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

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**Abstract: Background:** 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. **Methods:** We propose an approach for upper limb prosthetic grasp security feedback, delivered to the wearer through direct nerve stimulation proportional to the likelihood of objects slipping from grasp. This proportional feedback is based on a linear regression of the sensors embedded in a prosthetic hand to predict slip before it occurs. Four participants with transhumeral amputation performed pulling tasks with their prosthetic hand grasping an object at predetermined grip forces, attempting to pull the object with as much force as possible without slip. These trials were performed with two different prediction notification paradigms. **Results:** At lower grasp forces, where slip was more likely, a strong, single impulse notification of impending slip reduced the incidence of object slip by a median of 32%, but the maximum achieved pull forces did not change. At higher grasp forces, where slip was less likely, the maximum achieved pull forces increased by a median of 19% across participants when provided with a stimulation strength inversely proportional to the grasp security, but slip incidence was unchanged. **Conclusions:** These results suggest that this approach may be effective in recreating a lost sense of grip stability in the missing limb that can be incorporated into motor planning and ultimately prevent unanticipated object slips.

**Keywords:** amputation; myoelectric prosthesis; sensory feedback; prosthetic grasp; grasp security; slip prediction; slip detection; osseointegration; bone-anchored limb

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## 1. Introduction

The natural human hand is very effective in its capability of providing 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 [1–4]. There have been many developments in creating increasingly capable prosthetic hands [5]; 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 encoded 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 [6–11] or electrical feedback modalities [12–14]. However, the natural hand can interpret additional tactile sensations such as texture, pliability, and stability through the neural convolution of many different sensory inputs [15]. For example, understanding the security of a grasp requires understanding normal and shear forces, as well as proprioception, 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 [16]. For prosthetics to develop to the point where they are close or equal to natural hands, improvements are required in sensory fusion between biological and artificial sensory feedback.

Sensorized prosthetic hands on the market today are scarce, and those prostheses, which do contain internal sensors typically, feed these sensor data 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 the grasp when a slip is detected [17–21]. However, these resulting nonvolitional hand movements may reduce feelings of agency and thereby embodiment [22,23], resulting in lower user adoption. 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 impending 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 [19,24–31]; only one study has attempted to predict impending slip before onset [32]. Existing literature predominantly investigated slip with low grasp forces ($\leq$7 N) [26–29,31–39], which limits the usefulness of the presented solutions, as slip could easily be avoided by increasing the grasp force of the prosthesis. Only one study investigated a slippage detection algorithm at a high grasp force ($\geq$20 N) [30]. If slip detection is paired with an auto-close function of the prosthesis, the user is left completely out of the control loop. Only one study included a singular (blindfolded and acoustically isolated) person with amputation in-the-loop, allowing them to react to the slip detection stimulation [38]. However, because humans integrate visual information into state estimates, the benefit may not persist when no longer blindfolded [16]. 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 adjust their movement plan. Adjustments to the movement plan are quantified by participants self-determining their movements as a function of grasp security. This is performed during a novel pull task, in which participants pull against an increasing load and determine the maximum applied force before the grasp slips. Allowing human prosthesis users to self-limit their movement to prevent object slip has not been demonstrated thus far in upper limb prosthesis literature.

In the present study, we propose a method of grasp security feedback delivered through varied neurostimulation conditions proportional to the likelihood of objects slipping from grasp to determine its impact on amputee movement planning. We implemented a grasp security algorithm on a commercially available sensorized hand using a grasp security model formulated and trained using a generalized, hand-agnostic machine learning methodology. We investigated this paradigm with a user-in-the-loop test to determine the effect of grasp security feedback during high grasping force pulling tasks and observed the impact of grasp security feedback on amputee movement execution and slip avoidance. The proposed method is designed such that the users' senses and movements remain uninhibited to best reflect daily living.

## 2. Materials and Methods

### *2.1. 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, Mölndal, Sweden) for 7 ± 2 years, and had received nerve cuff stimulation during home-use for 5 ± 3 years [40,41]. Sensory stimulation feedback settings were determined for each participant at the start of their visit, with all stimulation amplitudes constrained between the participants' detection thresholds (monitored longitudinally in previous studies) and either their discomfort threshold or threshold for safe longitudinal stimulation (whichever was lower). Stimulation parameters were determined subjectively for each participant, based on participant feedback, which could create (1) a clear and immediately noticeable single-pulse sensation (single-pulse amplitude), (2) a noticeable but weak sustained sensation (minimum amplitude), and (3) a strong but non-painful sustained sensation (maximum amplitude; Table 1). These stimulation parameters were used for the stimulation schemes described in Section 2.4. EMG activation thresholds for the control were lowered from pre-experimental levels to minimize participant exertion, as fine prosthetic control was not required for this study.

**Table 1.** The stimulation settings for each participant (P1–P4), determined to be noticeable but non-painful at the start of each experimental session. The single-pulse amplitude was used for *spike stimulation* feedback, and the minimum and maximum amplitudes were used for *amplitude modulation* feedback.

| Stimulation Setting | P1 | P2 | P3 | P4 |
|---|---|---|---|---|
| Single-Pulse Amplitude (μA) | 130 | 450 | 620 | 700 |
| Min. Amplitude (μA) | 120 | 300 | 450 | 800 |
| Max. Amplitude (μA) | 140 | 450 | 650 | 500 |
| Frequency (Hz) | 30 | 30 | 30 | 30 |
| Pulse Width (μs) | 100 | 200 | 350 | 250 |

### *2.2. Materials*

The prosthetic end-effector used for all training and experiments was a SensorHand Speed (Ottobock SE & Co. KGaA, Duderstadt, 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 (Figure 1). The thumb pad housed one normal load sensor (light red in Figure 1), and two parallel and oppositely directed shear load sensors (dark red in Figure 1). The torque sensor (blue in Figure 1) located in the base of the thumb was calibrated such that it returned values of the linear force applied 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.

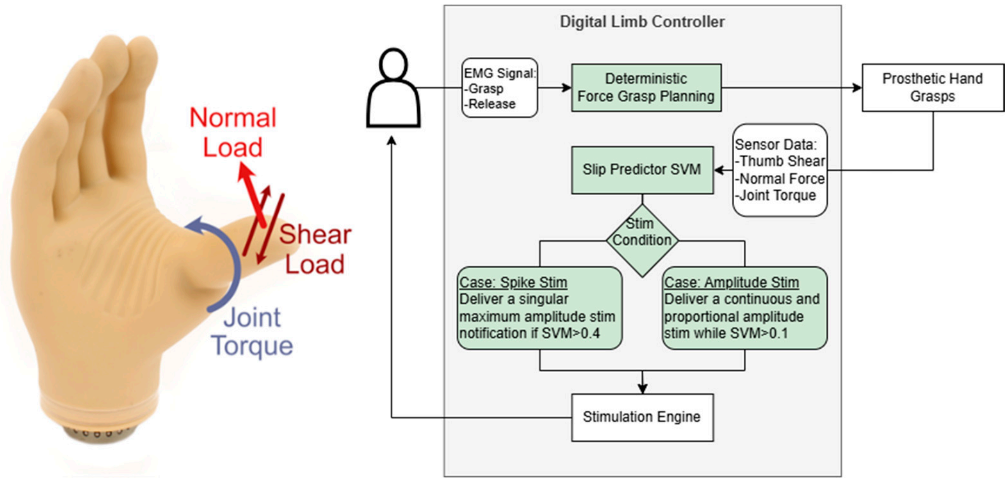


**Figure 1.** The Ottobock SensorHand Speed system (left) includes sensors measuring normal (light red) and shear loads (dark red) at the tip of the thumb, and joint torque (blue) at the thumb joint. These sensors were used to train a slip predictor model, which was incorporated into the Digital Limb Controller (right) as part of this study to provide grasp security sensory feedback.

Two objects of known dimensions 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 Figure 2a, was 3D printed in PLA filament with an untreated surface. The block was 18 mm high and 80 mm long to allow multiple slips while maintaining control of the object. The trial totem, shown in Figure 2b,c, was also printed with PLA; the contact area of the trial totem was also 18 mm high and 32 mm deep. Its widths were designed to narrowly match the contact areas of the prosthesis' silicon gloves, to promote the block slipping completely from the hand upon excessive pulling force.

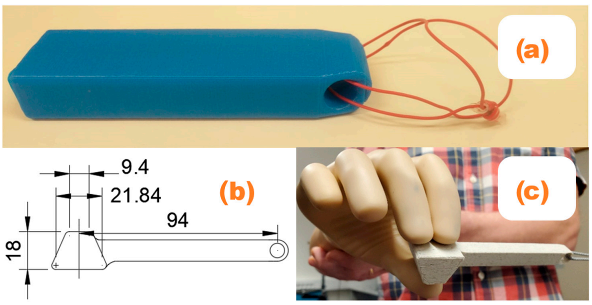


**Figure 2.** (**a**) Training block, (**b**) trial totem detail [mm], and (**c**) view of trial totem grasped by prosthetic before a pull attempt.

### 2.3. Grasp Security Model

The proposed model used supervised machine learning and the available data from the prosthesis to synthesize a sense of an oncoming slip. A linear regression was selected for grasp security, as it was computationally simple enough to implement on embedded 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, where sensor values were proportional for shear in the direction of the sensor, but zero for slip in the opposite direction. 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, shear and 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 (328 N/m) clamped to the benchtop, while all sensory data were recorded in MATLAB 2020b at a rate of one sensor data frame per 15 ms. 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 seen 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 labeled 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. Maintain tension to maintain 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 15 N, 20 N, 25 N, and 30 N. 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. Although the manual labeling of the data for classifier training may be susceptible to operator error, it also represents a utilitarian training method that can be performed by any researcher or prosthetic provider, agnostic to the prosthetic device.

The linear support vector machine (SVM) regression was trained using the MATLAB 2020b machine learning toolbox. The regressor was calculated from inputs consisting of the torque, normal (Y-axis), and shear forces (Z-axis) of the prosthetic fingertips and their first derivatives. After SVM training, the model was manually verified by the training researcher by repeating pull tasks while observing regressor values. Further detail on the development of the SVM regressor is presented in [42]. Positive shear was highly correlated with slip, and high joint torque was negatively correlated with slip. Slip was increasingly likely as the first derivative of the normal force decreased, meaning slip was inversely proportional to the rate of normal force decrease. In this way, the grasp security model may be more accurately thought of as a grasp (in)security model, with higher values representing lower grasp security and therefore a higher likelihood of slip. Representative prosthetic data and the regression of two opposite slip directions generated during manual verification are presented in Figure 3.

### 2.4. Experimental Protocol

Participants were expected to be able to both experience a greater understanding of the interaction between their prosthetic hand and the object with grasp security stimulation feedback available. To investigate this hypothesis, an experiment was designed to create scenarios in which participants attempted to avoid object slip, while being unsure of the security of their grasp on the target object. This was achieved through a prosthetic controller mode in which maximum force at the fingertips was controlled by the researcher.

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 during the pull. One of two elastics were used as determined by the randomized protocol ordering, with strengths of either 328 N/m or 657 N/m. The opposing side of the elastic was connected to a force gauge (FGV-50XY DART 2.0 Digital Force Gauge, Nidec Corporation, Kyoto, Japan) to record the maximum pull force per attempt. The purpose of the randomized elastics was not to blind the participant to their pulling force—this could still be felt through the skeletal attachment—but rather to ensure that pull distance could not be used to estimate pull force.

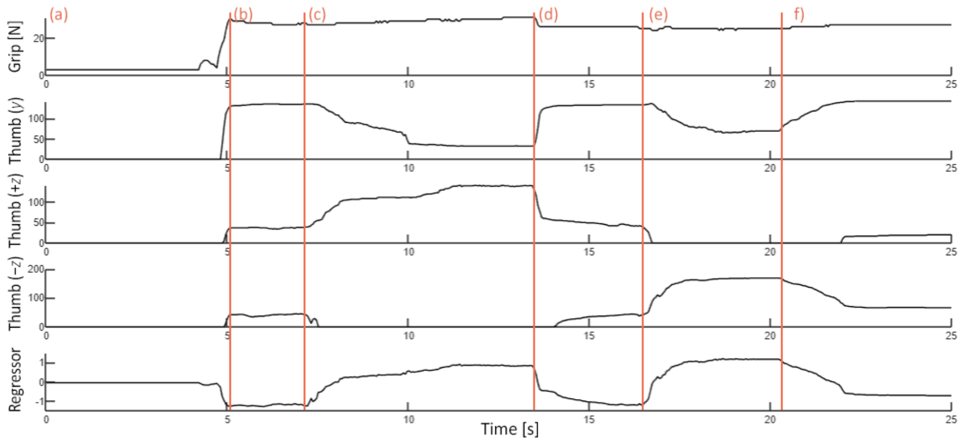


**Figure 3.** Visual example of relation between normal ($y$) and shear ($z$) sensor measurements from prosthetic fingertips and regressor output across grasp and pull movements. (**a**) Grasping object, (**b**) neutral grasp, (**c**) pulling object to right until slip, (**d**) returning to neutral grasp, (**e**) pulling object to left until slip, (**f**) returning to neutral grasp.

Grip forces were set to either 15 N or 25 N (±10% accuracy) as dictated by randomized protocol ordering; only two of the four grip forces used in the slip training dataset were tested to avoid participant fatigue and test generalizability of the grasp security model. Participants were instructed to pull the trial totem as hard as they could against increasing resistance from the elastic band without the totem slipping from their grasp. Performance was evaluated across two dimensions: improved perception of slippage should be correlated with (1) fewer objects slipping from grasp and (2) greater force being applied on trials when objects do not slip from grasp. Importantly, participants were not given control over the grip force; in an at-home situation, one would ideally be able to make corrections to their grip force to secure their grip on an object slipping from grasp; however, for the purposes of this study, we were interested in elucidating the improvements in the motor control loop in an unblinded user-in-the-loop task via the two aforementioned measures.

The experimental setup can be seen in Figure 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 to each participant. In the case of consecutive trials without change, the actions 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 a randomized order.

Three grasp security schemes were deployed to analyze the effect on amputee pulling behavior. Stimulation amplitude, frequency, and pulse width were based on values typically used for their neuromusculoskeletal prosthesis for sensory feedback at home [40]. *No stimulation* was used as a baseline of performance. *Spike stimulation* delivered a single quick and strong pulse when the grasp (in)security regressor reached 0.4. *Amplitude modulation stimulation* began continuous stimulation when the grasp security regressor reported 0.1, and proportionally increased stimulation amplitude (current) with prediction regression, reaching maximum stimulation amplitude at 0.9. A grasp security 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 a randomized order, resulting in 120 total pull attempts per participant.

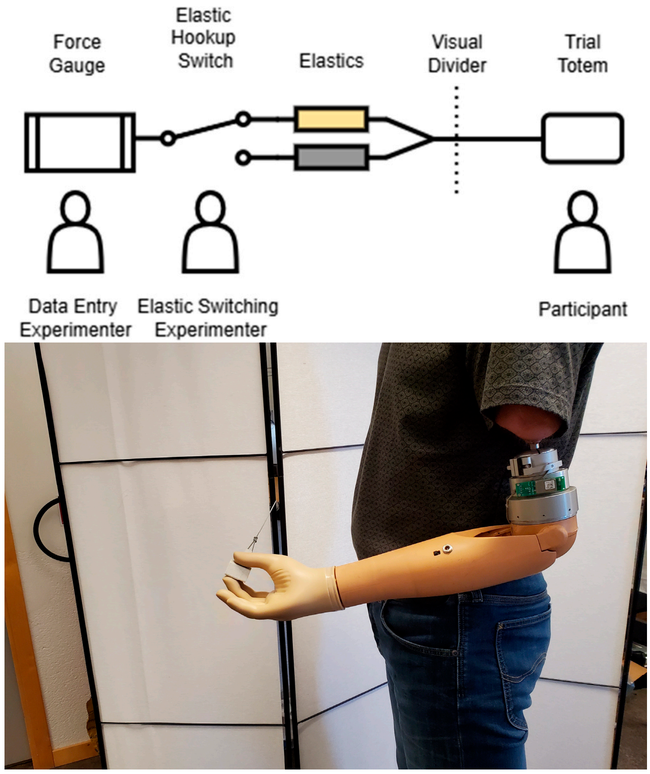


**Figure 4.** The experimental setup (above) involved one experimenter connecting the trial totem to different elastic bands to ensure that the participant used their sense of pull force, and not pull distance, during trials. A second experimenter recorded the maximum pull force for each trial. The opaque divider (below) blinded the participant to which elastic was in use and the force results from each trial.

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 themselves and learn which actions trigger stimulation. During these periods, the hand was set to grasp with 20 N of force, 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, participants rated their reliance on stimulation feedback, vision, and muscle/bone loads during the pull tasks on a scale of 1–10.

### 2.5. Statistical Analysis

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 totems and the maximum achieved pull force for non-slipped totems were recorded as primary outcomes. A three-level single factor study was conducted on stimulation conditions. 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 the 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 [43]. 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. All raw data can be found in Table S1 in the Supplementary Materials.

## 3. Results

### 3.1. Impact of Grasp Security Feedback on Slip Events

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* (Figure 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 but less uniform reduction in the median number of slips to 4.5 [0, 11] ($d$ = 0.866, $p$ = 0.177). At the higher grasping force of 25 N, 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 (Figure 5). There were no discernable differences in slip incidence between conditions ($d \leq 0.463$, $p \geq 0.431$). It is expected that every pull trial should have created a risk slip; however, warnings of slip (SVM output $\geq$ 0.4) occurred in only 69% of pulls in each of the *spike* and *amplitude stimulation* conditions. Slip incidence was nonetheless reduced for the stimulation conditions during the lower grasping force trials; however, the potential impact of this limitation is explored in the Discussions section.

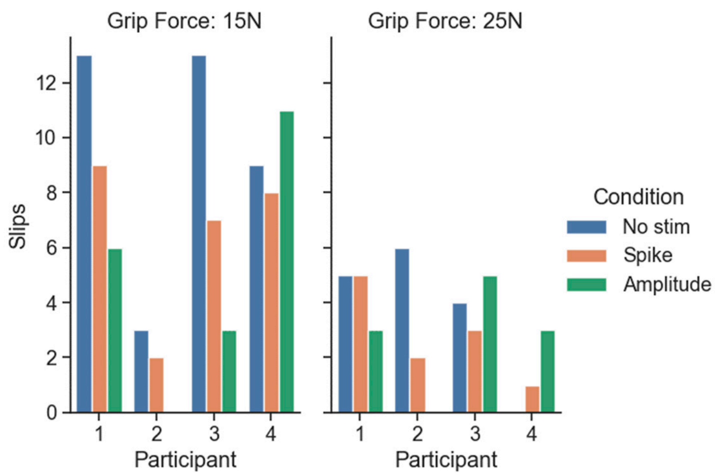


**Figure 5.** Median number of objects that slipped from lower-force grasp (15 N) when participants received *spike* or *amplitude stimulation* was reduced by 7.5 and 4.5, respectively, compared to *no stimulation*. Number of slips generally did not change discernably with higher-force grasp (25N).

### 3.2. Impact of Grasp Security Feedback on Pull Force

For low grasping force trials where the totem did not slip from the hand (no-slip trials), the median of pull forces per participant was 16.5 N [9.1 N, 19.0 N] with *no stimulation* (Figure 6). *Spike stimulation* had a very large effect on the median pull force, which increased consistently across participants to 17.2 N [10.1 N, 21.6 N] ($d$ = 1.325, $p$ = 0.058). *Amplitude stimulation* however had no discernable effect on pull force, with a median achieved pull force of 14.3 N [12.1 N, 22.4 N] ($d$ = 0.116, $p$ = 0.829). When the hand grasped with the higher grasping force, the median achieved pull force for the non-slip trials was also higher (Figure 6). *Amplitude stimulation* had a huge effect on median pull forces (21.5 N [17.8 N, 25.8 N]) compared to *no stimulation* (17.9 N [14.3 N, 23.5 N]) ($d$ = 3.306, $p$ = 0.009). The pull force also increased with *spike stimulation* (23.1 N [17.1 N, 24.4 N]), which is considered a large effect ($d$ = 1.194, $p$ = 0.098).

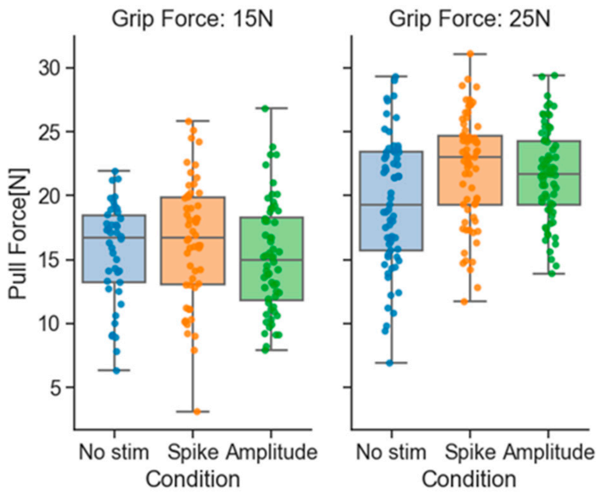


**Figure 6.** When pulling objects with a higher-force grasp (25 N), participants were able to impart greater pulling forces with *spike* and *amplitude stimulation* compared to *no feedback*. Only *spike stimulation* resulted in greater pull forces with a lower-force grasp (15 N). Points represent raw data, boxes represent median and quartiles, and whiskers extend to points within 1.5x the interquartile range.

Taken together, these results suggest that, at a low grip force where grasped objects are less secure and more likely to slip, a *spike stimulation* paradigm communicating a warning of impending slip may more reliably help to reduce the incidence of slipped objects (Figure 5). Furthermore, when more securely grasping objects, a *spike stimulation* scheme and, especially, a proportional *amplitude feedback* scheme, may better alert users when an object is at risk of slipping from their grasp, allowing the user to adjust their motion planning or grasp strength in response (Figure 6).

### 3.3. Impact of Grasp Security Feedback 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 hypothesized 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 Figure 7.

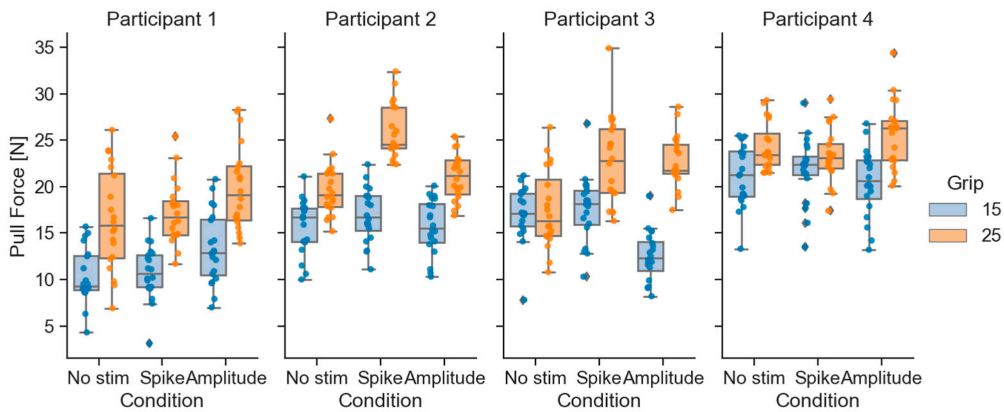


**Figure 7.** Pull forces were generally higher for high-force grasps (25 N) compared to low-force grasps (15 N), as expected. However, differences in median pull forces were larger when participants received *spike* or *amplitude stimulation*, indicating greater understanding of grasp security. Points represent raw data, boxes represent median and quartiles, and whiskers extend to points within 1.5x the interquartile range.

Separation between the average pull forces of high vs. low grip strengths appeared to increase in conditions with stimulation. Even with *no stimulation*, grip strength had a very large effect on pull force, with a median difference of 3.6 N [0.1 N, 5.2 N] ($d = 1.348$, $p = 0.054$). However, the effect sizes for both *spike stimulation* and *amplitude stimulation* were even larger, with differences in pull forces between high and low grip strengths of 6.0 N [1.5 N, 8.1 N] ($d = 1.851$, $p = 0.016$) and 5.3 N [3.4 N, 9.6 N] ($d = 2.215$, $p = 0.019$), respectively. Some degree of improvement was near universal; only P4's *spike stimulation* showed decreased performance compared to *no stimulation*. Conversely, as P3's *no stimulation* groupings were so close (0.1 N), *spike* and *amplitude stimulation* showed a huge rate of improvement (4.9 N and 9.6 N, respectively). We suggest that the increased separation of the pull forces in all participants indicates a greater understanding of the strength of the participants' grips.

### *3.4. Participant Perspectives*

Each experiment session ended with participants detailing the strategy they used to perform the pulling task. Self-reported reliance levels (Table 2) 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.

**Table 2.** Self-reported sensation reliance during pullint tasks, reported numerically (1–10).

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

Participants 1, 2, and 4 all stated heavy reliance on stimulation in mitigating slip during open dialog, despite prior numerical feedback (as seen in Table 1). 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 (Figure 7), and a reduction in the number of slipped totems (Figure 5), which may suggest a subconscious incorporation of the sensory information into their decision-making process.

P2 and P4 indicated a need for continued practice with and development of the grasp security 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, grasp security feedback nonetheless improved their performance, and most indicated interest in continued practice of the grasp security feedback at home.

## 4. Discussions

In this study, we investigated grasp security feedback in a sensorized prosthetic hand providing neural stimulation to transhumeral prosthesis users during an unblinded, user-in-the-loop task. This study was the first to implement a grasp slip mitigation protocol delivered using direct neural stimulation to multiple prosthesis users. Additionally, this study is the first to provide multiple grasp security stimulation paradigms and test their effect without inhibiting any of the participants' other senses such as vision. The method used in this experiment provided feedback on grasp security rather than rapidly detecting slip after grasp failure, which is predominant in the literature. This method also only provided notification stimuli to participants, rather than automatic correction movement to the prosthesis, which is also predominant in the literature. These two features of this study were implemented so that prosthesis users had full volitional control of their movements. During the study, participants' movements and senses were not limited, as seen in the only other mitigation strategy using neural feedback [38], which is more applicable for evolving this development beyond an experimental setting. However, despite the unrestricted incidental sensory information, our participants showed improved object manipulation performance when provided with neural feedback about grasp security.

The grasp security model was developed using a prosthesis agnostic method [42] and was computationally simple enough to deploy on a wide range of controller hardware. In the totem slip experiment, participants were asked to pull a totem as hard as possible without allowing it to slip from their 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 for the different grasping forces.

At low grasping force, objects are more likely to slip from the hand. In this condition, we found a consistent large reduction in the number of slipped totems when using *spike stimulation* compared to *no stimulation* (Figure 5). Likewise, at high grasping forces, participants were able to pull the totem harder without it slipping from the hand; in this condition, we found a large increase in the maximum achieved pull force when using *amplitude stimulation* compared to *no stimulation* (Figure 6). Finally, participants were able to differentiate their movement patterns to a greater degree between pulling tasks with low and high grip strength with either *spike* or *amplitude stimulation* active, enabling them to generate larger differences in maximum pull force (Figure 7). These results may suggest that the proposed feedback methods can improve the understanding of the security of the grasp but may be differently preferential in conditions of higher or lower slip likelihood. As a result, the selection of the feedback method may depend on the daily activities of the user, as we discuss in the next section. Furthermore, the *spike* and *amplitude stimulations* may feasibly be combined to provide the benefits of both methods.

The reduction in slipped totems with sensory feedback suggests that the ability to more reliably predict when the totem would slip from grasp aided participants in performing the task more successfully, while the increased pull forces during successful trials with sensory feedback suggests that participants had a greater sense of *when* slip might occur and were better able to approach that limit without failure. Taken together, our results indicate that a sensory feedback system, which provides users with estimates of the *likelihood* of object slip, allows them to more reliably *predict* when a slip may happen—rather than *detecting* and alerting them of a slip already in progress. Providing users with this grasp security information would subsequently allow them to decide how to handle the situation, perhaps by either adjusting their body position, increasing the prosthetic grip force, or bimanually grasping the object with both hands. Our participants generally indicated a preference towards this type of prosthetic setup, rather than relying on a self-correcting prosthetic grasp, which increases grasp force automatically when detecting a possible slip—a feature which our participants lamented as disconcerting, unreliable, and removing their agency, and which they frequently disable.

We used grip forces (15 N, 25 N) that are common in daily life and that were substantially higher than those found in similar prior works [26–29,31–39]. The maximum grip force in this study was limited to 25 N, 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 humeral rotation within this experiment, participants with transhumeral amputation sometimes helped push the prosthesis against the elastic band with their hip, which also prevented unintentional humeral rotation of the prosthetic elbow. Testing higher grip forces is not feasible due to this issue of unintentional humeral rotation.

The performance of the grasp security model was limited by the highly specific pulling angle dictated by the uniaxial 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 grasp security 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 grasp security feedback work, as hands with additional sensors in commercial and experimental use may address this issue using the same approach described here.

*Future Developments*

The quantitative system outcomes and, especially, the qualitative user feedback from people with lived experience indicate that there is justification in progressing the development of grasp security feedback for at-home use. In fact, one participant indicated that they would prefer grasp security stimulation over their current grasp force stimulation paradigm. A complete system including both grasp force and grasp security feedback could be beneficial for these users, with the feedback types differentiated by stimulation pattern or by using different neurostimulation waveform profiles. However, more work must be conducted before that is possible.

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, more work is needed to improve the quality of the prediction. The prosthetic hand had a very small sensorized area and a shear sensor along only one axis, meaning that shear occurring in a direction not parallel with the shear sensors were not accurately captured by the grasp security model. The prosthetic glove also affected the reliability of the shear sensors by causing deformation between the object contact and the sensors themselves. This contributed to warnings of slip occurring in only 69% of pulls in each of the *spike* and *amplitude stimulations*. Rectifying this may be achieved with a more versatile sensory suite onboard the prosthesis, or a more advanced processing of the regression output to select for local maxima of a certain prominence, rather than pre-determined hardcoded values.

One of the major obstacles to translating this system into the home is that the grasp security system is trained only on a single grasp aperture. Object shape presents challenges for system performance—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.

For a clinical application of grasp security 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 grasp (in)security 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 grasp security feedback need not be mutually exclusive with tactile feedback. Security 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 [44]. Stimulation paradigms invoking Apparent Moving Sensation algorithms have also been shown to elicit sensations perceived as slip, even with transcutaneous stimulation [45]. For a home-use grasp security 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.

## 5. Conclusions

Here, we presented the development of a stimulation paradigm for translating prosthetic sensory readings regarding grasp security into actionable inputs for amputee movement planning. In four transhumeral amputees, we found that grasp security feedback delivered by direct neural stimulation has a beneficial impact on prosthetic movement planning by providing information on the stability of the objects within 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 fusion is needed to replace lost sensation and has the capability to improve as prosthetic hands become increasingly sensorized.

**Supplementary Materials:** The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/prosthesis7010003/s1. Table S1: Raw study data.

**Author Contributions:** Conceptualization, M.O.-C.; methodology, A.B.S. and E.J.E.; software, A.B.S.; validation, A.B.S.; formal analysis, E.J.E.; investigation, A.B.S. and E.J.E.; writing—original draft preparation, A.B.S. and E.J.E.; writing—review and editing, A.B.S., E.J.E., N.J., and M.O.-C.; visualization, A.B.S. and E.J.E.; supervision, E.J.E., N.J., and M.O.-C.; project administration, E.J.E.; funding acquisition, M.O.-C. All authors have read and agreed to the published version of the manuscript.

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**Informed Consent Statement:** All individuals provided informed consent prior to participation in the research study to receive the neuromusculoskeletal prosthesis.

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