[N]	Slip?	Predict?
No Stim	Light	15	17.4	1	1
No Stim	Light	25	27.3	1	0
No Stim	Light	25	23.5	1	1
No Stim	Heavy	25	18.9	0	0
No Stim	Heavy	15	13.2	0	1
No Stim	Heavy	25	17.7	0	0
No Stim	Light	25	19.3	0	0
No Stim	Heavy	25	15.2	0	0
No Stim	Light	15	10	0	0
No Stim	Light	15	16.8	0	0
No Stim	Light	15	18.9	0	0
No Stim	Heavy	15	21.1	1	0
No Stim	Heavy	15	18.5	1	0
No Stim	Light	15	14	0	0
No Stim	Heavy	25	18.7	0	0
No Stim	Heavy	15	17.6	0	0
No Stim	Heavy	25	21.4	0	0
No Stim	Light	25	21.4	0	0
No Stim	Heavy	15	18.2	0	1
No Stim	Light	15	17.4	0	0
No Stim	Light	25	18.4	0	0
No Stim	Light	25	21.5	1	0
No Stim	Heavy	15	17.7	0	0
No Stim	Light	25	18.1	0	0
No Stim	Heavy	25	19.8	0	0
No Stim	Light	25	20.5	1	0
No Stim	Light	15	14.3	0	0
No Stim	Heavy	15	17.7	0	1
No Stim	Heavy	15	11.5	0	0
No Stim	Heavy	15	14.1	0	0
No Stim	Heavy	25	22	1	0
No Stim	Heavy	25	16.7	0	0
No Stim	Light	25	17.9	1	0
No Stim	Heavy	15	10.6	0	0
No Stim	Light	15	14.1	0	0
No Stim	Heavy	25	16.7	0	0
No Stim	Light	25	16.4	0	0
No Stim	Light	15	16.6	0	0
No Stim	Light	15	15.9	0	0
No Stim	Heavy	25	21.8	0	0
Amp.	Heavy	15	17.9	0	1
Amp.	Heavy	25	20.8	0	0
Amp.	Heavy	25	18.4	0	0
Amp.	Heavy	25	17.9	0	0
Amp.	Heavy	15	18.8	0	1
Amp.	Light	15	10.7	0	0
Amp.	Heavy	15	18	0	1

Spike	Light	25	16.1	1	1
Spike	Heavy	25	23.1	1	0
Spike	Light	25	18.2	1	1
Spike	Heavy	15	9.9	0	0
Spike	Heavy	25	20.9	0	1
Spike	Heavy	25	17.1	0	1
Spike	Heavy	25	18	0	1
Spike	Light	25	14.9	0	1
Spike	Light	15	12.3	1	1
Spike	Heavy	25	16.3	1	1
Spike	Heavy	15	9	0	1
Spike	Heavy	15	12.8	1	1
Spike	Heavy	15	3.1	0	1
Spike	Light	15	14.2	0	1
Spike	Light	25	14.2	0	1
Spike	Light	15	9.2	1	1
Spike	Light	15	11.1	0	1
Spike	Heavy	15	9.2	0	1
Spike	Heavy	15	11.2	0	1
Spike	Heavy	15	10.2	0	1
Spike	Light	15	16.6	0	1
Spike	Heavy	25	12.8	0	1
Spike	Heavy	15	13	1	1
Spike	Light	15	12.6	1	1
Spike	Light	25	11.7	0	1
Spike	Light	25	14.8	0	1
Spike	Light	25	15.5	0	1
Spike	Heavy	25	19.8	0	1
Spike	Heavy	25	25.4	0	1
Spike	Heavy	25	18.9	0	1
Spike	Light	25	18.3	0	1
Spike	Light	15	14.1	1	1
Spike	Light	25	14.7	0	1
Amp.	Heavy	25	16.2	0	1
Amp.	Light	25	16.5	0	1
Amp.	Heavy	15	19.8	0	1
Amp.	Heavy	25	22.1	0	1
Amp.	Light	25	28.3	1	1
Amp.	Light	25	19.5	0	1
Amp.	Light	15	14.2	0	1
Amp.	Heavy	25	28.1	1	1
Amp.	Heavy	15	9.6	1	0
Amp.	Light	25	20.8	0	1
Amp.	Heavy	25	27.2	0	1
Amp.	Light	15	20.8	1	1
Amp.	Light	15	14	1	1
Amp.	Heavy	15	16.4	0	1
Amp.	Light	25	24.9	0	1
Amp.	Heavy	25	21	1	1
Amp.	Light	15	12.4	0	1
Amp.	Heavy	25	17	0	1

Amp.	Heavy	15	14.8	0	1
Amp.	Heavy	25	19.9	0	1
Amp.	Heavy	15	15.3	0	0
Amp.	Heavy	25	19.3	0	0
Amp.	Heavy	15	14.1	0	1
Amp.	Light	15	20.1	0	1
Amp.	Light	15	10.3	0	0
Amp.	Light	25	24.4	0	0
Amp.	Light	25	17.4	0	0
Amp.	Light	15	19	0	1
Amp.	Light	25	23	0	0
Amp.	Light	15	15.2	0	0
Amp.	Light	25	25.4	0	0
Amp.	Heavy	15	19.2	0	1
Amp.	Light	25	22	0	0
Amp.	Heavy	15	18.7	0	1
Amp.	Heavy	25	22.8	0	0
Amp.	Heavy	25	20.1	0	0
Amp.	Heavy	25	16.9	0	0
Amp.	Light	15	16.7	0	1
Amp.	Light	25	21.6	0	1
Amp.	Light	15	13	0	0
Amp.	Heavy	15	16.9	0	0
Amp.	Light	25	22.4	0	0
Amp.	Heavy	15	14.5	0	1
Amp.	Light	15	11.1	0	1
Amp.	Light	15	15.8	0	1
Amp.	Light	25	22.2	0	1
Amp.	Heavy	25	18.9	0	0
Amp.	Heavy	25	24.3	0	1
Amp.	Light	15	13.8	0	1
Amp.	Light	25	19.8	0	0
Amp.	Light	25	25.3	0	1
Spike	Heavy	15	15.9	0	1
Spike	Heavy	25	32.4	1	0
Spike	Light	15	16.1	0	1
Spike	Heavy	25	22.9	0	0
Spike	Light	15	11.1	0	1
Spike	Light	25	22.5	0	0
Spike	Light	25	28.6	0	0
Spike	Light	25	24.2	0	0
Spike	Heavy	15	19.8	0	1
Spike	Light	15	16.9	0	1
Spike	Heavy	25	25.6	0	1
Spike	Light	15	19	0	0
Spike	Light	25	24.3	0	0
Spike	Light	15	15.9	0	0
Spike	Light	25	24.7	0	0
Spike	Light	25	29.1	0	0
Spike	Heavy	25	24.1	0	0
Spike	Heavy	25	24.3	0	0

Amp.	Light	15	10.1	0	1
Amp.	Light	15	9.7	0	1
Amp.	Heavy	15	7	1	1
Amp.	Light	15	18.2	0	1
Amp.	Heavy	15	12.1	1	1
Amp.	Heavy	25	15.6	0	1
Amp.	Light	25	21.6	0	1
Amp.	Heavy	15	13	1	1
Amp.	Light	15	7.9	0	1
Amp.	Heavy	15	13.1	0	1
Amp.	Light	25	17.8	0	1
Amp.	Light	25	14.5	0	0
Amp.	Heavy	25	16.7	0	1
Amp.	Heavy	25	15	0	1
Amp.	Light	15	18	0	1
Amp.	Light	25	18.7	0	1
Amp.	Heavy	25	22.5	0	1
Amp.	Heavy	15	16.7	0	1
Amp.	Heavy	15	10.9	0	1
Amp.	Light	15	12.8	0	1
Amp.	Heavy	15	10.6	0	1
Amp.	Light	25	13.9	0	1

Spike	Heavy	15	18	0	1
Spike	Light	15	14.1	0	0
Spike	Light	15	14.5	0	0
Spike	Heavy	15	13.1	0	0
Spike	Heavy	15	15.5	0	0
Spike	Light	25	23.4	0	0
Spike	Heavy	25	24.4	0	0
Spike	Light	15	18.8	1	0
Spike	Light	25	22.4	0	0
Spike	Heavy	15	20	0	1
Spike	Heavy	15	18.2	0	1
Spike	Light	25	26.5	0	0
Spike	Light	15	22.4	0	1
Spike	Heavy	15	21	1	1
Spike	Heavy	25	28.5	0	0
Spike	Light	25	24.4	0	1
Spike	Heavy	15	19	0	1
Spike	Heavy	25	29.4	1	0
Spike	Heavy	25	26	0	0
Spike	Heavy	15	13	0	1
Spike	Heavy	25	31.1	0	0
Spike	Light	15	16.5	0	1

P3	Band	Grip	Force[N]	Slip?	Predict?
Spike	Light	25	24.2	0	1
Spike	Heavy	25	34.9	1	0
Spike	Light	25	22.5	1	1
Spike	Heavy	15	19.5	1	1
Spike	Light	15	18.2	1	1
Spike	Heavy	25	20.6	0	1
Spike	Light	15	15.6	1	0
Spike	Heavy	25	17.2	0	0
Spike	Heavy	15	19.2	0	1
Spike	Light	15	12.8	0	0
Spike	Heavy	25	17.3	0	0
Spike	Light	25	19.4	0	1
Spike	Heavy	25	23	0	1
Spike	Light	15	18.1	0	1
Spike	Heavy	15	13.3	1	0
Spike	Heavy	15	18.5	0	0
Spike	Heavy	15	16.6	1	0
Spike	Light	25	17.3	0	0
Spike	Heavy	15	18.5	1	1
Spike	Light	15	10.3	0	1
Spike	Light	15	13	0	1
Spike	Light	25	19.5	1	0
Spike	Heavy	15	20.8	0	1
Spike	Heavy	25	24.6	0	1
Spike	Light	25	24.6	0	1
Spike	Light	25	27.1	0	1

P4	Band	Grip	Force[N]	Slip?	Predict?
Amp.	Heavy	15	22.7	1	1
Amp.	Light	25	27	0	1
Amp.	Heavy	25	34.4	1	1
Amp.	Heavy	15	20.2	1	1
Amp.	Heavy	25	27.3	1	0
Amp.	Heavy	15	20	1	1
Amp.	Light	15	19	1	1
Amp.	Light	15	23.2	0	0
Amp.	Heavy	15	22.7	1	1
Amp.	Light	25	26.4	0	0
Amp.	Light	25	29.4	0	0
Amp.	Light	15	17.9	1	1
Amp.	Light	25	26.4	0	0
Amp.	Light	15	14.2	1	0
Amp.	Light	15	13.2	1	1
Amp.	Heavy	25	23.1	0	0
Amp.	Light	25	30.4	1	0
Amp.	Heavy	25	22.1	0	0
Amp.	Heavy	25	22.9	0	1
Amp.	Light	25	20.6	0	1
Amp.	Light	25	20.1	0	0
Amp.	Heavy	25	26.3	0	0
Amp.	Light	25	27	0	0
Amp.	Heavy	25	29.3	0	0
Amp.	Light	15	16.7	1	0
Amp.	Heavy	25	21.5	0	1

Spike	Heavy	15	26.8	1	1
Spike	Heavy	25	27.5	0	1
Spike	Light	15	17.9	0	0
Spike	Heavy	15	17.2	0	1
Spike	Light	15	20.2	0	1
Spike	Heavy	25	19.3	0	1
Spike	Light	25	16.3	0	1
Spike	Light	15	19.9	0	1
Spike	Light	25	19.7	0	0
Spike	Heavy	25	27.3	0	1
Spike	Heavy	15	16	0	1
Spike	Light	25	26.1	0	0
Spike	Heavy	25	26.5	0	1
Spike	Light	15	20.2	0	0
No Stim	Light	15	16.9	1	1
No Stim	Light	25	18.7	0	0
No Stim	Light	25	20.2	0	1
No Stim	Heavy	15	14.9	1	0
No Stim	Heavy	25	15.2	1	0
No Stim	Heavy	15	15.2	1	0
No Stim	Heavy	15	16.3	0	0
No Stim	Light	25	22.5	0	0
No Stim	Heavy	15	19.2	1	1
No Stim	Light	25	14.4	0	0
No Stim	Heavy	25	10.8	0	1
No Stim	Light	15	17.1	0	0
No Stim	Heavy	25	16.8	0	0
No Stim	Light	15	7.8	0	0
No Stim	Heavy	15	17.1	0	0
No Stim	Heavy	15	17	1	1
No Stim	Light	25	17.5	0	0
No Stim	Light	25	22.4	1	1
No Stim	Light	25	11.8	1	1
No Stim	Light	25	14.7	1	0
No Stim	Heavy	25	14.6	0	1
No Stim	Light	15	20.7	1	0
No Stim	Light	15	15.8	1	0
No Stim	Light	15	15.5	0	0
No Stim	Light	25	18	0	1
No Stim	Heavy	25	13.6	0	1
No Stim	Light	15	19.8	0	0
No Stim	Light	15	14.1	1	0
No Stim	Heavy	25	15.8	0	1
No Stim	Light	15	18.3	1	1
No Stim	Heavy	25	14.9	0	0
No Stim	Heavy	25	22.9	0	1
No Stim	Heavy	25	23.9	0	1
No Stim	Heavy	15	17.2	1	1
No Stim	Heavy	15	21.2	1	0
No Stim	Light	25	15.7	0	0
No Stim	Light	15	19.5	0	0

Amp.	Light	15	19.5	0	1
Amp.	Heavy	15	21	0	1
Amp.	Heavy	25	22.8	0	0
Amp.	Heavy	15	15.6	0	1
Amp.	Heavy	25	25.8	0	0
Amp.	Light	15	22.4	0	1
Amp.	Light	25	24.2	0	1
Amp.	Heavy	15	23.8	0	1
Amp.	Heavy	15	23.2	0	1
Amp.	Light	15	25.9	1	1
Amp.	Heavy	15	20.1	0	1
Amp.	Light	15	26.8	0	1
Amp.	Light	25	26.3	0	0
Amp.	Heavy	15	22	1	1
Spike	Light	25	29.4	1	0
Spike	Heavy	15	17.7	0	0
Spike	Heavy	15	24.2	0	1
Spike	Light	25	24.5	0	0
Spike	Light	15	22.9	1	1
Spike	Heavy	15	13.5	0	0
Spike	Heavy	15	22.3	1	1
Spike	Heavy	15	18.2	0	1
Spike	Light	25	22.6	0	1
Spike	Heavy	25	23.4	0	1
Spike	Heavy	25	27	0	0
Spike	Light	25	27.5	0	1
Spike	Heavy	25	25.1	0	0
Spike	Light	25	23.1	0	0
Spike	Light	15	20.9	0	1
Spike	Heavy	15	25.1	0	1
Spike	Heavy	25	22.7	0	1
Spike	Heavy	25	19.3	0	1
Spike	Light	25	23.5	0	1
Spike	Heavy	25	27.1	0	1
Spike	Light	15	25.8	0	1
Spike	Light	15	29	1	1
Spike	Light	15	22.4	1	1
Spike	Light	25	21.7	0	1
Spike	Light	25	19.7	0	1
Spike	Heavy	15	16.1	0	1
Spike	Light	15	21.8	0	1
Spike	Light	25	22.2	0	1
Spike	Heavy	25	22.1	0	1
Spike	Heavy	25	21.7	0	1
Spike	Light	15	22.6	0	1
Spike	Heavy	25	23.6	0	1
Spike	Heavy	15	22.7	1	1
Spike	Light	15	21.4	1	1
Spike	Heavy	15	22.2	1	1
Spike	Light	15	23	1	1
Spike	Light	25	17.4	0	0

No Stim	Heavy	15	19.4	1	0
No Stim	Heavy	25	26.4	0	0
No Stim	Heavy	15	18.5	1	1
Amp.	Heavy	25	24.4	1	0
Amp.	Light	15	15.5	0	1
Amp.	Heavy	25	22.2	0	1
Amp.	Heavy	15	11.8	1	1
Amp.	Light	25	17.5	0	0
Amp.	Heavy	25	21.5	1	0
Amp.	Light	25	21.7	0	0
Amp.	Light	15	14.5	1	0
Amp.	Heavy	15	9.2	0	1
Amp.	Heavy	15	12.5	0	1
Amp.	Heavy	15	12.1	0	0
Amp.	Heavy	15	9.9	0	0
Amp.	Light	25	21.6	0	1
Amp.	Heavy	15	8.2	0	1
Amp.	Heavy	25	25.1	1	1
Amp.	Light	15	11.9	0	1
Amp.	Heavy	15	9.1	0	1
Amp.	Heavy	25	25.4	0	1
Amp.	Heavy	15	12.9	1	0
Amp.	Light	15	13.9	0	1
Amp.	Heavy	25	19.4	0	1
Amp.	Heavy	25	21.8	1	1
Amp.	Light	25	21.6	0	1
Amp.	Heavy	25	18.9	0	0
Amp.	Heavy	25	20.9	0	1
Amp.	Heavy	15	15.2	0	1
Amp.	Light	25	24.9	0	1
Amp.	Light	25	28.6	1	1
Amp.	Light	25	27.8	0	1
Amp.	Light	15	15.2	0	1
Amp.	Light	15	13.2	0	1
Amp.	Light	15	19	0	1
Amp.	Light	15	11.3	0	1
Amp.	Light	25	23.9	0	1
Amp.	Heavy	25	21.2	0	1
Amp.	Heavy	15	11.6	0	1
Amp.	Light	15	13.6	0	1
Amp.	Light	25	21.7	0	1
Amp.	Light	15	9.1	0	1
Amp.	Light	25	23.6	0	1

Spike	Light	15	21.4	0	1
Spike	Heavy	25	23.1	0	1
Spike	Heavy	15	24.5	0	1
No Stim	Light	25	25	0	1
No Stim	Heavy	15	23.7	1	1
No Stim	Heavy	25	23.5	0	1
No Stim	Heavy	15	23.2	1	1
No Stim	Light	25	27.6	0	1
No Stim	Heavy	25	23.4	0	0
No Stim	Light	15	21.3	0	1
No Stim	Heavy	15	19.9	0	0
No Stim	Light	15	19.2	0	0
No Stim	Heavy	15	21.2	0	1
No Stim	Light	25	21.5	0	0
No Stim	Heavy	25	29	0	1
No Stim	Light	25	22.4	0	0
No Stim	Heavy	15	25.4	1	0
No Stim	Light	15	17.8	0	1
No Stim	Light	15	19.2	1	1
No Stim	Light	25	23.7	0	0
No Stim	Light	25	21.5	0	1
No Stim	Heavy	15	25.2	1	1
No Stim	Light	15	17.3	0	1
No Stim	Heavy	25	27.4	0	0
No Stim	Light	15	24.3	1	1
No Stim	Heavy	15	25.5	1	1
No Stim	Light	15	23.6	1	1
No Stim	Light	25	23.4	0	1
No Stim	Light	25	23.7	0	1
No Stim	Heavy	25	23.1	0	0
No Stim	Light	25	22.2	0	1
No Stim	Heavy	25	23.4	0	0
No Stim	Heavy	25	21.5	0	1
No Stim	Light	15	21.9	0	1
No Stim	Heavy	15	13.3	0	0
No Stim	Heavy	25	25.2	0	0
No Stim	Light	15	18.5	0	0
No Stim	Heavy	15	25.2	1	0
No Stim	Light	25	29.3	0	0
No Stim	Heavy	25	27.8	0	1
No Stim	Light	15	18.7	0	1
No Stim	Heavy	15	19	0	1
No Stim	Heavy	25	22	0	0