33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

A comparison of the effects of majority vote and a decision-based velocity ramp on real-time pattern recognition control

Ann M. Simon, Levi J. Hargrove, *IEEE Member*

Abstract—**Movement misclassifications often occur during real-time pattern recognition control. Majority vote and a decision-based velocity ramp are two different post-processing methods that have been suggested to improve real-time control. With majority vote, spurious misclassifications are removed at the expense of an additional controller delay. With a decision-based velocity ramp, the effect of misclassifications is minimized by attenuating movement speed following a change in decision from the classifier. The goal of the study was to determine which, if any, post-processing method improved real-time control above a baseline condition that did not involve post-processing. Five non-amputee subjects controlled a virtual prosthesis in real time using pattern recognition. While performing a challenging target achievement test in a virtual environment, subjects had significantly higher completion rates ($p < 0.04$) and more direct paths to the target ($p < 0.02$) while using the velocity ramp than while using majority vote or the control condition. There were no significant differences in completion rate or path efficiency between the majority vote conditions and the control condition ($p > 0.6$). The benefits of removing misclassifications through majority vote may be offset by the added controller delay. These results highlight the need for real-time performance measures, as methods that have been shown to reduce errors during offline analysis may not improve real-time control.**

I. Introduction

Effective real-time use of a prosthesis requires quick and accurate responses to the user's commands. Myoelectric pattern recognition allows users to control their prostheses in an intuitive way and has the potential to improve the current level of control. With pattern recognition, movement is decoded through a series of steps that include data windowing, feature extraction, dimensionality reduction, and classification. Previous research shows that various combinations of feature sets and classifiers have offline error rates below 5% [1-4]. Movement speed can be decoded in parallel with classification [5, 6]. By varying muscle contraction levels, users are able to perform fast or slow prosthesis movements [7]. Two post-processing methods, majority vote [8] and a decision-based velocity ramp [9], applied after classification have been proposed for improving pattern recognition control.

Manuscript received April 14, 2011. This work was supported by National Institute of Health - National Institute of Child Health and Human Development award R01-HD-05-8000.

A. M. Simon and L. J. Hargrove are with the Center for Bionic Medicine, Rehabilitation Institute of Chicago, Chicago, IL 60611. L. J. Hargrove is also with Department of Physical Medicine and Rehabilitation, Northwestern University, Chicago, IL, 60611. Corresponding author: A. M. Simon (phone: 312-238-1158; fax: 312-238-2081; e-mail: asimon@ric.org).

In a majority vote scheme, the class that occurs most frequently across the last *n* decisions is selected as the class output (Fig. 1A). The movement speed remains unchanged. Majority vote has the potential to reduce classification errors by removing spurious misclassifications but adds an additional controller delay. For this study, the controller delay is defined as the length of time between the users' commands (i.e. myoelectric intent) and the corresponding action of the device. The number of votes and length of controller delay that can exist before the control of a prosthetic system degrades has been debated [8, 10] but currently no research exists on users' real-time performance using a pattern recognition system with majority vote.

In a decision-based velocity ramp scheme, the decision remains unchanged but the movement speed is altered (Fig. 1B). The velocity ramp attenuates the speed of any motion after a change in the classifier decision and has the potential to reduce the effect of misclassifications [9]. This post-processing method may prove beneficial because misclassifications often occur at movement onset or during transitions. The velocity ramp does not add an additional controller delay since the decision stream remains unchanged.

The goal of this study was to determine which, if any, post-processing method improves users' real-time pattern recognition performance. We hypothesized that due to the fact that there is no additional controller delay associated with the velocity ramp, users should perform better while using the velocity ramp than while using majority vote.

II. Methods

A. Experimental Setup

Five non-amputee subjects participated in this study. All subjects had experience controlling a virtual prosthesis in real time using a pattern recognition system. Subjects provided written informed consent.

Four self-adhesive silver/silver chloride bipolar EMG electrodes were placed in a ring at the proximal portion of the forearm. The EMG signals were amplified and high-pass filtered at 20 Hz. Data were sampled at a frequency of 1 kHz and processed in real time using custom Matlab programs.

Subjects trained the system to recognize seven motion classes: wrist flexion/extension, forearm supination/ pronation, hand open/close, and no movement. Subjects were prompted with a demonstration of each movement and were asked to perform the movement at a comfortable level of effort. Each contraction was held for three seconds and

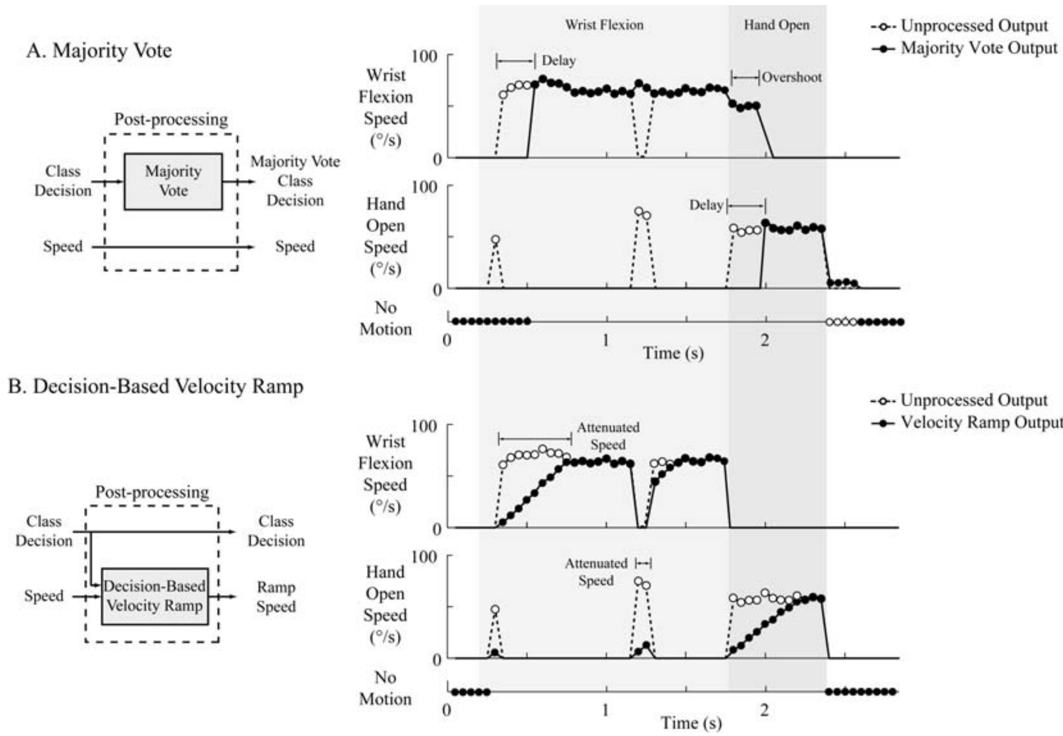

Fig 1. Post-processing comparison between 500 ms A) majority vote and B) decision-based velocity ramp. With a majority vote the class decision may change but the movement speed remains the same; spurious misclassifications are removed but at the cost of delayed movement and position overshoot. With a velocity ramp the class decision remains the same but the movement speed may change; the effect of misclassifications are minimized through an attenuation of the movement speed following a change in decision from the classifier.

performed in the order of wrist rotation, wrist flexion/ extension, and hand open/close. Movements were repeated eight times. Twelve seconds of data per class were used to train a linear discriminate analysis (LDA) classifier and twelve seconds of data per class were 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 [8]) were extracted from the EMG data. The LDA classifier was used to predict user commands and control a virtual prosthesis.

Movement speed was extracted from the same analysis window as the data used for the class decision. Speeds were calculated by averaging the mean absolute values of EMG signals for all channels, k, and were multiplied by an empirically determined boost factor, B:

$$Desired\ Speed = B\left(\frac{1}{N}\sum_{k=1}^{N} MAV_k\right). \quad (1)$$

B. Post-Processing Methods

Majority Vote: Because there is no existing literature on the use of majority vote during real-time pattern recognition control, we investigated three different majority vote lengths:

1) *MV 150ms*: According to Farrell and Weir [11], when using majority vote with overlapping windows, the optimal controller delay, D, is dependent upon the data analysis window, T_a; data window increment, T_{inc}; number of votes, n; and the signal processing time, T_d.

$$D = \frac{1}{2}T_a + \left(\frac{n}{2}\right)T_{inc} + T_d. \quad (2)$$

With the current study's pattern recognition settings, T_d was negligible in comparison to T_{inc}. Using an optimal controller delay, D, of 150 ms [12], n was calculated to be equal to three votes (2), which is equivalent to a majority vote length of 150 ms.

2) *MV 250ms*: Based on (2), the 250 ms majority vote length, which is equivalent to five votes, results in a controller delay of 200 ms and still satisfies the range of optimal controller delays found by [12].

3) *MV 500ms*: Based on (2), the 500 ms majority vote length, which is equivalent to ten votes, results in a controller delay of 325 ms. Although this length exceeds the 300 ms controller delay threshold that is generally accepted as being perceivable to the user [8], it was included in the study since it uses the same amount of time history as the *Ramp 500ms* condition.

Velocity ramp: The velocity ramp attenuated movement speed following a change in class decision [9]. 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 (3):

$$V_{out} = RG_i * V_{in}. \quad (3)$$

The velocity ramp attenuated speed following a change in the class decision by applying a gain that varied linearly between 0 and 1. The ramp gain was calculated by (4):

$$RG_i = C_i \frac{1}{L}. \quad (4)$$

where C is the value of a counter associated with the current class and L is the ramp length defined by the experimenter. The minimum of each counter was 0 and the maximum was equal to the ramp length. The ramp length defined the amount of time it took RG to increase to 1.

Based on pilot data with non-amputee subjects, we investigated two different velocity ramp lengths: *Ramp 500ms* and *Ramp 1000ms*.

C. Performance Tests

Subjects performed the Target Achievement Control (TAC) Test [13] in the virtual environment to quantify performance. During this test, subjects were instructed to move the virtual arm in real time to a prompted target posture (Fig. 2). Subjects were required to perform a combination of three motions (e.g. wrist flexion, forearm supination, and hand close) to reach the target posture. To provide visual feedback, the virtual hand changed color when it reached the target posture within an acceptable tolerance (±5 degrees for each degree of freedom). Subjects had to remain in the target for 2 s and had 20 s to complete each trial. The maximum speed of each degree of freedom was 100 degrees per second. Trials were completed more quickly if subjects were able to control the virtual arm without producing unwanted motions. Overshooting the target posture or producing an incorrect class decision would require subjects to correct the unnecessary movement.

Subjects performed TAC Tests in the following conditions: *Control* (no post-processing), *MV 150ms*, *MV 250ms*, *MV 500m*s, *Ramp 500ms,* and *Ramp 1000ms*. Following a practice session for each condition, subjects performed a set of three tests per condition. Each set consisted of eight target postures and the order of conditions was randomized.

Performance metrics included completion rate, completion time, and path efficiency. 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 posture or the 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 prosthesis.

We performed a repeated measures ANOVA followed by planned contrasts to test for differences in completion rate, completion time, and path efficiency across the conditions. The *MV 500ms* condition was not included in the statistical analysis of TAC Test performance metrics since it was only included as a time-matched comparison to the *Ramp 500ms* condition and likely exceeded the optimal controller delay. The *MV 500ms* condition was included in the statistical analysis for classification error.

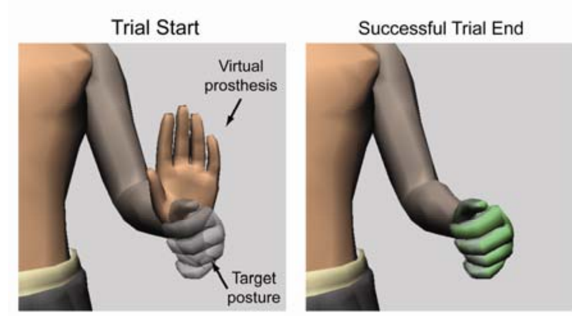

Fig 2.Example of the Target Achievement Control (TAC) Test. A) In this trial, the subject needed to flex the wrist, supinate the forearm, and close the hand to reach the target posture outlined in grey. B) The virtual hand turned green once the target posture was achieved.

III. Results

With no post-processing, average off-line classification error was 5.1% ± 3.3%. Classification error significantly decreased during all majority vote conditions compared to the control (4.1% ± 2.8% for *MV 150ms*; 3.3% ± 2.3% for *MV 250ms*; and 1.7% ± 1.2% for *MV 500ms*) ($p < 0.05$).

Subjects completed significantly more TAC Test trials during the velocity ramp conditions compared to the majority vote ($p = .002$) or control ($p = 0.04$) conditions (Fig. 3A). There was no significant difference in completion rate between the majority vote and control conditions ($p = 0.73$). Subjects completed trials in a significantly shorter amount of time while using the velocity ramp compared to majority vote ($p = 0.01$). No significant differences in completion time were found when post-processing methods were compared to the control condition (control vs. velocity ramp: $p = 0.36$, control vs. majority vote: $p = 0.30$) (Fig 3B). Subjects significantly increased their path efficiency with the velocity ramp compared to the majority vote ($p < 0.001$) or control conditions ($p = 0.02$) (Fig. 3C). No significant differences were found for path efficiency between the majority vote conditions and the control condition ($p= 0.67$).

IV. Discussion

The post-processing method of using a decision-based velocity ramp resulted in the most controllable real-time pattern recognition system. Since the velocity ramp did not change the classifier's decision, it was presumed that the percentage of misclassifications did not change between the velocity ramp conditions and the control condition. Misclassifications still occurred, but their effect on prosthesis positioning was reduced, thereby allowing subjects to be successful during the TAC Test. Another advantage of this post-processing method is that a larger data history can be used. The large ramp lengths used in this study (i.e. 500 and 1000 ms) did not adversely affect users' performance and may have improved performance by increasing users' fine control.

To our knowledge, this is the first demonstration of using majority vote during real-time pattern recognition control. Previous studies have suggested that majority vote can

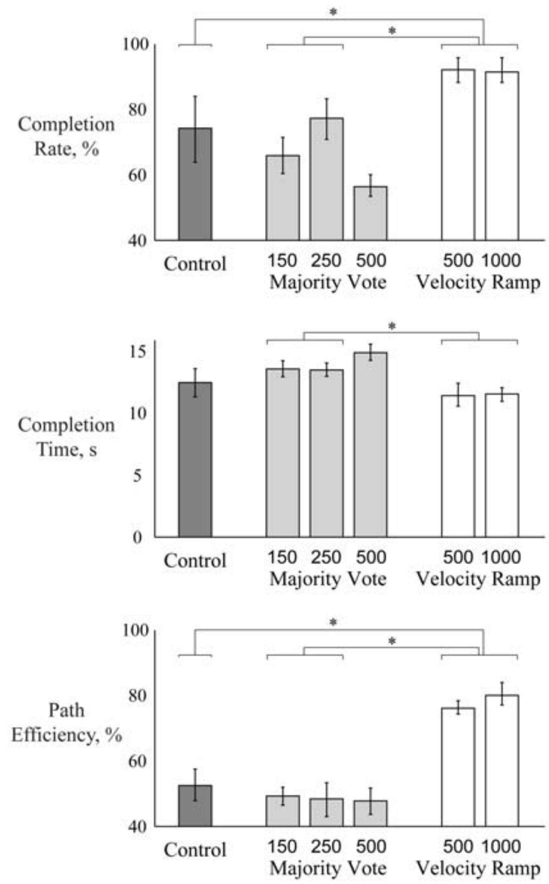

Fig 3. TAC Test performance metrics: A) completion rate, B) completion Time, and C) path efficiency. Error bars denote standard error and * denotes a significant difference ($p < 0.05$) between conditions. The *MV 500ms* condition was not included in the statistical analysis but is included in this figure for comparison.

improve control by decreasing classification errors [8, 11]. Our offline data analysis demonstrated a significant decrease in classification error with majority vote, but our real-time results show no significant differences in performance when compared to the control condition. The benefit of having fewer classification errors is most likely offset by the additional controller delay. The majority vote queue lengths tested in this study illustrate this trend. The *MV 150ms* condition potentially had too short a queue (i.e. three decisions) to see a performance benefit as overall classification error only decreased from 5.1% to 4.1% . The *MV 500ms* condition had the longest queue (i.e. ten decisions), reducing classification errors to less than 2%, but added a lengthy controller delay. The *MV 250ms* condition, which better balanced this tradeoff, did not show a change in performance compared to the control condition These results highlight the need for real-time performance measures, as methods that have been shown to reduce errors during offline analysis may not improve real-time control.

The current study had some limitations. This study was limited to a 50 ms window increment since that was as fast as the current virtual environment could be rendered. This increment may have been too long to see benefit with majority vote. With a smaller window increment, a larger majority vote queue could be used, thereby increasing the benefit of a voting scheme without a large increase in additional controller delay, but this remains to be tested.

The results also are for a limited number of non-amputee subjects with relatively low classification errors. Further testing is necessary to see if similar results are found with individuals with an amputation who may have higher error rates during real-time pattern recognition control.

V. Conclusion

Even with low classification errors, real-time pattern recognition control is affected by movement misclassifications. This study demonstrated that the post-processing method of using a decision-based velocity ramp improved real-time control compared to using majority vote or no post-processing. Since the velocity ramp was independent of the decision stream and did not add an additional controller delay, it has the potential to be used with a wide variety of pattern recognition settings (e.g. different classifiers, window lengths, window increments, etc) to improve real-time control.

References

[1] B. Hudgins, *et al.*, "A new strategy for multifunction myoelectric control," *IEEE Transactions on Biomedical Engineering,* vol. 40, pp. 82-94, JAN 1993.

[2] Y. H. Huang, *et al.*, "A Gaussian mixture model based classification scheme for myoelectric control of powered upper limb prostheses," *IEEE Transactions on Biomedical Engineering,* vol. 52, pp. 1801-1811, NOV 2005.

[3] K. Englehart, *et al.*, "Classification of the myoelectric signal using time-frequency based representations," *Medical Engineering & Physics,* vol. 21, pp. 431-438, 1999.

[4] L. Hargrove, *et al.*, "A comparison of surface and intramuscular myoelectric signal classification," *IEEE Transactions on Biomedical Engineering,* 2007.

[5] L. Hargrove, *et al.*, "The effect of ECG interference on pattern-recognition-based myoelectric control for targeted muscle reinnervated patients," *IEEE Trans Biomed Eng,* vol. 56, pp. 2197-201, Sep 2009.

[6] B. A. Lock, *et al.*, "Real-time myoelectric control in a virtual environment to relate usability vs. accuracy," in *MyoElectric Controls Symposium*, New Brunswick, Fredericton, 2005, pp. 122-127.

[7] H. H. Sears and J. Shaperman, "Proportional myoelectric hand control: an evaluation," *Am J Phys Med Rehabil,* vol. 70, pp. 20-8, Feb 1991.

[8] K. Englehart and B. Hudgins, "A robust, real-time control scheme for multifunction myoelectric control," *IEEE Trans Biomed Eng,* vol. 50, pp. 848-54, Jul 2003.

[9] A. M. Simon, *et al.*, "A strategy for minimizing the effect of misclassifications during real time pattern recognition myoelectric control," *Conf Proc IEEE Eng Med Biol Soc,* vol. 2009, pp. 1327-30, 2009.

[10] T. R. Farrell and R. F. Weir, "The optimal controller delay for myoelectric prostheses," *IEEE Trans Neural Syst Rehabil Eng,* vol. 15, pp. 111-8, Mar 2007.

[11] T. R. Farrell and R. Weir, "Analysis Window Induced Controller Delay for Multifunctional Prostheses," in *Myoelectric Controls Symposium*, Fredericton, NB, 2008, pp. 225-228.

[12] L. H. Smith, *et al.*, "Determining the Optimal Window Length for Pattern Recognition-Based Myoelectric Control: Balancing the Competing Effects of Classification Error and Controller Delay," *IEEE Trans Neural Syst Rehabil Eng,* vol. 19, pp. 186-92, 2011.

[13] A. M. Simon, *et al.*, "The Target Achievement Control Test: Evaluating real-time myoelectric pattern recognition control of a multifunctional upper-limb prosthesis," *J Rehabil Res Dev, vol. 46(8), 2011.*