Sensory Feedback by Direct Neural Stimulation Improves Amputee Prediction of Object Slip

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***Abstract*— Prostheses are becoming more advanced and biomimetic with time, providing additional capabilities to their users. However, prosthetic sensation lags far behind its natural limb counterpart, limiting the use of sensory feedback in prosthetic motion planning and execution. Without actionable sensation, prostheses may never meet the functional requirements to match biological performance. We propose an approach for upper-limb prosthetic object slip prediction and notification, delivered to the wearer through direct nerve stimulation. The method is based on sensory synthesis, training a linear regression of the sensors embedded in a prosthetic hand to predict slip before it occurs. Four participants with transhumeral amputation performed block pulling tasks against increasing resistance, attempting to pull the block as far as possible without slip. These trials were performed with two different prediction notification paradigms. At lower grasp forces, spike notification stimulation reduced the incidence of object slip by 32%, and at higher grasp forces, the maximum achieved pull forces increased by 19% across participants when provided with stimulation proportional to the likelihood of a predicted slip. These results suggest that this approach may be effective in recreating a lost sense of grip stability in the missing limb and may reduce unanticipated slips.**

***Index Terms*—amputation, myoelectric prosthesis, sensory feedback, prosthetic grasp, slip prediction**

I. INTRODUCTION

THE natural human hand is very effective in its capability to provide strong but dexterous movements, as well as in the wide range of sensations it provides to understand the physical properties of objects and the nature of the current grasp. Upper-limb amputations result in diminished independence through decreases in object manipulation capability [1], [2], [3], [4]. There have been many developments in creating increasingly capable prosthetic hands, however due to the difficulty in providing long-term, stable, and impactful sensory feedback, wide-ranging biomimetic sensory suites in prosthetic hands are not currently commercially available.

The most common sensation delivered from a prosthetic hand to its user is a magnitude of applied force felt at the sensor's location on the prosthesis; this is relatively easy to implement in the prosthesis mechanically, and to calculate the feedback response computationally, and is the focus of most prosthesis sensory feedback literature, typically involving tactile [5], [6], [7], [8], [9], [10] or electrical feedback modalities [11], [12], [13]. However, the natural hand can interpret additional sensations such as texture, pliability, and stability through the neural convolution of many different sensory inputs [14]. As an example, understanding the quality of a grasp requires understanding normal and shear forces, as well as proprioception – senses which are typically not all provided to the wearer by current prostheses. The lack of sensory feedback forces wearers to make assumptions about the grasp from looking at their prosthesis, and guesses at the frictive and compliance qualities of the target object [15]. For prosthetics to develop to the point where they are close or equal to natural hands, improvements are required in sensory synthesis and feedback.

Sensorized prosthetic hands on the market today have little sensory capability, and are scarce. Often, sensors in these prostheses feed into closed-loop control strategies which do not directly provide sensory information to the user, instead providing corrective movements to the hand such as tightening grasp when a slip is detected. However, our research participants have reported that these resulting nonvolitional hand movements are disconcerting, unreliable, and reduce feelings of ownership, all resulting in low user compliance. Consequently, our users would often switch off such a feedback functionality in their hands each time their device powered on. This indicates a need to provide quality of grip feedback in an unintrusive manner such that users can execute corrective movements of their own accord.

A particular interest lies in the notification of the prediction of slip. To best provide useful grasp stability information, some metric of stability should be provided to the user before a slip occurs, so that the slip can be avoided. Most existing literature on hand prosthesis slip has focused on detecting slip rapidly after slip onset [16], [17], [18], [19], [20], [21], [22], [23], [24], only [25] attempted to predict slip before onset. When paired with an auto-close function of the prosthesis, the user is left

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completely out of the control loop. Only [26] included a singular (blindfolded, and acoustically isolated) person with amputation in-the-loop, allowing them to react to the slip detection stimulation. However, because humans integrate visual information into state estimates, the benefit may not persist when no longer blindfolded [15]. We propose an alternative and proactive method to prevent slips before they occur by providing the wearer with information on the stability of their grasp, allowing them to make volitional corrections.

In the present study, we propose slip prediction delivered through varied neurostimulation conditions to determine impact on amputee movement planning. The proposed method is designed such that the users' senses and movements remain uninhibited, to best reflect daily living. Additionally, the study uses grip forces similar to those which would be used in daily life. The goal of this study is to implement a slip prediction algorithm on a commercially available sensorized hand, to facilitate widespread application of findings. The slip prediction model was formulated for this hand using a generalized, hand-agnostic methodology. Additionally, we propose a user-in-the-loop test to determine the efficacy of slip prediction. Finally, we use this test to demonstrate the impact of slip prediction feedback on amputee movement execution and slip avoidance.

II. Methods

A. Subjects

This study received approval from both the Office of Research Ethics at the University of Waterloo (ID#42485), and the Swedish Ethical Review Authority (Dnr: 2020-04600). All subjects provided informed consent before starting the study.

Four people with transhumeral amputations participated in this study, all users of a neuromusculoskeletal prostheses (Integrum AB, Sweden) for 7±2 years, and had received nerve cuff stimulation during home-use for 5±3 years [27], [28], [29], [30]. New sensory stimulation feedback settings were determined for each participant at the start of their visit. Stimulation parameters were determined for each participant which could create (1) a clear and immediately noticeable single pulse sensation, (2) a noticeable but weak sustained sensation, and (3) a strong but non-painful sustained sensation (see TABLE S1). EMG activation thresholds for control were lowered from pre-experimental levels to minimize participant exertion, as fine prosthetic control was not required for this study.

B. Materials

The prosthetic end-effector used for all training and experiments was a SensorHand Speed (Ottobock, Germany). This model was selected due to its sensory suite, featuring three sensors located in the thumb pad, and one in the base joint of the thumb (**Fig. 1**). The thumb pad housed one normal-load sensor (light red in Fig. 1), and two parallel and oppositely directed shear-load sensors (dark red in Fig. 1). The torque sensor (blue in Fig. 1) located in the base of the thumb was calibrated such that it returned values of the linear force applied

Fig. 1 The Ottobock SensorHand Speed system includes sensors measuring normal (light red) and shear loads (dark red) at the tip of the thumb, and joint torque (blue) at the thumb joint.

at the thumb pad. All participants were familiar with the operation of the hand and have used it in daily life since receiving their osseointegrated prosthesis.

Two objects of known dimension were used for this experiment: one to create the regressor training data, and one used by the participant in pulling trials, called the training block and the trial totem, respectively. The training block, shown in **Fig. 2a**, was 3D printed in PLA filament with an untreated surface. The block was 18mm high, and 80mm long to allow multiple slips while maintaining control of the object. The trial totem, shown in **Fig. 2b-c**, was also printed with PLA, but the contact surfaces were smoothed with 120-grit sandpaper. The contact area of the trial totem was also 18mm high, however it tapered 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 gloves.

C. Slip Predictor Model

The proposed predictor used supervised machine learning and the available data from the prosthesis to synthesize a sense of oncoming-slip. A linear regression was selected for slip

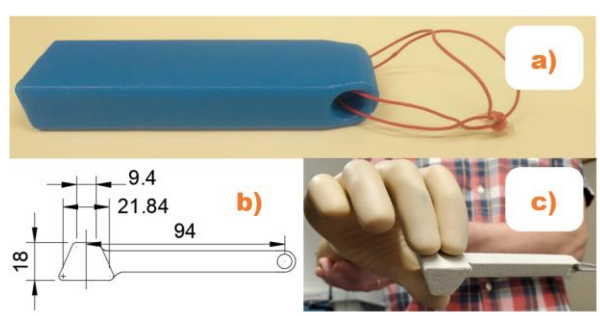

Fig. 2 a) Training block, b) trial totem detail [mm], c) view of trial totem grasped by prosthetic before a pull attempt.

prediction, as it would be computationally simple enough to implement on subsequent firmware platforms. However, the implementation of the two independent shear sensors in the SensorHand Speed created two linearly discontinuous regions of slip in the sensor data. The output of the two parallel, uniaxial shear sensors were combined through the absolute magnitude of their subtraction, to synthesize a unified net magnitude of shear. This shear magnitude removed the distinction of shear direction and created a continuous data region.

To create a slip dataset, slip events were created by an experimenter manually pulling on the prosthesis with the SensorHand Speed holding the training block, which was connected to an exercise elastic (328N/m) clamped to the benchtop, while all sensory data were recorded in MATLAB at a rate of one sensor data frame per 15ms. Labels of ‘stable’ and ‘unstable/slipping’ were manually applied in real time through keyboard input. Data were labeled as ‘stable’ if the training block was held securely in the prosthetic hand during pulling, and were labeled as ‘unstable/slipping’ if the training block was sliding within the grasp of the prosthetic hand. The label was applied to the previous three data frames, but not to the current frame, and all data recorded without a label applied were discarded. A fully labelled pull task consisted of applying a label selection at each of the following stages:

1. Grab object
2. Pull object lightly to apply a small amount of shear
3. Increase pull force to increase shear
4. Increase pull force to record two slip events
5. Hold tension after second slip
6. Decrease pull force to slightly reduce shear
7. Decrease pull force to a very low level

Pulling tasks were performed while the prosthetic hand grasped the training totem with grip forces of 15N, 20N, 25N, and 30N. For each pulling task, the training totem was pulled from the left and right side of the hand, twice each. Additionally, ‘stable’ data were collected with the prosthesis sitting motionless with the hand empty and open.

The linear support vector machine (SVM) regression was trained using the MATLAB Machine Learning toolbox.

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

The output regressor is shown in (1), where x is the independent vector consisting of the torque, normal, and shear forces and their first derivatives; μ and σ are normalizing factors; and β is the SVM generated weight for given i input. Magnitudes of the SVM generated weights illustrating the relative importance of each system input; positive shear was highly correlated with slip, and high joint torque is negatively correlated with slip. Slip is increasingly likely as the first derivative of the normal force decreases, meaning slip is inversely proportional to the rate of normal force decrease. Representative prosthetic data and regression of two opposite slip directions are presented in **Fig. 3**

D. *Experimental Protocol*

An experiment was designed to create scenarios in which participants attempted to avoid slip, while being unsure of the stability of their grasp on the target object. This was achieved through an experiment-mode prosthetic controller, in which maximum force at the fingertips was controlled by the

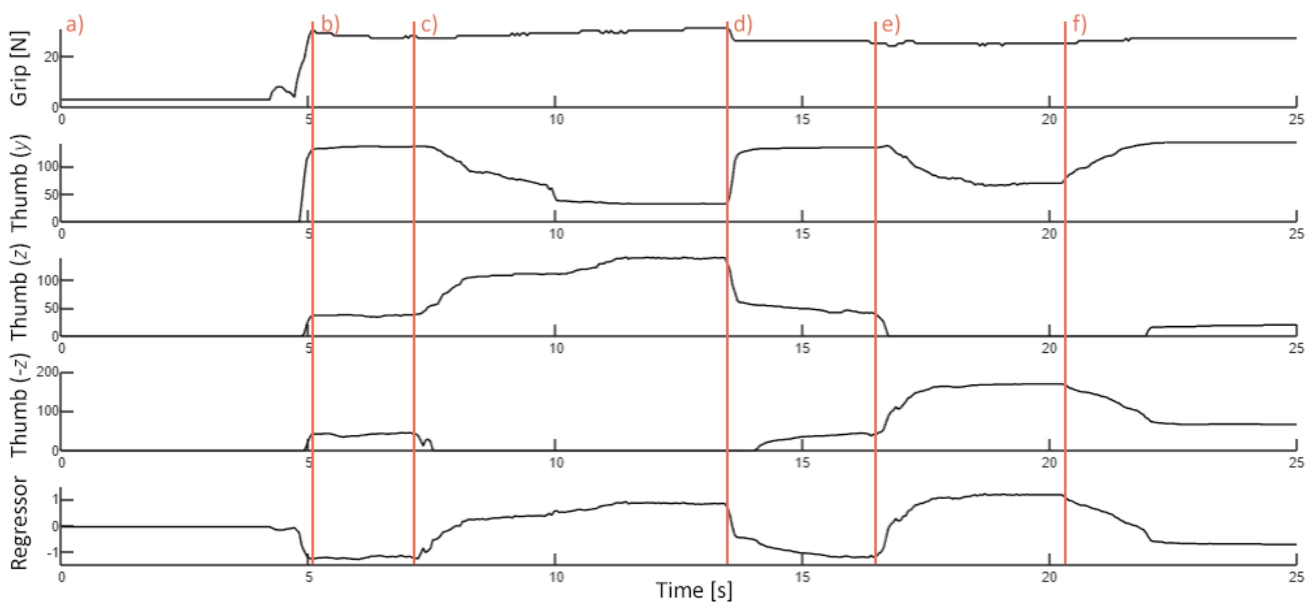

Fig. 3 Visual example of the relation between each sensor value and regressor output across grasp and pull movements. a) grasping object, b) neutral grasp, c) pulling object to the right until slip, d) returning to neutral grasp, e) pulling object to the left until slip, f) returning to neutral grasp.

Fig. 4 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.

researcher. Grip forces were set to either 15N or 25N (±10% accuracy) as dictated by randomized protocol ordering.

Participants grasped the trial totem with their prosthetic hand at the prescribed grip force; a cord was connected to the totem by an elongated neck, which was designed to discourage rotating the block while pulling. The other termination of the cord was connected to an exercise elastic band, providing increasing load over during the pull. One of two elastics were used as determined by the randomized protocol ordering, with strengths of either 328N/m or 657N/m. The opposing side of the elastic was connected to a force gauge (Nidec FGV-50XY DART 2.0 Digital Force Gauge) to record maximum pull force per attempt.

Participants were instructed to pull the trial totem as far as they could against increasing resistance from the elastic band, without the totem slipping from their grasp. Participants sometimes performed the pulling task by holding the prosthetic arm with their intact hand to stabilize against humeral rotation. The experimental set-up can be seen in **Fig. 4** from the perspective of both the participant and the researcher. Participants were able to see and hear their prosthesis during the trials, however the grip force was controlled by the experimenter and was not communicated to the participant. The elastic bands and the force gauge were located behind an opaque barrier so that the participant could not predict the elastic band modulus. Grip strength and band conditions each 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 in randomized order.

Three slip notification schemes were deployed to analyze the effect on amputee pulling behavior. *No stimulation* was used as a baseline of performance. *Spike stimulation* delivered a single quick and strong pulse when the slip prediction regressor reached 0.4. *Amplitude modulation stimulation* began continuous stimulation when the slip prediction regressor reported 0.1, and proportionally increased stimulation amplitude with prediction regression, reaching maximum stimulation amplitude at 0.9. A slip prediction regressor value of 0.4 was heuristically determined to be used in the *spike stimulation* condition, as this value was reached after significant load was applied to the target object, but reliably before slip occurred. Each feedback condition was performed sequentially in randomized order, resulting in 120 total pull attempts per participant.

After readying the prosthesis for the experiment, the participants were given undirected time to familiarize themselves with the new force control and stimulation paradigm. This undirected time was repeated at the start of every new stimulation condition so that participants could familiarize to and learn when the stimulation occurs. During these periods, the hand was set to reach 20N, and the participants could pull at the totem with both elastics connected in parallel, to prevent familiarization with the experimental conditions. Due to the highly discretized nature of the experiment, participants were instructed that they could take rests whenever needed, and rests were additionally taken between stimulation conditions. After all attempts were completed, subjects completed a short semi-structured interview which consisted of guided numerical feedback, and then open dialogue. During guided numerical feedback asked participants to rate their reliance on stimulation feedback, vision, and muscle/bone forces during the pull tasks on a scale of 1-10. The open dialogue portion was annotated by one experimenter recording the points and opinions of the participants.

A three-level single factor study was conducted on stimulation condition. Order effects were mitigated through balanced randomization, however three conditions and four participants resulted in one repeated condition in each order placement (*No stimulation*, *Spike stimulation*, *Amplitude modulation stimulation*, respectively). Differences in number of slip events and achieved pull force during non-slipped trials were statistically analyzed using a non-parametric bootstrapped paired *t*-test, which provides greater statistical power while maintaining type I error probability for small sample size studies, when compared to traditional parametric or non-parametric tests [31]. Effect sizes are reported using Cohen's d (large: d = 0.8, very large: d = 1.2), and *p*-values are provided for convenience, however all statistical claims are considered exploratory.

The number of slips were expected to decrease in stimulation conditions, compared to the no-stim condition. This condition effect was compared with order effect, which was also expected to decrease slips as attempts increased. Statistical significance of stimulation was calculated for each feedback condition.

Participants were expected to be able to both experience fewer slip events, and to generate higher pulling forces, with stimulation enabled, indicating a greater understanding of the interaction between their prosthetic hand and the object. To quantify these changes in behavior, the number of slipped

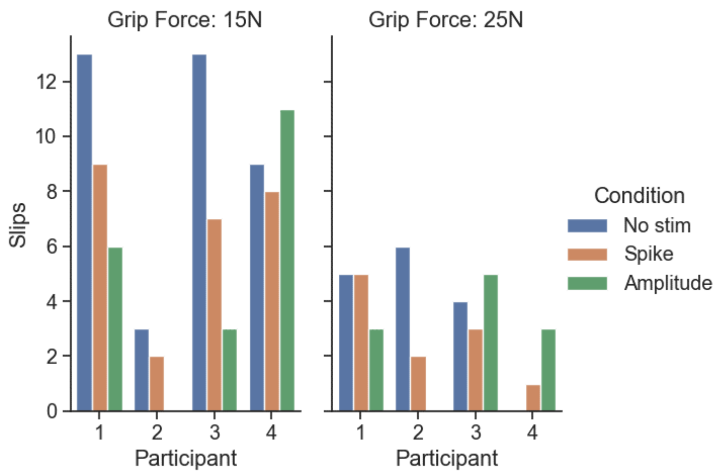

Fig. 5 Slip sums from each participant by feedback condition.

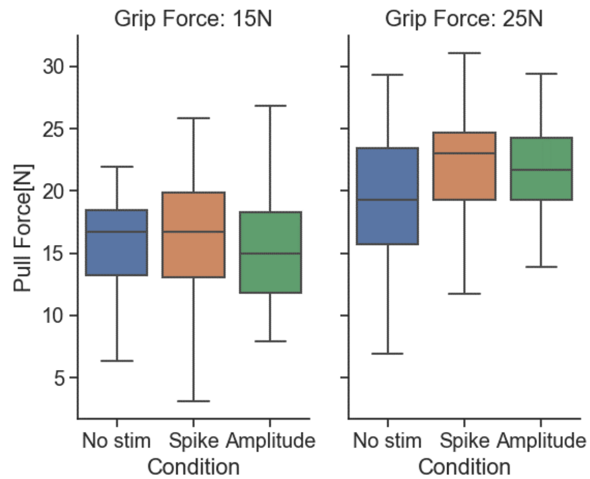

Fig. 6 Maximum pull forces from each successful (no-slip) attempt across all participants.

totems and the maximum achieved pull force for non-slipped totems were recorded.

III. Results

A. Impact of Slip Prediction on Slips and Pull Force

The number of slip events and the achieved pulling force during non-slip trials were both heavily dependent on the grasping force. At the lower grasping force of 15N, the totem slipped a median of 11 times [range: 3, 13] with *no stimulation* (**Fig. 5**). With *spike stimulation*, the median number of slips demonstrated a very large reduction to 7.5 [2,9] (Cohen's d = 1.225, p = 0.086). *Amplitude stimulation* also demonstrated a large reduction in the median number of slips to 4.5 [0,11] (d = 0.866, p = 0.177). For trials where the totem did not slip from the hand (no-slip trials), the median of pull forces per participant had a median of 16.5N [9.1N, 19.0N] with *no stimulation* (**Fig. 6**). *Spike stimulation* had a very large effect on median pull force, which increased to 17.2N [10.1N, 21.6N] (d = 1.325, p = 0.058). *Amplitude stimulation*, however, had no discernable effect on pull force, with a median achieved pull force of 14.3N [12.1N, 22.4N] (d = 0.116, p = 0.829).

At the higher grasping force of 25N, the totem slipped out of the hand less frequently than at the lower grasping force – 4.5 [0,6] times with *no stimulation*, 2.5 [1,5] times for *spike stimulation*, and 3 [0,5] times for *amplitude stimulations* (**Fig. 5**). There were no discernable differences in slip incidence between conditions ($d \leq 0.463$, $p \geq 0.431$). The median achieved pull force for non-slip trials was also higher, consequently, at the higher grasping force (**Fig. 6**). *Amplitude stimulation* had a huge effect on median pull forces (21.5N [17.8N, 25.8N]) compared to *no stimulation* (17.85N [14.3N, 23.5N]) (d = 3.306, p = 0.009). The pull force was also increased with *spike stimulation* (23.1N [17.1N, 24.4N]), which is considered a large effect (d = 1.194, p = 0.098).

Taken together, these results suggest that, at low grip force where grasped objects are less secure, a spike stimulation paradigm communicating a warning of impending slip may help to reduce the incidence of slipped objects. Furthermore, when more securely grasping objects, a proportional feedback scheme, especially, may better alert users when an object is at risk of slipping, allowing the user to adjust their motion planning or grasp strength in response.

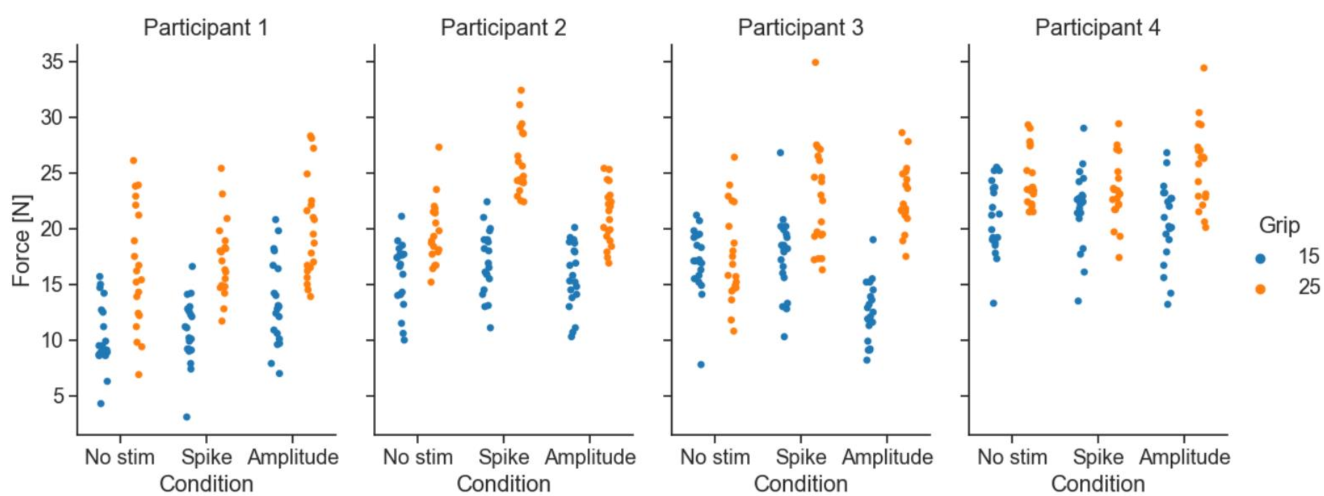

Fig. 7 Maximum pull force from every trial separated by grip strength within each condition.

B. *Impact of Slip Prediction on Grasp Comprehension and Amputee Movement*

Observed differences in movement planning between the grip strength conditions may provide insights into the understanding of grip capabilities in each of the participants. Participants were able to see, hear, and feel the prosthesis during their pull tasks resulting in a baseline understanding of grip stability, where a more stable grip would allow the participants to exert more force on the totem. We hypothesize that improvement in participants' grip stability estimation would come in the form of greater separations in the pull forces between high and low strength grasps. The pull forces from each participant separated by stim condition and grip strength are shown in **Fig. 7**.

Separation between the average pull forces of high vs low grip strengths was found to increase in conditions with stimulation. Using *no stimulation* as a baseline, *spike stimulation* showed a 68% median improvement in the difference in pull forces between grip strengths across all participants, and *amplitude stimulation* showed a 39% median improvement. Some degree of improvement was near universal, only P4's *spike stimulation* showed decreased performance. Conversely, as P3's *no stimulation* groupings were so close (0.46N), *spike* and *amplitude stimulation* showed a huge rate of improvement (5.12N and 10.12N respectively). We suggest that the increased separation of pull forces in all participants indicate greater understanding of the strength of the participants' grips.

C. *Participant Perspectives*

Each experiment session ended with participants detailing the strategy they used to perform the pulling task, numerically and through unstructured interview. Self-reported reliance levels (TABLE I) of different senses were recorded, however they did not provide the full picture, and no relation could be found from their reported strategy and their performance measured by slips or max force.

Participants 1, 2, and 4 all stated heavy reliance on stimulation in mitigating slip during open dialogue, despite prior numerical feedback (seen in TABLE I). P3 stated near exclusive reliance on visual feedback while simultaneously stating being very effectively blinded to grip-strength and elastic conditions. Even so, their results show an improvement in grasp capability understanding (**Fig. 7**), and a reduction in the number of slipped totems (**Fig. 5**), which may suggest a subconscious incorporation of the sensory information into their decision-making process.

P2, and P4 indicated need for continued practice with and development of the slip prediction system. P4 was interested in further development of this stimulation paradigm, and was confident that a similar system would be more beneficial than their current stimulation directly proportional to grip strength. P4 stated their strategy was to pull a little bit more after receiving stimulation onset. As a result, he demonstrated his ability to fuse slip information provided via stimulation with his own visual and proprioceptive estimates of slip to maximize the totem pull force. Although most participants reported continued reliance on visual cues during the task, slip prediction feedback nonetheless improved their performance, and most indicated interest in continued practice of the slip prediction feedback at home.

TABLE I
SELF-REPORTED SENSATION RELIANCE DURING PULLING TASKS, REPORTED NUMERICALLY [1-10].

Sense	**P1**	**P2**	**P3**	**P4**
Stimulation Sensation	7	5	1	2
Vision	4	9-10	8	9
Muscle/Bone Forces	3	8	4	5

IV. Discussion

In this study we demonstrated, for the first time, slip prediction in a sensorized prosthetic hand providing neural feedback of grasp stability to multiple transhumeral prosthesis users. Additionally, this study is the first to provide multiple slip stimulation paradigms, and test efficacy without inhibiting any of the participants' other senses such as vision. The slip prediction model was developed using a prosthesis-agnostic method and was computationally simple enough to deploy on a wide range of controller hardware. The slip prediction system provides prosthetic users with information on the security of their current grasp. The delivered sensation begins before slip has started; thus, participants can prevent slip, rather than correcting their grip after an object has already begun to slip, which is predominant in the literature. During the study, participants' movements and senses were not limited, which is most applicable for evolving this development beyond an experimental setting.

In the totem slip experiment, participants were asked to pull a totem as hard as possible without allowing it to slip from the grasp. Thus, there were two success conditions, and therefore two outcomes, which are intrinsically related: the number of slipped totems, and the maximum achieved pull force. These two outcomes were shown to have different importance at the different grasping forces.

At low grasping force, objects are more likely to slip from the hand. In this condition, we showed a large reduction in the number of slipped totems when using *spike stimulation*, compared to *no stimulation* (**Fig. 5**). Likewise, at high grasping forces, participants were able to pull the totem harder without it slipping from the hand; in this condition, we showed a very large increase in the maximum achieved pull force when using *amplitude stimulation*, compared to *no stimulation* (**Fig. 6**). These results may suggest that the different feedback methods are differently preferential in conditions of higher or lower slip likelihood. As a result, the selection of feedback method may depend on the daily activities of the user, as we discuss in the next section. Furthermore, the *spike* and *amplitude stimulation* may be combined to provide the benefits of both methods.

We used grip forces (15N, 25N) that are common in daily life and that were substantially higher than those found in similar prior works [19], [20], [21], [22], [23], [24], [25]. The maximum grip force in this study was limited to a maximum of 25N, which was found to be appropriate for the number of trials performed, as all participants took breaks between conditions, but few breaks within a condition. Due to the repeated lateral shoulder rotation within this experiment, participants sometimes helped push the prosthesis against the elastic band with their hip. Testing higher grip forces is not feasible with the lateral shoulder rotation used here.

The performance of the slip prediction model was limited by the highly specific pulling angle dictated by the uni-axial shear sensor. Misalignment within the grasp was a recurring issue due to the design of the totem, which just barely fit in the fingers of the prosthetic to promote obvious slip. These failures of prediction took the form of a premature plateau of the slip prediction regressor, remaining below the threshold for prediction. However, even with the very narrow sensor array, slips were still able to be predicted and behavior was observed to have changed. This is promising for the future of slip prediction work, as hands with additional sensors in commercial and experimental use may address this issue.

A. Future Developments

The quantitative system efficacy and qualitative user feedback results indicate that there is justification in progressing development of slip prediction for at-home use. In fact, one participant indicated that they would prefer slip prediction stimulation over their current grasp force stimulation paradigm. A complete system including both grasp force and slip prediction feedback could be beneficial for these users, with the feedback types differentiated by stimulation pattern or by using different neurostimulation waveform profiles. There is more work to be done before that is possible though. 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 prediction. This is most apparent in no-prediction pulls where the predictor reaches a local maximum during the pull that is still too low for classification. This limitation was observed during pulls with a poorly-grasped totem, and when pull force was sufficiently out of alignment with the shear sensors. These were caused by a limitation in the sensorization of the prosthesis, which had a very small sensorized area, and a shear sensor along only one axis. This contributed to warnings of slip occurring in only 69% of pulls in each of *spike* and *amplitude stimulations*. Rectifying this may be done with a more versatile sensory suite onboard the prosthesis, or more advanced processing of the regression output to select for local maxima of a certain prominence, rather than pre-determined hardcoded values. This may assist in more accurate prediction in objects of different size and shape than what was used in the experiment.

Reapplying the practices from this work on a wider range of testing conditions is required to migrate this system to daily widespread application. Due to the exploratory nature of this study, additional objects were not analyzed. However, the pre-slip nature of this detection system mitigates much of this risk, as any materials with an equal or greater coefficient of static friction should have similar prediction outcomes as seen in this experiment. The objects used in training the system and in the experiment were smooth PLA, thus it is likely that many objects will satisfy the friction requirements. Object shape presents a more pertinent risk - prediction performance for grasps which do not have a perpendicular surface-thumb orientation are yet to be verified. Application of this method to additional sensorized hands is needed to prove that this methodology is stable over the changes in hardware which are sure to occur in time. Advancing that notion further, the breadth of sensor arrays which these methods remain functional is unknown.

For a clinical application of slip prediction feedback, there is some amount of fine-tuning that can be performed to adjust the performance to a user's preference. Our spike stimulation methods sent a single stimulation pulse at a normalized slip prediction of 0.4, and our amplitude stimulation varied linearly between 0.1 and 0.9. Of our participants, one indicated a desire for stimulation to trigger earlier when pulling, and another routinely intentionally pulled beyond the trigger. It should also be noted that slip prediction feedback need not be mutually exclusive with tactile feedback. Slip and grip force may be differentiated by stimulating with different intensities or pulse trains. Alternatively, stimulating with a waveform other than the standard square wave may elicit a different sensation "quality" which can be associated with slip [32]. For a home-use slip prediction feedback system, these parameters could be tuned to the user's preference, thereby allowing sensory feedback that works in conjunction with the user's needs and daily routines, and ultimately providing the greatest functional benefit in terms of independence and quality of life.

V. Conclusions

Here, we presented the development of a stimulation paradigm for translating prosthetic sensory readings, to actionable input for amputee movement-planning. With four transhumeral amputees, we demonstrated that slip prediction delivered by direct neural stimulation has a beneficial impact on prosthetic movement planning, by providing information on the capabilities of the grasp. Benefits caused by stimulation took the form of decreased slips, and greater separation between the pull force outcomes of each grip strength. This improvement was observed in a singular binary stimulation, and a continuous variable stimulation, with a greater impact observed through binary stimulation at low grip strengths, and continuous stimulation at higher grip strengths. The achievements may also be applicable to home implementation, as the experiment was run without limiting vision, hearing, or movement of the participants. Performance of the predictor was limited by the narrow receptive fields of its sensors. Nevertheless, prosthetic sensory synthesis is needed to replace lost sensation and has the capability to improve as prosthetics become increasingly sensorized.

VI. Acknowledgment

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