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Real-time Comparison of Conventional Direct Control and Pattern Recognition Myoelectric Control in a two-dimensional Fitts' Law Style Test

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Abstract **Few studies have directly compared real-time control performance of pattern recognition to direct control for the next generation of myoelectric controlled upper limb prostheses. Many different implementations of pattern recognition control have been proposed, with minor differentiations in the feature sets and classifiers. An objective and generalizable evaluation tool quantifying the control performance, other than classification accuracy, is needed. This paper used the implementation of such a tool through the design of a target acquisition test, similar to a Fitts' law test, relating movement time of the target acquisition to the difficulty of the target, for a given control strategy. Performance metrics such as throughput (bits/sec), completion rate (%) and path efficiency (%) allow for a complete evaluation of the described strategies. We compared direct control and pattern recognition control with the proposed test and found that 1) the test was valid for control system evaluation by following Fitts' law with high coefficients of determination for both types of control and 2) that pattern recognition significantly outperformed direct control in throughput with similar completion rates and path efficiencies. In this framework, the present pilot study supports pattern recognition as a promising strategy and forms a basis for the development of a general and objective tool for the performance evaluation of upper limb control strategies.**

I. Introduction

Ideally, powered upper-limb prostheses should be controlled with a reliable and robust control strategy that can be intuitively operated by end-users. Measuring the intuitiveness and robustness of such control systems is very challenging. To date, there is no simple, objective tool for the evaluation and comparison of upper limb prosthetics control strategies during real-time control operation.

Myoelectric control systems for upper limb prostheses can be based on the conventional direct control (DC) or on pattern recognition control (PR). DC often uses a residual pair of agonist-antagonist muscles in the remnant limb and maps their isolated contractions to one degree of freedom (DOF) of the motorized prosthesis. An increased number of operable DOFs is enabled by implementing a mode switch event that allows changing between DOFs [1]. PR control maps patterns of muscle activation rather than an isolated contraction of a specific muscle to one DOF of a prosthesis. It relies on the assumption that a set of features describing the myoelectric signal at an electrode location is repeatable for the same state of muscle activation but distinguishable from other states [2]. This technique is intuitive and allows the operation of multiple DOFs independently. While it does have some limitations such as imposing the sequential operation of each DOF, it has been identified as a good option for controlling the next generation of multifunctional prostheses [3-6].

A standard performance evaluation metric of PR control strategies is the analysis of offline classification accuracies (or errors). This metric has been shown to correlate with real-time control performance [7, 8] but there are many other factors that influence functional outcomes. Few objective functional tests to assess the usability (not just the control strategy) of powered prostheses exist and require the use of a physical prosthesis [9], which is not always possible in fundamental research. As such, virtual environments have been proposed as a low-cost alternative to measure real-time control performance. In this framework, Simon et al. developed a target achievement control test (TAC test) to test PR real-time performance in a virtual environment [10]. The TAC test evaluates the controllability of a prosthesis through the positioning of a multi-functional virtual limb from an initial target position back to a neutral position. The test allows inferring user performance with metrics such as path efficiency, completion rate and completion time in one given difficulty that is manually adjustable by defining tolerance in the end-position, time-out or number of motions required. While the TAC test can only evaluate one difficulty level at the time, it is further limited by the visualization of the task in the virtual environment, especially when several motions need to be performed to achieve the target posture.

T TAC test has a close analogy to a so-called Fitts' law test. In 1954, Fitts first evaluated human motor performance in a one-dimensional target acquisition test, relating the time of the pointing movement to the difficulty of the target [11]. The outcome described the performance of the human motor system in terms of speed and accuracy of the inferred pointing movements in one single metric called throughput (TP), in bits per second. Fitts postulated that the TP reflected on the capabilites of the control system to transfer information. Since then, Fitts' law has been widely used in the validaton of human-computer interfaces (HCIs) and has been integrated into a standard for the evaluation of pointing devices [12].

In 2008, Williams and Kirsch compared three different cursor control systems, one of them with surface

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electromyography (EMG) signals from neck muscles, in a two-dimensional Fitts' law test [13]. They used a set of complementary performance metrics similar to those in the TAC test. In 2012, Engelhart and Scheme compared surface EMG classification schemes for three-DOF PR control strategies in a pseudo-three dimensional Fitts' law test [14].

The aim of the present pilot study was the evaluation and comparison of DC and PR control strategies for upper-limb prosthetics in a two dimensional center-out target achievement test in analogy to a Fitts' law style test. The test was designed to compare the control strategies in a repeatable and general setting in real time. Reported performance evaluation included the fitting of the obtained data to Fitts' law, the TP of the two strategies as well as path efficiency (PE), completion rate (CR) and the typical signature of each control strategy. This preliminary study served as basis for a complete study in which three control strategies (DC, sequential PR and simultaneous PR control) are evaluated on able-bodied and amputee subjects in a two dimensional Fitts' law style test.

II. METHODOLOGY

Subjects. Five able-bodied right-handed students were recruited, gave informed consent and participated in the institutional review board approved study.

EMG-based control strategies. The source signal for each of the three control strategies was surface EMG. For DC, a pair of bipolar electrodes was placed on the wrist flexor-extensor muscle pair on the proximal forearm. For PR control, four bipolar electrodes were positioned at equal distances around the circumference of the proximal forearm. The recorded EMG signals were amplified using a Texas Instruments TI-ADS1299 analog front end system and sampled at a frequency of 1 kHz. The signal was filtered with a 3rd order Butterworth filter at a 20 Hz cut-off frequency to reduce motion artifact. For direct control, the mean absolute value (MAV) extracted over a 150 ms sliding window of the EMG signal of the electrode pair was directly mapped to one operational DOF. A second DOF could be selected by a short co-contraction of flexors and extensors. The DC thresholds were manually set so that the user could easily operate either DOF without accidentally switching into the other one. For PR control, a set of autoregressive and time-domain features commonly reported was used to represent the EMG data from each channel using 150 ms windows and a linear discriminant analysis (LDA) classifier was used to discriminate between movement classes [4]. Post processing of the data was achieved using the decision-based velocity ramp described by Simon et al [15].

Test set-up. The test was implemented in a MATLAB (Mathworks Inc., Natick, MA) graphical user interface (GUI) and consisted in a two-dimensional Cartesian space of size (-100,100) x (-100,100) distance units with the origin at the center (0,0) of the GUI. A trial required moving the cursor rapidly from the origin into a target circle with the control schematic in table 1. The width of the target and position with respect to the origin were programmable by the experimenter or could be randomized for a range of difficulties (see equation 2).

TABLE I: CURSOR CONTROL MAP

Simple motions for sequential control
Hand open → (+) x-axis control
Hand close → (-) x-axis control
Wrist extension → (+) y-axis control
Wrist flexion → (-) y-axis control

A trial was successful when the cursor was moved into the target circle and dwelled inside for two seconds; this time was subtracted from the movement time in the subsequent analysis. Trial failure occurred either through time-out (if acquisition time exceeded 15 sec) or through difficulty, when the cursor overshot the target more than 5 times in an attempt to stop inside and dwell. Visual feedback guided the subject in the target acquisition: the target circle turned green whenever the cursor was inside and was red if not. The cursor was reset to the origin after each trial.

Performance evaluation. Subject performance and the validity of the test were evaluated through the fit to Fitts' law, predicting a linear relationship between the movement time (MT) of the target acquisition and the index of difficulty (ID) of the target. Fitts' law predicts the linearity between MT and ID according to

$$MT = a + b \times ID, \tag{1}$$

where a and b are the parameters of the law and ID is the index of difficulty of the targets in bits, defined by MacKenzie et al [16] as follows:

$$ID = \log_2\left({}^{D}/_{W} + 1 \right), \tag{2}$$

with D the distance from the origin to the center of the target and W the width of the target. Further, the control systems were evaluated by their throughput TP in bits/sec, calculated by the mean of means method suggested in ISO 9241-9 [12]:

$$TP = {}^{1}/_{y} \sum \left({}^{1}/_{x} \sum \left({}^{ID}/_{MT} \right) \right), \tag{3}$$

with y the number of subjects and x the number of different ID conditions. Additional metrics for the control strategy evaluation included path efficiency (PE) and completion rate (CR). Because both control types were sequential, PE was calculated as the ratio of the cursor trajectory to the city-block distance between target and origin. CR was computed as the percentage of successful trials over the total trials.

Protocol. Fitts' law analysis was performed on fifty different targets per session. The target width and distance from the origin varied so that fifty different ID values ranging from 0.77 to 5.53 were obtained. Additionally, one-DOF targets were defined as targets on horizontal or vertical axis and two-DOF targets, as targets that were off-axes. Subjects completed a training session in order to familiarize with both the test set-up and the control system. The protocol for one control strategy consisted in four sessions of fifty trials each.

Statistical analysis. A 2-way analysis of variance was performed with subject as a random factor and target type, control strategy and session as fixed factors to assess the statistical difference between control modes and target types for the performance metrics TP, PE and CR. The difference between DC and PR for correlation and regression coefficients of Fitts' law (offset and slope) was assessed with a paired *t*-test for each target type.

III. Results

The obtained regression lines show a strong linear relationship between MT and ID for each control strategy and for both one-DOF and two-DOF targets with high correlation coefficients R^2 (Figure 1).

The parameters of the linear regression, averaged across subjects, are presented in table 2, part b. The slope (parameter b) of the linear regression was similar for both strategies within each target type, but significantly increased from one-DOF targets to two-DOF targets. The offset (parameter a) was significantly higher for DC when compared to PR for both target types and there was also a substantial increase in offset from one-DOF to two-DOF targets within each control strategy.

PR control performed with significantly better TP than DC but there was no difference between control strategies for either PE or CR (Table 2, part a.). In terms of target types, there was no significant difference in PE, but both TP and CR had significantly higher scores in one-DOF targets.

Figure 2 shows the cursor trajectories for both control strategies and both target types for the entire dataset. The grid intersection of the two-DOF targets corresponded to the two-DOF target locations, whereas one-DOF targets were located on the axes. The signature of both control strategies is due to the sequential operation mode of both control types.

IV. Discussion

The proposed Fitts' law style test was designed in an attempt to provide an objective framework for the comparison of two upper limb prosthetics control strategies. The test was simple in its two-dimensional target acquisition design, informative through the testing of several difficulty levels and overcame limitations associated with visualization from more immersive testing, such as the TAC test.

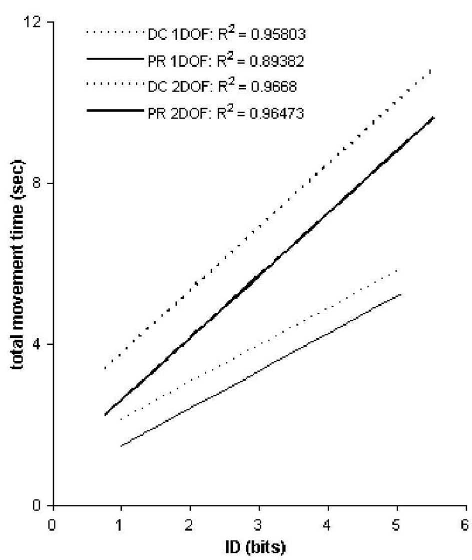

Figure 1: Regression equations and coefficients for Fitts' law, averaged across subjects.

Table II: RESULTS FOR PR AND DC IN THE EVALUATED PERFORMANCE METRICS. MEAN ± STANDARD ERROR

a. Performance metrics *(general linear models)*	**Throughput (bits/sec)**	**Path efficiency (%)**	**Completion rate (%)**
		One-DOF targets	
Direct Control	0.811 ± 0.02	86.58 ± 1.38	98.17 ± 1.01
Pattern Recognition	1.008 ± 0.03	88.21 ± 1.26	97.88 ± 1.7
		Two-DOF targets	
Direct Control	0.447 ± 0.01	87.27 ± 0.60	91.83 ± 2.05
Pattern Recognition	0.572 ± 0.01	83.67 ± 0.74	94.08 ± 1.06
		p-values	
Control strategy	p = 0.021	p = 0.729	p = 0.746
Target type (# DOFs)	p < 0.001	p = 0.239	p = 0.032
b. Linear regression parameters *(paired t-test)*	**R^2**	**Offset (parameter a)**	**Slope (parameter b)**
		One-DOF targets	
Direct Control	0.958	1.2222 } *	0.9163
Pattern Recognition	0.894	0.5351	0.9291
		Two-DOF targets	
Direct Control	0.967	2.2043 } **	1.5610
Pattern Recognition	0.965	1.0480	1.5447

* p = 0.056, ** p = 0.022

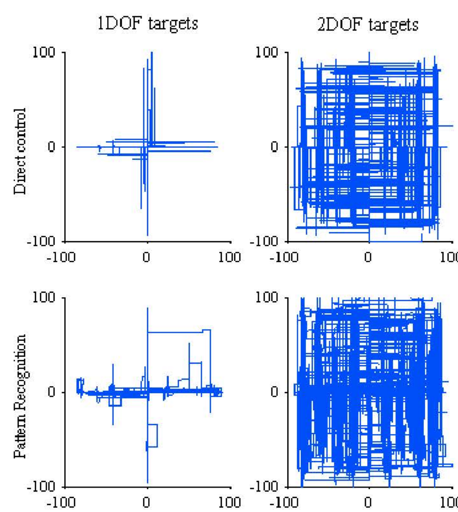

Figure 2: Cursor control signatures for 1 and 2 DOF targets.

In this context, we have compared DC and PR and found that PR provides substantial advantages over DC. These findings support previous work by Hargrove et al [17] which found that PR outperformed DC in a 3-DOF virtual clothespin placement task. The appropriateness of our test has been established through high correlation coefficients R^2 for each of the four cases (Figure 1 and Table 2). Our results support the growing use of such a test which has been performed previously by other researchers [13, 14].

We noticed that DC yielded a significantly higher offset for both 1 and 2 DOF tasks compared to PR (Table 2). This was most likely caused by the time required for the co-

contraction switch. Even though the implemented PR control could not perform simultaneous movements, subjects could seamlessly transition between DOFs which saved a substantial amount of time. This significant difference was translated in the metric TP, presenting with significantly higher scores for PR than for DC, even though the slopes of the regression equations, defined as the ratio of MT to ID were not statistically different between control strategies for target types. As such, both control strategies may convey instantly the same amount of information and are in that sense equally good. However, the amount of time required to mode-switch between DOFs for DC lowers its average TP and is coupled to higher fatigue as reported by subjects, consisting in a major limitation when compared to PR.

Both R^2 and the values we obtained for TP with PR in one-DOF targets (Table 2) compare favorably to those previously reported by Scheme et al. in a similar three-DOF Fitts' law style test used to compare two PR controls (TP_{LDA}=1.1±0.03 and TP_{1vs1}=1.07±0.02) [14]. The targets in their test had one complexity level and could be achieved by one DOF, depending on location or size. As such, they apply to being compared to the one-DOF targets of this experiment only. Nevertheless, the differences in the number of DOFs controlled, the variable maximum cursor speed between the studies, and the differences in IDs tested prevent a direct comparison of TPs from being made.

The two control strategies had satisfying CR, both with significantly higher CR for one-DOF targets. It was noticed that the most difficult targets were two-DOF targets with the smallest width. These targets required subjects to be very precise in two DOFs which made it more difficult than for one-DOF targets.

The cursor trajectories had a regular grid appearance (Fig. 2) due to the sequential nature of both controls. For DC, the DOF under control at the start of one trial was left as the last DOF controlled during the previous trial. This required subjects to sometimes switch DOFs at the beginning of a new trial depending on the location of the subsequent target. As a seamlessly sequential control strategy, this was not necessary for PR.

A limitation of the present work can be seen in the fact that the test was only performed on able-bodied subjects. Furthermore, some additional performance metrics could be useful to draw a complete picture for a control, such as overshooting or stopping capabilities.

V. Conclusion

The present work has proven to be a valid test for the evaluation and comparison of upper limb prosthetics control strategies. The proposed framework evaluated the DC and PR as strategies with their throughput and demonstrated a significant advantage of PR over DC in both one- and two-DOF tasks. It further provides evidence for its advantage over DC in one- and two-DOF tasks through a seamless sequential operation mode. This results in a faster and less fatiguing control strategy that conveys more information. The development of a simultaneous PR control would further enhance the described benefits of the strategy and could be evaluated in the proposed test, supporting this framework as a general and objective evaluation tool.

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