Effects of Confidence-Based Rejection on Usability and Error in Pattern Recognition-Based Myoelectric Control

Jason W. Robertson, *Member, IEEE*, Kevin B. Englehart, *Senior Member, IEEE*, and Erik J. Scheme, *Senior Member, IEEE*

***Abstract*—Rejection of movements based on the confidence in the classification decision has previously been demonstrated to improve usability of pattern recognition based myoelectric control. To this point, however, the optimal rejection threshold has been determined heuristically, and it is not known how different thresholds affect the trade-off between error mitigation and false rejections in real-time, closed-loop control. To answer this question, 24 able-bodied subjects completed a real-time Fitts' law-style virtual cursor control task using a support vector machine (SVM) classifier. It was found that rejection improved information throughput at all thresholds, with the best performance coming at thresholds between 0.60 and 0.75. Two fundamental types of error were defined and identified: operator error (identifiable, repeatable behaviours, directly attributable to the user), and systemic error (other errors attributable to misclassification or noise). The incidence of both operator and systemic errors were found to decrease as rejection threshold increased. Moreover, while the incidence of all error types correlated strongly with path efficiency, only systemic errors correlated strongly with throughput and trial completion rate. Interestingly, more experienced users were found to commit as many errors as novice users, despite performing better in the Fitts task, suggesting that there is more to usability than error prevention alone. Nevertheless, these results demonstrate the usability gains possible with rejection across a range of thresholds for both novice and experienced users alike.**

***Index Terms*—Pattern recognition, myoelectric control, rejection, error correction, electromyography**

I. Introduction

MYOELECTRIC control of prostheses – the use of electromyographic (EMG) signals to control an artificial limb – is a paradigm that has been under investigation for several decades [1]. In pattern recognition (PR) control, one or more classification algorithms are used to train a model using sample EMG data representing different movements; this model is then used to classify subsequent movements by the user. While PR is well-established in laboratory settings, it has only recently been commercialized for clinical use [2, 3].

One of the main impediments to clinical adoption is the rate of erroneous movements by current PR systems. When an erroneous movement occurs, the user must correct the error and move the prosthesis back onto its intended course. This requires additional time, cognitive burden, and risk, as they must correctly identify and elicit the antagonist motion to the unintended activation before resuming their planned trajectory. This unplanned correction can lead to even more errors, creating the potential for a vicious cycle [4]. While laboratory-based studies consistently report low error rates during offline testing, prosthesis users nonetheless report a frustrating lack of control, leading some to abandon their devices [5, 6].

There are many systemic factors responsible for poor control, including electrode shift, limb position, and signal variation across days (reviewed in [7]). Solutions have been proposed to address these issues, including adaptive algorithms [8-13], additional sensory modalities [14-18], and alternate training protocols [17-21]. These approaches have all shown various levels of promise in offline analyses and in online usability tasks [11-15]. However, they also carry some potential disadvantages, such as additional expense, design complications, and extra training load for the user. A solution that has been shown to improve usability without additional overhead is the rejection of uncertain movement decisions. If the device does not move when the classification decision is unclear, there is no need for corrective action, giving the user a better opportunity to clearly elicit their intended movement. Rejection also builds in some tolerance to novel, unprogrammed, or otherwise unintended contractions that would normally cause the device to activate in an unexpected manner [22, 23]. Furthermore, as a post-processing step, rejection could effectively be combined with many of the previously mentioned solutions.

A recently-proposed method rejects movements based on the posterior probability estimate output by a classifier, or *confidence* [24], and has been found improve real-time control in both able-bodied and amputee subjects. Further refinement of this idea used a time-delay neural network as a supervisor layer, providing a form of context sensitivity [25]. Both of these

This work was supported in part by the Natural Science and Engineering Research Council of Canada Post-Graduate Scholarship (Doctoral) No. PGSD-459812-2014 and Discovery Grants 217354-15 and 2014-04920.

J. W. Robertson, K. B. Englehart and E. J. Scheme are with the Institute of Biomedical Engineering at the University of New Brunswick, 25 Dineen Drive, Fredericton, New Brunswick, Canada, E3B 5A3 (email: jason.robertson@unb.ca)

studies were performed using the linear discriminant analysis (LDA) classifier, the current *de facto* standard for myoelectric control, however the confidence characteristics of the LDA are somewhat limiting. The optimal rejection threshold for LDA was determined heuristically to be 0.97 for able-bodied users and 0.90 for amputees [24], leaving very little range to adjust the threshold for subjects or movements that prove problematic. Thus, a subsequent study [26] examined the confidence characteristics of several popular classifiers to establish which might be better suited for rejection. It was found that a support vector machine (SVM) produced correct decisions over a wider range of confidence values than the LDA, with an optimal rejection threshold projected to fall between 0.60-0.70, and with false rejection and acceptance rates changing much more slowly as a function of rejection threshold. Such an expanded range of viable confidence values would provide better opportunities to tune rejection thresholds for different subjects or movements to produce cleaner control. This finding, however, came from offline analysis of training data, which does not bear a consistent relationship with online usability [27-32]. The primary objective of this study was therefore to determine what rejection threshold – or range of thresholds – resulted in optimal usability.

Many methods to evaluate usability have been proposed, however Fitts' Law-style studies have recently become popular in the PR literature [4, 24, 30, 33-36]. These studies report usability in terms of *throughput*, a measure of information transfer rate that describes the motor system's finite capacity to produce both speed and accuracy commonly used in the field of human-computer interaction [37]. This framework has been extended to provide further context using additional metrics, including path efficiency, stopping distance, and overshoot [4, 33, 34]. These additional metrics reflect different phenomena than throughput: for example, in the case of over-rejection, one may see path efficiency improve due to increased rejection of erroneous movements, but throughput decline due to increased rejection of non-erroneous movements, leading to longer trial times. What is missing from this analysis, however, is some understanding of how well users execute specific sub-movements. Recently, we presented a novel method for classifying erroneous movements in a continuous, unguided decision stream [38], and examined how error rates were affected by rejection threshold. A secondary objective of this study was therefore to extend that analysis into the Fitts' Law-style framework and to determine how error and usability were related.

II. Methods

Twenty-four able-bodied human subjects were recruited to participate in this study (50% female, 92% right-hand dominant, age 26 ± 3.2 years); eight subjects reported having prior experience with myoelectric control. Subjects gave informed consent in accordance with the Declaration of Helsinki and was approved by the University of New Brunswick Research Ethics Board (REB #2015-101).

A. Apparatus

Subjects were seated comfortably in an office chair with armrests, facing the testing computer. A UNB smart electrode cuff [39] was placed around their dominant forearm, just distal to the elbow, with the eight electrodes distributed equidistantly around the circumference of the forearm. The cuff was connected to a desktop computer and data collection was executed using custom Matlab® software [40]. Subjects were instructed to rest their instrumented arm on the armrest so that they could freely move their arm without disturbing the electrodes.

The EMG signals were sampled at 1 kHz and filtered for power-line noise using 3rd order Butterworth notch filters at 60, 180, and 300 Hz. The filtered signals were then divided into 160 ms windows at 16 ms intervals prior to extraction of Hudgins' time-domain features [41].

B. Protocol

Subjects first sat quietly for several minutes to allow the electrodes to acclimate to their skin. They were then prompted to provide two-second sample contractions for four active motion classes – wrist pronation, wrist supination, chuck grip ("hand closed"), and hand open – as well as a baseline no-motion class. Subjects were instructed to start in a neutral, resting position, then slowly increase their contraction strength over the collection period [42]. Eight sample contractions were collected for each class and used to train an SVM pattern classifier with a linear kernel. This number of repetitions is greater than normally employed and not strictly necessary; the increase improves the density of the feature space but is unlikely to have influenced the SVM decision boundaries.

Once the classifier was trained, subjects were presented with a two degree-of-freedom (DOF) virtual target acquisition task, as previously described in [4, 24]. A target was displayed on the screen, randomly selected from combinations of two distances, three sizes, and eight directions, for 48 total trials. Using proportional, velocity-controlled, sequential movements facilitated by the previously-trained classifier, subjects moved a cursor as quickly and accurately as possible to the target and held it inside for one second; trials were failed if this was not accomplished within ten seconds. The vertical axis corresponded to wrist supination (up) and pronation (down), while the horizontal axis corresponded to hand open (right) and close (left); the horizontal directions were reversed for left-hand dominant subjects to avoid confusion.

The subjects performed this target acquisition task several times. First, they completed a shortened, simplified version of the task for the sake of familiarization: novice subjects were allowed as much practice time as they needed to get comfortable with the basic use of the controller. All subjects then completed a 48-trial block with no rejection (NR) to serve as a baseline, followed by seven more blocks with rejection threshold levels set between 0.50 and 0.80, at intervals of 0.05, presented in random order. While previous offline work [26] estimated that the ideal rejection threshold for SVM classification should be between 0.60 and 0.70, that range was extended in both directions to ensure completeness. For each block, several standard Fitts' Law-based summary statistics [4, 24, 30, 33-36] were calculated.

- *Movement time* (MT), the time required for the subject to complete each trial.
- *Throughput* (TP), the classical Fitts measure of information bandwidth required by a task, based on the tradeoff

between movement speed and accuracy [37].

- *Path efficiency* (EFF), a measure of how close the subject's traveled path was to the ideal path.
- *Overshoot* (OS), the number of times, per trial, the subject exited the target after entering it.
- *Stopping distance* (SD), how far the cursor travelled while the subject attempted to stop, measured from the first entry to the target.
- *Trial completion rate* (COMP), the number of trials completed out of the total number attempted.

C. Error Classification

An *error* was defined as any movement that inhibited the goal of entering and staying within the target [38]: this included all movements away from the target, and all movements initiated after the subject had already stopped within the target. This set of *total errors* (E_{TOT}) was then divided into two main categories:

1) *Operator errors* (E_{OP}), user-generated mistakes in accomplishing the task. These were defined based on common errors observed while transitioning or stopping.
2) *Systemic errors* (E_{SYS}), which made up the remainder of the errors, were assumed to be due to classifier limitations or noise, and therefore beyond the influence of the user.

Three commonly-observed operator errors are illustrated in Fig. 1. Because the task is sequential and unconstrained, each of these errors could occur at any given time, not just at the end of the movement. However, because subjects completed the task one DOF at a time (i.e., choosing to reach the target area horizontally first, then vertically, or vice versa), it was possible to define errors according to changes in output class and cursor position relative to the target area in the *x* or *y* direction. This allowed errors to be detected during both transitions and stops, and also allowed rejected movements to be correctly classified.

1) *Overshoot error* (E_{OS}) was defined as when the cursor passed through the target area and out the other side.
2) *Bounceback error* (E_{BB}) was defined as a sudden class change during deceleration that moved the cursor backward along the same DOF.
3) *Bounceback Perpendicular error* (E_{BBP}) was defined as a sudden class change during deceleration that moved the cursor along the perpendicular DOF.

While the two Bounceback error types are described separately, both are presumed to occur when the subject performs "braking" contractions at the end of a movement instead of relaxing their muscles. Because the activations for each Bounceback type likely differ, however, it is possible that E_{BB} and E_{BBP} may be affected differently by rejection. Additionally, while E_{BB}, E_{BBP}, and E_{SYS} were defined in terms of class changes at any point during the trial, E_{OS} was defined as starting when the subject exited the target and ending when a class change finally occurred.

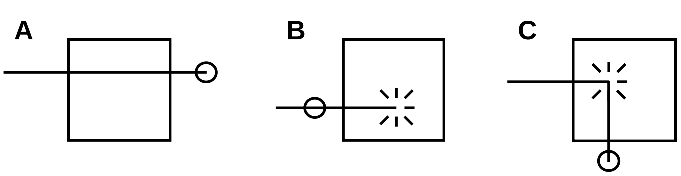

Fig. 1. Illustration of the three operator errors. A) *Overshoot* (E_{OS}) error, in which the subject passes through the target without stopping. B) *Bounceback* (E_{BB}) error, in which the subject attempts to stop, but the cursor moves backward instead. C) *Bounceback Perpendicular* (E_{BBP}) error, in which the subject attempts to stop, but the cursor moves along the opposite DOF instead.

D. Statistical Analysis

To meet the first aim of this study, performance for each block of target acquisition trials was compared using a repeated measures analysis of variance (RM-ANOVA), with a within-subjects factor of *Threshold* (8 levels) and a between-subjects factor of *Experience* (2 levels); *Experience* was included as a factor to ensure that the disparity in experience levels between subjects did not affect the comparisons of interest. Mauchley's sphericity test was used to determine whether the variances of each pairwise difference between *Threshold* levels were similar; if not, the Greenhouse-Geisser correction was applied. Pairwise comparisons were subsequently calculated across *Threshold* levels with a Bonferroni *post hoc* correction. All comparisons were considered significant at the $\alpha = 0.05$ level.

To meet the second aim of this study, the same RM-ANOVA was run for all error measures. Specifically, the total error rate in the output decision stream and the rate of each error subtype were compared across the same *Threshold* and *Experience* levels as before. Additionally, the rate at which erroneous and correct actions were rejected was compared with a separate RM-ANOVA by *Threshold* (7 levels) and *Experience* (2 levels). In this comparison, *Threshold* had one fewer level because it did not include a NR condition. Finally, to establish which error types might influence usability, the error rates in the output stream were compared to the Fitts metrics by a two-tailed Pearson correlation.

III. Results

A. Fitts' Law Metrics

Fig. 2 illustrates the changes in each Fitts metric due to rejection threshold. Significant main effects of *Threshold* were found for all six measures ($p < 0.01$). Pairwise comparisons for MT, TP, and EFF found that all rejection thresholds produced significantly different values from NR; for OS, only thresholds of 0.60 and 0.70-0.80 were significantly better than non-rejection. For SD, only 0.70-0.80 were significantly different from NR. Additionally, TP was significantly higher for thresholds of 0.60-0.75 compared to 0.50; EFF was significantly greater at 0.70-0.80 compared to 0.50; and SD was significantly lower at 0.70-0.80 compared to 0.50, and at 0.70-0.75 compared to 0.55. For COMP, no pairwise differences were found. For the main effect of *Experience*, significant differences were found between novice and experienced users for MT and TP (Fig. 3). No interaction effects of *Threshold* × *Experience* were found.

B. Error Rates

The error rates for accepted movements are illustrated in Fig. 4A. Significant main effects of *Threshold* were found for all error variables. Pairwise comparisons for E_{BB}, E_{SYS}, and E_{TOT}

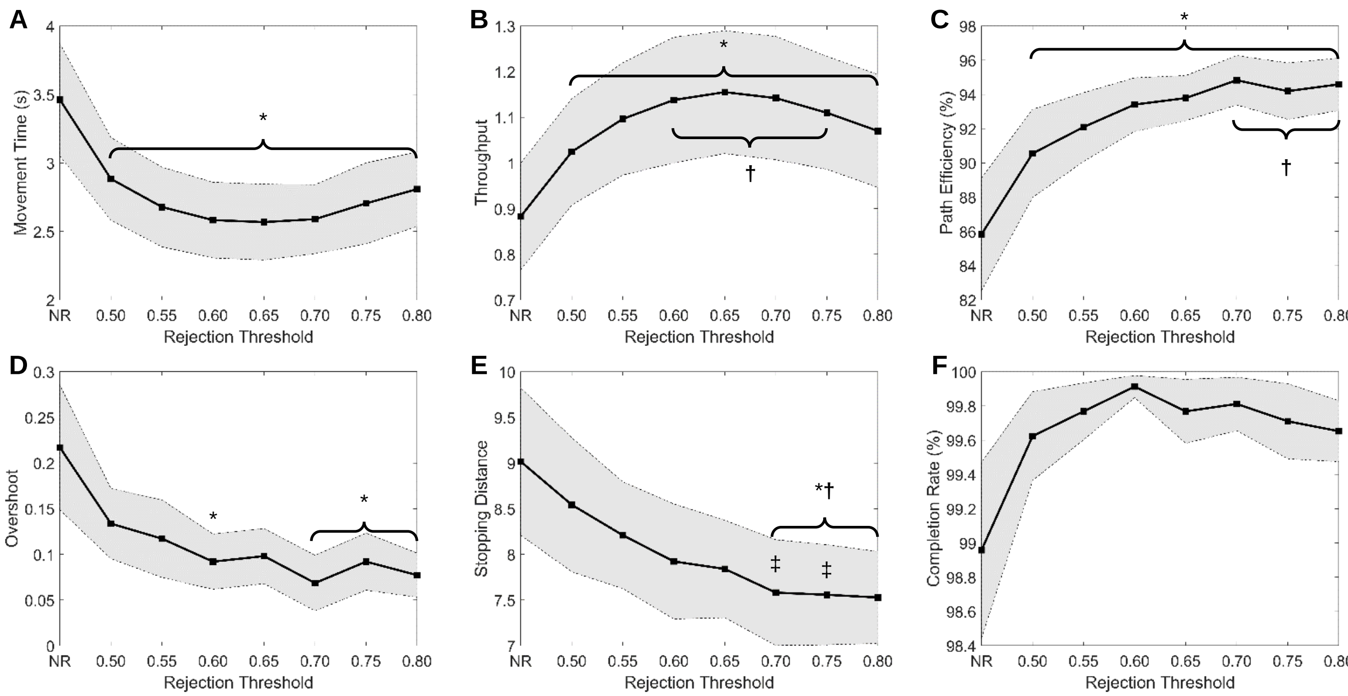

Fig. 2. Fitts summary statistics with respect to rejection threshold: (A) movement time; (B) throughput; (C) path efficiency; (D) overshoot; (E) stopping distance; (F) completion rate. Black lines show the data means; shaded grey areas represent 95% confidence intervals. Significance markers: * significant difference from no rejection; † significant difference from 0.50; ‡ significant difference from 0.55.

found significant differences at all rejection thresholds compared to NR, whereas E_{BBP} was different from NR only at thresholds above 0.55. In total, fewer errors occurred above 0.70 compared to 0.50, and above 0.65 compared to 0.55. No main effects of *Experience* or interaction effects of *Threshold* × *Experience* were found.

The error rates for rejected movements are illustrated in Fig. 4B. Main effects of *Threshold* were observed for rates of E_{BBP}, E_{SYS}, and E_{TOT}, all of which decreased with *Threshold*. Specifically, errors made up a lower proportion of rejected samples at thresholds above 0.60 compared to 0.50 and 0.55, and lower still above 0.75 compared to 0.60. No main effect of *Experience* was observed. A significant interaction effect of *Threshold* × *Experience* was found for E_{BBP}, though it was not clinically relevant.

The correlations between Fitts metrics and error rates are summarized in Table I. Generally, MT and TP had few and weaker correlations with operator error rates, while EFF, OS, SD, and COMP correlated strongly with nearly all error rates. Furthermore, all Fitts metrics correlated strongly with both systemic and total error, apart from MT, which only weakly correlated with E_{TOT}.

TABLE I
LINEAR CORRELATIONS BETWEEN FITTS METRICS AND ERROR RATES

	E_{OS}	E_{BB}	E_{BBP}	E_{SYS}	E_{TOT}
MT	0.124	-0.009	**0.189†**	**0.501***	**0.303***
TP	-0.013	0.084	-0.095	**-0.390***	**-0.176‡**
EFF	**-0.641***	**-0.396***	**-0.712***	**-0.805***	**-0.868***
OS	**0.619***	**0.479***	**0.598***	**0.378***	**0.666***
SD	**0.456***	**0.498***	**0.509***	**0.402***	**0.629***
COMP	**-0.386***	-0.119	**-0.435***	**-0.650***	**-0.549***

Values are Pearson's correlation coefficient *r*. Significance markers: * - $p < 0.001$; † - $p < 0.01$; ‡ - $p < 0.05$.

IV. DISCUSSION

One of the essential problems facing pattern recognition-based control is that a classifier must necessarily force every pattern it encounters into one of the categories it has been trained to recognize, even if it bears little statistical resemblance to any of them. While classifiers can be trained recognize additional, non-productive movements and ignore them as appropriate [22, 23], this is an impractical approach for real-world use. By contrast, rejection allows the classifier to account for unfamiliar movements and random noise without any additional information. This is affirmed by the present study: *all* Fitts summary metrics were improved significantly with *any* level of rejection compared to NR, while systemic error – representing misclassifications and noise – decreased significantly across the board. This, along with the finding that systemic error rate was the only one to correlate strongly with all Fitts metrics, including throughput, suggests that an important aspect of the usability gain was the simple reduction in noisy, unfamiliar, or otherwise easily misidentified classifications.

By contrast, while operator errors were also reduced with rejection compared to NR, they correlated weakly if at all with MT and TP, the two principal usability metrics. This suggests that user-generated behavioral errors don't affect the overall comparison between different classification conditions. Furthermore, while less experienced subjects produced lower TP values across the board, the trend with respect to rejection threshold was the same as that observed with the more experienced users (Fig. 3). These findings together reinforce the validity of Fitts throughput as a measure of classifier controllability. Indeed, this finding mirrors previous studies showing that able-bodied and amputee subjects – the latter of

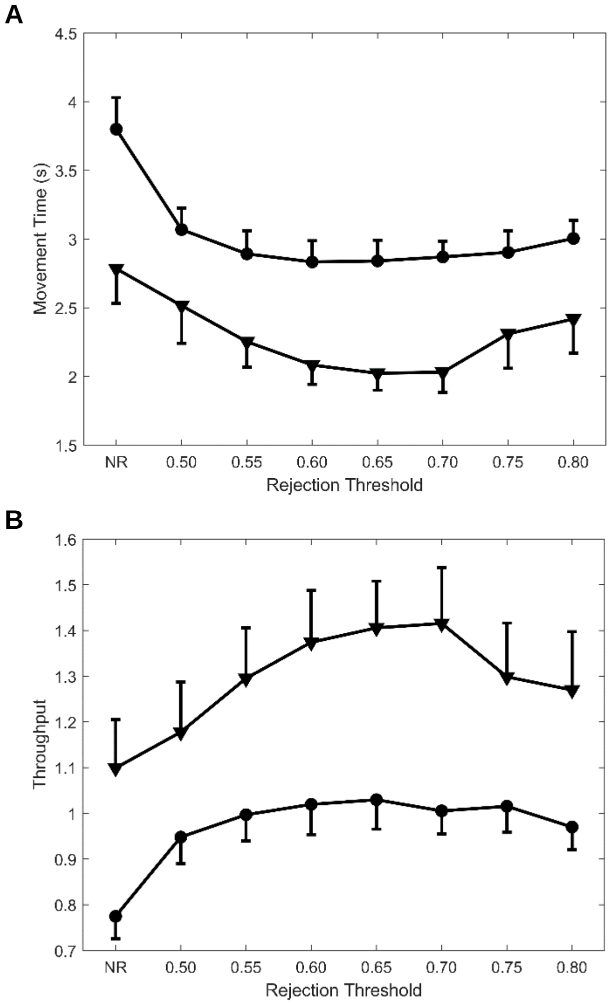

Fig. 3. Comparison of usability outcomes for experienced (triangle) and inexperienced (circle) subjects: (A) movement time; (B) throughput. Error bars represent standard error of the mean.

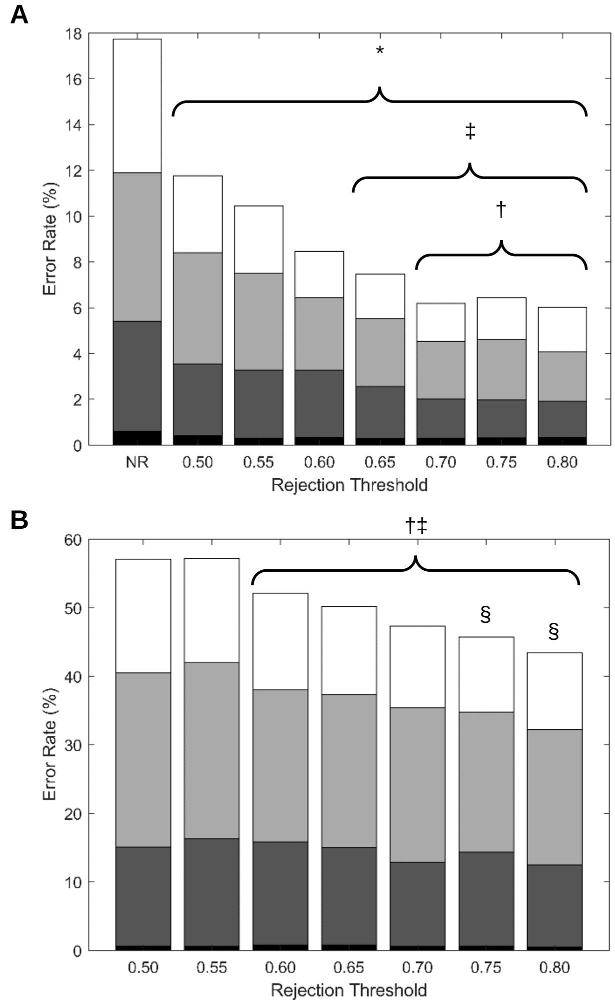

Fig. 4. Total error rates for (A) accepted, and (B) rejected movements, subdivided by type: E_{OS} (black), E_{BB} (dark grey), E_{BBP} (light grey), E_{SYS} (white). Significance markers (E_{TOT} only): * significant difference from no rejection; † significant difference from 0.50; ‡ significant difference from 0.55; § significant difference from 0.60.

whom have fewer and more limited control sites – experience similar changes in accuracy [22] and usability [24] across different classification conditions. Virtual usability has previously served as the testbed for ideas later applied to prosthetic control [29], and very recent work has found direct correlations between virtual task performance and the usability of physical prostheses [43], meaning that these findings should in turn translate to future work with amputees and prosthetic limbs.

While throughput improved across the board with rejection, it peaked at thresholds of 0.60-0.75, as predicted in [26]. Many subjects reported difficulty completing the task at the 0.80 rejection threshold, often finding that the controller was sluggish or failed to start. By contrast, the path-based metrics – EFF, OS, and SD – reached their best values at thresholds above 0.70. This reflects the findings of the error analysis: while errors continued to be suppressed by the rejection mechanism as the threshold increased, the rate at which correct decisions were falsely rejected increased much faster. This over-rejection likely produced the decrease in usability observed at high rejection thresholds even as the path metrics continued to improve. Whereas throughput reflects an overall ability to swiftly and correctly perform the task, the path metrics essentially serve as a form of online accuracy, and are more directly affected by error rate (Table I). Thus, not only does offline accuracy not relate to usability, as previously established [27-32], but it appears that online accuracy has a limited relationship, as well.

Further to this, MT and TP were the only Fitts metrics to be affected by *Experience*. While superficially this would appear to be obvious – get more experience with a task, do it faster and better – it's not entirely clear *how* this occurs since only systemic error, and not operator error, correlated with these measures. Moreover, the path-related metrics, completion rate, and all error rates, were also unaffected by *Experience*. This suggests that some other behavioral adaptation is taking place: given the differences observed in MT and TP, more experienced subjects are likely better at controlling the system at higher speeds than novice subjects. This in turn may imply the development of a stronger *internal model* [44-47] of the control task, though the present data cannot strongly affirm this.

The range of viable thresholds is a positive result which presents a clear argument that SVM produces a more forgiving classifier than LDA. This then opens up several potential avenues for future investigation which would have been considerably more difficult previously. One possibility would be to incorporate more data into the rejection decision. Currently, each rejection decision is made independently of the overall decision or confidence stream, which updates much faster than is possible for the human motor system [48]. It has been demonstrated that a time-delay neural network, informed by training data classification outcomes, was able to produce more accurate classification and error prevention than rejection alone [25]. Combining a temporal approach with the more robust confidence characteristics of the SVM and a richer set of observations (e.g., the characteristics of an operator error) could then further improve upon this approach. It could be possible to predict and immediately reject an operator error as it starts to occur, instead of responding to it on a sample-by-sample basis. Beyond the scope of the errors observed in the present study, there may also be time series for which it proves more advantageous to reject to the previous motion, instead of no motion. Furthermore, rejection may also benefit, and benefit from, one or more of the other avenues of improvement listed in the Introduction: for example, additional information from inertial or visual sensors could help clarify whether a subject is likely to be changing motions or stopping altogether, preventing spurious "jumps" like the Bounceback errors observed here.

V. Conclusion

This study has found that confidence-based rejection improves usability outcomes for support vector machine-driven myoelectric control, particularly at rejection thresholds between 0.60 and 0.75. Several characteristic operator errors were identified within the movement data, as were other systemic errors. These operator errors were each affected by rejection in distinct ways, both from each other and from the systemic errors; cumulatively, rejection reduced nearly all types of error in some fashion. This work has also demonstrated how over-rejection occurs at high thresholds: the proportion of errors within the rejected movements decreased as threshold increased, meaning that more false rejections were occurring overall. By contrast, very few differences in performance due to experience could be identified, suggesting that learning of a myoelectric PR task does not necessarily come from reducing error, and certainly not from that alone. It appears, therefore, that subjects' ability to maintain control at higher speeds within the task affects performance in a way that has not been well-captured to this point.

References

[1] P. Parker, K. Englehart, and B. Hudgins, "Myoelectric signal processing for control of powered limb prostheses," *J Electromyogr Kinesiol,* vol. 16, no. 6, pp. 541-8, Dec, 2006.

[2] "CoApt Engineering," 4 Apr, 2017; https://coaptengineering.com/.

[3] "Infinite Biomedical Technologies: Products," 4 Apr, 2017; http://www.i-biomed.com/products.html.

[4] E. J. Scheme, and K. B. Englehart, "Validation of a selective ensemble-based classification scheme for myoelectric control using a three-dimensional Fitts' Law test," *IEEE Trans Neural Syst Rehabil Eng,* vol. 21, no. 4, pp. 616-23, Jul, 2013.

[5] A. D. Roche, H. Rehbaum, D. Farina, and O. C. Aszmann, "Prosthetic myoelectric control strategies: a clinical perspective," *Curr Surg Rep,* vol. 2, no. 3, pp. 1-11, 25 Jan, 2014.

[6] F. Cordella, A. L. Ciancio, R. Sacchetti, A. Davalli, A. G. Cutti, E. Guglielmelli, and L. Zollo, "Literature review on needs of upper limb prosthesis users," *Front Neurosci,* vol. 10, no. 209, 12 May, 2016.

[7] E. Scheme, and K. Englehart, "Electromyogram pattern recognition for control of powered upper-limb prostheses: State of the art and challenges for clinical use," *J Rehabil Res Dev,* vol. 48, no. 6, pp. 643-659, 2011.

[8] T. Tommasi, F. Orabona, C. Castellini, and B. Caputo, "Improving control of dexterous hand prostheses using adaptive learning," *IEEE Trans Robot,* vol. 29, no. 1, pp. 207-19, Feb, 2013.

[9] X. Chen, D. Zhang, and X. Zhu, "Application of a self-enhancing classification method to electromyography pattern recognition for multifunctional prosthesis control," *J Neuroeng Rehabil,* vol. 10, no. 1, pp. 44, 1 May, 2013.

[10] J. Liu, "Adaptive myoelectric pattern recognition toward improved multifunctional prosthesis control," *Med Eng Phys,* vol. 37, no. 4, pp. 424-30, Apr, 2015.

[11] M. M. C. Vidovic, H. J. Hwang, S. Amsüss, J. M. Hahne, D. Farina, and K. R. Muller, "Improving the robustness of myoelectric pattern recognition for upper limb prostheses by covariate shift adaptation," *IEEE Trans Neural Syst Rehabil Eng,* vol. 24, no. 9, pp. 961-970, Sep, 2016.

[12] X. Zhu, J. Liu, D. Zhang, X. Sheng, and N. Jiang, "Cascaded adaptation framework for fast calibration of myoelectric control," *IEEE Trans Neural Syst Rehabil Eng,* vol. 25, no. 3, pp. 254-64, Mar, 2017.

[13] J. L. Betthauser, C. L. Hunt, L. E. Osborn, M. R. Masters, G. Lévay, R. R. Kaliki, and N. V. Thakor, "Limb position tolerant pattern recognition for myoelectric prosthesis control with adaptive sparse representations from extreme learning," *IEEE Trans Biomed Eng,* vol. 65, no. 4, pp. 770-8, Apr, 2018.

[14] S. Došen, C. Cipriani, M. Kostić, M. Controzzi, M. C. Carrozza, and D. B. Popović, "Cognitive vision system for control of dexterous prosthetic hands: experimental evaluation," *J Neuroeng Rehabil,* vol. 7, pp. 42, 23 Aug, 2010.

[15] A. Krasoulis, I. Kyranou, M. S. Erden, K. Nazarpour, and S. Vijayakumar, "Improved prosthetic hand control with concurrent use of myoelectric and inertial measurements," *J Neuroeng Rehabil,* vol. 14, no. 1, pp. 71, 11 Jul, 2017.

[16] A. A. Adewuyi, L. J. Hargrove, and T. A. Kuiken, "Resolving the effect of wrist position on myoelectric pattern recognition control," *J Neuroeng Rehabil,* vol. 14, no. 1, pp. 39, 4 May, 2017.

[17] A. Fougner, E. Scheme, A. D. Chan, K. Englehart, and Ø. Stavdahl, "Resolving the limb position effect in myoelectric pattern recognition," *IEEE Trans Neural Syst Rehabil Eng,* vol. 19, no. 6, pp. 644-51, Dec, 2011.

[18] R. J. Beaulieu, M. R. Masters, J. Betthauser, R. J. Smith, R. Kaliki, N. V. Thakor, and A. B. Soares, "Multi-position training improves robustness of pattern recognition and reduces limb-position effect in prosthetic control," *J Prosthet Orthot,* vol. 29, no. 2, pp. 54-62, Apr, 2017.

[19] L. Hargrove, K. Englehart, and B. Hudgins, "A training strategy to reduce classification degradation due to electrode displacements in pattern recognition based myoelectric control," *Biomed Signal Process Control,* vol. 3, no. 2, pp. 175-180, Apr, 2008.

[20] R. N. Khushaba, A. Al Timemy, S. Kodagoda, and K. Nazarpour, "Combined influence of forearm orientation and muscular contraction on EMG pattern recognition," *Expert Syst Appl,* vol. 61, pp. 154-61, 1 Nov, 2016.

[21] D. Yang, Y. Gu, L. Jiang, L. Osborn, and H. Liu, "Dynamic training protocol improves the robustness of PR-based myoelectric control," *Biomed Signal Process Control,* vol. 31, pp. 249-56, Jan, 2017.

[22] E. J. Scheme, K. B. Englehart, and B. S. Hudgins, "Selective classification for improved robustness of myoelectric control under nonideal conditions," *IEEE Trans Biomed Eng,* vol. 58, no. 6, pp. 1698-705, Jun, 2011.

[23] X. Li, S. Chen, H. Zhang, O. W. Samuel, H. Wang, P. Fang, X. Zhang, and G. Li, "Towards reducing the impacts of unwanted movements on identification of motion intentions," *J Electromyogr Kinesiol,* vol. 28, pp. 90-8, Jun, 2016.

[24] E. J. Scheme, B. S. Hudgins, and K. B. Englehart, "Confidence-based rejection for improved pattern recognition myoelectric control," *IEEE Trans Biomed Eng,* vol. 60, no. 6, pp. 1563-70, Jun, 2013.

[25] S. Amsüss, P. M. Goebel, N. Jiang, B. Graimann, L. Paredes, and D. Farina, "Self-correcting pattern recognition system of surface EMG signals for upper limb prosthesis control," *IEEE Trans Biomed Eng,* vol. 61, no. 4, pp. 1167-76, Apr, 2014.

[26] E. Scheme, and K. Englehart, “A comparison of classification based confidence metrics for use in the design of myoelectric control systems,” *Conf Proc IEEE Eng Med Biol Soc,* vol. 37, pp. 7278-83, Aug, 2015.

[27] B. A. Lock, K. Englehart, and B. Hudgins, "Real-time myoelectric control in a virtual environment to relate usability vs. accuracy," *MEC '05: Integrating Prosthetics and Medicine.* pp. 112-5, 2005.

[28] L. Hargrove, Y. Losier, B. Lock, K. Englehart, and B. Hudgins, “A real-time pattern recognition based myoelectric control usability study implemented in a virtual environment,” *Conf Proc IEEE Eng Med Biol Soc,* vol. 29, pp. 4842-5, Aug, 2007.

[29] A. M. Simon, L. J. Hargrove, B. A. Lock, and T. A. Kuiken, “A decision-based velocity ramp for minimizing the effect of misclassifications during real-time pattern recognition control,” *IEEE Trans Biomed Eng,* vol. 58, no. 8, pp. 2360-8, Aug, 2011.

[30] N. Jiang, I. Vujaklija, H. Rehbaum, B. Graimann, and D. Farina, “Is accurate mapping of EMG signals on kinematics needed for precise online myoelectric control?,” *IEEE Trans Neural Syst Rehabil Eng,* vol. 22, no. 3, pp. 549-58, May, 2014.

[31] I. Vujaklija, A. D. Roche, T. Hasenöhrl, A. Sturma, S. Amsüss, D. Farina, and O. C. Aszmann, “Translating research on myoelectric control into clinics—are the performance assessment methods adequate?,” *Front Neurorobot,* vol. 11, no. 7, 14 Feb, 2017.

[32] J. M. Hahne, M. Markovic, and D. Farina, “User adaptation in myoelectric man-machine interfaces,” *Sci Rep,* vol. 7, no. 1, pp. 4437, 30 Jun, 2017.

[33] M. R. Williams, and R. F. Kirsch, “Evaluation of head orientation and neck muscle EMG signals as command inputs to a human-computer interface for individuals with high tetraplegia,” *IEEE Trans Neural Syst Rehabil Eng,* vol. 16, no. 5, pp. 485-96, Oct, 2008.

[34] A. M. Simon, L. J. Hargrove, B. A. Lock, and T. A. Kuiken, “Target Achievement Control Test: evaluating real-time myoelectric pattern-recognition control of multifunctional upper-limb prostheses,” *J Rehabil Res Dev,* vol. 48, no. 6, pp. 619-27, 2011.

[35] L. H. Smith, T. A. Kuiken, and L. J. Hargrove, “Myoelectric control system and task-specific characteristics affect voluntary use of simultaneous control,” *IEEE Trans Neural Syst Rehabil Eng,* vol. 24, no. 1, pp. 109-16, Jan, 2016.

[36] J. Gusman, E. Mastinu, and M. Ortiz-Catalan, “Evaluation of computer-based target achievement tests for myoelectric control,” *IEEE J Transl Eng Health Med,* vol. 5, pp. 2100310, 29 Nov, 2017.

[37] P. M. Fitts, “The information capacity of the human motor system in controlling the amplitude of movement,” *J Exp Psychol,* vol. 47, no. 6, pp. 381-91, Jun, 1954.

[38] J. W. Robertson, K. B. Englehart, and E. J. Scheme, “Rejection of systemic and operator errors in a real-time myoelectric control task,” *Conf Proc IEEE Eng Med Biol Soc,* vol. 40, Jul, 2018.

[39] A. W. Wilson, Y. G. Losier, P. A. Parker, and D. F. Lovely, “A bus-based smart myoelectric electrode/amplifier—system requirements,” *IEEE Trans Instrum Meas,* vol. 60, no. 10, pp. 3290-9, Oct, 2011.

[40] E. J. Scheme, and K. Englehart, "A flexible user interface for rapid prototyping of advanced real-time myoelectric control schemes," *MEC '08: Measuring Success in Upper Limb Prosthetics*, 2008.

[41] B. Hudgins, P. Parker, and R. N. Scott, “A new strategy for multifunction myoelectric control,” *IEEE Trans Biomed Eng,* vol. 40, no. 1, pp. 82-94, Jan, 1993.

[42] E. Scheme, and K. Englehart, “Training strategies for mitigating the effect of proportional control on classification in pattern recognition based myoelectric control,” *J Prosthet Orthot,* vol. 25, no. 2, pp. 76-83, 1 Apr, 2013.

[43] L. Hargrove, L. Miller, K. Turner, and T. Kuiken, “Control within a virtual environment is correlated to functional outcomes when using a physical prosthesis,” *J Neuroeng Rehabil,* vol. 15, no. Suppl 1, pp. 60, 5 Sep, 2018.

[44] K. A. Thoroughman, and R. Shadmehr, “Electromyographic correlates of learning an internal model of reaching movements,” *J Neurosci,* vol. 19, no. 19, pp. 8573-88, 1 Oct, 1999.

[45] M. Kawato, “Internal models for motor control and trajectory planning,” *Curr Opin Neurobiol,* vol. 9, no. 6, pp. 718-27, Dec, 1999.

[46] R. E. Johnson, K. P. Kording, L. J. Hargrove, and J. W. Sensinger, “Adaptation to random and systematic errors: Comparison of amputee and non-amputee control interfaces with varying levels of process noise,” *PLoS One,* vol. 12, no. 3, pp. e0170473, 16 Mar, 2017.

[47] A. W. Shehata, E. J. Scheme, and J. W. Sensinger, “Evaluating internal model strength and performance of myoelectric prosthesis control strategies,” *IEEE Trans Neural Syst Rehabil Eng,* vol. 26, no. 5, pp. 1046-55, May, 2018.

[48] T. R. Farrell, and R. F. Weir, “The optimal controller delay for myoelectric prostheses,” *IEEE Trans Neural Syst Rehabil Eng,* vol. 15, no. 1, pp. 111-8, Mar, 2007.

Jason W. Robertson (S’01–M’11) received his first B.Sc. in electronics engineering technology from DeVry University in Calgary, Alberta, Canada, in 2003, and his second in biomechanics from the University of Calgary in 2011. He then completed a M.Sc. in Biomedical Engineering at the University of Calgary in 2014, and is now a Ph.D. Candidate in Electrical Engineering at the University of New Brunswick in Fredericton, NB, Canada.

He has worked as a research student in various capacities since 2004, and has published four peer-reviewed papers in that time. His research interests include signal processing, rehabilitation engineering, and motor control.

Kevin B. Englehart (S’86–M’99–SM’03) received the B.Sc. degree in electrical engineering and the M.Sc. and Ph.D. degrees from the University of New Brunswick, Fredericton, NB, Canada, in 1989, 1992, and 1998, respectively.

He is the Director of the Institute of Biomedical Engineering at the University of New Brunswick, Fredericton, NB, Canada. His research interests include neuromuscular modeling and biological signal processing using adaptive systems, pattern recognition, and time-frequency analysis.

Dr. Englehart is a Registered Professional Engineer, and a Fellow of the Canadian Academy of Engineering. He is a member of the IEEE EMBS, the International Society of Electrophysiology and Kinesiology, and the Canadian Medical and Biological Engineering Society.

Erik J. Scheme (S’09–M’13–SM’18) received the B.Sc., M.Sc., and Ph.D. degrees in electrical engineering from the University of New Brunswick (UNB), Fredericton, NB, Canada, in 2003, 2005, and 2013, respectively.

He is currently the New Brunswick Innovation Research Chair in Medical Technologies, an Assistant Professor in the Department of Electrical and Computer Engineering, and an Adjunct Professor in the Faculty of Medical Education at Dalhousie University, New Brunswick. His current research interests include biological signal processing, pattern recognition, human–computer interfaces, and the clinical and commercial deployment of research.

Dr. Scheme is a Registered Professional Engineer and a member of the IEEE Engineering in Medicine and Biology Society.

2019

Effects of Confidence-Based Rejection on Usability and Error in Pattern Recognition-Based Myoelectric Control

Robertson, Jason W.

Institute of Electrical and Electronics Engineers

http://dx.doi.org/10.1109/JBHI.2018.2878907