Title: Skill assessment in upper limb myoelectric prosthesis users: Validation of a clinically feasible method for characterising upper limb temporal and amplitude variability during the performance of functional tasks.

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ABSTRACT (200 words)

Upper limb myoelectric prostheses remain challenging to use and are often abandoned. A proficient user must be able to plan/execute arm movements while activating the residual muscle(s), accounting for delays and unpredictability in prosthesis response. There is no validated, low cost measure of skill in performing such actions. Trial-trial variability of joint angle trajectories measured during functional task performance, linearly normalised by time, shows promise. However, linear normalisation of time introduces errors, and expensive camera systems are required for joint angle measurements.

This study investigated whether trial-trial variability, assessed using dynamic time warping (DTW) of limb segment acceleration measured during functional task performance, is a valid measure of user skill. Temporal and amplitude variability of forearm accelerations were determined in 1) seven myoelectric prosthesis users and six anatomically-intact controls and 2) seven anatomically-intact subjects learning to use a prosthesis simulator over repeated sessions.

1: temporal variability showed clear group differences ($p<0.05$). 2: temporal variability considerably increased on first use of a prosthesis simulator, then declined with training (both $p<0.05$). Amplitude variability showed less obvious differences. Analysing forearm accelerations using DTW appears to be a valid low-cost method for quantifying movement quality of upper limb prosthesis use during goal-oriented task performance.

Keywords

Myoelectric prostheses, dynamic time warping, accelerations, variability, upper limb.

1. INTRODUCTION

As a result of concerted efforts over recent decades, there have been significant advances in myoelectric prostheses design. The motors used have become smaller and more powerful, cosmetic covers have become more life-like, and, of most note, multi-functional hands, such as the i-Limb (Touch Bionics, Livingston, UK) and Be-Bionic (Steeper, Leeds, UK) have been developed. Yet, prosthesis users are still greatly limited by the available control modalities and lack of sensory feedback from the prosthesis [1]. Hence it is not surprising that such devices remain challenging to use and are often poorly utilized, or rejected [2, 3]. As more expensive multi-function myoelectric prostheses have become available, such as the i-limb full hand and i-limb digits (Touchbionics Inc., Livingston UK), there is an urgent need for well-validated and robust quantitative measures that allow for informed selection of a particular technology (to achieve a better match between user and device), and that have the potential to inform user training.

Currently, quantifying the effectiveness of a given device, or the proficiency with which it is used, remains limited by the available outcome measures [4].Clinical tests often capture self-reported capabilities (e.g. Orthotics and Prosthetics Users' Survey "OPUS" [5]), evaluate performance subjectively (e.g. Assessment of capacity for myoelectric control [6]), or measure speed of performance of a pre-defined set of tasks (e.g. Southampton Hand Assessment Procedure "SHAP" [7]). Research has discussed the limitations with many of these measures, such as reliance upon self-report and/or observer ratings [8-10]; self-report does not directly measure the person's physical capabilities and can be influenced by subject bias, and observer-dependent measures are susceptible to (inter-/intra-) rater bias, which inherently reduces reliability compared to performance-based measures in which the administrator does not form part of the instrument. Previous research has also shown that whilst important [10], speed of task completion is only one of several factors which characterize skilled prosthetic use; other measures, notably gaze and kinematics may further enhance our understanding of user performance and skill level [11].

Accordingly, Major et al. recently compared the kinematics of myoelectric prosthesis users and able-bodied controls without known pathology [12]. Specifically, considering that motor variability (motor variance across task repetition) has shown to decrease with skill acquisition [13, 14], and given the redundant degrees of freedom (DoFs) in the upper body musculoskeletal architecture that permit various task-equivalent motor strategies, Major et al. [12] focused on studying kinematic variability of these DoFs. Their results showed that joint kinematic variability is higher in prosthesis users than controls, and was correlated with years of experience of prosthesis use. Their findings suggest that increased compensation may be reflected in increased joint kinematic variability above able-bodied individuals.

In common with almost all studies of upper limb functional task performance, in [12] joint angle trajectories were calculated as follows. Angle trajectories were first linearly normalized with respect to time, and joint level kinematic variability was defined as the variability around a kinematic profile averaged across multiple time-normalized trials. The standard deviation and coefficient of multiple determination then served as outcome measures to characterize variability and repeatability, respectively. However, non-cyclic kinematics are subject to two different aspects of trajectory variability: temporal and amplitude variability (Figure 1). Specifically, the relative duration of different phases of a given functional movement can vary from trial to trial, and linear time normalization of the entire task cannot take this into account [15]. Hence, while these traditional measures can inform on overall differences in movement variability, they remain limited in that they do not consider temporal variability separately to variations in signal amplitude, yet this has shown to be advantageous in the assessment of non-cyclic functional upper limb tasks [15,16].

Thies et al. previously introduced a novel methodology based on dynamic time warping (DTW) for curve registration across multiple trials to calculate measures of amplitude and timing variability over entire trajectories of functional movements [15]. In their approach a chosen target signal is warped to a declared reference signal by compressing or stretching the target signal along the time-axis with respect to the reference signal in a non-uniform manner. Warp Cost reflects the amount of time-warping needed to achieve the best possible temporal match between curves and serves as a measure of temporal variability. Following the time warping of signals, RMS error then informs on amplitude variability. Separating out temporal from amplitude variability is of particular advantage during processing of non-cyclic upper limb kinematics: we take the stand that DTW is a more appropriate method to analyse kinematic inter-trial variability of the upper limbs during functional task performance since it minimizes the mismatch of the different movement components (Figure 2).

A first demonstration of the DTW method involved characterization of acceleration trajectories derived from an arm-worn accelerometer during performance of two daily-living activities in subjects with stroke and matched controls. Findings showed increased timing variability for the stroke subjects as compared to controls, and this outcome was reliably reproduced on a second test day one month later [15]. This finding of increased variability following stroke was consistent with numerous previous studies, which have generally used simpler tasks and discrete, rather than continuous, measures of variability (e.g. variability of end point error in pointing tasks [17, 18]. A more recent study used the DTW method to demonstrate differences in trajectory variability when comparing stroke survivors with right and left hemisphere lesions, as well as to healthy controls [16]. They showed increased timing variability in the paretic arm of stroke survivors with right compared with left hemisphere lesions and further confirmed previous finding [15] of increased variability following stroke compared with controls. The DTW method which assesses contributions of temporal and amplitude variability separately proved particularly suitable to identify differences between left and right hemispheric stroke survivors.

Although already demonstrated for assessment of upper limb kinematics in people with stroke, the potential and validity of this methodology to characterize upper limb movements in relation to functional performance for upper limb prosthesis users has yet to be explored. Hence this paper reports on the characterization of functional task performance with an upper limb myoelectric prosthesis using the DTW method. The purpose of this retrospective study was to investigate whether DTW is a valid tool for assessing temporal and amplitude variability of upper limb prosthesis kinematics through a known-groups assessment (Study 1) and a responsiveness assessment (Study 2).

2. METHODS

In Study 1 we investigated the use of DTW to characterize upper limb function of myoelectric prosthesis users and anatomically intact (AI) controls and its ability to discriminate between these two groups, based on temporal and amplitude variability. In Study 2 we report on the changes in temporal and amplitude variability with practice in using a myoelectric prosthesis simulator (AI subjects), to assess if DTW can identify changes in temporal and amplitude variability resulting from practice of goal-oriented tasks. Since accelerometers are wearable, inexpensive and clinically-accessible devices, we here apply DTW to simulated accelerometer trajectories derived from position data, however, the method is applicable to a range of kinematic data, including joint angle trajectories and data from other segment-mounted inertial measurement units.

2.1 DTW for assessment of temporal and amplitude variability

As previously described [15], the DTW method employed in these two studies utilized dynamic programming [19] to separately quantify timing and amplitude variability across multiple trials. Using custom software in Matlab (Mathworks, Natick, MA), the algorithm first time-warps a chosen target signal to a declared reference signal by compressing or stretching the target signal along the time-axis with respect to the reference signal in a non-uniform manner. Warp Cost is returned as a unitless measure indicating the amount of time-warping needed to achieve the best possible temporal match between curves. Warp Cost is hence reported as a measure of temporal variability between trials. Figure 3 stresses the need for DTW for accurate assessment of upper limb kinematic variability in an anatomically intact subject, an anatomically intact subject using a prosthesis simulator, and an actual prosthesis user. After time warping, the algorithm calculates the remaining root mean square error (RMS Error) between signals after time-warping is complete. We interpret the reported RMS Error as a measure of signal amplitude variations after temporal variations have been addressed.

2.2 Study 1 (Known-groups assessment)

Study 1 was carried out at Northwestern University, USA. Full details of the protocol are provided in [12]. Following ethical approval by the Northwestern University Institutional Review Board, six AI individuals (3 male, 35±11 years of age) and seven myoelectric transradial prosthesis users (5 male, 49±18 years of age, 20±18 years of prosthesis experience) were recruited and tested. Subjects visited the lab on one occasion and, after providing informed consent, performed five trials of three seated, goal-oriented tasks (selected from the SHAP [7]): 1) lifting a carton and emptying liquid contents into a jar using their non-dominant or prosthetic limb, 2) lifting and transferring a weighted container across a low-level barrier using their non-dominant or prosthetic limb, and 3) lifting and transferring a tray across a low-level barrier using both hands. The non-dominant limb of able-bodied individuals was chosen for sensible comparison with prosthesis users whose prosthetic limb we assumed to act as the non-dominant limb [20]. The number of trials (5) was comparable with other studies concerned with assessment of prosthesis kinematics [21, 22]. Subjects were asked to perform the task as quickly as possible and the start and end of each trial was denoted by a button-push. Both groups also completed the entire SHAP protocol with their non-dominant hand to assess general upper limb functional abilities. SHAP has shown to have good reliability and validity for assessment of hand function [7], with scores of less than 100 indicating how impaired hand function is. During each task, marker position approximating location of the radial and ulnar styloid processes were collected and used to track the virtual wrist joint centre. Three markers on the forearm (radial styloid, ulnar styloid, and medial epicondyle) were used to define the forearm local reference frame. The 3D position data were collected at 120 Hz using a twelve camera motion capture system (Motion Analysis Corporation, Santa Rosa, CA, USA). Wrist joint three-axis accelerations were calculated in the global frame, then gravity was added to the vertical acceleration component. Finally, the acceleration vector was rotated from the global to the forearm frame [23]. These simulated accelerometer data were used to calculate inter-trial temporal (Warp Cost) and amplitude (RMS Error) variability [15].

This known-groups assessment was deemed to support validity of the methodology if the trends in the variability assessed with DTW reflected those previously observed in joint-level kinematics [12], i.e., we hypothesized that prosthesis users would demonstrate greater variability than controls. Moreover, use of DTW in this study would identify individual contributions of temporal- and amplitude-specific variability to overall movement variability. Data were statistically analysed using independent group t-tests to compare mean differences in Warp Cost, RMS Error, and SHAP score between AI and prosthesis user cohorts, and significance was evaluated based on equality of variances as estimated by the Levene's Test.

2.3 Study 2 (Responsiveness assessment)

Study 2 was carried out at the University of Salford, UK. Following ethical approval by the University of Salford Research Ethics Committee, seven AI individuals (4 male, 6 right handed, 36±10 years of age) provided informed consent and were recruited to the study. AI subjects rather than novel myolecetric prosthesis users were recruited because of the very small numbers of traumatic upper limb amputees referred to limb fitting centres. For example, in 2004/5, there were just 54 new referrals of trans-radial amputees in the UK. Subjects visited the lab on 9 occasions over approximately a 2-week period; full details of the full protocol are published in [24], however, only a subset of visits is reported on here. On their first visit, subjects were asked to perform a seated task which involved reaching with their anatomic hand for a juice carton, picking it up and pouring the liquid into a cup, before returning it to its original location, then moving their hand back to the original resting point (anatomic hand baseline). The location of the carton, cup and starting point for the hand were fixed for each subject across all trials. Subjects repeated the task 12 times. During their second functional task assessment as well as during their final functional task assessment, subjects performed the same task with the same number of repeats but with a custom-made myoelectric prosthesis simulator [24]. In between these prosthesis simulator sessions, subjects carried out the SHAP on four occasions for practicing with the prosthesis simulator. During task performance, 3D position data of a cluster of 4 reflective markers located on the forearm were collected at 100 Hz using a ten camera Vicon 612® motion capture system (Vicon Motion Systems, Los Angles, USA). The position data of their anatomic hand baseline, their first prosthesis simulator session, and their final session with the prosthesis simulator (after SHAP training) were then used to calculate the simulated output of a three-axis accelerometer [23]. Subsequently, temporal and trajectory variability within session were calculated. It was hypothesized that introduction of the prosthesis would increase variability (anatomic baseline versus initial Prosthesis simulator session), and that training through practice to use a prosthesis simulator would reduce variability. Following checks for their normal distribution, warp cost and remaining RMS error were statistically analyzed using a one-way repeated measures ANOVA (SPSS General Linear Model tab) with post-hoc Bonferroni correction for Type 1 Error.

For all statistical analyses, the critical α was set at 0.05 to guide interpretation of the results, and statistics were conducted using SPSS software (IBM, Armonk, New York).

3. RESULTS

3.1 Study 1 (Known-groups assessment)

Significant differences in temporal variability (Warp Cost) were found between prosthesis-users and able-bodied controls. Specifically, prosthesis users exhibited greater temporal variability than controls, and this was so for all three tasks (Figure 4 and Table 1). Results suggested that amplitude variability was greater for prosthesis users than able-bodied across tasks, but these group differences were not statistically significant (P>0.05 for all tasks, Figure 4 and Table 1). Average SHAP Index of Function scores for able-bodied and prosthesis users were 96(±3 SD) and 53(±12 SD) (p<0.001), respectively, suggesting lower upper limb functional abilities for prosthesis users.

3.2 Study 2 (Responsiveness assessment)

Clear changes in temporal variability emerged throughout the study period (Figure 5 (left) and Table 2). Specifically, when AI subjects were asked to use the prosthesis simulator for the first time, their temporal variability increased as compared to their baseline performance with the anatomical hand (P=0.022), but as they learned how to use the prosthesis simulator, their variability decreased again (P=0.043) and returned to levels similar to baseline (P=0.267). Changes in amplitude variability likewise emerged, although with a direction of continuous reduction in RMS Error throughout the study period (Figure 5 (right) and Table 2). Specifically, RMS Error slightly decreased from baseline as subjects were introduced to the prosthesis simulator (P=1.000), and a further reduction in RMS Error occurred with practice to use the simulator (P=0.003), interestingly to levels much lower than baseline (P=0.043).

4. DISCUSSION

The combined results from Studies 1 and 2 support the validity and usefulness of the DTW method for characterizing movement quality of task execution when using an upper limb prosthesis. Study 1 found significant differences in temporal inter-trial variability between prosthesis users and controls, but not in amplitude variability. This finding demonstrates for the first time the nature of differences in trial-to-trial variability between experienced users of myoelectric prostheses and controls. Specifically, by separating out the two elements of trajectory variability, DTW revealed the primary contribution of temporal variability to overall movement quality, with less apparent contributions of amplitude variability. Moreover, that prosthesis users exhibited greater kinematic variability as compared to controls across all three tasks along with reduced function, as quantified by lower SHAP scores, is in agreement with previous findings [12], thereby supporting the validity of this method. It should be noted that one of the possible reasons for the lack of statistical significance in amplitude variability was the low statistical power due to a small sample size. Although consistent group differences in amplitude variability existed across tasks, with magnitudes greater than those found with training in Study 2, these differences were not large enough to reach significance given the within-group variability.

Although not unexpected, no-one has previously demonstrated that variability reduces with practice with a prosthesis simulator. In Study 2 we investigated the extent by which temporal and amplitude variability each contribute to this outcome and demonstrated that temporal variability in a carton pouring task increased considerably on first use of a prosthesis simulator, then declined with goal-oriented training (SHAP). Temporal variability hence showed to be responsive to effects of training. Consistent with the findings in Study 1, amplitude variability showed less clear changes, especially on first introduction of the prosthesis simulator. Two limitations of Study 2 are that AI subjects used a prosthesis simulator and performed only one functional task. Therefore further research involving actual myoelectric prosthesis users and a more comprehensive task protocol is required to substantiate the findings of Study 2.

Consistent with our previous study in stroke [15] temporal variability, as compared to amplitude variability, emerged as the more insightful measure. As all of the tasks studied involved acquiring and releasing objects using the prosthetic hand, and since opening the hand to acquire or release an object is a common challenge in prosthesis control, then hesitations upon grasp and release may be one of the sources of the higher timing variability seen in prosthesis users. It is noteworthy that temporal variability varied significantly across tasks (see Table 1), each of which involved a single grasp and release, and further work is needed to interpret this finding. Furthermore, given the trends observed in Studies 1 and 2, higher prosthesis user amplitude variability and a decrease with simulator training respectively, the contribution of amplitude variability to movement quality should be explored further. Previous work has suggested that below-elbow amputees are able to generate an accurate internal model of the prosthetic limb [25] which implies self-integration of the limb to refine relationships between physiological input and performance output. For example, one explanation for the decrease in amplitude variability with practice (Figure 5) is that learning to use a prosthesis simulator with reduced DoFs may require some development of a new internal model with training to minimize limb amplitude variability. The increase (Prosthesis 1, Figure 5) and subsequent decrease (Prosthesis Final, Figure 5) in temporal variability upon introduction to the prosthesis simulator would be reflective of skill acquisition.

Overall, analysing forearm accelerations using the DTW method appears to be a valid method for quantifying movement quality of upper limb prosthesis use during the execution of goal-oriented tasks. The information delivered from such assessment offers a valuable, objective outcome for monitoring rehabilitation progress that would complement other performance-based and self-report clinical outcome measures. A rich set of outcome data would aid in development of more appropriate, patientcentric training programs with the aim of maximizing functional performance and minimizing potential for device abandonment. Yet, further work is needed to understand the implications of our work for clinical training. We have shown that in simulator users both amplitude and temporal trajectory variability decrease with practice, suggesting our metrics may be of value in assessing skill. However, research is needed to understand whether patients would benefit from training specifically targeted at reducing variability.

Importantly, the studies reported here used camera based techniques to derive overall task completion time and simulated accelerometer trajectories. However, both of these parameters could be derived from a forearm-mounted accelerometer and hence the approach offers the potential for clinicians to characterise both overall task completion time and trial-trial temporal and trajectory variability using low cost instrumentation. Accelerometers have previously been used for classification of hand movements [26, 27], and this study shows their potential in assessment of kinematic variability as an aspect of movement quality. Future work should continue to explore use of wearable devices as a simple, reliable, and clinically-accessible method for assessing prosthesis-use skill. When combined with the use of low cost instrumentation, reliability of the DTW method for assessing prosthesis user movement quality should be investigated to complete an evaluation of its psychometric properties.

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DECLARATIONS

Ethics approval and consent to participate: For testing of human subjects, Study 1 (Known-groups assessment) received ethical approval from the Northwestern University Institutional Review Board, USA (Ref # STU00028580), whilst Study 2 (Responsiveness Assessment) received ethical approval from the University of Salford Research Ethics Committee (Ref # REPN09/174). All participants provided informed consent. Animals were not part of the study.

Conflicts of interest: The authors declare that no financial and personal relationships with other people or organizations exist that could have inappropriately influenced (biased) this work.

AUTHOR'S CONTRIBUTIONS

All substantial contributions of authors to the paper were as follows: (1) the conception and design of the study (all), or acquisition of data (MS, RS), or analysis and interpretation of data (SBT, LPJK, MJM); (2) drafting the article or revising it critically for important intellectual content (all); (3) final approval of the version to be submitted (all).

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TABLES

Table 1. Known-groups assessment (Study 1)

	Group	Carton Pouring		Weighted Container Transfer		Tray Transfer	
		Mean (SD)	***P* [95% CI]**	**Mean (SD)**	***P* [95% CI]**	**Mean (SD)**	***P* [95% CI]**
Warp Cost	Anatomically Intact	85.80 (27.14)	0.02 [-158.55, -18.33]	6.92 (2.31)	0.004 [-100.63, -29.03]	13.55 (9.14)	0.019 [-73.96, -9.40]
	Prosthesis User	174.24 (74.48)		71.75 (38.71)		55.23 (34.70)	
RMS Error [m/s^2]	Anatomically Intact	0.60 (0.09)	0.07 [-934.53, 43.69]	0.93 (0.28)	0.127 [-750.20, 106.65]	1.26 (0.41)	0.164 [-833.74, 160.12]
	Prosthesis User	1.04 (0.53)		1.25 (0.40)		1.60 (0.41)	

Group mean (standard deviation "SD") and statistical t-test results for Warp Cost and RMS Error for the three functional tasks. 95%CI: 95% Confidence Interval of Mean Difference.

Table 2. Responsiveness assessment (Study 2)

	Warp Cost		RMS Error [m/s^2]	
	Mean (SD)	***P*† [95% CI]**	**Mean (SD)**	***P*† [95% CI]**
Anatomic	60.45 (17.02)	0.022 [-141.55; -13.07]	0.47 (0.09)	1.000 [-0.15; 0.19]
Prosthesis 1	137.77 (43.92)		0.45 (0.07)	
Prosthesis 1	137.77 (43.92)	0.043 [2.15; 125.48]	0.45 (0.07)	0.003 [0.05; 0.18]
Prosthesis Final	73.95 (19.27)		0.33 (0.04)	
Prosthesis Final	73.95 (19.27)	0.267 [-8.38; 35.37]	0.33 (0.04)	0.043 [-0.26; -0.01]
Anatomic	60.45 (17.02)		0.47 (0.09)	

†Adjustment for multiple comparisons: Bonferroni.

Group mean (standard deviation "SD") of Warp Cost and RMS Error for AI subjects at baseline (anatomic hand) and during learning to use a prosthesis simulator (myoelectric prosthesis) together with repeated measures GLM pairwise comparisons for test sessions. 95%CI: 95% Confidence Interval of Mean Difference.

FIGURE CAPTIONS

Figure 1. Illustration of temporal and amplitude variability.

Figure 2. Illustration of the effects of uniform time normalization as compared to DTW. Example (adapted from Thies et al. 2009): "drinking from a glass" involves a reach forward, grasp of the glass, lifting, drinking and replacing the glass onto the table top. Note that for uniform time normalization (left) trials remain inadequately aligned, as evident from the mismatch of the different movement components, thereby leading to inappropriate estimation of inter-trial variation in signal amplitude when RMS Error is calculated subsequently. This is not the case for DTW (right).

Figure 3. Use of time-normalization versus non-linear time warping for assessment of upper limb kinematic variability. Example plots show distal-to-proximal forearm acceleration for an anatomically intact individual (top), an anatomically intact individual using a prosthesis simulator (middle), and an amputee (bottom), each pouring juice from a carton into a glass. Shown are original signals of 2 trials (left), the same signals after time normalization (middle) and after time warping (right). A mismatch of movement components remains after time normalization, whilst temporal alignment is optimized through use of DTW for more accurate estimation of amplitude variability.

Figure 4. Known-groups assessment (Study 1). Group means and corresponding standard deviations for temporal variability (Warp Cost, left) and amplitude variability (RMS Error, right) for all functional tasks.

Figure 5. Responsiveness assessment (Study 2). Group means and corresponding standard deviations for temporal variability (Warp Cost, left) and amplitude variability (RMS Error, right). Anatomic: baseline with anatomic hand; Prosthesis 1: first session with a myoelectric prosthesis simulator, Prosthesis Final: final session with a prosthesis simulator (after four SHAP training sessions).

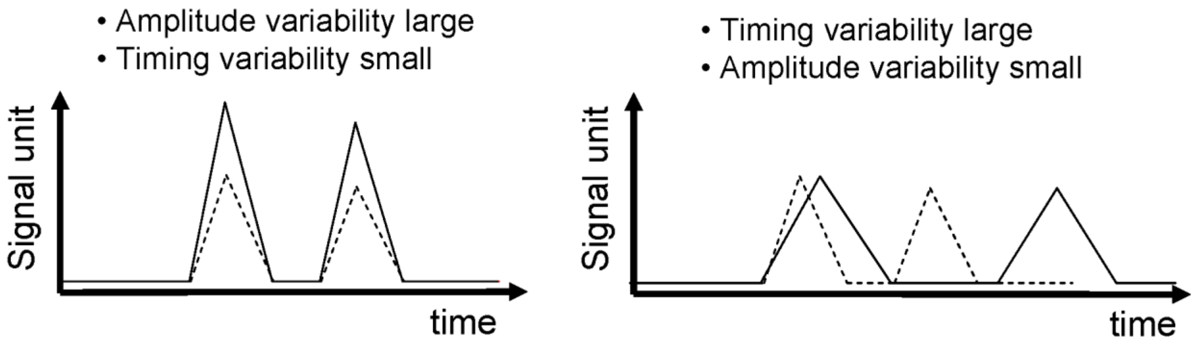

• Amplitude variability large
• Timing variability small
Signal unit
time
• Timing variability large
• Amplitude variability small
Signal unit
time

Figure 1.

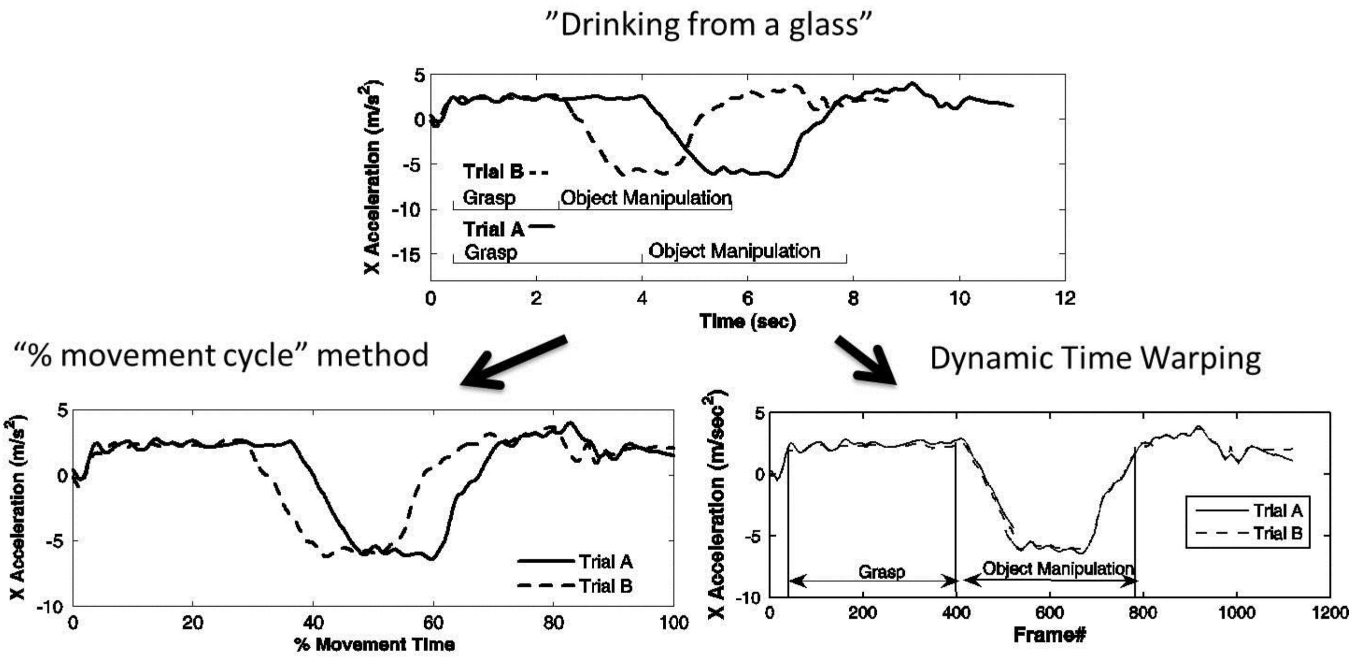
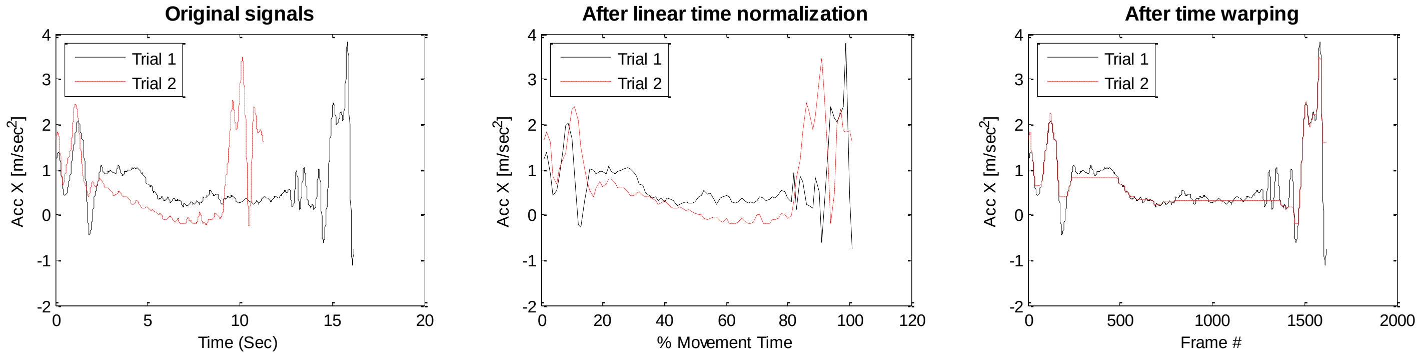
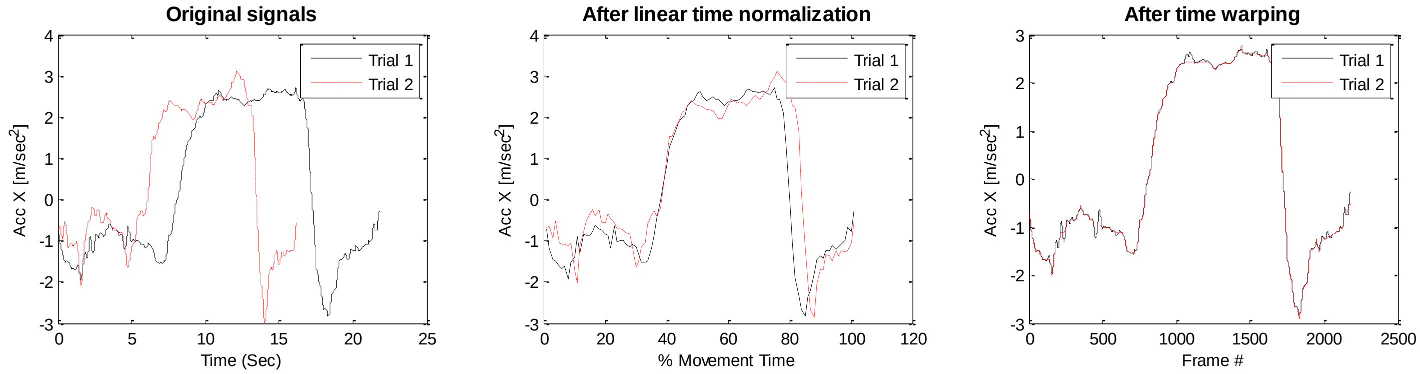

"Drinking from a glass"
Trial B
Grasp
Object Manipulation
Trial A
Grasp
Object Manipulation
X Acceleration (m/s²)
Time (sec)
"% movement cycle" method
X Acceleration (m/s²)
% Movement Time
Trial A
Trial B
Dynamic Time Warping
X Acceleration (m/sec²)
Frame#
Grasp
Object Manipulation
Trial A
Trial B

Figure 2.

Healthy subject anatomic arm "carton pouring task":



Healthy subject prosthesis simulator "carton pouring task":



Myoelectric prosthesis user "carton pouring task":

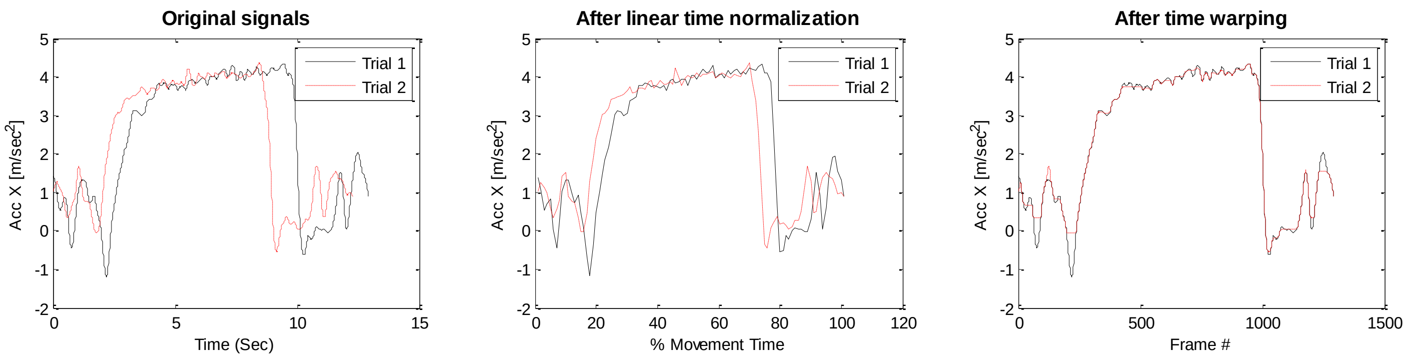
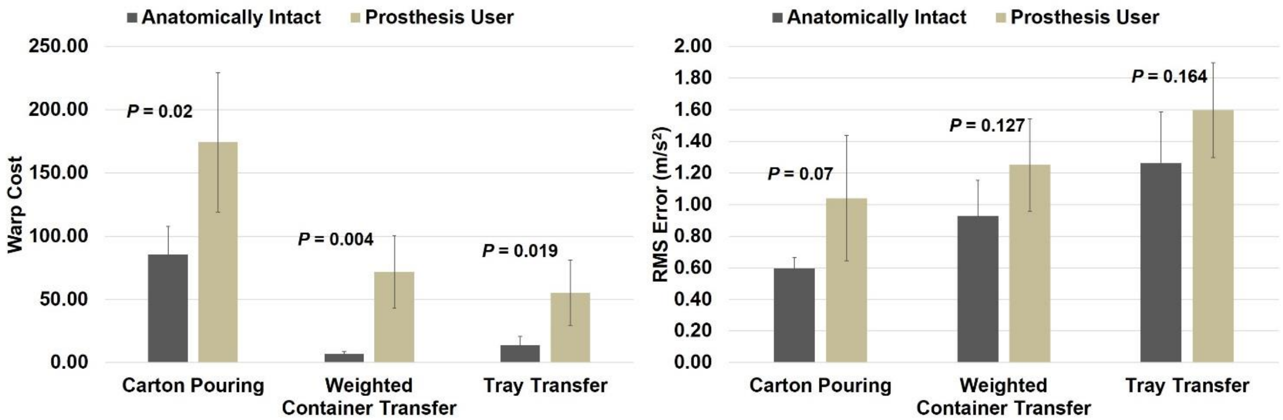


Figure 3.



Anatomically Intact
Prosthesis User
Warp Cost
250.00
200.00
150.00
100.00
50.00
0.00
P = 0.02
P = 0.004
P = 0.019
Carton Pouring
Weighted Container Transfer
Tray Transfer
Anatomically Intact
Prosthesis User
RMS Error (m/s^2)
2.00
1.80
1.60
1.40
1.20
1.00
0.80
0.60
0.40
0.20
0.00
P = 0.07
P = 0.127
P = 0.164
Carton Pouring
Weighted Container Transfer
Tray Transfer

Figure 4.

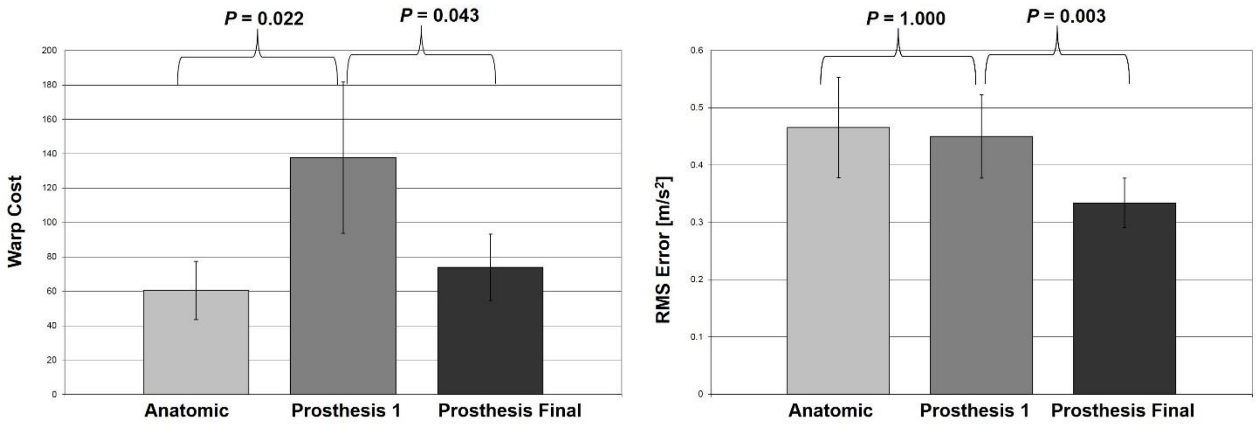

P = 0.022
P = 0.043
Warp Cost
200
180
160
140
120
100
80
60
40
20
0
Anatomic
Prosthesis 1
Prosthesis Final
P = 1.000
P = 0.003
RMS Error [m/s2]
0.6
0.5
0.4
0.3
0.2
0.1
0
Anatomic
Prosthesis 1
Prosthesis Final

Figure 5.