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A decision-based velocity ramp for minimizing the effect of misclassifications during real-time pattern recognition control

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Abstract

Real-time pattern recognition control is frequently affected by misclassifications. This study investigated the use of a decision-based velocity ramp that attenuated movement speed after a change in classifier decision. The goal was to improve prosthesis positioning by minimizing the effect of unintended movements. Non-amputee and amputee subjects controlled a prosthesis in real-time using pattern recognition. While performing a target achievement test in a virtual environment, subjects had a significantly higher completion rate ($p < 0.05$) and a more direct path ($p < 0.05$) to the target with the velocity ramp than without it. Using a physical prosthesis, subjects stacked a greater average number of 1” cubes ($p < 0.05$) in three minutes with the velocity ramp than without it (76% more blocks for non-amputees; 89% more blocks for amputees). Real-time control using the velocity ramp also showed significant performance improvements above using majority vote. Eighty-three percent of subjects preferred to control the prosthesis using the velocity ramp. These results suggest that using a decision-based velocity ramp with pattern recognition may improve user performance. Since the velocity ramp is a post-processing step, it has the potential to be used with a variety of classifiers for many applications.

Index Terms

myoelectric control; pattern recognition; prosthesis; surface electromyography; upper limb

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I. Introduction

Pattern recognition control has been proposed for control of multifunctional myoelectric prostheses [1, 2]. In pattern recognition, a computer program identifies an individual's intended movements by looking at the patterns produced by several channels of surface electromyography (EMG) signals [3]. This method of control relies on the assumption that EMG signal patterns are repeatable for the same movement and distinct for different movements [4]. With myoelectric pattern recognition control, motions can be voluntarily elicited by the user in any order, and if classification is performed on successive windows of data, users can smoothly transition from one class to another.

A great deal of research has been applied to pattern recognition algorithms to find techniques that result in the highest correlation between a user's intended movement and the algorithm's predicted movement. Movement is decoded through a series of steps including windowing, feature extraction, dimensionality reduction, and classification (Fig. 1). Feature extraction involving time-domain [5, 6], frequency-domain [7], or time-frequency feature sets [8] is an important step that significantly influences classifier performance [9]. When provided with a good feature set, various classifiers such as linear discriminate analysis [2, 9], Bayesian statistical methods [10, 11], artificial neural networks [4, 5, 12], and fuzzy logic [13, 14] have demonstrated offline accuracies ranging from 92% to 98%. Post-processing methods applied after classification, such as majority vote, can further improve accuracy [15] but at the expense of a longer control delay. An intensity calculation performed on the same data window, in parallel with classification, can decode movement speed (Fig. 1A) [16, 17]; this provides a proportional output signal [18]. By varying muscle contraction levels, users are able to perform fast or slow prosthesis movements.

Another significant step towards multifunctional prosthesis control is the development of a new surgical technique, called targeted muscle reinnervation (TMR), for individuals with an amputation [19, 20]. In TMR surgery, residual nerves that originally innervated muscles of the amputated limb are transferred to alternative muscles that are no longer biomechanically functional. Surface electrodes can record EMG signals from the reinnervated muscles, and these signals can be used to control physiologically appropriate functions in a prosthesis [21]. The combination for TMR and pattern recognition has recently been demonstrated as useful for real-time control of an upper limb prosthesis with a mean classification accuracy of 88% across eleven movements [21].

No pattern recognition system has yet been found to be 100% accurate. Additionally, the reported classification accuracies are only an offline measurement of the percentage of correctly predicted decisions, as real-time performance metrics have only recently been used to assess the control of multifunction prostheses [21, 22]. Therefore, even during a feed-forward movement, a state-of-the-art pattern recognition system will have misclassifications. In order for myoelectric pattern recognition control to be a viable option for individuals with an amputation, the effects of these misclassifications need to be mitigated. Otherwise, unintended prosthesis movements may cause users to become frustrated, drop items they are manipulating, and/or be unsuccessful at a task they are trying to complete.

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We developed a way to minimize the effect of unintended movements during myoelectric pattern recognition control of multifunctional prostheses. Based on previous work described by Hudgins et al [5], we implemented a decision-based velocity ramp as a post-processing step after the intensity calculation (Fig. 1A). The decision-based velocity ramp limited the speed of any motion after a change in the classifier decision. Only the movement speed was altered; the decision stream remained unchanged (no additional control delay). The speed then increased to 100% of the desired speed when the decision stream remained constant (Fig. 1B). The velocity ramp increased quickly to full desired speed if only a few misclassifications occurred within a continuous stream of correct classifications.

We assessed users' closed-loop prosthesis control using a myoelectric pattern recognition system with the decision-based velocity ramp. In the current study, subjects moved a virtual prosthesis into a target posture and/or used a physical prosthesis to complete a task. We hypothesized that prosthesis control performance using myoelectric pattern recognition would improve with the velocity ramp compared to a control condition in which the velocity ramp was turned off. The results suggested that subjects had less frustration, improved prosthesis positioning, and improved overall control while using the velocity ramp.

II. Methods

A. Decision-Based Velocity Profile

In the experimental condition, a decision-based velocity ramp was added to the pattern recognition system and applied after the intensity calculation (Fig. 1A). Ramp output speed, V_{out}, was calculated by multiplying the ramp gain, RG, for each class, i, by the desired speed, V_{in}, according to (1):

$$V_{out}=RG_i*V_{in} \quad (1)$$

The velocity ramp attenuated speed following a change in the class decision by applying a gain that varied between 0 and 1. The ramp gain was calculated by a linear function (2):

$$RG_i=C_i\frac{1}{L} \quad (2)$$

where C is the value of a counter associated with the current class and L is the ramp length defined by the experimenter. With each decision, the value of the associated counter increased by one, and the value of all other class counters decreased by two. The minimum of each counter was zero and the maximum was equal to the ramp length.

When a new class decision was made, the movement would initially be performed very slowly, due to the low value of the associated counter. The ramp output speed increased as continuous, same-class decisions were made (Fig. 1B). The decision-based velocity ramp allowed the output speed to increase more quickly if the misclassifications occurred within a continuous stream of correct classifications. The ramp had no effect on the termination of a movement (i.e. no additional control delay when transitioning to the no motion class).

For this experiment, the desired speed was calculated by averaging the mean absolute values (MAV) of all channels, *k*, of EMG signals for a given data window and multiplying by a class boost factor, *B* [16, 17].

$$V_{in}=B_i\left(\frac{1}{N}\sum_{k=1}^{N}MAV_k\right) \quad (3)$$

This equation is similar to a previously proposed proportional speed calculation [16]; however, MAVs were used instead of root mean square (RMS) signal values because they were already computed as part of the feature set. We confirmed that using MAV instead of RMS values resulted in no detectable change in speed during pilot experiments. The boost settings were configured for each class during the control condition such that a moderate force contraction resulted in a nominal speed (i.e. 50 degrees per second for the virtual prosthesis). Subjects could achieve a minimum speed with a lower force contraction and maximum speed with a higher force contraction. The outputs were scaled so that the maximum EMG amplitude approximately corresponded to the maximum motor speeds (100 degrees per second).

B. Subjects

The study participants included 12 non-amputee control subjects (8 men and 4 women). Six subjects were naive users and six had previous experience with pattern recognition. Six individuals with an amputation who had undergone TMR surgery also participated in this study: a man with a bilateral transradial amputation (TR1), a woman (TH2) and a man (TH3) with a left transhumeral amputation, a man with a right transumeral amputation (TH4), a woman with a left shoulder-disarticulation amputation (SD5), and a man with a right shoulder-disarticulation amputation (SD6). All TMR subjects were myoelectric users and had previous experience with pattern recognition. The study was approved by the Northwestern University Institutional Review Board. All subjects gave written informed consent to participate.

C. Virtual Prosthesis

Experiment 1—Ten non-amputee subjects (NA1–10) and six TMR subjects (TR1, TH2–4, SD5–6) controlled a virtual prosthesis with and without the decision-based velocity ramp. Six self-adhesive bipolar surface EMG electrodes were used to record muscle activity. For non-amputee subjects, electrodes were placed in a ring on the proximal portion of the forearm around the apex of the muscle bulge (2 to 3 cm distal to the elbow crease). For TR1, two electrodes were placed over the reinnervated muscles and four additional electrodes were placed in a ring around the proximal portion of the forearm. For TH2–4 and SD5–6, electrodes were placed over the reinnervated muscles: four electrodes were placed on the clinical sites [23] used for each patient’s myoelectric prosthesis, and two additional electrodes were placed over the remaining reinnervated muscle area. EMG signals were amplified and high-pass filtered with a cutoff frequency of 20 Hz. Data were sampled at a frequency of 1 kHz and processed in real-time using custom software [21].

The control algorithm was trained to recognize seven motions. For non-amputee subjects and TR1, the classes included wrist flexion, wrist extension, forearm supination, forearm pronation, hand open, one hand grasp, and no movement. All other TMR subjects used elbow flexion and extension to a replace wrist motion, based on their choice: subjects TH2, SD5, and SD6 replaced wrist flexion and extension, and subjects TH3 and TH4 replaced forearm supination and pronation. Subjects were prompted with a demonstration of each movement and asked to perform the movement at a comfortable level of effort. Each contraction was held for 3 s and repeated eight times.

The data were split into two groups, with 12 s of data from each class used to train a linear discriminate analysis (LDA) classifier [2] and 12 s of data from each class used to test the classifier. The pattern recognition system segmented the EMG data from each channel into a series of 150 ms analysis windows with a 50 ms window increment. Four time-domain features (mean absolute value, number of zero crossings, waveform length, and number of slope sign changes [5]) were extracted from the EMG data in each analysis window. After the LDA classifier was trained, it was used to predict user commands and control a virtual and/or real prosthetic arm. The desired speed of the selected class was extracted from the same analysis window as the data used for the class decision and was calculated by (3).

Subjects performed the Target Achievement Control (TAC) Test within a virtual reality environment to quantify performance with and without the decision-based velocity ramp [24]. Prior to testing, they were given 5 to 10 min. of practice to become familiar with the virtual environment. Subjects were informed that when the velocity ramp was turned on, movement speed would start out slowly and then increase as they continued to perform the motion. During the test, subjects were required to move a virtual prosthesis into a prompted target posture. To provide visual feedback, the virtual hand changed color when it reached the target within an acceptable tolerance (± 5 degrees for each degree of freedom). Trials ended successfully when subjects were able to keep the virtual hand in the target for 2 s. In order to remain in the target subjects needed to relax their muscles and elicit the ‘no movement’ decision from the classifier. The subjects were only required to perform a single motion (e.g. wrist flexion) to achieve each target posture, but all other trained motions were active. The maximum speed of each degree of freedom was 100 degrees per second. Tests were completed more quickly if the subjects were able to control the virtual arm without producing unwanted motions. Overshooting the target posture or producing an incorrect class decision would force the subject to correct the unnecessary movement. Trials ended unsuccessfully if the subject did not reach the target position or sustain the 2 s dwell time within 15 s.

Subjects performed four sets of the TAC Test for each conditions: no ramp (Control), and the ramp with ramp lengths of 10 (Ramp 10), 20 (Ramp 20) and 30 (Ramp 30). With a 50 ms frame increment, output speed increased to 100% of the desired speed in 0.5 s, 1.0 s, and 1.5 s, respectively, with the three ramp conditions. The order of conditions was randomized. Each set consisted of two repetitions of six target postures for a total of 12 trials. The first set was used as practice and the last three sets were used for data analysis. Target postures corresponded to the trained motions.

Upon completion of each condition, subjects qualitatively described their level of control with the prosthesis. Subjects ranked their level of frustration using a 7-point scale where "1" indicated subjects were very frustrated and "7" indicated subjects were not frustrated. Other performance metrics included completion rate, completion time, and path efficiency [24]. Completion rate was the percentage of successfully completed postures. Completion time was the time from the start of the trial to the successful achievement of the target posture or trial timeout, not including the 2 s dwell time. Path efficiency was calculated as the shortest path to the target divided by the total distance traveled by the virtual hand [25].

We performed a one-way ANOVA with repeated measures to test for differences in completion rate, completion time, path efficiency, and frustration levels across the four conditions. Significant ANOVAs were followed by a planned contrast to locate the differences between the control and velocity ramp conditions.

Experiment 2—Five non-amputee subjects (NA11–15) completed an experiment to compare the performance of the velocity ramp to majority vote. Experimental protocol was the same as Experiment 1 except a ring of four electrodes, instead of six electrodes, was used. Conditions tested were: no post-processing (Control), majority vote queue of lengths of 3 (MV 3), 5 (MV 5), and 10 (MV 10) decisions, and velocity ramps lengths of 10 (Ramp 10) and 20 (Ramp 20). User frustration levels were not recorded. We performed a repeated measures ANOVA to determine to test for differences in completion rate, completion time, and path efficiency. A planned contrast was used to determine if there were differences between the majority vote and ramp conditions. The MV 10 condition was not included in the statistical analysis since it was only included as a time-matched comparison to the Ramp 10 condition and likely exceeded the optimal controller delay.

D. Physical Prosthesis

Experiment 3—Four non-amputee subjects (NA9–10, NA16–17) and five TMR subjects (TR1, TH2–4, SD5) completed a challenging performance test in which they stacked one-inch wooden blocks using an experimental multifunctional prosthesis with and without the velocity ramp. Non-amputee subjects wore an upper-limb able-body adaptor which consisted of a socket that allowed for the attachment of the prosthesis at the shoulder and constrained movement of one arm and hand (Fig. 2). For non-amputee subjects, six bipolar EMG electrodes were placed in a ring on the proximal portion of the forearm, one on the biceps, and one on the triceps. For TMR subjects, electrodes were placed on the clinical sites used for each patient's myoelectric prosthesis (two electrodes for TR1 and four electrodes for TH2–4 and SD5). Four additional electrodes (TR1, TH2–3) or eight additional electrodes (SD5) were placed over the remaining reinnervated muscle area. For TR1, three degrees of freedom were included in the pattern recognition classifier: wrist flexion and extension, forearm supination and pronation, hand open and close, and no movement (for a total of seven classes). For TH2–4 and SD5, elbow flexion and extension was added to the pattern recognition classifier for a total of four degrees of freedom (nine classes). Methods for collecting and training the classifier were the same as described for the virtual prosthesis experiment. Subjects used a prosthetic arm with six degrees of freedom developed at the Rehabilitation Institute of Chicago [26]. The prosthesis was capable of powered shoulder flexion/extension, humeral rotation, elbow flexion/extension, wrist rotation, wrist flexion/extension, and hand control.

All subjects were familiar with operating a multifunctional prosthesis and were given 5 to 10 min. of practice prior to testing. Testing with the physical prosthesis involved stacking as many 1” cubes on top of one another as possible during a 3 min. trial (Fig. 2). This task required increased fine motor control as the tower grew (e.g. unintended wrist or elbow motion during block placement had the potential to collapse the tower). For trials using the velocity ramp, one ramp length per subject was tested based on their preference during the practice period. TMR subjects All TMR subjects used a ramp length of 10. Non-amputee subjects used a ramp length of 20. Subjects performed three trials with the velocity ramp and three trials without it, in a randomized order. Data was analyzed for the best two out of three trials per condition.

Performance metrics included the number of blocks stacked, the tallest tower height, and the number of blocks dropped. A stacked block was counted if it was successfully placed on the tower. A dropped or misplaced block was counted if it was dropped at any point after it was lifted from the table and prior to being successfully placed on the tower. The tallest tower was the highest number of blocks stacked one on top of another within the three minutes. Within a trial, the number of stacked blocks was sometimes greater than the tallest tower height, indicating that blocks (other than the one being manipulated) had been knocked off the existing tower.

III. Results

A. Virtual Prosthesis

Experiment 1—Average classification accuracy was 97.2% ± 3.2% (mean ± standard deviation) for non-amputee subjects and 91.4% ± 8.6% for TMR subjects.

Non-amputee subjects reached significantly higher completion rates during the velocity ramp conditions than during the control condition (ANOVA, $p < 0.02$) (Fig.3, Fig. 4A). TMR subjects completed significantly more trials during the two shortest ramp conditions than during the control (ANOVA, $p < 0.04$) (Fig. 4A). Path efficiency significantly increased during the ramp conditions compared to the control condition for both groups (ANOVA, non-amputee group: $p < 0.001$; TMR group: $p < 0.002$) (Fig. 4B).

For non-amputees, completion times were significantly shorter during all ramp conditions compared to the control condition (ANOVA, $p < 0.01$) (Fig. 4C). For non-amputee subjects, completion times were significantly shorter during the Ramp 10 and 20 conditions compared to the control condition (ANOVA, $p < 0.001$).

Using a 7-point scale (where “1” indicated that subjects were very frustrated), non-amputee subjects reported significantly less frustration while controlling the virtual prosthesis with the velocity ramp (5.1 ± 1.4 for Ramp 10; 5.7 ± 1.2 for Ramp 20; and 5.2 ± 1.5 for Ramp 30) compared to without it (3.1 ± 1.4) (ANOVA, $p < 0.005$). TMR subjects also reported significantly less frustration during the Ramp 10 condition (5.2 ± 1.9) compared to during the control condition (3.0 ± 1.9) (ANOVA, $p = 0.049$). TMR subject frustration levels for the Ramp 20 and Ramp 30 conditions were 5.6 ± 2.0 and 4.6 ± 2.4, respectively.

Experiment 2—Average classification accuracy with no-post processing was 94.9% ± 3.3%. Accuracy significantly increased for all majority vote conditions (95.9% ± 2.8% for MV 3; 96.8% ± 2.3% for MV 5; and 98.3% ± 1.2% for MV 10) ($p < 0.05$).

There were no significant differences between the control, MV 3, and MV5 conditions for all performance metrics ($p = 0.73$ for completion rate; $p = 0.30$ for completion time; and $p = 0.67$ for path efficiency) (Fig. 5) even when the MV 10 condition was excluded from the analysis due to its poor performance. While using the velocity ramp, subjects completed significantly more trials than with the control ($p = 0.04$) or majority vote ($p = 0.002$). Subjects significantly increased their path efficiency with the velocity ramp compared to the majority vote ($p < 0.001$) or control ($p = 0.02$) conditions. A separate analysis confirmed that 500 ms majority vote condition performed significantly worse ($p<0.05$) than the control condition.

B. Physical Prosthesis

Experiment 3—Across all nine trained movements, classification accuracy was 99.0% ± 1.4% for non-amputee subjects and 90.7% ± 4.2% for TMR subjects. Subjects stacked significantly more blocks using the velocity ramp compared to the control condition (paired t-test, non-amputee group: $p =0.035$; TMR group: $p = 0.004$) (Fig. 2 and 6). All subjects had less dropped blocks in three minutes during the ramp condition compared to the control condition (paired t-test, non-amputee group: $p = 0.011$; TMR group: $p = 0.053$). All subjects created significantly higher towers using the velocity ramp compared to the control condition (paired t-test, non-amputee group: $p = 0.002$; TMR group: $p = 0.022$)

IV. DISCUSSION

The goal of myoelectric pattern recognition systems is to provide reliable multifunction control to users. One measure of success is pattern recognition accuracy. A well-planned combination of feature set and classifier can result in a pattern recognition algorithm that has offline accuracies of 92% to 98% [2, 9, 13, 27]. In the current study, the combination of time domain features and linear discriminant analysis resulted in an average classification accuracy of 97% for non-amputee subjects and 91% for TMR subjects. Similar accuracies have previously been reported with amputees who had undergone TMR surgery [21]. With accuracies less than 100%, pattern recognition control will have mismatches between the user's intended movement and the classifier's predicted movement. This study presented the use of a decision-based velocity ramp that improved prosthesis control by minimizing the effect of misclassifications.

Since the velocity ramp did not change the classifier's decision, it was presumed that the percentage of misclassifications did not change between conditions. The velocity ramp relied on the assumption that misclassifications occur intermittently with a properly functioning classifier, often at the beginning and end of intended motions [28]. These misclassifications still occurred with the ramp, but their effect on prosthesis movement was attenuated. Accurate motion classifications were also affected by the ramp, with the initial speed of intended motions similarly attenuated. Decreasing initial speed of all movements did not adversely affect users' performance and may have lead to more fine control of the multifunctional prosthesis.

For Experiments 1 and 3, five of the six TMR subjects and ten of the twelve non-amputee subjects preferred to control the physical and/or virtual prosthesis using the velocity ramp compared to control without it. Four subjects openly voiced this preference after only one or two prosthesis movements. Subjects reported less frustration and finer positioning for small adjustments while using the velocity ramp. One amputee subject commented that she felt like she had "fewer false starts" with the velocity ramp. The prosthesis more closely followed her initial intended motion. One non-amputee subject described his ability to trust the prosthesis more while using the velocity ramp to stack blocks. He had more confidence that the prosthesis was not going to do something unexpected, like quickly open the hand before he was positioned correctly.

The two non-amputee subjects and one TMR subject who favored the control condition stated that they preferred the increased initial speed of the prosthesis when the velocity ramp was turned off. During the velocity ramp conditions, these subjects tended to produce very large muscle contractions in attempts to increase initial movement speed. This strategy did not produce the desired effect since initial speed was limited by the ramp. Even though these subjects preferred the control, they had improved performance (increased completion rate and path efficiency) during the velocity ramp conditions.

Comparing subjects' performance and preference between the three ramp lengths revealed that the longest ramp length may have required too long of a consistent decision stream. Although non-amputee subjects showed similar performance improvements while using any of the velocity ramps, several subjects reported that the Ramp 30 condition felt very slow. For TMR subjects, the two shortest ramp length conditions (Ramp 10 and Ramp 20) had consistent improved performance over the longest ramp length (Ramp 30) and control conditions. While using a physical prosthesis, only subjects' preferred ramp length was tested. Subjects were able to stack more blocks with less dropped blocks with the velocity ramp than without it.

Post-processing techniques, such as majority vote [15] and EMG mean/median filter, have previously been suggested as ways to improve pattern recognition controllability. Important distinctions should be made between the velocity ramp and these techniques. Majority vote outputs the class decision with the greatest number of occurrences over a given analysis window but does not alter the desired speed (Fig. 6A). Majority vote removes spurious misclassifications; however, it adds an additional controller delay as decisions propagate through the majority vote queue [29, 30]. A simple EMG mean or median filter outputs the current decision to the actuator, but will smooth out fluctuations in the velocity control (Fig. 6B). Misclassified movements still have the potential to have an associated large velocity signal. The velocity ramp outputs the current decision to the actuator but with a potentially attenuated actuation velocity (Fig. 1).

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Our results demonstrated a significant increase in classification accuracy with majority vote, but our real-time tests show no significant difference in performance compared to the control condition. The MV 3 and MV 5 conditions (corresponding to 150 ms and 250 ms majority vote windows, respectively) were chosen based on the literature investigating the optimal controller delay for pattern recognition systems [31] and the relationship between controller delay and majority vote window length [15, 30]. Qualitatively, we observed that there were no spurious misclassifications when using majority vote, but the users consistently overshot the target position. Therefore, the benefit of having fewer classification errors with majority vote is most likely offset by the additional controller delay. The 50 ms window increment used in the current study may have affected the results. A smaller increment might improve performance, but this remains to be tested. Regardless of the window increment used, these results highlight an important finding that methods that have been shown to reduce errors during offline analysis may not improve real-time control.

The results of the majority vote study emphasize another advantage of using the decision-based velocity ramp. With this method, a longer data history can be used. The longer ramp lengths of the Ramp 10 and Ramp 20 conditions (500 ms and 1000 ms, respectively) did not adversely affect users' performance. In fact it significantly improved performance above the control and above majority vote conditions which used shorter data histories. The time-matched majority vote of 500 ms, which added a controller delay longer than what the literature suggests is reasonable, significantly impaired performance.

The decision-based velocity ramp described in this study had some limitations. It required a level of consistency in the decision stream to allow movement speed to ramp up to the desired speed. If the decision stream for a particular movement never stabilized on the motion class, adding the velocity ramp most likely hindered performance. In this case, motion speed would continuously be attenuated, making movement slow in any direction. While stacking blocks, subject TH2 did not have a consistent stream of hand open decisions when she wanted to release a block. Other motions were fairly consistent and benefitted from the velocity ramp, but hand opening was hindered. Overall, she created a taller tower of blocks without the ramp because she was able to open the hand using intermittent hand open decisions with higher speeds. With the velocity ramp, she spent more time trying to release each block on the top of the tower, a task that often result in the tower being knocked down. Subject TH2 may have benefited from customization of the ramp for each degree of freedom, much like the customization of gains and thresholds for current myoelectric prostheses. If a user has difficulty eliciting some movements, it may be beneficial to alter the ramp lengths for those movements, allowing them to speed up more quickly. Furthermore, this modification would allow subjects to use a velocity ramp with movements where they desire finer control (e.g. hand open/close) but not with movements they prefer to perform quickly (e.g. elbow flexion/extension).

With the current configuration, the velocity ramp reduced the amplitude of unintended motions and allowed for finer positioning and improved control of multifunctional prostheses (both virtual and physical). The improved control was immediate, with subjects needing little to no adjustment time. Majority vote did not improve the real-time performance. In fact, long majority vote queues (>500 ms) significantly impairs users' ability to control the prosthesis in real-time. Finally, since the decision-based velocity ramp is independent of the decision stream, it has the potential to be used with a wide variety of classifiers for a variety of applications to improve user performance.

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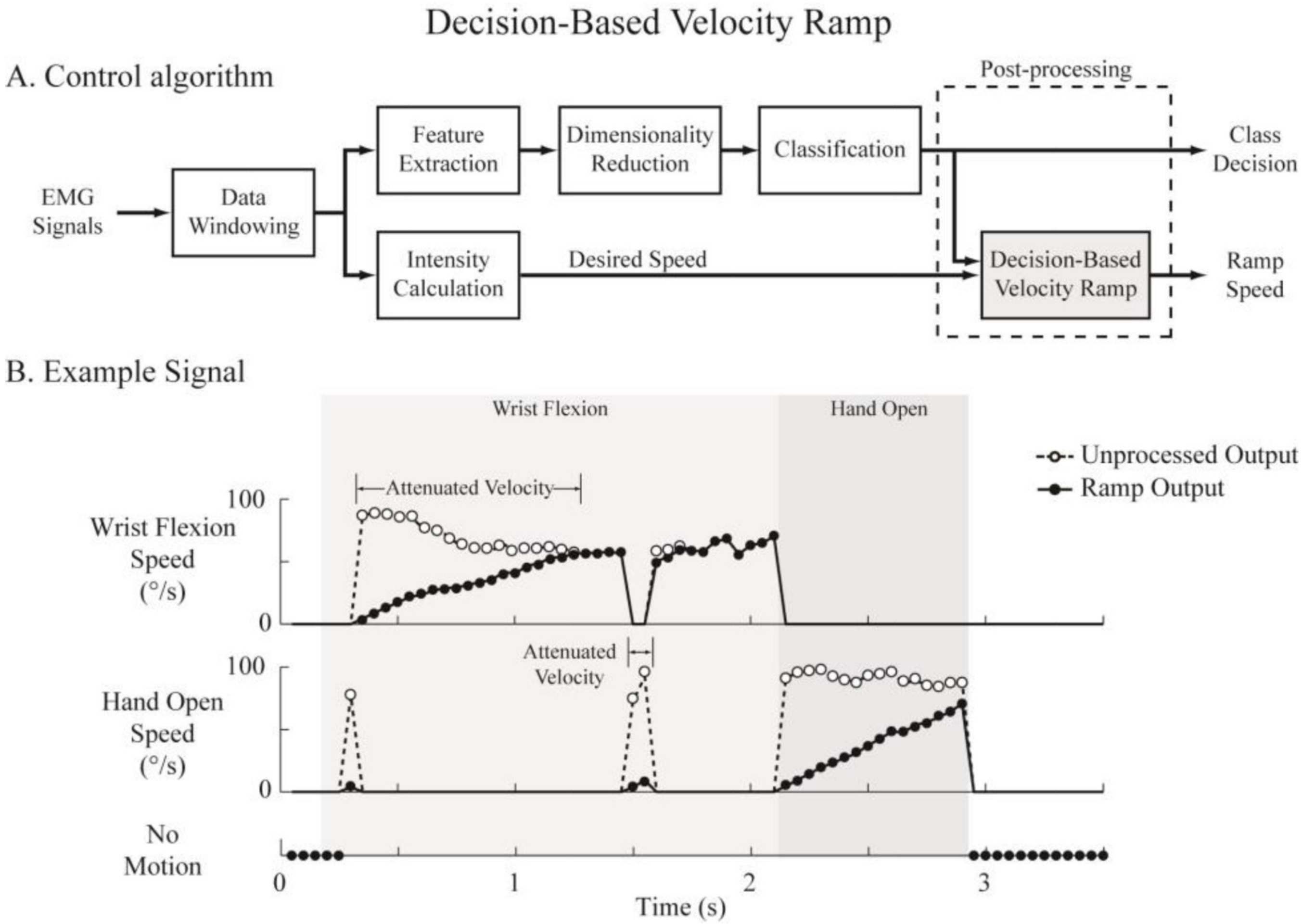

Fig. 1.

(A) Myoelectric pattern recognition algorithm using a decision-based velocity ramp. The velocity ramp kept the original class decision and altered only the movement speed. (B) Desired speed and ramp output speed versus time shown for three classes. As the subject flexed her wrist, the first class decision was hand open (i.e. a misclassification). The desired speed, 77°/s, was attenuated to 3.9°/s using the velocity ramp. The next decision was an accurate wrist flexion classification. The desired speed, 88°/s, was attenuated to an output speed of 4.4°/s. With ramp length equal to 20, the output speed increased to 100% of the desired speed (55–65°/s) after 1 s of continuous wrist flexion decisions.

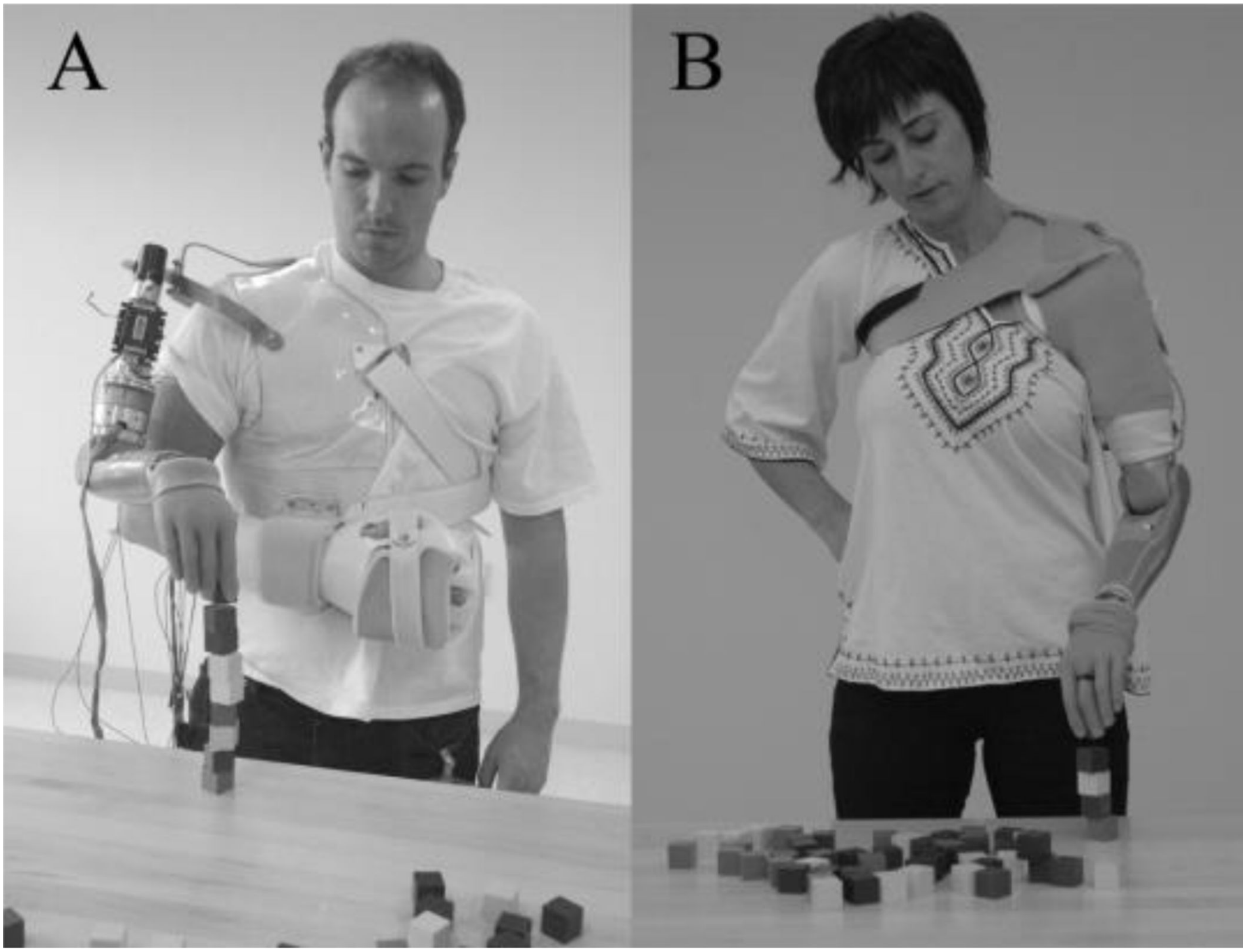

Fig. 2.
(A) A non-amputee subject wearing a bypass prosthesis and (B) a subject with a transhumeral amputation who had undergone TMR surgery stacking blocks while using the velocity ramp.

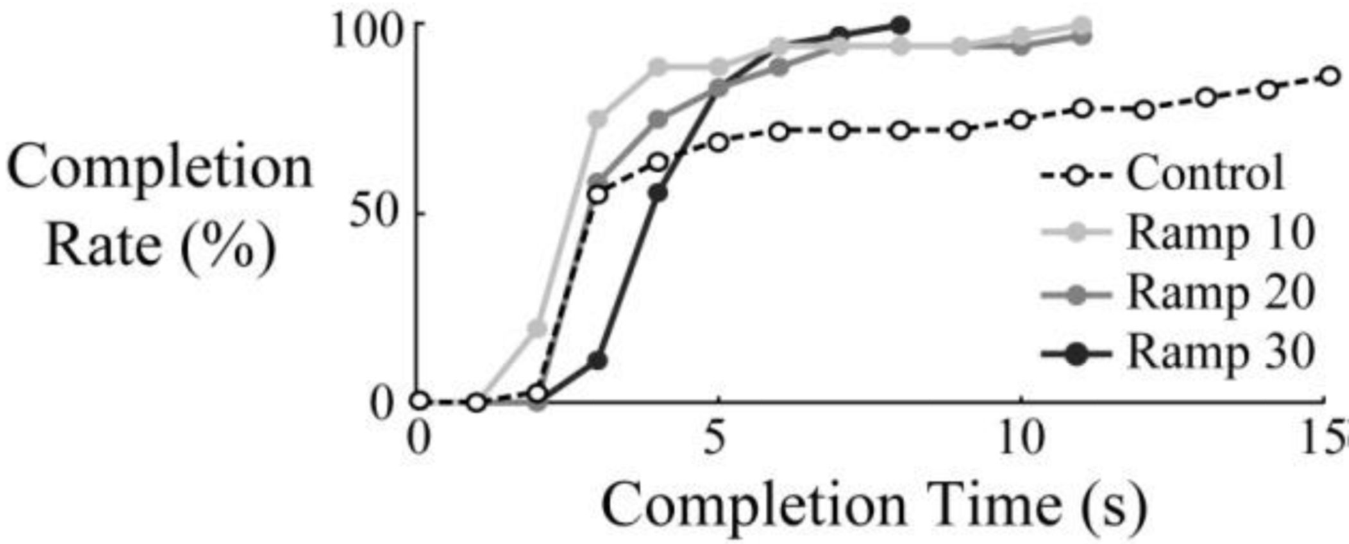

Fig. 3.
Completion rates for a typical non-amputee subject. This subject had a higher completion rate for the ramp conditions compared to the control.

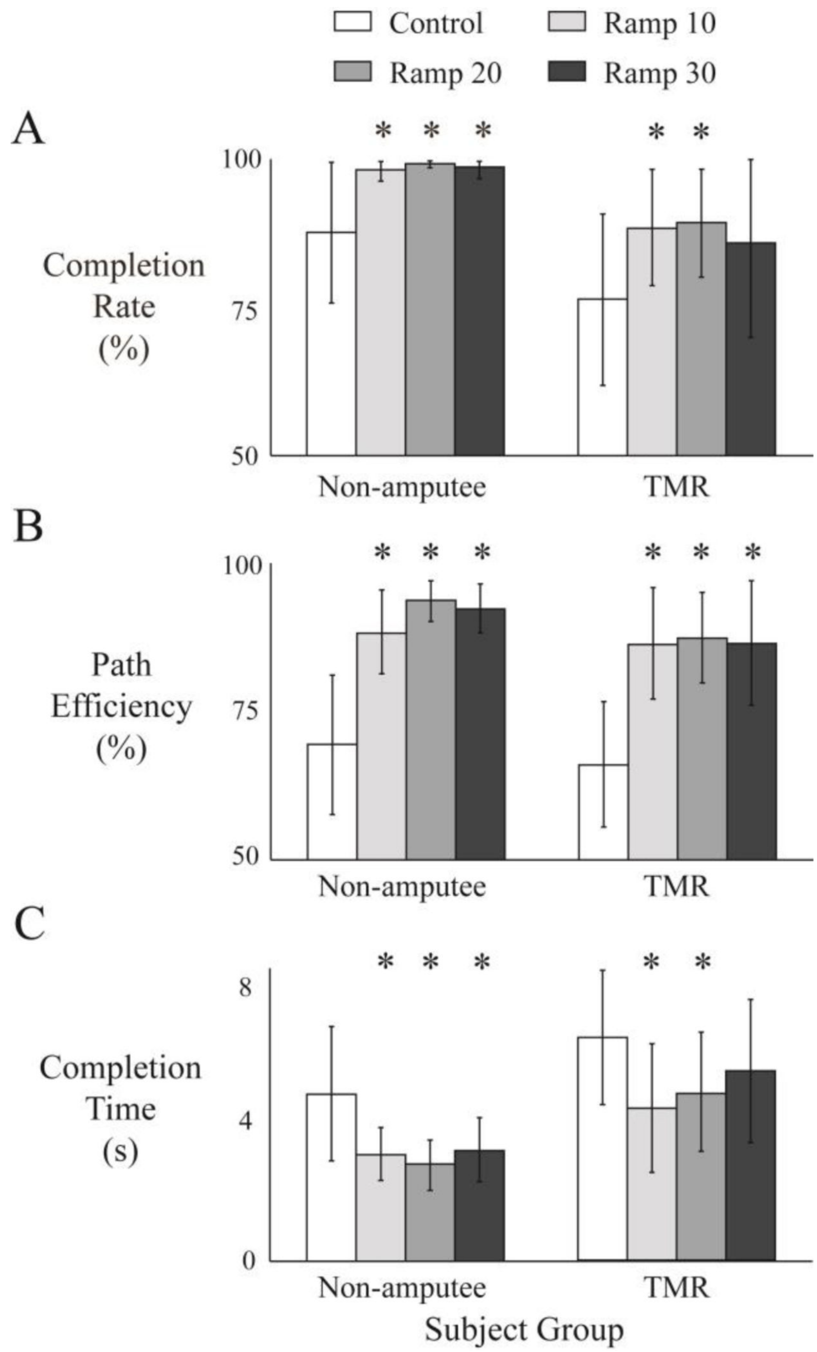

Fig. 4.

Experiment 1: TAC Test performance metrics. (A) Compared to the control condition, completion rate significantly increased for all ramp conditions for non-amputee subjects and for the Ramp 10 and Ramp 20 conditions for TMR subjects. (B) Path efficiency increased during the ramp conditions compared to the control for both the non-amputee group and the TMR group. (C) Non-amputee subjects showed a significant decrease in completion time for the all ramp conditions compared to the control condition. TMR subjects showed a significant decrease in completion time for the Ramp 10 and Ramp 20 conditions. Error bars denote standard deviation and * denotes a significant difference ($p < 0.05$) from the control condition.

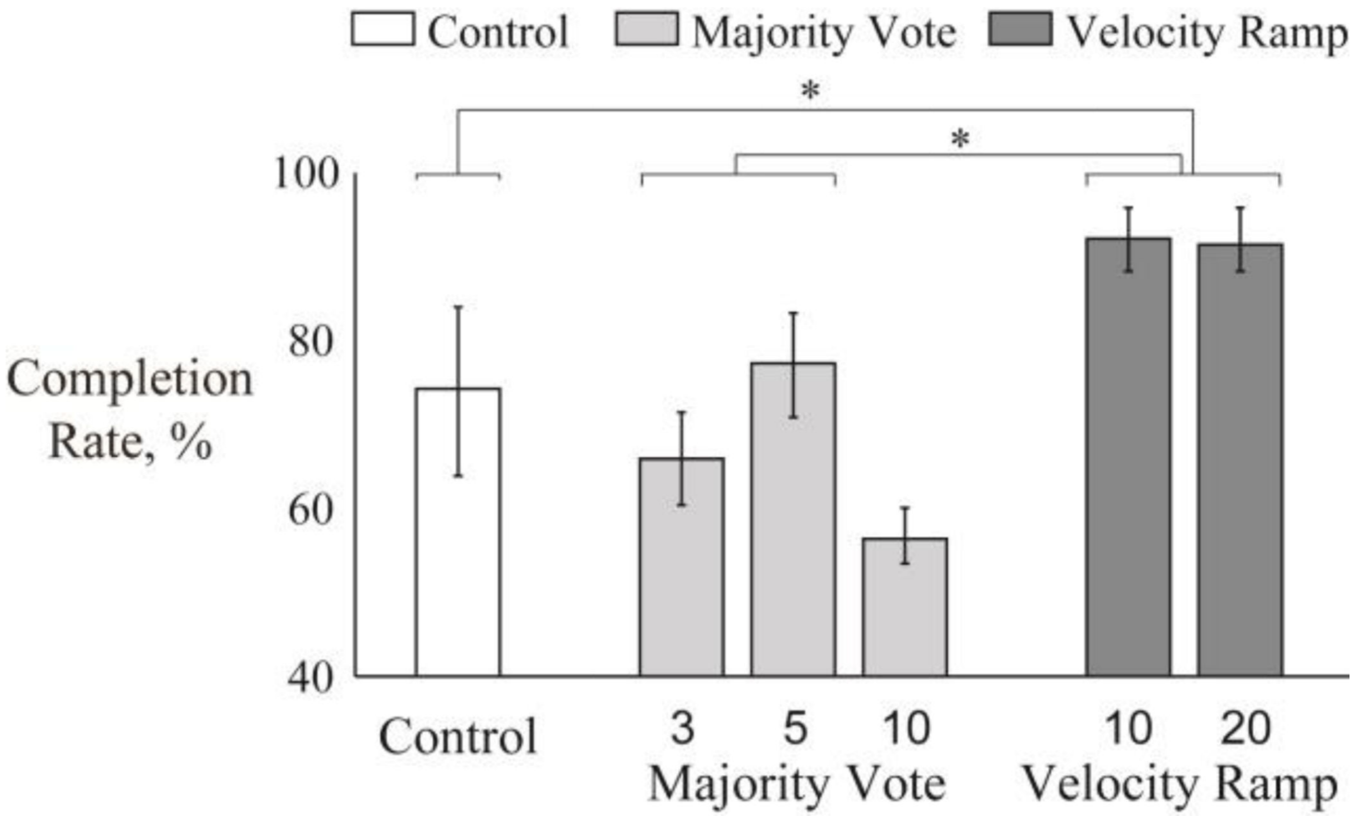

Fig. 5.

Experiment 2: TAC Test completion rates. Error bars denote standard error and * denotes a significant difference ($p < 0.05$) between conditions. The *MV 500ms* condition was not included in the statistical analysis.

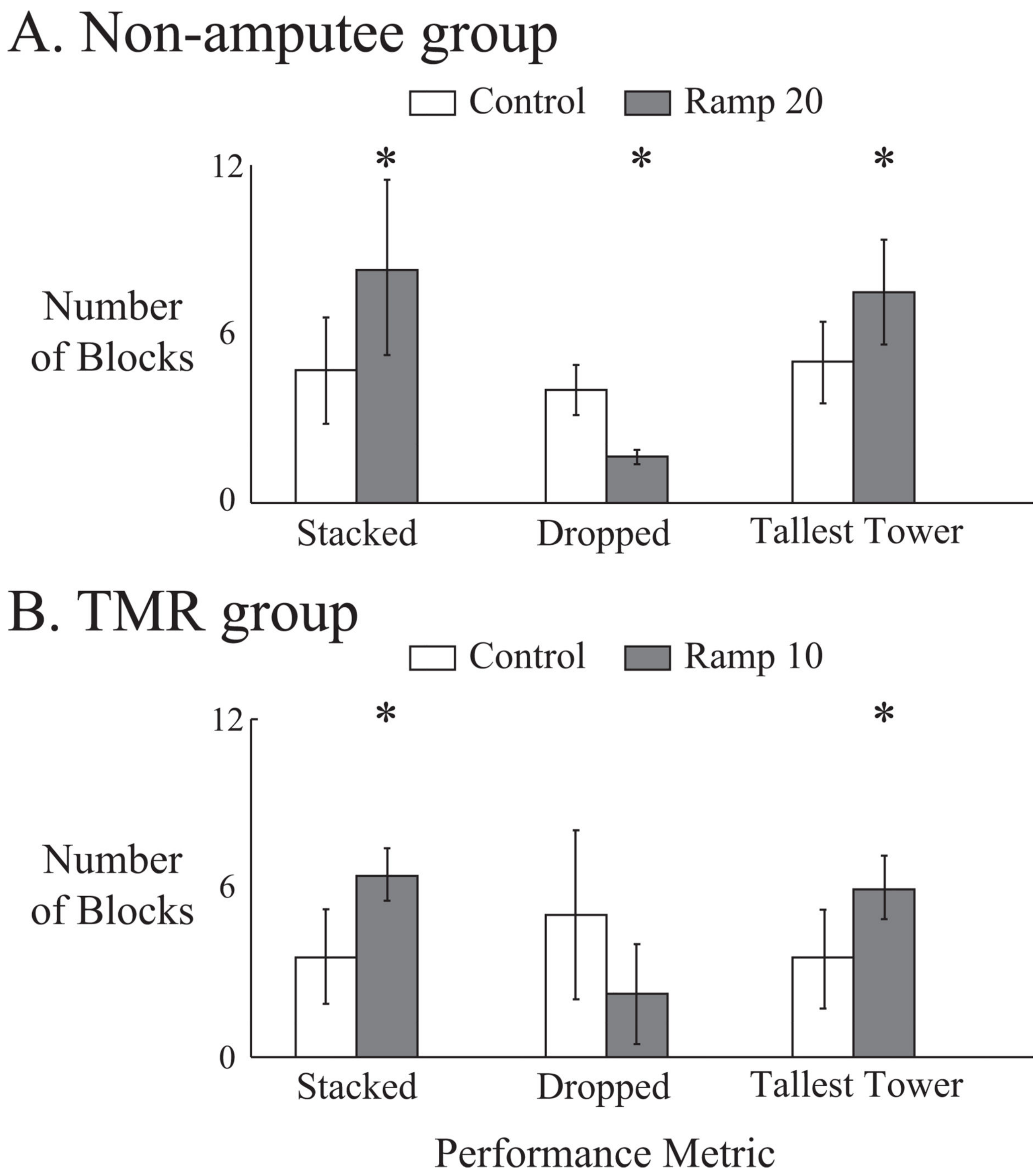

Fig. 6.

Experiment 3: Block-stacking performance metrics. (A) Non-amputee and (B) TMR subjects showed significantly better performance during the ramp condition compared to the control. Error bars denote standard deviation and * denotes a significant difference ($p < 0.05$) between conditions.

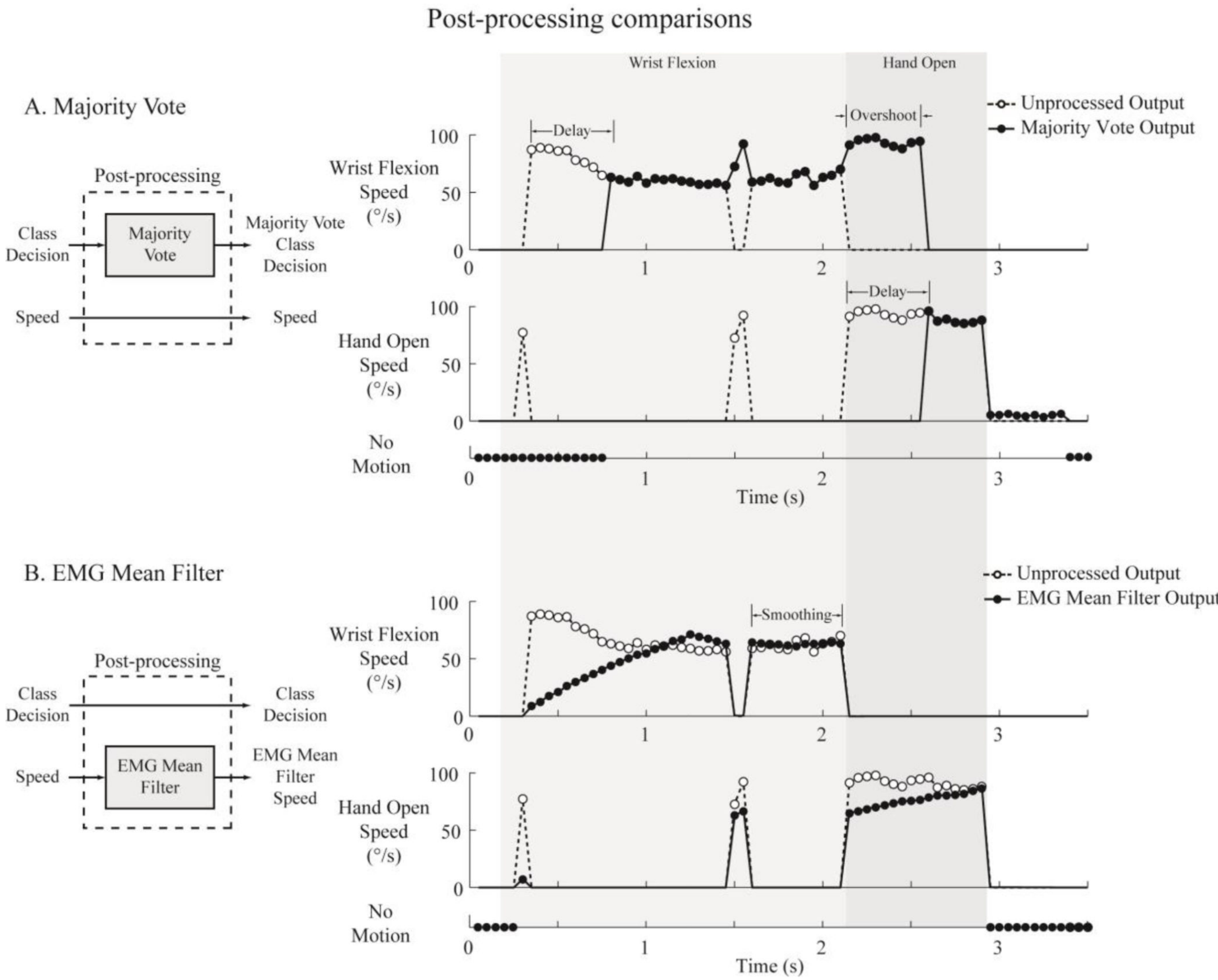

Fig. 6.

Post-processing comparison between (A) majority vote and (B) EMG mean filter as a subject flexed the wrist then opened the hand. Majority vote removed spurious misclassifications but led to onset delay of movements and position overshoot. EMG mean filter smoothed out fluctuations in the velocity control but misclassified movements still had the potential to have an associated large velocity signal.