Motion Normalized Proportional Control for Improved Pattern Recognition-Based Myoelectric Control

Erik Scheme, *Student Member, IEEE*, Blair Lock, *Member, IEEE*, Levi Hargrove, *Member, IEEE*, Wendy Hill, Usha Kuruganti, and Kevin Englehart, *Senior Member, IEEE*

***Abstract*—This paper describes two novel proportional control algorithms for use with pattern recognition-based myoelectric control. The systems were designed to provide automatic configuration of motion-specific gains and to normalize the control space to the user's usable dynamic range. Class-specific normalization parameters were calculated using data collected during classifier training and require no additional user action or configuration. The new control schemes were compared to the standard method of deriving proportional control using a one degree of freedom Fitts' law test for each of the wrist flexion/extension, wrist pronation/supination and hand close/open degrees of freedom. Performance was evaluated using the Fitts' law throughput value as well as more descriptive metrics including path efficiency, overshoot, stopping distance and completion rate. The proposed normalization methods significantly outperformed the incumbent method in every performance category for able bodied subjects ($p < 0.001$) and nearly every category for amputee subjects. Furthermore, one proposed method significantly outperformed both other methods in throughput ($p < 0.0001$), yielding 21% and 40% improvement over the incumbent method for amputee and able bodied subjects, respectively. The proposed control schemes represent a computationally simple method of fundamentally improving myoelectric control users' ability to elicit robust, and controlled, proportional velocity commands.**

***Index Terms*—amputee, electromyogram (EMG), myoelectric, pattern recognition, prostheses, proportional control, velocity control.**

I. Introduction

PATTERN recognition-based myoelectric control has garnered significant attention in the research community as evidenced by a vast body of literature. Great advances have been shown in signal preprocessing, feature extraction, classification, channel reduction, and many other areas. A thorough overview of these issues is provided in [1]–[4]. Now, with the commercial availability of multi-articulated hands and the promise of advanced multi-degree of freedom limbs [5], [6], international interest in its clinical deployment has been elevated. As such, research has begun to shift toward the clinical considerations of the approach [4], [7].

The current state-of-the-art pattern recognition-based myoelectric control is generally accepted to be some variant of the system proposed by Hudgins *et al.* [8]. They introduced a set of time-domain (TD) features that have since been widely adopted. These are commonly paired with a simple linear discriminant analysis (LDA) classifier [9], yielding a simple and reasonably robust control scheme [4], [10]–[12]. This classification scheme has been widely used to decipher user motion intent but does not inherently incorporate a method of estimating the desired velocity of movement.

The innate ability of individuals to modulate the amplitude of the electromyogram (EMG) provides a convenient means of velocity control. This method, where the speed of the device is controlled by modulating the intensity of contraction, is often referred to as *proportional velocity control*, or simply *proportional control*.

Even the earliest descriptions of myoelectric control included mention of varying contraction strength for enhanced control. In 1955, Battye *et al.* [13] proposed a simple system that would map contraction strength to the force exerted by the terminal device. Others followed in the 1960s by expanding on these ideas [14]–[16]. In the 1980s, several groups looked at the optimal method of deriving proportional control signals from EMG, with a simple low-pass rectification approach eventually being widely adopted [17], [18]. Over the years, the relative merits of proportional control have been debated [19]–[22], but it is currently offered in some form by all manufacturers of commercial myoelectric prostheses [23].

More recently, several groups have investigated using mapping techniques to generate simultaneous proportional control of the wrist degrees of freedom (DOF) [24]–[26]. These techniques use neural networks to establish a relationship between EMG and generated force or limb position. The possibility of controlling several DOFs simultaneously justifies this area of research, but its clinical robustness and viability have yet to be addressed.

Manuscript received September 27, 2012; revised February 07, 2013; accepted February 10, 2013. Date of publication March 07, 2013; date of current version January 06, 2014. This work was supported in part by NSERC Discovery Grant 217354-10 and the Atlantic Innovation Fund.

E. Scheme is with the Institute of Biomedical Engineering, University of New Brunswick, Fredericton, NB Canada (e-mail: escheme@unb.ca).

B. Lock is with the Center for Bionic Medicine, Rehabilitation Institute of Chicago, Chicago, IL 60611 USA (e-mail: b-lock@northwestern.edu).

L. Hargrove is with the Center for Bionic Medicine, Rehabilitation Institute of Chicago, Chicago, IL 60611 USA, and the Department of Physical Medicine and Rehabilitation, Feinberg School of Medicine, Northwestern University, Chicago, IL 60611 USA (e-mail: l-hargrove@northwestern.edu).

W. Hill is with the Atlantic Clinic for Upper Limb Prosthetics, Fredericton, NB, Canada (e-mail: whill@unb.ca).

U. Kuruganti is with the Department of Kinesiology, University of New Brunswick, Fredericton, NB, Canada (e-mail: ukurugan@unb.ca).

K. Englehart is with the Institute of Biomedical Engineering, University of New Brunswick, Fredericton, NB, Canada (e-mail: kengleha@unb.ca).

Digital Object Identifier 10.1109/TNSRE.2013.2247421

Despite the literature regarding proportional control and the large body of evidence supporting pattern recognition-based myoelectric control there has been little reference to validation of their use in conjunction with each other. In [23], Fougner *et al.* referred to such a control scheme and termed a system combining the two as a *proportional mutex*. In pattern recognition-based control practice, the corresponding proportional control signal is often derived from a simple weighted average of the mean absolute value (MAV) of the EMG channels used for pattern recognition, which may be normalized for each class of movement [27]. Scheme *et al.* [28] recently reported a study investigating the effect of using proportional control on the robustness of pattern recognition-based myoelectric control.

In 2011, Simon *et al.* were the first to publish a comparison of this method with conventional direct proportional control and binary on/off pattern recognition control [29]. Their results showed that a proportional pattern recognition-based system outperformed an ON/OFF system in a position tracking test. It was found to be inferior to a conventional direct control system which used two electrode sites over antagonist muscle pairs to determine direction and velocity. Their study, however, compared three degrees of freedom made available by using pattern recognition with only a single forearm DOF available via direct control.

In 1954, Fitts first quantified human motor performance using principles from Shannon's work in communication theory [30], [31]. He postulated that all human motor tasks convey a finite amount of information, limited by the capabilities of the control system and exhibiting a tradeoff between speed and accuracy. Fitt's law testing has since been widely used in the validaton of human-computer interfaces (HCI) [32] and forms the basis for an international standard (ISO9341-9).

In 2008, Williams and Kirsch [33] used a Fitts' law test to evaluate an HCI using EMG signals from neck muscles for individuals with high tretraplegia. In their paper, they presented an additional set of performance metrics that helped to describe the nature of the control, in addition to a form of *throughput* value output from the Fitts' law test. In [34], Simon *et al.* proposed a similar set of metrics when describing their Target Achievement Control (TAC) test. The TAC test requires users to move a virtual limb into a target position and remain there for a set period of time, a close analog to the Fitts' law paradigm. A combination of these proposed metrics comprising *throughput*, *path efficiency*, *overshoot, stopping distance* and *completion rate* provides a comprehensive set of metrics for evaluating myoelectric control schemes.

In this work, two novel methods of proportional control are proposed for use with pattern recognition-based myoelectric control. These are compared to the standard method described by Simon *et al.* using a 1-D Fitts' law task.

II. Methodology

Ten healthy, able-bodied subjects ranging in age from 19–52, and three trans-radial amputee subjects, ranging in age from 25 to 45 (one acquired and two congenital deficiencies) performed a 1-D Fitts' law test. All experiments were approved by the University of New Brunswick's Research Ethics Board.

Able-bodied subjects were fitted with a cuff made of thermoformable gel that was embedded with six equally spaced pairs of stainless steel dome electrodes. Amputee subjects used the same cuff, but with only five pairs of electrodes due to space limitations. The cuff was placed around the dominant forearm for able-bodied participants, at approximately one third of the length of the forearm, proximal to the elbow. The cuff was placed around the area of largest muscle bulk on the deficient limb for amputees. An additional monopolar Red Dot (3M®) monitoring electrode was placed at the elbow for use as a reference electrode.

The channels of EMG were differentially amplified using remote ac electrode-amplifiers (BE328 by Liberating Technologies, Inc.) and low-pass filtered at 450 Hz with a fifth-order Butterworth filter. Data were sampled with a sampling frequency of 1000 Hz using a 16-bit analog-to-digital converter. Data were digitally high-pass filtered using a third-order Butterworth filter with a cutoff of 20 Hz in order to remove any motion artifact.

A. Control

A 1-D Fitts' Law task was chosen to allow for simplification of the classification problem, to focus on the effect of the proportional control algorithms. Three degrees of freedom were sequentially tested to validate the suitability of the algorithms for different motions. For each trial, subjects were prompted to elicit contractions corresponding to one of the following degrees of freedom: *wrist flexion/extension, wrist pronation/supination*, or *hand open/close*, along with a baseline *no motion* contraction. Four repetitions of 2 s were collected for each motion, during which the subjects dynamically (and subjectively) *ramped* from no contraction up to a moderate level. Subjects were instructed to stay within a comfortable and sustainable range. Including dynamic data during training has been reported to improve classifier robustness, as it captures more of the variability introduced during functional use [28]. Furthermore, the dynamics of proportional control are included in the training data and are therefore built into the classification boundaries. Prior to training, data were segmented for feature extraction using 160 ms windows with an overlap of 16 ms [4], [35], [36]. Using a set of TD features (introduced by Hudgins *et al.* [8]), an LDA classifier was trained using data from all four repetitions of each class [4].

Fig. 1 illustrates the data flow of the control scheme used, with one of the three proportional control methods being enabled for a given task. As in training, classification decisions were made every 16 ms using 160 ms windows. Proportional control outputs were calculated using the same windows of data and used to control velocity in the direction determined by the classifier output.

Three different proportional control algorithms were tested. For all cases, the mean absolute value was calculated using

$$\mathrm{MAV}_j = \frac{1}{N_S}\sum_{n=1}^{N_S}|x_j[n]| \qquad (1)$$

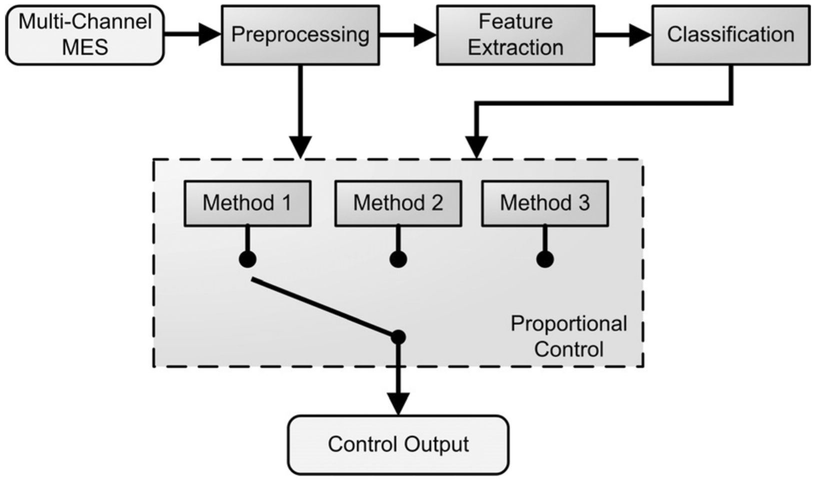

Fig. 1. Block diagram illustrating the data flow of the control schemes used.

where MAV_j is the mean absolute value of channels j, x_j is the window of data for channel, andN_S is the number of samples per window.

Method 1: Method 1 consisted of the system described in [29], using

$$\mathrm{PC}_i^1 = \frac{G_i}{N_\mathrm{CH}} \sum_{j=1}^{N_\mathrm{CH}} \mathrm{MAV}_j \tag{2}$$

where PC_i^1 is the proportional control output given class i and N_CH is the number of channels used. G_i is a class-specific gain determined during training that maps the average class-specific amplitude to 50% of full speed.

Method 2: Method 2 consisted of an algorithm first proposed in an interdepartmental white paper by Blair Lock, as shown in (3). The algorithm was inspired by a need for auto-calibration of class-specific gains which, at the time of conception, required manual configuration after training. The squaring operator shown in (3) was added to bias the dynamic control range towards increased resolution at slow speeds. This algorithm has not been previously published, but has seen extensive use in clinical testing at the Rehabilitation Institute of Chicago

$$\mathrm{PC}_i^2 = \left(\frac{1}{C_i} \sum_{j=1}^{N_\mathrm{CH}} S_{i,j} \mathrm{MAV}_j \right)^2 \tag{3}$$

where N_CH is as above and $S_{i,j}$ is the stored set of values representing the *centers* of each class i and channel j that were calculated and stored during classifier training by

$$S_{i,j} = \frac{1}{K_{i,j}} \sum_{k=1}^{K_{i,j}} \mathrm{MAV}_{i,j,k}^\mathrm{Tr} \tag{4}$$

where $\mathrm{MAV}_{i,j,k}^\mathrm{Tr}$ is the mean absolute value of the training data from class i, channel j, and computation window k, and $K_{i,j}$ is the total number of computation windows (k) for class i and channel j. C_i is the stored set of per-class *normalization factors* calculated and stored during classifier training by using (5). These are the channel-sum of squared *centers* found using (4) in the following:

$$C_i = \sum_{j=1}^{N_\mathrm{CH}} S_{i,j}^2 \tag{5}$$

where, again, N_CH is the total number of channels.

Method 3: Method 3 was calculated using (6) as follows:

$$\mathrm{PC}_i^3 = \frac{\sum_{j=1}^{N_\mathrm{CH}} \mathrm{MAV}_j - \mathrm{TH}_{\mathrm{Min},i}}{\mathrm{TH}_{\mathrm{Max},i} - \mathrm{TH}_{\mathrm{Min},i}} \tag{6}$$

where MAV_j and N_CH are as above, i is the current class, and $\mathrm{TH}_{\mathrm{Min},i}$ and $\mathrm{TH}_{\mathrm{Max},i}$ are the stored sets of values representing the lower and upper bounds of class i, calculated and stored during pattern classifier training using

$$\mathrm{TH}_{\mathrm{Min},i} = \left(1 - \frac{P_{\mathrm{TH}^\mathrm{min}}}{100}\right) \mathrm{MAV}_{\mathrm{Min},i}^\mathrm{Tr} + P_{\mathrm{TH}^\mathrm{min}} \mathrm{MAV}_{\mathrm{Max},i}^\mathrm{Tr} \tag{7}$$

$$\mathrm{TH}_{\mathrm{Max},i} = \left(1 - \frac{P_{\mathrm{TH}^\mathrm{max}}}{100}\right) \mathrm{MAV}_{\mathrm{Min},i}^\mathrm{Tr} + P_{\mathrm{TH}^\mathrm{max}} \mathrm{MAV}_{\mathrm{Max},i}^\mathrm{Tr} \tag{8}$$

$P_{\mathrm{TH}^\mathrm{min}}$ and $P_{\mathrm{TH}^\mathrm{max}}$ are the desired lower and upper boundaries, expressed in percent of maximum contraction. Through pilot work, the optimal values of $P_{\mathrm{TH}^\mathrm{min}}$ and $P_{\mathrm{TH}^\mathrm{max}}$ were determined to be 10% and 70%, respectively. $\mathrm{MAV}_{\mathrm{Min},i}^\mathrm{Tr}$ and $\mathrm{MAV}_{\mathrm{Max},i}^\mathrm{Tr}$ are calculated using

$$\mathrm{MAV}_{\mathrm{Min},i}^\mathrm{Tr} = \min_{k=1:k_i} \sum_{j=1}^{N_\mathrm{ch}} \mathrm{MAV}_{i,j,k}^\mathrm{Tr} \tag{9}$$

$$\mathrm{MAV}_{\mathrm{Max},i}^\mathrm{Tr} = \max_{k=1:k_i} \sum_{j=1}^{N_\mathrm{ch}} \mathrm{MAV}_{i,j,k}^\mathrm{Tr} \tag{10}$$

TABLE I
COMBINATIONS OF DISTANCES (D) AND WIDTHS (W) WITH RESULTING INDICES OF DIFFICULTY (ID)

D	W	ID
50	3	4.14
50	5	3.46
50	8	2.86
50	15	2.12
100	3	5.10
100	5	4.39
100	8	3.75
100	15	2.94

where $\mathrm{MAV}_{i,j,k}^{\mathrm{Tr}}$ is the mean absolute value of the training data from class i, channel j, and computation window k, and K_i is the total number of computation windows (k) for class i and channel j. In other words, $\mathrm{TH}_{\mathrm{Min},i}$ and $\mathrm{TH}_{\mathrm{Max},i}$ are the values of EMG intensity corresponding to the 10th and 70th percentile rank of contractions elicited for class i.

B. Fitts' Law Task

Fitts' law testing uses repeated trials with varying target distances and widths to compute a single *throughput* (TP) statistic measured in bits per second. Throughput is defined as

$$\mathrm{TP} = \frac{1}{N}\sum_{i=1}^{N}\frac{\mathrm{ID}_i}{\mathrm{MT}_i} \tag{11}$$

where i is one of N trials, MT is the movement time (in seconds) taken to acquire the target and ID is the index of difficulty (in bits) which relates the target distance, D, and width W, through

$$\mathrm{ID} = \log_2\left(\frac{D}{W}+1\right) \tag{12}$$

where D and W are in units of distance (normalized to the graphical interface boundaries).

Table I shows the values of D and W, and the resulting indexes of difficulty, used in this work.

C. Testing Protocol

Users were instructed to complete each test as quickly and as naturally as possible. A *test* required the user to move the cursor from the central neutral position to a randomly ordered target location of distance D and size W. During their respective trials, *wrist flexion*, *wrist pronation* and *hand close* were used to move the cursor in the direction of flexion (e.g., left, for right-handed subjects), while *wrist extension*, *wrist supination*, and *hand open* were used to move the cursor in the direction of extension. The test was considered complete when the user successfully placed and kept their cursor within the target range for a full second (the *dwell time*). If unsuccessful after 15 s, the test was timed out and considered incomplete. The user cursor was reset to the neutral position between each test. Fig. 2 shows example screen captures of the Fitts' law test during use.

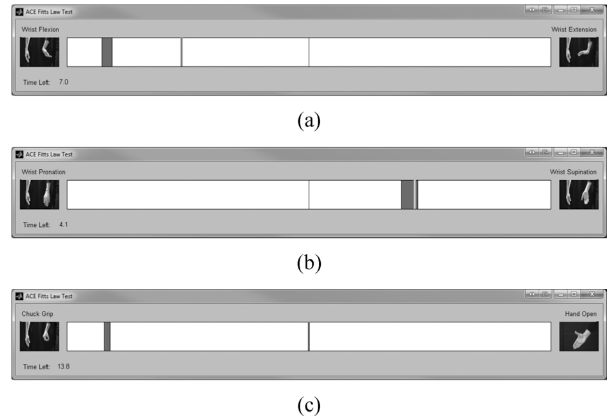

Fig. 2. Screen captures of Fitts' law task used for (a) wrist flexion/extension, (b) wrist rotation (target acquired), and (c) hand close/open.

TABLE II
PERFORMANCE METRICS USED

Metric	*Description*
Throughput	Overall performance; tradeoff between speed and accuracy
Efficiency	Quality of control; a ratio of the shortest path to the target to the actual path travelled
Overshoot	Target acquisition; number of times the target was acquired and then lost per test
Stopping Distance	Stopping ability; the total distance travelled during the 1 second dwell time
Completion Rate	Task success; percentage of tests completed within the 15 seconds of allowed time

Tests were completed for all combinations of distance and width, resulting in 32 tests per proportional control method, per DOF. After a full trial of all three control schemes was fully completed, the entire process (data collection, classifier training, and Fitts' law testing) was repeated for another DOF. This resulted in a total of 96 tests per subject for each control scheme.

D. Performance Metrics

The throughput measurement of the Fitts' law test is appealing because it concisely represents the overall performance during the task in terms of the tradeoff between speed and accuracy. Many popular clinical tests of prosthetic function (such as the Assessment for Capacity of Myoelectric Control (ACMC) [37]), however, employ observational assessments of the naturalness, spontaneity and compensatory motions during use. Throughput alone cannot wholly describe these more observational and descriptive aspects of the control task. Consequently, the additional metrics proposed by Simon *et al.* [12], and Williams and Kirsch [33] can be combined with their description of throughput to provide a more complete description of the control performance. Table II provides a brief overview of the performance metrics used in the analysis of the proportional control schemes.

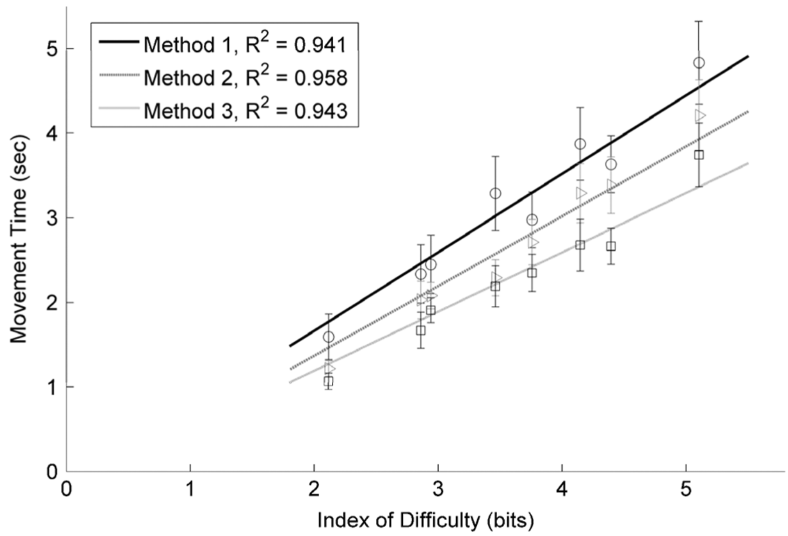

Fig. 3. Relationship between movement time (MT) and index of difficulty (ID) for the Fitts' law task.

Statistical analyses of these performance metrics were conducted using a multi-way ANOVA with a *post hoc* multiple comparison (Tukey-Kramer) test. The alpha level was set at 0.001.

III. RESULTS

Fig. 3 shows a regression plot of movement time (the time taken to accomplish the task) versus index of difficulty for the Fitts' law task. The linear relationship between movement time and index of difficulty supported by the high R^2 values for all three methods (average $\mathrm{R}^2 = 0.947$), strongly supports the suitability of using Fitts' law for testing velocity-based proportional myoelectric controls. The clear vertical separation between the three control methods shows the significant improvement of the proposed methods.

Table III summarizes the performance of the proportional control schemes for the various performance metrics, averaged across all users and trials. Method 2 produced significantly better scores than Method 1 for all performance metrics $(p < 0.001)$, except for throughput and stopping distance for the amputee group. Method 3 produced significantly better results than Method 1 in all but stopping distance and completion rate for the amputee group and showed significant improvement in throughput over Methods 1 and 2 for both groups. On average, Method 3 produced nearly 40% higher throughput (21% for amputees), 22% higher efficiency (10% for amputees), and 72% less overshoot (44% for amputees) than Method 1.

Fig. 4 shows histograms of the velocities elicited during the Fitts' law test using the different methods of proportional control. It can be seen that, on average, users were unable to produce near-zero velocities using Method 1, leading to frequent overshooting of targets. Method 2 clearly shows the ability to produce low velocity commands, with a bias towards these slower speeds being introduced by its squaring operation. Method 3 showed the most even distribution of velocities used indicating more efficient use of the dynamic range of contractions.

Table IV shows the relative performance of the different DOFs, averaged across all three control methods. The wrist flexion/extension (WF/WE) DOF yielded significantly better results for many metrics, most glaringly throughput and efficiency. Physiologically, this may be due to the fact that wrist flexion and extension are driven mainly by the large flexor/extensor muscles. The other DOFs are more complex, requiring a wider selection of smaller and deeper muscles of the forearm.

TABLE III
RESULTS OF 1-D FITTS' LAW TEST FOR ABLE BODIED AND AMPUTEE SUBJECTS (IN BRACKETS), COMPARING PROPORTIONAL CONTROL METHODS

	Method 1	*Method 2*	*Method 3*
Throughput	1.31 ± 0.13	1.58 ± 0.11 *	1.83 ± 0.14 †
	(1.71 ± 0.13)	(1.85 ± 0.09)	(2.07 ± 0.12) †
Efficiency (%)	72.70 ± 3.17	88.06 ± 2.05 *	88.51 ± 2.06 *
	(82.69 ± 2.33)	(90.76 ± 1.41) *	(90.39 ± 1.18) *
Overshoot	2.19 ± 0.41	0.79 ± 0.21 *	0.61 ± 0.16 *
	(0.90 ± 0.23)	(0.47 ± 0.11) *	(0.50 ± 0.10) *
Stopping Distance	4.73 ± 0.61	3.86 ± 0.48 *	3.72 ± 0.47 *
	(4.08 ± 0.48)	(3.81 ± 0.43)	(3.78 ± 0.46)
Completion Rate (%)	92.40 ± 3.29	98.85 ± 1.40 *	98.85 ± 0.95 *
	(97.92 ± 1.47)	(100.00 ± 0.00)*	(99.65 ± 0.53)

* indicates significant improvement over Method 1 ($p < 0.001$)
† indicates significant improvement over Methods 1 & 2 ($p < 0.001$)

Fig. 5 shows an overlay of the proportional control velocity profiles for all users and DOF. The proportional control algorithms were applied to those portions of the training data that were classified as active motion. All data points in these figures therefore represent the proportional control outputs for the full range of active classification decisions; contractions of any lower intensity resulted in *no motion* classifier decisions. It is evident that the users were unable to perform any active motions at speeds of less than approximately 20% when using Method 1. Using Method 1, some motions also never reached 100% velocity during training, meaning that the users would have had

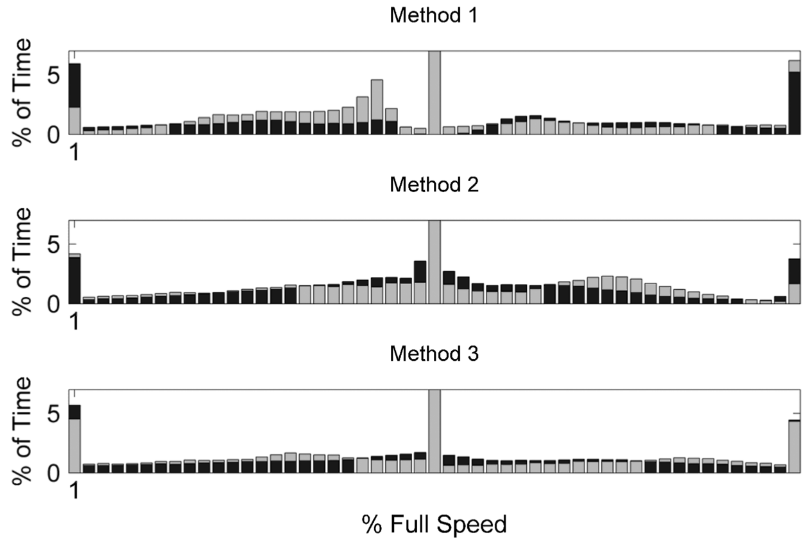

Fig. 4. Histogram of control velocities elicited during the Fitts' law test using Method 1 (top), Method 2 (middle) and Method 3 (bottom). Abled bodied subject results are shown using black bars, while amputee subjects' results are shown in gray.

TABLE IV
RESULTS OF 1-D FITTS' LAW TEST FOR ABLE BODIED AND AMPUTEE SUBJECTS (IN BRACKETS), COMPARING DEGREES OF FREEDOM

	WF/WE	*WP/WS*	*HC/HO*
Throughput	1.98 ± 0.14 *†	1.36 ± 0.11	1.38 ± 0.12
	(2.09 ± 0.13) *†	(1.57 ± 0.11)	(1.97 ± 0.09) *
Efficiency (%)	90.77 ± 1.89 *†	79.40 ± 2.93	79.11 ± 2.97
	(90.04 ± 1.55) *†	(83.52 ± 2.09)	(90.27 ± 1.56) *
Overshoot	0.73 ± 0.23*†	1.34 ± 0.34	1.52 ± 0.33
	(0.56 ± 0.10)	(0.68 ± 0.18)	(0.63 ± 0.19)
Stopping Distance	3.90 ± 0.49 †	3.96 ± 0.49 †	4.45 ± 0.60
	(3.98 ± 0.49)	(3.96 ± 0.43)	(3.73 ± 0.45)
Completion Rate (%)	99.06 ± 1.34 *†	95.1 ± 2.73	95.94 ± 2.26
	(99.65 ± 0.53)	(98.26 ± 1.39)	(99.65 ± 0.53)

* indicates a significantly better result than WP/WS ($p < 0.001$)
† indicates a significantly better result than HC/HO ($p < 0.001$)

to elicit considerably harder contractions to achieve full speed during testing. Method 2 permitted much lower speeds at the onset of active classification and produced 100% velocity commands within the range of the training data. Method 3 exhibited a period of zero velocity for lower intensity active decisions (of varying motion-specific lengths), as well as a similar buffer range at full speed. This suggests that the user was able to traverse the full range of velocities using a subset of the contraction intensities elicited during training.

IV. DISCUSSION

The conventional method of deriving proportional control while using pattern recognition, where a medium (or the mean) contraction is mapped to 50% speed, makes two rather naïve assumptions. The first is that the user is able to generate a class specific contraction of double the amplitude of the mean value, corresponding to 100% full speed. The upper right side of Fig. 5—Method 1—shows that, on average, this assumption fails and the user's comfortable range often does not reach 100% speed. This results in either slower overall movement times or forces the users to elicit undesirably (and unsustainably) strong contractions. The second assumption is that, on transition from no motion to an active class, the resultant signal amplitude is essentially zero. There are several factors that influence the amplitude at this transition which include the EMG noise floor, ambient or electronic noise, and the boundaries in feature space determined during classifier training. Fig. 5 Method 1 shows that at this transition point, on average, users elicited contractions corresponding to velocities of approximately 20%. This affected their ability to operate the cursor at low speeds, resulting in increased overshoot, stopping distance and lower efficiency.

The design criteria for Methods 2 and 3 were to normalize the control outputs to better reflect the users' usable range of class-specific contractions. Using these approaches, the proportional control schemes are able to compensate for differences in EMG amplitude inherent to each motion class. Method 2 does this by scaling the real-time output amplitudes using coefficients that represent the average per-class, per-channel EMG mean absolute values. An additional squaring term was added to increase proportional control fidelity for lighter-than-medium contractions, and conversely, to provide more coarse control for harder contractions. In this manner, similar to many joystick controllers, Method 2 shows a smoothed bi-modal behavior; an algorithmic enhancement to the similar two-motor analogue in devices like Otto Bock's Electrohand 2000.

Method 3 is founded on using the same calculation for the average mean absolute value across EMG channels. This was chosen after pilot work testing several channel weighting schemes such as uncorrelated linear discriminant analysis [38], principle components analysis, and linear regression. These approaches failed because they relied heavily on assumptions about the linearity of user elicited "ramp" contractions, but also because they "over-tuned", counting on small changes from single EMG channels. It was decided that the smoothing

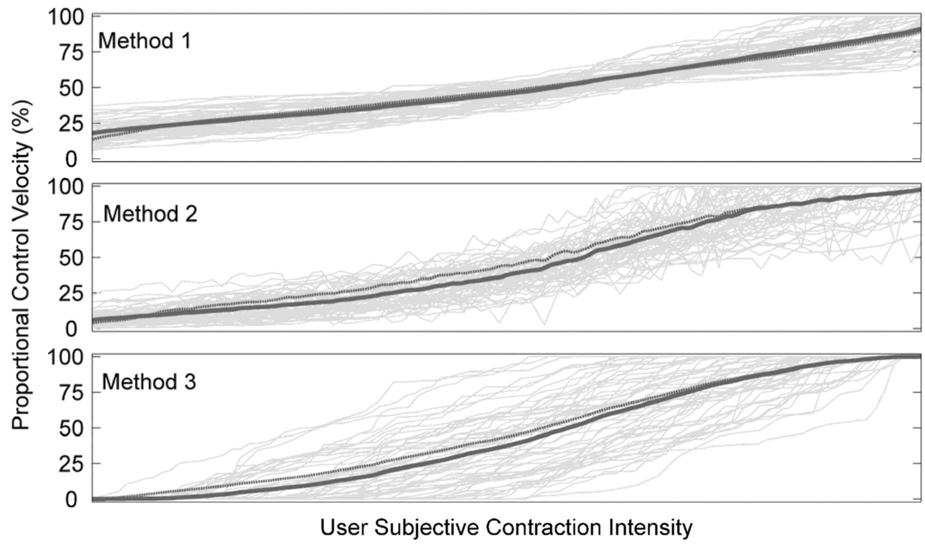

Fig. 5. Comparison of proportional control profiles versus user perceived contraction intensity during active classes for the three control methods. Dark bold lines represent the average able bodied profiles, while the dark medium lines represent the average amputee profiles.

effect resulting from averaging across all EMG channels used for pattern recognition would ultimately improve robustness. Method 3 refined this averaging by then normalizing between user and class-specific maximums and minimums, calculated from the dynamic training data. In this way, the entire 100% range of control speeds was guaranteed to be usable within the user's true class-specific dynamic range. This is evidenced by the fact that Fig. 5—Method 3—shows no nonzero vertical axis intercepts at low intensities, and no sub-100% vertical axis intercepts at high intensities.

Testing was performed in a random blind fashion, wherein users were not told which control scheme they were using for any given test. Nonetheless, all subjects were easily able to identify which proportional control scheme was being used during nearly every test. This further validates, observationally, the use of Fitts' law testing for proportional myoelectric control studies, as differences in control are readily distinguishable to the user. It also speaks to the significant effect that improving the proportionality of control can have on the overall control experience. One subject anecdotally described the difference between the three methods as follows: Method 1 was described as driving a car on icy roads; the user was able to perform that task, but with low confidence in their ability to change direction or stop. Method 2 was comparatively described as driving a family car on dry pavement; the user had good control, but would have liked the vehicle to be able to accelerate more quickly. Method 3 was described as driving a sports car on dry pavement; the user had good control, acceleration, and stopping ability. While this was simply one user's subjective (and creative) perspective, it is strongly correlated with the performance metrics for both the able-bodied and amputee groups.

Tables III and IV indicate that, in general, the amputee subjects outperformed their able bodied counterparts. This is in contrast to many pattern recognition-based myoelectric control studies that show a relative drop in classification accuracy for amputee subjects. It is important to differentiate that in this work, classification was limited to a single DOF at a time in order to limit the effect of misclassification and to emphasize the effect of proportional control. It is possible that the amputee subjects, who regularly use proportional conventional myoelectric control of their prostheses, benefitted from a familiarity with proportional myoelectric control without suffering from the commonly reported decrease in multiclass classification rates. Furthermore, it was noted that able bodied subjects appeared more susceptible to a certain amount stretch reflex when stopping a contraction. This occasionally caused the activation of antagonist muscles and elicitation of small motions in the opposite direction, resulting in increased stopping distance and overshoot.

Prosthetic fittings are always a personal endeavor, with each patient facing different challenges and having different abilities. The authors believe that customizing proportional control outputs to fit each individual user's ability while performing different motions is an important step towards making robust pattern recognition-based myoelectric control available to the widest possible range of users. Ongoing research is currently investigating the use of improved proportional control schemes during multi-DOF control.

V. Conclusion

Two novel methods of deriving proportional velocity control commands were proposed. These methods were compared with the standard "average of channels" method using a repeated 1-D Fitts' law test. The resultant *throughput* performance metric was combined with additional, more tangible, metrics (*efficiency*, *overshoot, stopping distance* and *completion rate*) to evaluate the overall usability of the control schemes. The high coefficient of determination value obtained from linear regression fittings ($\mathrm{R}^2 = 0.947$) of the Fitts' law task confirmed the suitability of the test for evaluating proportional myoelectric control algorithms.

The proposed algorithms (Methods 2 and 3), vastly outperformed the incumbent method (Method 1) in almost every performance category. For Method 2, the improvement was statistically significant ($p < 0.001$) for every metric with the able bodied group and all but throughput and stopping distance for the amputee group. Method 3 also showed significantly better results over all metrics ($p < 0.001$) for all able bodied subjects and all but stopping distance and completion rate for the amputee group. Method 3 also obtained significantly higher throughput ($p < 0.0001$) than both Methods 1 and 2.

The performance of Method 3 strongly suggests that it can significantly improve the usability of pattern recognition-based control. It can be easily implemented on a microprocessor-based controller, and has very low computational requirements. It requires no special considerations in training other than instructing the user to perform ramp contractions, which has been shown to improve classifier robustness. Thresholds can be automatically determined from the training data. Ongoing work involves evaluating these methods on physical prosthetic devices.

ACKNOWLEDGMENT

The authors would like to thank K. Bühler and C. Stephenson for their help with collection of pilot data.

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Erik Scheme (S'09) received the B.Sc. and M.Sc. degrees in electrical engineering from the University of New Brunswick (UNB), Fredericton, NB, Canada, in 2003 and 2005, respectively. He is currently working toward the Ph.D. degree at the Institute of Biomedical Engineering, UNB.

He is a Project Engineer and his research interests include biological signal processing and the clinical application of prosthetic control research.

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

Blair Lock (M'13) received the B.Sc. and M.Sc. degrees in electrical engineering, in 2003 and 2005, respectively, from the University of New Brunswick, Fredericton, NB, Canada, where he also received a diploma in technology management and entrepreneurship in 2003.

He is currently the Director of Operations for the Center for Bionic Medicine at the Rehabilitation Institute, Chicago, IL, USA. His research interests include pattern recognition for improved control of powered prostheses and user experience in rehabilitation technology development.

Mr. Lock is a Registered Professional Engineer.

Levi Hargrove (S'05–M'08) 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 2007 respectively.

He joined the Center for Bionic Medicine, Rehabilitation Institute of Chicago, Chicago, IL, USA, in 2008. His research interests include pattern recognition, biological signal processing, and myoelectric control of powered prostheses. He is also a Research Assistant Professor in the Department of Physical Medicine and Rehabilitation (PM&R) and Biomedical Engineering, Northwestern University, Evanston, IL, USA.

Dr. Hargrove is a member of the Association of Professional Engineers and Geoscientists of New Brunswick.

Wendy Hill received the B.Sc. degree in occupational therapy from Dalhousie University, Halifax, NS, Canada, in 1992.

She is currently a Research Occupational Therapist for the Atlantic Clinic for Upper Limb Prosthetics, housed within the Institute of Biomedical Engineering at the University of New Brunswick (UNB), Fredericton, NB, Canada. She assesses and treats upper limb amputees from Atlantic Canada, specializing in externally powered prosthetic systems.

She is a member of the Upper Limb Prosthetic Outcome Measures group, the International Society of Prosthetics and Orthotics, and the Association of Children's Prosthetic and Orthotic Clinics.

Usha Kuruganti received the B.Sc. and M.Sc. degrees in electrical engineering and the Ph.D. degree in human factors engineering from the University of New Brunswick (UNB), Fredericton, NB, Canada.

She is currently an Associate Professor in the Faculty of Kinesiology at UNB and a Researcher in the Andrew and Marjorie McCain Human Performance Laboratory within the Richard J. CURRIE Centre at UNB. Her research interests include human movement analysis, neuromuscular physiology, electromyography and human factors.

Dr. Kuruganti is a Registered Professional Engineer, a Fellow of Engineers Canada, and a member of the International Society of Electrophysiology and Kinesiology, and the Association of Canadian Ergonomists.

Kevin Englehart (S'90–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 (UNB), Fredericton, NB, Canada, in 1989, 1992, and 1998, respectively.

He is currently the Director of the Institute of Biomedical Engineering at UNB. 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 member of the IEEE Engineering in Medicine and Biology Society, the International Society of Electrophsiology and Kinensiology, and the Canadian Medical and Biological Engineering Society.