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On the robustness of real-time myoelectric control investigations: A multiday Fitts' law approach

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ABSTRACT

Background and Aim: Real-time myoelectric experimental protocol is considered as means to quantify usability of myoelectric control schemes. While usability should be considered over time to assure clinical robustness, all real-time studies reported thus far are limited to a single session or day and thus the influence of time on real-time performance is still unexplored. In this study, the aim was to develop a novel experimental protocol in order to quantify the effect of time on real-time performance measures over multiple days using a Fitts' law approach.

Methods: Four metrics: throughput, completion rate, path efficiency and overshoot, were assessed using three train-test strategies: (i) An artificial neural network (ANN) classifier was trained on data collected from the previous day and tested on present day (BDT) (ii) Trained and tested on the same day (WDT) and (iii) trained on all previous days including present day and tested on present day (CDT) in a week-long experimental protocol.

Results: It was found that on average, Completion rate (98.37 ± 1.47 %) of CDT was significantly better (P<0.01) than BDT (86.25 ± 3.46 %) and WDT (94.22 ± 2.74 %). Throughput (0.40 ± 0.03 bits/s) of CDT was significantly better (P=0.001) than BDT (0.38±0.03 bits/s). Offline analysis showed a different trend due to the difference in the training strategies.

Conclusion: Results suggest that increasing the size of training set over time can be beneficial to assure robust performance of the system over time.

Keywords: Pattern recognition; Real-time control; Myoelectric control; Multiday Fitts' law

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I. INTRODUCTION

The natural human arm/hand can perform diverse controlled movements with ease. The appropriate and modulated activity of each muscle in the upper limb contributes to improving the dexterity of motions. But any type of amputation in the upper limb (transradial or transhumeral) can severely limit the abilities to perform activities of daily life. Commercially available upper limb prostheses reproduce a lot of these motions, but they are still behind in intuitively and finesse in their ability to mimic the natural hands [1].

Most electrically powered prostheses use the amplitude of the Electromyogram (EMG) signal as input to control motions of a terminal device [2]. Two approaches (i) pattern recognition-based techniques, which focus in extracting more useful information in EMG signal and classifying multiple motions [3-5], (ii) regression techniques based on force/position estimation which focus on providing proportional control [6-8], have been the interest of researchers in recent times.

Pattern recognition (PR) techniques have been widely reported in the literature and have great potential in improving the functionalities of myoelectric prostheses [3-5]. With these methods, EMG patterns from multiple electrodes are used to decode multiple classes of motions under the assumption that each pattern from the set of selected muscles generates repeatable EMG signals. Many different PR implementations have been investigated with different classifiers, feature sets, signal conditioning, or post-processing techniques [9-10]. In this regard, researchers have evaluated the offline effects of limb positions, inter-electrode distance, force variation, muscle fatigue and electrode shift, on PR, just to mention some of the challenges that are faced by these systems [11-13]. Although offline evaluation of PR control strategies is a useful performance metric, studies have shown that it is not a good representative of usability [14-16].

Researchers have demonstrated multiple approaches to real-time myoelectric control in the literature. First of its type was used by Englehart et al. (2003), who used a continuous classification algorithm to find real-time accuracy and response time [17]. It was suggested that the response time of a control system should not introduce a delay that is perceivable by the user. This threshold is generally regarded to be roughly 300 ms. Lock et al. (2005) developed CEVEN (Classifier Evaluation in a Virtual ENvironment) implemented in MATLAB. Subjects were asked to perform virtual clothes pin task and found a weak correlation between classification accuracy and usability in real-time [18]. Hargrove et al. (2007) performed a similar test by including transient state data in the training of classifier and found that offline classification accuracy may reduce but this will result in a reduction of completion time in real-time performance [19]. Kuiken et al. (2009) introduced the target achievement control (TAC) test in which users move a virtual arm into a target posture using PR. The need for feedback in myoelectric control was highlighted in the study as it can provide more information about user experience in real-time myoelectric control [20].

Fitts' law test has been used in myoelectric control to quantify and illustrate human motor performance in detail using principles derived from Shannon's work in communication theory [21-22]. Fitts' law test has also been extensively applied in Human-computer interfaces including various human motion testing and devices such as mouse, touchpads [23-24]. A Fitts' law approach using EMG based PR has proven to significantly improve the control (sequential, proportional and simultaneous) over the conventional myoelectric control strategy (direct control) [25-28]; suggesting that a PR algorithm can be used in real-time as a control strategy to predict the user's intended movements with high performance. As robustness over time is an essential parameter for clinical translation of PR schemes, a number of studies have been conducted for longer periods of time in off-line evaluation [29-32]. These studies have shown that offline performance decreases with increasing time difference between training and testing days of PR based myoelectric control and daily calibration can improve the overall performance. However, most studies have assessed EMG based PR in acute settings only [33-35]. Smith et al. (2016) studied the ability of linear regression model to decode patterns of muscles co-activation using intramuscular EMG [33]. Kamavuako et al. (2014) studied the usability of intramuscular EMG in short-term scenarios for two-degree freedom using Fitts' law approach [34]. Scheme et al. (2013) validated a novel PR technique in a 3-D environment using Fitts' law [35]. Therefore, it remains unknown whether real-time performance can be maintained when the tests are performed on multiple days and with different training-testing strategies.

In this study, we aimed to develop an experimental protocol in order to quantify the robustness of the real-time investigations over time with multiple train-test strategies. Most of the studies performed online recently underwent training and testing of the classifier on the same day, providing an ideal condition for reporting performance. This may not be representative of clinical usability which requires users to perform activities over time including the effect of donning and doffing the electrodes. To understand the effect of different training strategies of the classifier over time in real time, a week-long experiment was performed on ten able-bodied subjects. Fitts' law was implemented with three train-test strategies (i) training of classifier and testing within a day (ii) training of classifier and testing with one-day difference (iii) training of classifier on combined data from all days and testing on the current day. Offline classification performance was evaluated using three train-test strategies (i) Within-day classification error (WCE) (ii) Between-day classification error (BCE) (iii) Combined-day classification error (CCE).

II. METHODS

a) Subjects

Ten able-bodied subjects participated in the experiment (8 men/2 women age range: 22-36, mean 26.4). Participation of all subjects was voluntary, and each subject provided informed written consent. All subjects had no history of a known upper extremity or musculoskeletal disorders. The procedures were in accordance with the Declaration of Helsinki and approved by the local ethical committee of the region of Northern Jutland (approval no: N-20160021).

b) Data Collection

EMG signals for different motions were recorded using the Myo armband (MYO) which is commercially available and developed by Thalamic Labs (Figure 1a). It has eight circularly arranged surface electrodes worn around the forearm muscles. The sampling frequency is fixed at 200 Hz with 8-bit precision. The signal from the hardware is transmitted wirelessly to a computer using the Bluetooth Low Energy (BLE) protocol. This system provides a good research platform and has now been used in different studies [36-38].

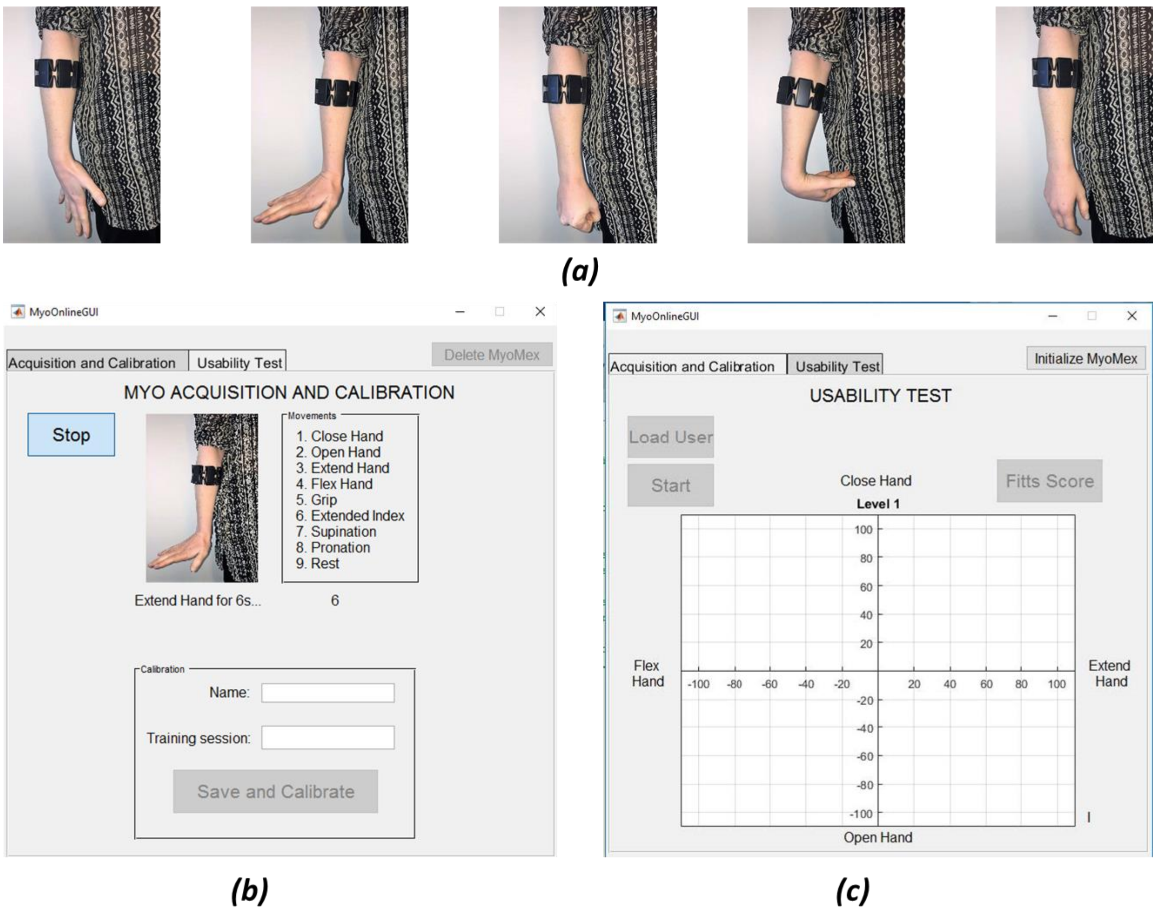

Figure 1. Experiment setup with (a) number of motions for which data was recorded (b) GUI for off-line training and (c) for real-time testing.

c) *Experimental Procedure*

A week-long experimental protocol was designed, and data were recorded during the first four days and on the seventh day. No recording was performed on day four and five to measure the effect of a break on performance. In each experimental session, subjects were first guided about the experimental protocol and they were asked to produce a medium level contraction from rest to motion, prompted by the image of the selected motion using a custom-made Graphical User Interface (Figure 1b). Training data were collected as followed: Four active motions (Hand open, Hand close, Wrist flexion, wrist extension) and one rest (no motion) were collected each with six seconds duration. The order of the motions was randomized, and a six seconds break was allowed between motions. Furthermore, a rest time of twelve seconds was given after completion of each set. After this round of data recording, the signals were processed as described in section II followed by the online experiment (Fitts' law).

Table 1: Scheme of online testing in the experiment.

	Day 1	**Day 2**	**Day 3**	**Day 4**	**Day7**
	TrainDay1	***TrainDay2***	***TrainDay3***	***TrainDay4***	***TrainDay7***
BDT		***TrainDay1TestDay2***	***TrainDay2TestDay3***	***TrainDay3TestDay4***	***TrainDay4TestDay7***
WDT	***TrainDay1TestDay1***	***TrainDay2TestDay2***	***TrainDay3TestDay3***	***TrainDay4TestDay4***	***TrainDay7TesDayt7***
CDT		***TrainDay1-2TestDay2***	***TrainDay1-2-3TestDay3***	***TrainDay1-2-3-4TestDay4***	***TrainDay1-2-3-4-7TestDay7***

During Fitt's law implementation, subjects were required to move the cursor from the origin of the axis (no motion) to a target location (randomly selected among the 8 possible locations) having distance D from origin and Width W. The cursor moved upwards for hand open, downwards for hand close, left for wrist flexion and right for wrist extension. The index of difficulty (ID) was calculated for each target location based on its distance D from its origin and width W of the target. Table 2 shows a different combination of target distances and widths. The ID was computed as provided in Eq. (1).

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

Table 2: ID is the index of difficulty (in bits). D and W are the distance and width of the target.

Distance(D)	Width(W)	Index of Difficulty (ID)
50	5	3.46
50	10	2.59
50	20	1.81
100	5	4.39
100	10	3.46
100	20	2.59

During the online tests, the subject was asked to hold the position within the target for one second (dwell time) for the trial to be considered successful [39-40]. If the subject was unable to reach the target within a 15 second time limit, the online trial was considered unsuccessful and the subject moved on to the next target with the cursor back at the origin. Three sessions per train-test combination were performed per day. In each session, each motion was tested six times (thus 18 times in total for all three sessions) so in total 24 targets to be reached per session. In order to quantify the performance of the real-time system, four performance metrics were assessed: Throughput, Path Efficiency, Overshoot, and Completion Rate. Throughput describes usability through the tradeoff of speed and accuracy and, when averaged over the entire test, it is a convenient summary of performance [21]. Throughput is mathematically defined as the ratio between the index of difficulty and movement time, which is the time (in seconds) taken to acquire the target. It is a measure of the amount of information the subject can convey through a command source as it relates to the task [34]. Path Efficiency describes the systems quality of control. It is computed by dividing the straight-line distance by the actual distance traveled [40] Overshoot describes the ability to stop on a target. It is the number of occurrences of the cursor being on target and then leaving the target before the end of the 1-s dwell time (across all targets), divided by the total number of targets. Completion Rate describes the overall success; the percentage of tests completed within the allowed time [41]. Three types of test were performed online (Figure 1c) on each day, besides for day one, where only one test was performed: (i) A classifier was trained on data collected from the previous day and tested on present day (BDT) (ii) Trained and tested on data from the present day (WDT) and (iii) trained on all previous days including present day and tested on present day (CDT). This is the main focus of this study in order to assess whether inclusion of previous data would surpass the WDT performance. On day 1 only WDT was performed. Each motion was tested 18 times per training strategy. For BDT and CDT, training data from different days were concatenated and used to train the classifier prior to the online tests.

d) Signal Processing

From the six seconds of contraction time, Steady state part, the middle four seconds of the six seconds data segment, was segmented using an overlapping window of 200ms with 50ms increment. Six features were investigated for this study: Waveform Length (WL), Mean Absolute Value (MAV), Willison Amplitude (WAMP), Cardinality (CARD), Slope Sign Changes (SSC) and Zero Crossings (ZC). An Artificial Neural Network (ANN) was used as a training and testing classifier. The ANN consisting of 15 neurons in the hidden layer was trained using the training data and stored in a file. The trained ANN was loaded to the Fitts' law test to classify the hand gestures, mapped for cursor control. For the sake of completeness, offline classification analysis was conducted on data recorded for training using the same training-testing strategies applied to online experiments except for CDT, where the present data was not included in the training. This was done to avoid lengthy data recording during training. Classification error, computed as the ratio between the number of misclassification and the total number of classification, was used as the offline performance measure. Between-day classification error (BCE) was defined as training and testing data from two different days, Error *ij* was obtained by training data on day *i* and testing on day *j*. Within-day classification error was defined as training and testing data from the same day. Error *ij* was obtained by applying two-fold validation. Combined-day classification error (CCE) was defined as training data from all previous days or day and test data from the current day.

e) Statistics

To evaluate the overall offline performance based on classification error, two-way repeated measures analysis of variance (ANOVA) with factor types (WCE, BCE, and CCE) and the day (without Day 1) was used. P-values less than 0.05 were considered significant. To investigate the suitability of Fitts' law test for the online experiment the relationship between completion time and ID was examined. The R^2 coefficient of the linear model was examined to determine how the obtained data fit the computed linear model. For the overall performance based on each performance metric, two-way repeated measures analysis of variance (ANOVA) was used to quantify the difference between days (without Day 1) and sessions. P-values less than 0.05 were considered significant. Results are presented as mean ± standard deviation.

III. RESULTS

a) Offline Results

Two-way repeated ANOVA showed that classification accuracies were significantly affected by training schemes ($P \leq 0.01$) and days ($P \leq 0.01$). Multiple comparison showed no significance ($P = 0.55$) between average WCE (0.98 ± 0.57 %) and BCE (1.55 ± 1.25%). Averaged WCE and BCE were significantly ($P \leq 0.01$) lower than CCE (4.99 ± 1.63%). Multiple comparisons revealed a significant difference between (Days = 2, 3, 4) and Day 7 (11.52 ± 2.58%) in CCE. No significant difference was found between days 2,3 and 4 (P (2,3) =0.86, P (2,4) =0.75, P (3,4) = 0.99). In BCE, classification performance improved over time (BCE of day 7 is less than day 4, day 4 is less than day 3 and so on) but found no significance between days. Figure 2 represents the offline classification performance comparison between BCE and CCE over time.

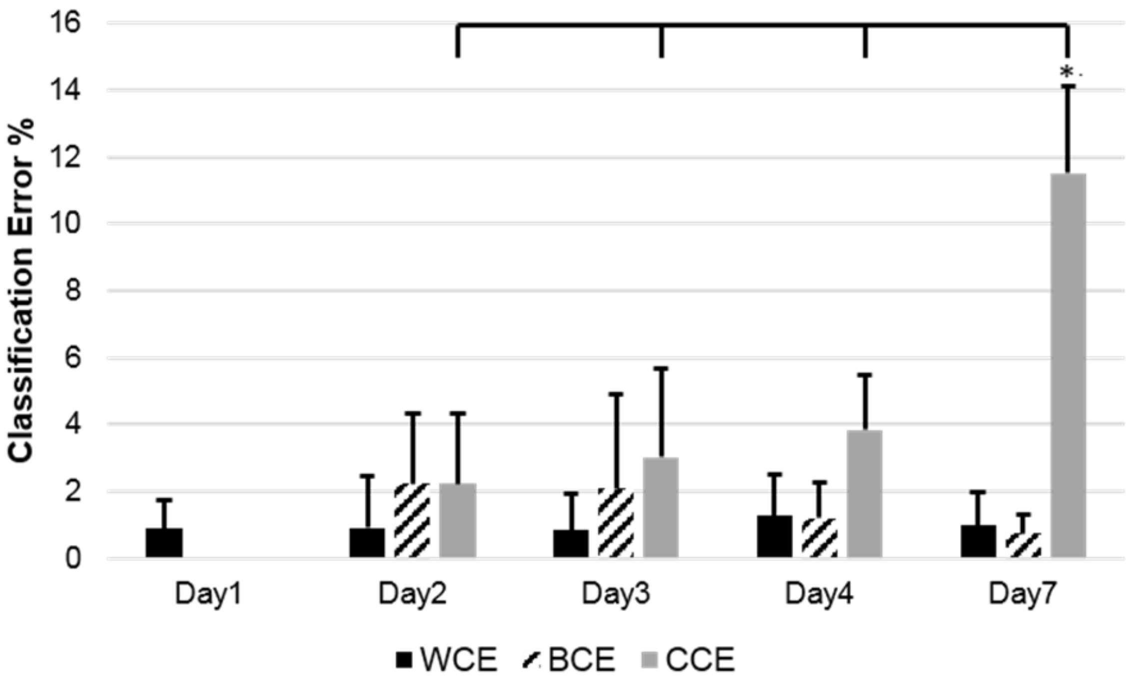

Figure 2: Offline Classification performance comparison between WCE, BCE, and CCE over a week. Star (*) indicate the case where there is a significant difference.

Table 3 represents the confusion matrix for all classes of CCE on Day7. Higher level of misclassifications for close hand and open hand were observed. It may be attributed to the co-activation of several muscles during recording of these motions.

Table 3: Confusion matrix for all hand motions on Day 7 for CCE.

CONFUSION MATRIX CCE (DAY 7)					
	PREDICTED CLASS				
True	***Close Hand***	***Open Hand***	***Extend Hand***	***Flex Hand***	***Rest***
Close Hand	80.25%	19.18%	0.27%	0.08%	0.22%

Open Hand	17.03%	67.16%	5.17%	7.90%	2.73%
Extend Hand	0.84%	0.79%	97.56%	0.02%	0.80%
Flex Hand	0.93%	1.21%	0.02%	97.60%	0.24%
Rest	0.11%	0.03%	0.03%	0.00%	99.83%

b) Fitt's Law Test

A strong linear relationship was found between completion time and index of difficulty for all strategies (within day testing WDT, between day testing BDT and combined days testing CDT) and days (coefficient of determination $R^2 \geq 0.91$) as depicted in Figures 3 and 4. This supports the suitability of using Fitt's Law test. It was found that average completion time for all IDs in CDT was significantly better than ($P \leq 0.01$) BDT and ($P=0.04$) WDT (Table 4).

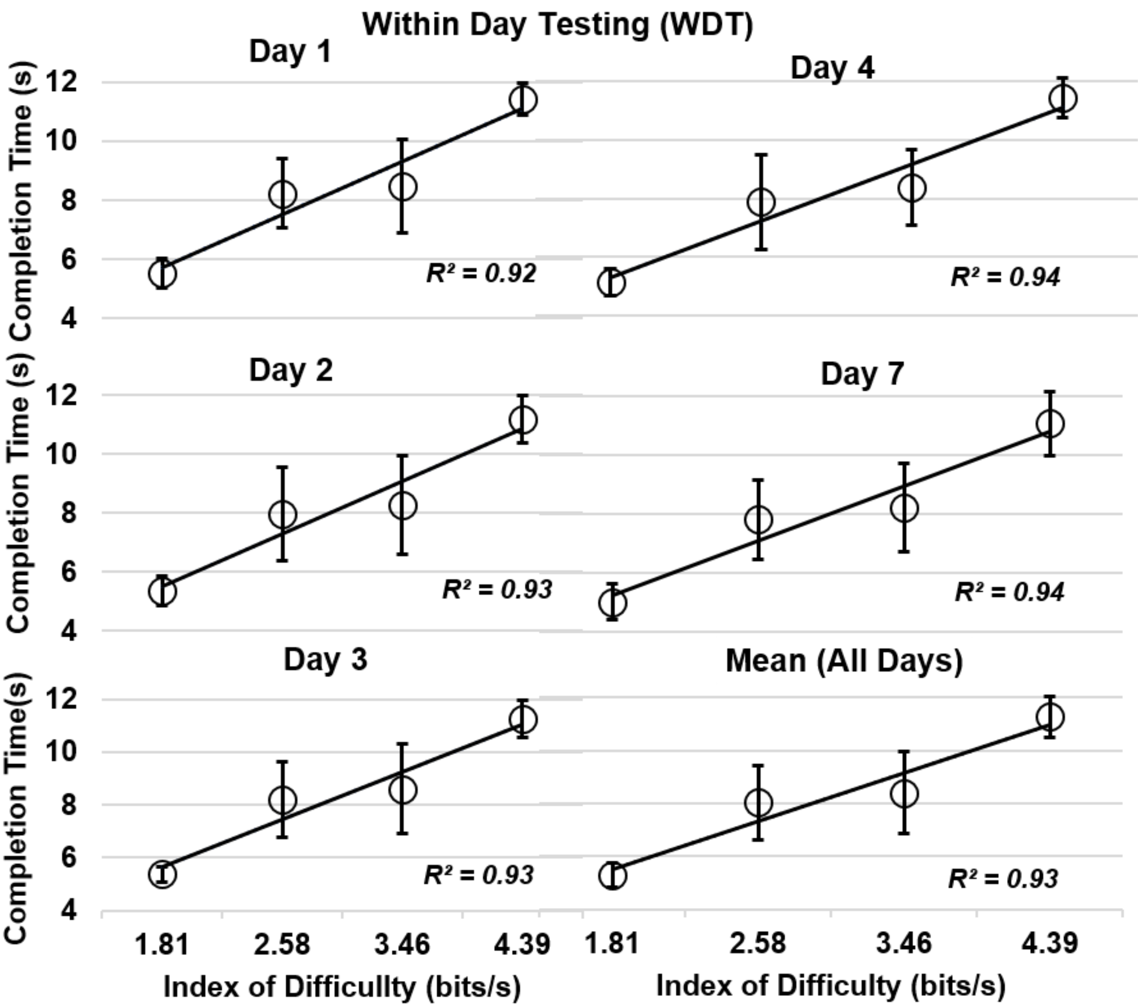

Figure 3: Relationship between completion time (CT) and index of difficulty for Within day testing(WDT).

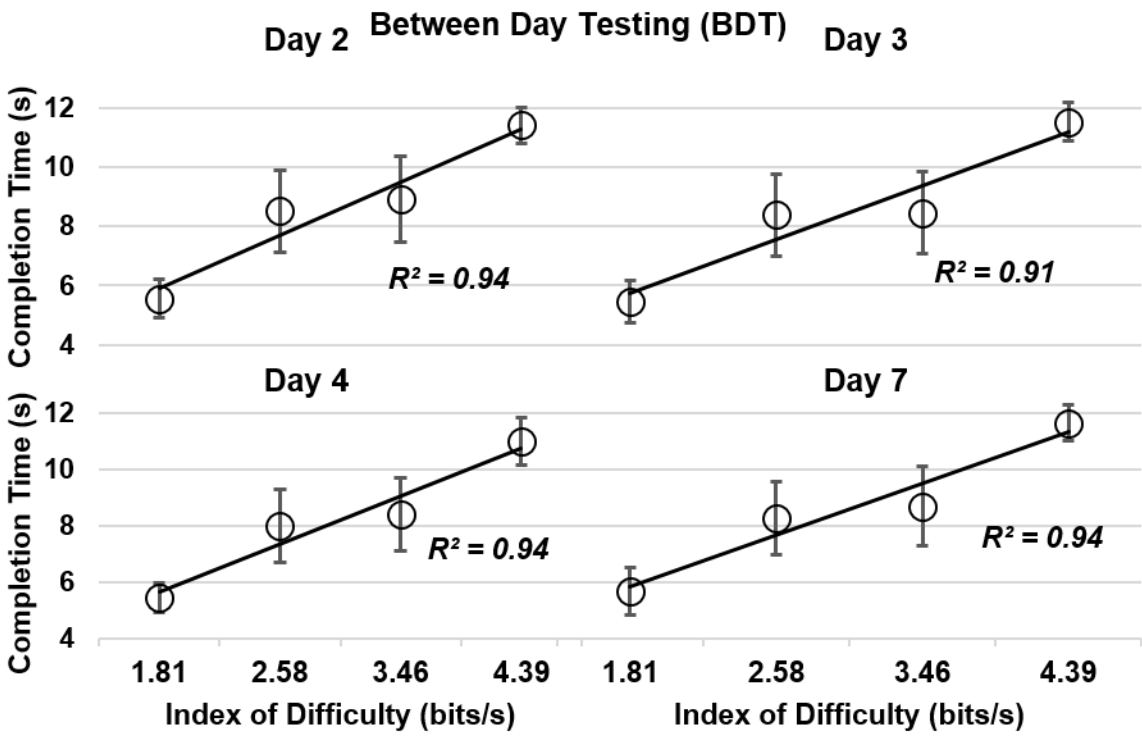

Figure 4: Relationship between completion time (CT) and index of difficulty for between day testing (BDT).

Table 4: Average completion time and index of difficulty for BDT, WDT, and CDT.

ID	**BDT**	**WDT**	**CDT**
1.81	5.49±1.33	5.09±0.70	4.96±0.20
2.58	8.33±2.69	8.19±2.72	7.86±1.72
3.46	8.64±2.77	8.48±2.55	8.36±1.55
4.39	11.48±1.23	11.27±1.48	10.97±1.33

There was no significant difference between days for all the performance metrics in WDT, BDT and CDT (Figure 5). A summary of all performance metrics per session across all days is provided in Table 5.

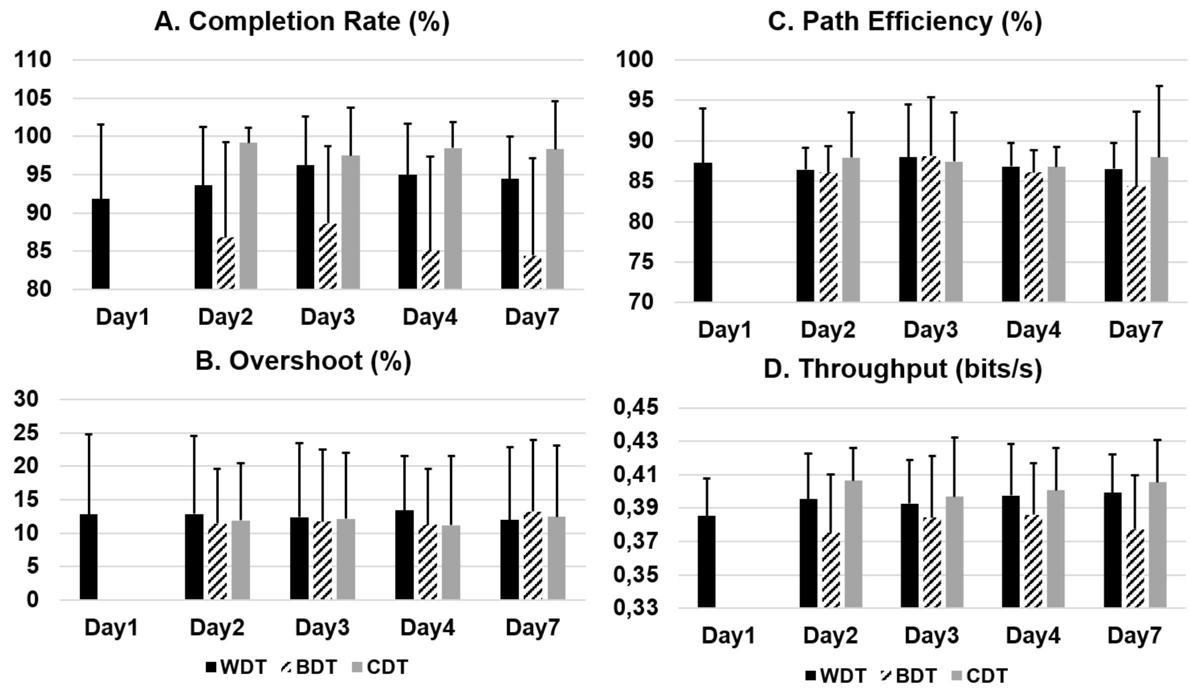

Figure 5: The overall results for all the performance metrics over days (A. Completion rate (%), B. Overshoot (%), C. Path Efficiency (%), D. Throughput (bits/s)) in within day testing (WDT), Between day testing (BDT) and Combine day testing (CDT).

Table 5: WDT, BDT and CDT session wise comparison of, performance metrics. A significant difference in each session of performance metric was presented in star (*) in Table 4.

Within-Day Testing (WDT)			
	Session 1	**Session 2**	**Session 3**
Completion rate	94.42±4.09	93.17±3.64	95.08±3.35
Overshoot	14.86±4.14 (*)	11.84±6.01	11.35±5.25
Path efficiency	86.86±1.75	87.50±2.70	86.69±2.51
Throughput	0.41±0.02(*)	0.39±0.02	0.38±0.02
Between Day Testing (BDT)			
	Session1	**Session 2**	**Session 3**
Completion rate	89.06±5.45(*)	86.56±5.53	83.13±6.50
Overshoot	14.26±4.27(*)	11.06±4.73	10.39±4.60
Path efficiency	85.55±2.37	86.78±4.61	86.18±4.89
Throughput	0.39±0.01(*)	0.39±0.01	0.36±0.02
Combined Day Testing (CDT)			
	Session 1	**Session 2**	**Session 3**
Completion rate	99.79±0.29(*)	98.85±1.22	96.45±3.69
Overshoot	14.75±4.31(*)	10.61±4.45	10.38±4.79
Path efficiency	87.03±1.31	86.93±1.01	88.55±5.03
Throughput	0.41±0.01(*)	0.40±0.01	0.38±0.02

When pulling the days in training-testing strategies, the overall comparison of performance metrics between WDT, BDT, and CDT is shown in Figure 6. Completion rate (98.37 ± 1.47 %) of CDT was significantly better ($P<0.01$) than BDT (86.25 ± 3.46 %) and WDT (94.22 ± 2.74 %). Throughput (0.40 ± 0.03 bits/s) of CDT was significantly better ($P=0.001$) than BDT (38.07±0.03 bits/s). Path efficiency and Overshoot were not different between the strategies ($P>0.3$).

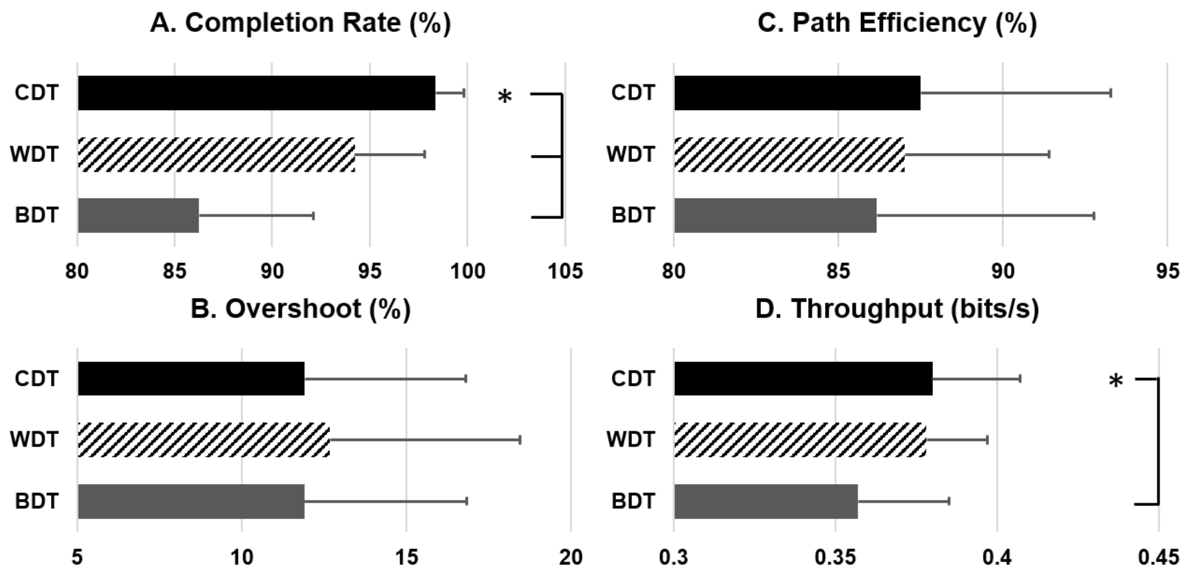

Figure 6: Performance metrics (A. Completion Rate (%), B. Overshoot (%), C. Path Efficiency (%), D. Throughput (bits/s)) averaged across all days in CDT, WDT and BDT. Stars (*) indicate the case where there is a significant difference.

IV. DISCUSSION

Historically researchers have quantified EMG PR performance by comparing classification accuracies of different algorithms in offline settings. However recent studies have focused more on real-time evaluation in acute settings, meaning in a single session. In this study, multiple train-test schemes were assessed over seven days in the context of real-time usability test using a Fitt's Law approach. Evaluation of the Fitts' Law showed high $R^2 \geq 0.92$ values from regression plots for all days in all train-test strategies supporting the suitability of a Fitts' Law approach.

For the overall performance based on throughput and completion rate, two-way ANOVA revealed a significant difference between combined day testing (CDT), within day testing (WDT) and between day testing (BDT) (Figure 6. On average for all days, completion rate (98.37 ± 1.47 %) and throughput (0.40 ± 0.027 bits/s) of CDT was significantly better (P≤0.01) than BDT and WDT. This indicates the acute behavior of the system after initial training. The lack of difference between BDT and CDT is quite interesting and indicating a possible adaptation of the system. Although not captured fully in this study, combining data from several days might, in fact, provide a stable system performance. Nevertheless, the increased amount of data may also require deeper network in order to generalize well. This observation has an important implication on real-world myoelectric based on PR, which provides the possibility of reducing the level of system recalibration for prostheses training based on data from longer periods of time.

The slopes of the regression lines indicate differences between train-test strategies in terms of completion time (Table 3). Performance descriptors and task requirements, which involve the acquisition of target location through control of cursor are a close analog to previously reported real-time studies. Path efficiency describes the system quality of control was recorded (87.02 ± 4.38 %), higher than reported in previous studies 73.1% ± 2.8%, 77.09 ± 0.89 %, 71.5 ± 3.8% [33-35]. Similarly, lower value of overshoot (0.12 ± 0.06 %) compared to (0.45 ± 0.07%) in [33] and (0.56 ± 0.04%) in [35] indicate that users were more effective on stopping at the target. Subjects were able to maintain a similar degree of path efficiency and overshoot across days over time. Within-day sessions, however, showed significant differences between them. This indicates the changes in EMG characteristics that may occur within short time periods, supporting the above arguments about the need for capturing an increased amount of data.

Offline analysis showed a different trend most probably due to the difference in the training strategies. For example WCE was computed using two-fold validation providing half sample size compared to BCE and CCE. Furthermore, offline CCE did not include data from the present day. Nevertheless, the effect is more prominent between day four and seven. This suggests that, although training strategies for short-time scenarios produce low errors, it is not a useful metric to capture the variabilities in human hand movements. A way to solve this is by encouraging concatenation of training data of hundreds of days to capture the natural variabilities in movement execution. However, with such large training size standard machine learning and features may not cope and thus we encourage the use of deep learning networks for future PR control schemes.

Limitations:

The ratio between distance and target width determines the ID for each target and the combination used in this study yielded only four unique ID instead of six, resulting in the larger spread of ID values. In the future, we will consider targets positions that will produce unique IDs for improved resolution in the level of challenge of the task. The proposed framework evaluated training schemes based on their ability to predict hand motions (classification, in PR based approaches) using constant speed. Thus, the outcome of such a study may be different with the introduction of proportional control where users may be able to update different in terms of speed. The number of classes chosen for this study is only a limitation from the offline analysis point of view where a higher number of classes have been used in the past [30,32]. However, for the online evaluation, 2 –DOF is typically used in the literature. While the results of this study have shown a significant difference in training-testing strategies, it is just a step towards quantification of robustness. Clinical experiments are ongoing with amputees using real prostheses.

V. CONCLUSION

In this study, real-time myoelectric control of different training-testing schemes for four functional motions of hand was evaluated using Fitts' law. Our results have shown that time has an effect on the robustness of real-time PR based myoelectric control. Specifically, increasing the training size by pulling data from several days tend to improve real-time performance. A feature that is not captured using offline classification error. This is relevant for intuitive control of prostheses and future usability tests, where we recommend multiple sessions/days as the acute results may not be the true picture of the performance of the system.

LIST OF ABBREVIATIONS

PR: Pattern recognition; ANN: Artificial neural networks; WDT: Within-day testing; BDT: Between-day testing; CDT: Combined-day Testing; EMG: Electromyogram; TAC: Target achievement test; WCE: Within-day classification error; BCE: Between-day classification error; CCE: Combined-day classification error; MYO: Myo armband; WL: Waveform length; MAV: Mean absolute value; WAMP: Willison amplitude; CARD: Cardinality; SSC: Slope sign change; ZC: Zero crossings; ID: Index of difficulty; ANOVA: Analysis of variance.

DECLARATIONS

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

The study was approved by the local ethical committee of the region of Northern Jutland (approval no: N-20160021), Denmark. The subjects participated in the study provided their written informed consent prior to enrolment.

CONSENT OF PUBLICATION

Not applicable.

AVAILABILITY OF DATA AND MATERIALS

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

COMPETING INTERESTS

The authors declare that they have no competing interests. The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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AUTHORS CONTRIBUTIONS

AW and ENK designed the study concept, experimental protocol and performed data acquisition. They analyzed the data, drafted and completed the manuscript. IM developed the GUI for real-time testing and assisted in data collection. KE, WJ contributed to data analysis and provided critical revision of the manuscript. All authors read and approved the final manuscript.

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Figure 1

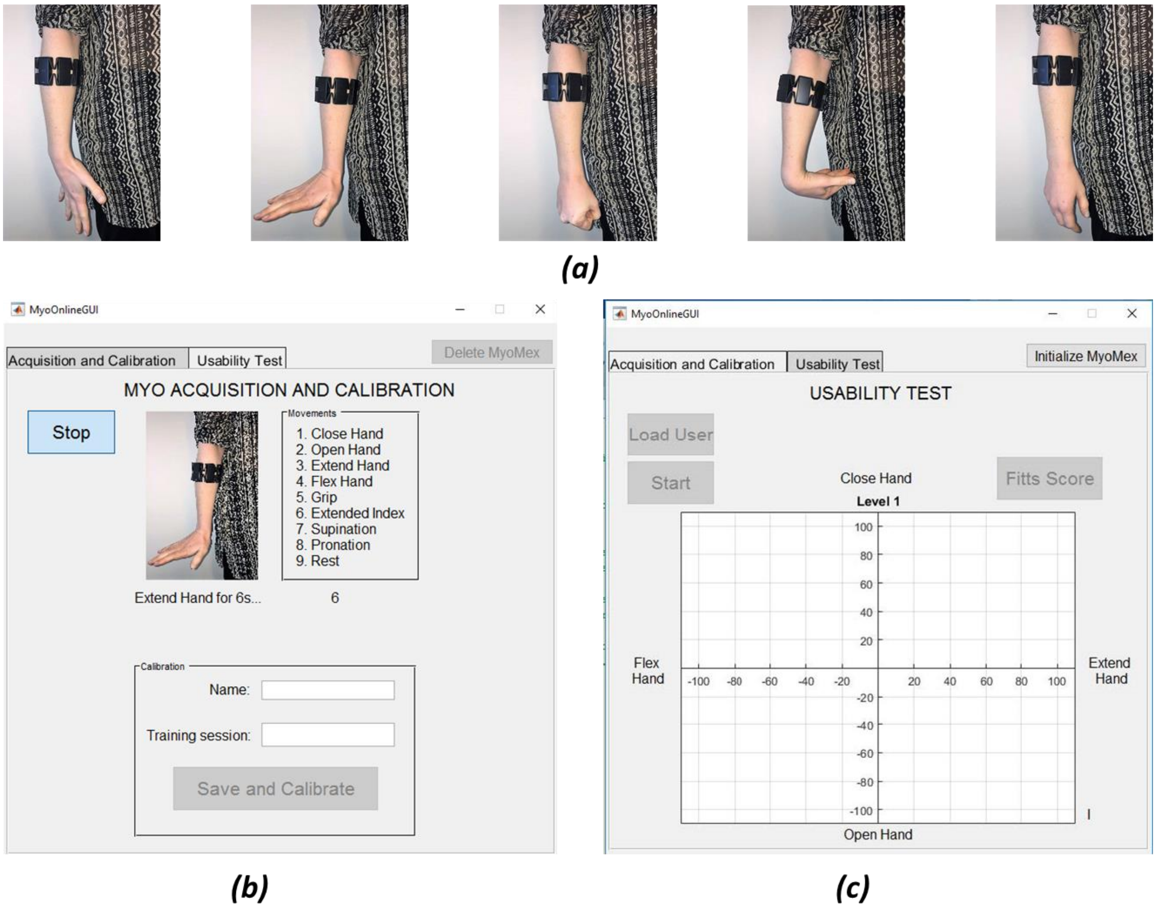

Figure 1. Experiment setup with (a) number of motions for which data was recorded (b) showed the GUI for off-line training and (c) for real-time testing.

Figure 2:

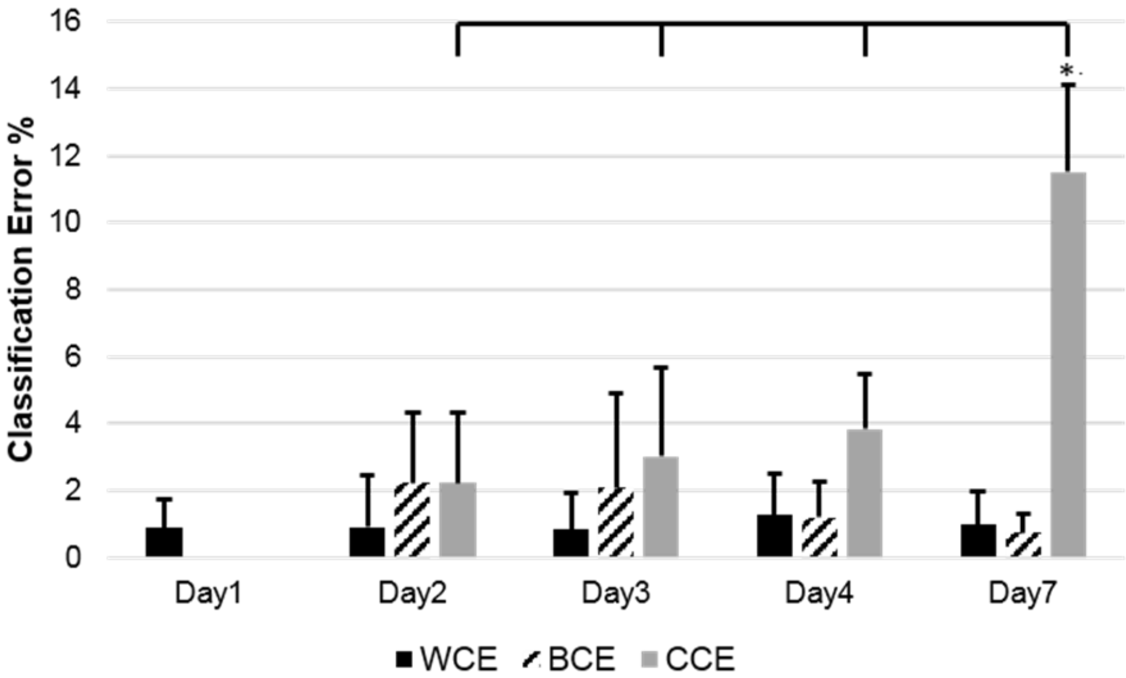

Figure 2: Offline Classification performance comparison between WCE, BCE, and CCE over a week. Star (*) indicate the case where there is a significant difference.

Figure 3:

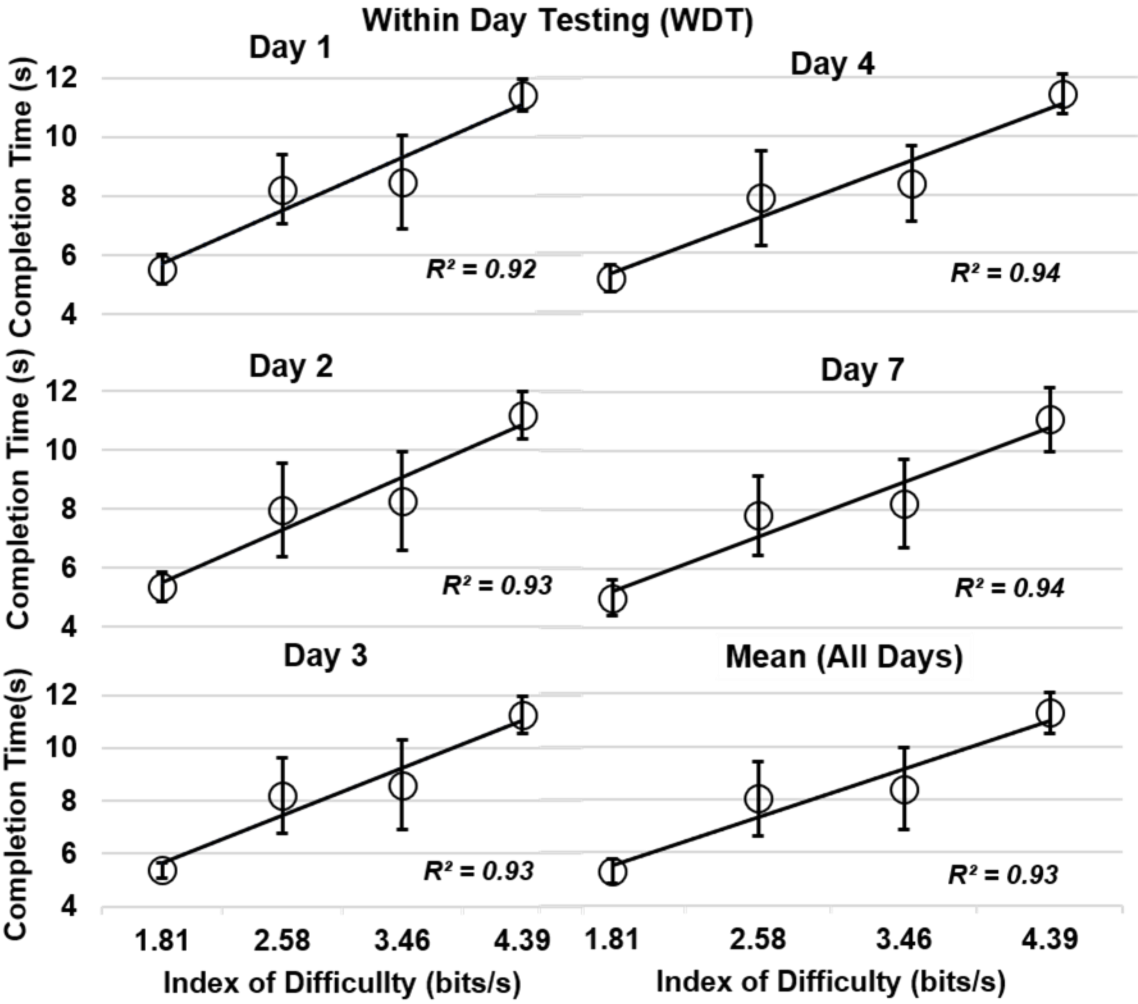

Figure 3: Relationship between completion time (CT) and index of difficulty for Within day testing(WDT).

Figure 4:

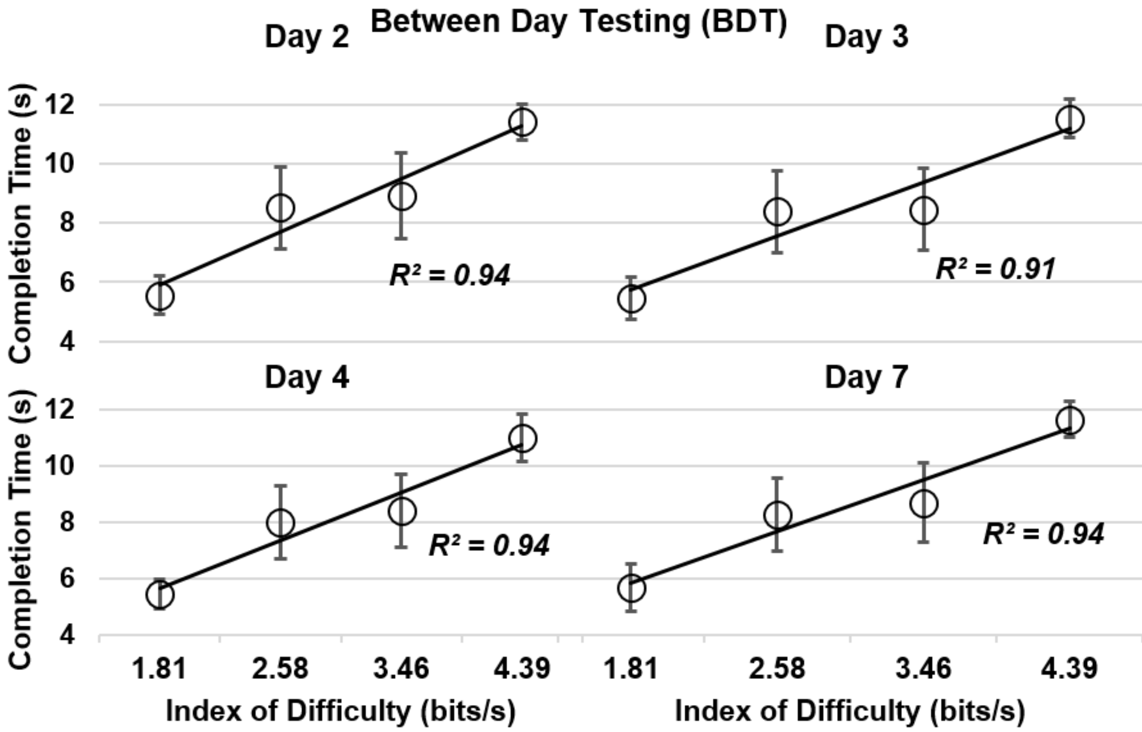

Figure 4: Relationship between completion time (CT) and index of difficulty for between day testing (BDT).

Figure 5:

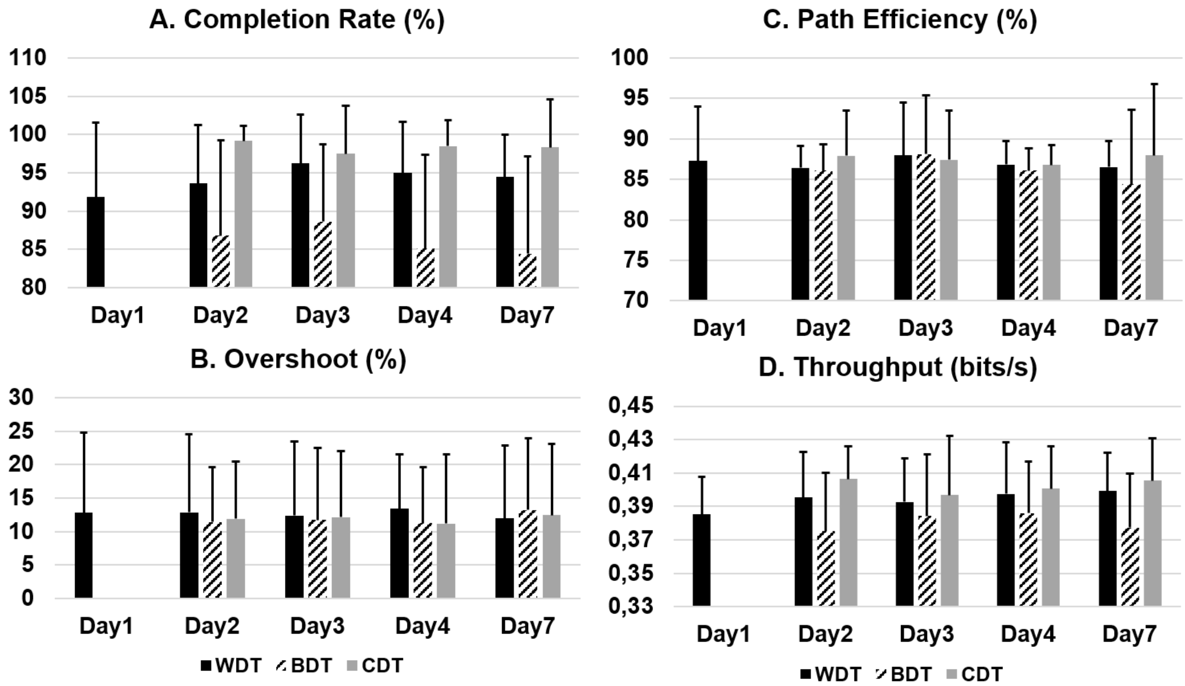

Figure 5: The overall results for all the performance metrics over days (A. Completion rate (%), B. Overshoot (%), C. Path Efficiency (%), D. Throughput (bits/s)) in within day testing (WDT), Between day testing (BDT) and Combine day testing (CDT).

Figure 6:

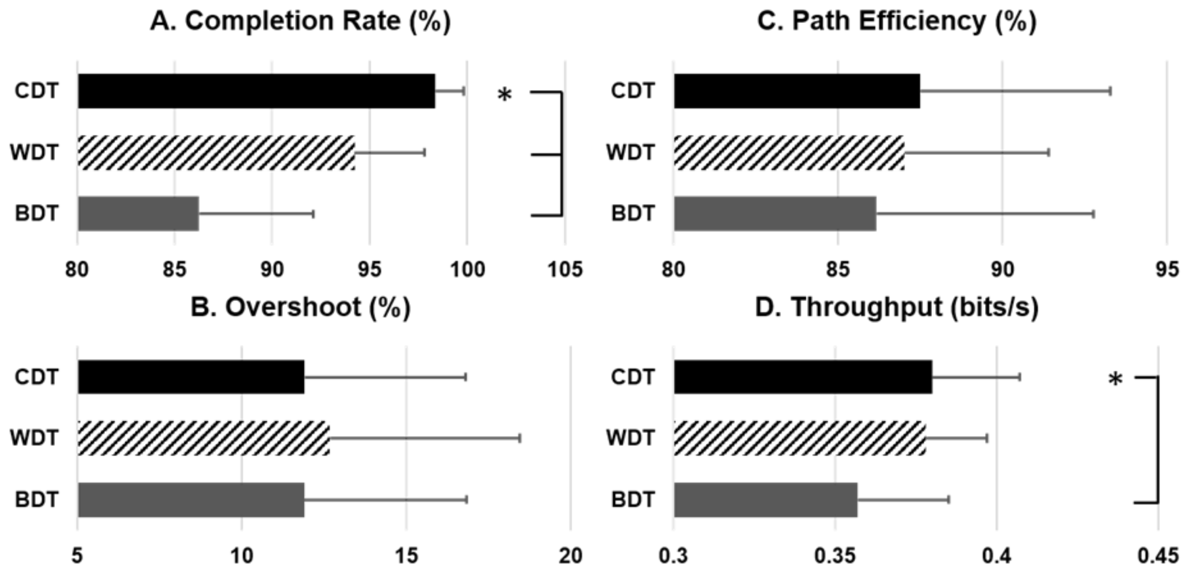

Figure 6: Performance metrics (A. Completion Rate (%), B. Overshoot (%), C. Path Efficiency (%), D. Throughput (bits/s)) averaged across all days in CDT, WDT and BDT. Stars (*) indicate case where there is a significant difference**.**