The Effect of Fatigue on Wheelchair Users' Upper Limb Muscle Coordination Patterns in Time-Frequency and Principal Component Analysis

Liping Qi, Shuo Guan, Li Zhang, Hai-Long Liu, Chang-Kai Sun, and Martin Ferguson-Pell

***Abstract*—An assessment of shoulder muscle coordination patterns is important to gain insight into muscle fatigue during wheelchair propulsion. The objective of the present study was to quantify muscle coordination changes over time during fatiguing wheelchair propulsion, as the muscles go through distinct levels of fatigue, a) non-fatigued, b) transiting to fatigue and c) fatigued to exhaustion. We recorded surface electromyography (sEMG) signals of the *anterior deltoid* (AD), *middle deltoid* (MD), *posterior deltoid* (PD), *infraspinatus* (IS), *upper trapezius* (UT), sternal head of the *pectoralis major* (PM), *biceps brachii* (BB), and *triceps brachii* (TB) during a wheelchair incremental exercise test. Nine wheelchair users with a diagnosis of spina bifida or T6-T12 spinal cord injury volunteered for the study. Oxygen uptake and SmartWheel kinetic parameters were also recorded during the test. EMG signals were processed by wavelet and principal component analysis (PCA), allowing for an assessment of how wheelchair users modify their muscle coordination patterns over time. Analyses of covariance (ANCOVA) were conducted to identify the main effect of fatigue levels on muscle coordination patterns by controlling for the effect of increased workload as covariate. A significant effect of fatigue levels on the PC1 and PC3 loading scores was found after controlling for the effect of increasing workloads (with $p < 0.05$ both cases). In addition, PC3 reflects the most dominant fatigue effect on muscle coordination patterns which are not affected by increased ergometer workload. PC3 indicates muscle imbalance when muscles are fully fatigued and muscle co-contraction when muscles are beginning to fatigue. We conclude that fatigue-related changes in neuromuscular activity during wheelchair propulsion contribute to muscle imbalance and reflect a strategy of stiffening the shoulder joint.**

***Index Terms*—Wheelchair ergometer, kinetics, surface electromyography, spinal cord injury, energy expenditure.**

I. Introduction

MUSCLE fatigue is defined as a decline in a muscle's capacity to generate force that is induced by maximal and submaximal exercise [1]–[3]. As the physiology of the shoulder is not well adapted to the monotonous nature and peak force requirements of wheelchair use, the excessive use of the upper extremities leads to muscle fatigue [4]. The process of fatigue is gradual and leads to increased variability of movement and force [5]. During wheelchair propulsion, wheelchair users may compensate for muscle fatigue by changing the movement patterns. These fatigue-induced changes can bring about a redistribution of muscle activity level among muscles and change inter-joint and inter-muscular coordination [6], [7]. Previous studies have reported alternating levels of muscle activity between push muscles (*anterior deltoid* and *pectoralis major*) and recovery muscles (*posterior deltoid* and *upper trapezius*) during fatiguing wheelchair propulsion [7]. Several studies have also reported stroke pattern changes associated with muscle fatigue during prolonged wheelchair propulsion [8], [9].

Previous studies have frequently reported small kinetic and kinematic changes allowing subjects to coordinate their joint motions while maintaining performance when fatigued [9], [10]. It has been suggested that a method is needed to determine changes in muscle coordination patterns over the course of a fatigue induced protocol [11]. Electromyographic (EMG) signals have been used widely to study muscle coordination, which usually report muscle activity profiles. From the EMG profile, information can be extracted about muscle activation timing and level of muscle activity [12]. However, when the activities of several muscles around a complex joint are recorded simultaneously, the individual muscle activity profiles can be difficult to interpret in terms of muscle

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coordination patterns. Multivariate statistical tools such as factor analysis, non-negative matrix factorization or principal components analysis (PCA) have been used to decompose data from multi-joint muscles into smaller sets of highly representative variables (principal components) [13].

PCA generates principal component eigenvectors (principal weightings) and a set of eigenvalues (principal loading scores) for each principal component (PC). PCA classifies quantitatively the coordination patterns recorded across muscles by using the PC weightings and PC loading scores. The component patterns can be represented by principal weightings, whereas the loading scores define how much of each component pattern is present in the individual movements. Typically, the first few components explain most of the variance in the original data. Patterns can then be reconstructed from the vector product of the first few PC weightings and PC loading scores. PCA has been used successfully to identify subtle differences between coordination patterns in several studies [14] [15].We recently proposed an approach based on a combined use of wavelet analysis and PCA that is capable of decomposing large EMG datasets into the summed activation of functional units of coordination in the form of synergies or coordinative structures [16], [17].

Studies of localized muscle fatigue have so far worked mostly with a binary opposition of fatigued versus non-fatigued conditions, where a fresh, rested muscle is described as "non-fatigued" and muscle in the state of exhaustion as "fatigued". For a closer look at the process of fatigue, researchers have been working more recently with an intermediary state, the transition to fatigue that manifests itself by an increased recruitment of additional motor units at the point when the muscle is beginning to fatigue [18]. The transition to fatigue during an incremental exercise test can be detected by surface electromyography (sEMG), where the break point is determined by a sudden increase in the recruitment of motor units as apparent in the sEMG signal [3].

The present study was designed to quantify the effect of fatigue on muscle coordination during wheelchair propulsion, beginning at "non-fatigued", then "transitioning to fatigue", and finally "fatigued" to exhaustion. sEMG activity was recorded in 8 muscles around the shoulder during an incremental wheelchair propulsion test performed until task failure. In addition to a classical analysis of the changes in both muscle activity levels and individual EMG profiles, PCA was used to identify the muscle coordination patterns. PCA could provide insight into wheelchair users' control strategies as they adapt their muscle coordination patterns to the changing state of fatigue. The purpose of the present study was to quantify how muscle coordination changes over time (non-fatigued, transitioning-to-fatigue, and fatigued) during the incremental wheelchair test. We hypothesized that fatigue would induce changes in muscle coordination patterns during the incremental fatiguing task.

II. Methods

A. Participants

Nine individuals with paraplegia (6 males, 3 females, 43±8.4 age, 81.1±20.1kg weight.) participated in this study.

TABLE I
Physical and Injury Characteristics of Participants

Code	Sex	Age (year)	Weight (kg)	Type of injury	Time since injury (year)	ASIA Impairment Scale grade
1	M	45	68.3	SCI	2.5	T12/L1 AIS A
2	M	49	80.5	SCI	2	T11 AIS A
3	M	34	68.4	SCI	17	T12 AIS A
4	F	51	64.1	SCI	18	T12 AIS A
5	M	47	99.2	SCI	12	T6 AIS B
6	M	44	125.4	SCI	10	T11 AIS A
7	F	55	73.4	SCI	3.5	T11 AIS A
8	F	29	57.8	SB	12	L2
9	M	33	93.1	SB	18	T10
Mean (SD)		43 (8.4)	81.1 (20.1)		10.6 (6.2)	

SCI: spinal cord injury; SB: spina bifida

They were community-based wheelchair users. The physical and injury characteristics of each participant was shown in Table I. Participants provided informed consent in accordance with the procedures approved by the University of Alberta Ethics Committee (ID: Pro00015185).

1) Instruments: sEMG (DE-3.1 double differential sensor, 1cm inter-electrode distance, Bagnoli™, Delsys Inc., Boston, MA, USA) signals were detected on eight muscles: *anterior deltoid* (AD), *middle deltoid* (MD), *posterior deltoid* (PD), *infraspinatus* (IS), *upper trapezius* (UT), sternal head of the *pectoralis major* (PM), *biceps brachii* (BB), and *triceps brachii* (TB) on the right shoulder after the skin was shaved and cleaned with alcohol swipes. The sampling rate was 2000Hz.

Oxygen uptake (VO_2, l/min) and carbon dioxide output (VCO_2, l/min) were continuously measured using a wireless gas analyzing system (Oxycon Mobile, CareFusion Respiratory Care, CA, The USA). Heart rate (HR, beats/min) was monitored continuously during the test by telemetry (Timex, TIMEX Group Canada, Inc., Ontario, Canada).

A SmartWheel (Three Rivers Inc., LLC, Mesa, AZ, USA) was used to record kinetic data. SmartWheel sampling rate was 240 Hz. The SmartWheel was fitted on the right side of the participant's own wheelchair. The wheelchair was then secured to an instrumented roller ergometer [19], [20], connected to a screen placed in front of the participant to provide visual speed feedback. Work load was controlled through friction applied to each roller by a fabric strap attached to pneumatic actuators of a digital pressure controller (FESTO, Esslingen am Neckar, Germany), with a proportional valve to regulate the required air pressure [19], [20]. The desired work load through friction was controlled by a computer program (NI LabVIEW 2012, National Instruments Corporation, Austin, TX, USA).

B. Test Procedure

Participants performed a 5-minute warm up while getting used to the wheelchair ergometer and visual propulsion speed feedback. Participants were instructed to perform a wheelchair incremental exercise test at a constant speed of 1 m/s to volitional exhaustion. The termination of the test was determined when the participants volitionally stopped because of fatigue or when the investigators determined that the participant could not maintain the expected speed after 3 alerts. The work-load began at 10 Watts and was increased by 5 Watts every minute until volitional fatigue. Two of the participants were engaged in regular paraplegia sports. For them the work load was increased in steps of 10W so that volitional exhaustion could occur within 8-12 min [21]. Blood pressure was measured with an arm sphygmomanometer before and after the incremental test. Perceived exertion ratings (RPE) were elicited every two minutes during the test.

C. Data Analysis

The SmartWheel output data were used to calculate some of the key kinetic variables. The resultant force (F_{tot}) is the total force applied to the handrim. Push frequency is the number of pushes per second; push length is the length of 'hand-on' to 'hand-off', in degrees. M_z is the moment causing forward motion. The start of the propulsion cycle was determined as the point at which M_z was applied to the Smartwheel, and the end of propulsion was determined as the point at which M_z returned to zero. The recovery phase was defined as the time between the end of propulsion and its resumption, when the Smartwheel M_z was zero. The time base of the propulsion cycle was normalized to 100% to facilitate the comparison across participants.

Energy expenditure (EE) was calculated from the average respiratory exchange ratio (*RER*) and VO_2 of the last minute of the incremental wheelchair propulsion test, based on the following formula [22], [23].

$$\mathrm{EE\ (W)} = (4940\ RER + 16040)(VO_2/60)$$

where *RER* is the ratio of VCO_2/VO_2.

The EMG signals were resolved into intensities in time-frequency space using a wavelet analysis method [24]. This method has been described in detail in previous papers [13], [25], [26]. A filter bank of 11 non-linearly scaled wavelets was used, index by k, with center frequency, f_c, ranging from 7 Hz (wavelet 0) to 395 Hz (wavelet 10). The EMG intensities for each muscle and participant were normalized to the mean of the total intensities. The intensities from the wavelets (10-350 Hz, k = 1-10) were summed to give the total EMG intensity. Transition to fatigue during an incremental exercise test was determined by EMG threshold, which was estimated by the bi-segmental linear regression algorithm [27], [28].

The EMG intensities were synchronized with the kinetic data and then interpolated to 100 evenly spaced time-points for each propulsion cycle (1-100% cycle). Principal component analysis (PCA) was used to identify the effect of fatigue on shoulder muscle coordination. The PCA method used in the present study has been described in detail in previous papers [16], [17]. Briefly, the EMG intensities from 8 upper extremity muscles were used to construct grids defining the muscle coordination pattern for each propulsion cycle. For each wheelchair incremental exercise test, the initial 30 seconds (approximately 30 propulsion cycles) was considered as non-fatigued state; the next 30 seconds, the critical part of the VT, as transition-to-fatigue state, and the final 30 seconds of propulsion as the fatigued state. PCA was applied to the set of 748 propulsion cycles (265 cycles from all participants in the non-fatigues state, 250 cycles from all participants as they transit to fatigue, and 233 cycles from all participants as they have reached the point of fatigue to exhaustion). A matrix A of $p \times N$ was arranged, where $p = 800$ values per pattern (8 muscles $\times$ 100 time points for the EMG intensity), and $N = 748$ cycles analyzed. The covariance matrix B was calculated from matrix A. Each of the components contains information from 8 muscles and time points, so the major components can be used to evaluate the important features of the muscle coordination patterns. Coordination patterns can be reconstructed from the vector product of the PC weightings and PC loading scores. PC1 typically represents a coordination pattern that is similar to the average coordination pattern, and the lesser components account for ways in which this coordination pattern varies between speeds and participants.

III. Statistical Analysis

Multiple cycles from one participant were averaged. Then the averaged data from each one participant was used for the statistical analysis as variables. Statistical analysis was performed using IBM SPSS (version 22, SPSS Inc., Chicago, IL, USA). Since the workload of ergometer was increased once every minute during the incremental wheelchair exercise test, a combination of regression analysis and analysis of variance. Analysis of covariance (ANCOVA) was used to determine the effect of fatigue level on EMG total intensity, kinetic variables, heart rate, and energy expenditure, as well as principal component loading scores, always with the respective ergometer workload as covariate. The normality assumption of data was tested by checking for kurtosis and skewness. A homogeneity-of-regression (slope) assumption was tested before conducting an ANCOVA to evaluate the interaction between covariate and the independent variable in the prediction of the dependent variables. All data are reported in the text as mean $\pm$ standard deviation (SD). The significant level was set at $p < 0.05$ for all statistical procedures.

IV. Results

The average time to maximum volitional exhaustion during the incremental wheelchair test is 620 $\pm$ 172 seconds. The average RPE values reported by the participants at the end of the test was 17.3 $\pm$ 2.0. Table II displays the descriptive statistics of kinetic, heart rate, and energy expenditure at different levels of fatigue. A preliminary analysis evaluating the homogeneity-of-regression (slopes) assumption indicated that the relationships between the covariate (ergometer workload) and the dependent variables did not differ significantly as a function of the independent variable (fatigue levels). No significant effects of fatigue level on Peak F_{tot}, push length, peak frequency, push phase (%) were found after controlling for the effect of the ergometer workload. Also, there was no significant effect of fatigue level on heart rate

TABLE II
DESCRIPTIVE STATISTICS REPORTED DURING WHEELCHAIR INCREMENTAL EXERCISE TEST IN DIFFERENT LEVEL OF FATIGUE: NON-FATIGUED, TRANSITION TO FATIGUE, AND FATIGUED. DATA ARE REPORTED AS MEAN ± SD

Variables	Non-fatigued	Transition to fatigue	Fatigued
Kinetics			
Peak F_{tot} (N)	59 ± 11.2	94 ± 27	111 ± 29
Push frequency (1/s)	1.0 ± 0.3	1.0 ± 0.2	1.1 ± 0.2
Push length (degree)	67 ± 17	74 ± 13	67 ± 10
Push phase (%)	33.4 ± 3.8	40.9 ± 3.8	45.8 ± 6.0
Energy expenditure (W)	197 ± 89	304 ± 128	456 ± 155
Heart rate (beat/min)	99 ± 19	116 ± 19	139 ± 15
RPE	8.4 ± 0.7	11.2 ± 1.8	17.3 ± 2.0

and energy expenditure after controlling for the effect of the ergometer workload. However, the covariate, the workload of the ergometer, was significantly related to the peak F_{tot}, $F(1, 23) = 6.9$; push phase (%), $F(1, 23) = 4.5$; and energy expenditure, $F(1, 23) = 22.3$; with $p < 0.05$ all the cases.

Instead of calculating mean values of EMG intensities or selecting typical propulsion cycles from each muscle, we used PCA to classify quantitatively the coordination patterns across 8 upper limb muscles by giving PC weightings and loading scores. The sets of component patterns are represented by PC weightings, whereas the loading scores define how much of each component coordination pattern is present in the individual propulsion cycles. The weightings of the first principal component (PC1), the second principal component (PC2), and the third principal component (PC3) are shown in Figure 1. PC1 weightings represent a general coordination pattern throughout the muscle synergy. The first 5 PC loading scores for different states of fatigue and percentage weights are shown in Table III. The higher PC1 loading scores are associated with higher muscle activity. PC2 and PC3 contain both positive and negative weightings and loading scores, which shows the variations between different coordination patterns in different states of fatigue. Since the shoulder-muscle complex is capable of a wide range of movement, this might result in considerable variability of repetitive movements of the upper limb. In addition, there was continuous fluctuation in the level of muscle fatigue, probably owing to the participants' modified coordination patterns to cope with mounting fatigue. As shown in the PC loading scores (Table III), the high standard deviation is associated with a wide variety of movement pattern changes among the participants.

The first 10 PCs explain more than 75% of the signals. We interpret the PC1 weightings as reflecting the general activation pattern throughout the synergy. 42.1% of the overall coordination pattern is explained by the PC1 component. The higher PC1 loading scores are associated with higher muscle activities. The ANCOVA shows that the fatigue level has a significant effect on the PC1 loading scores after controlling for the effect of an increasing work load, $F(2, 23) = 27.5$, $p < 0.05$. PC1 loading scores increased significantly over time (from non-fatigued, to transition-to-fatigue, and fatigue), $p < 0.05$.

PC2 explains 9.3% of the signal. There was no significant effect of fatigue levels on PC2 loading scores after controlling

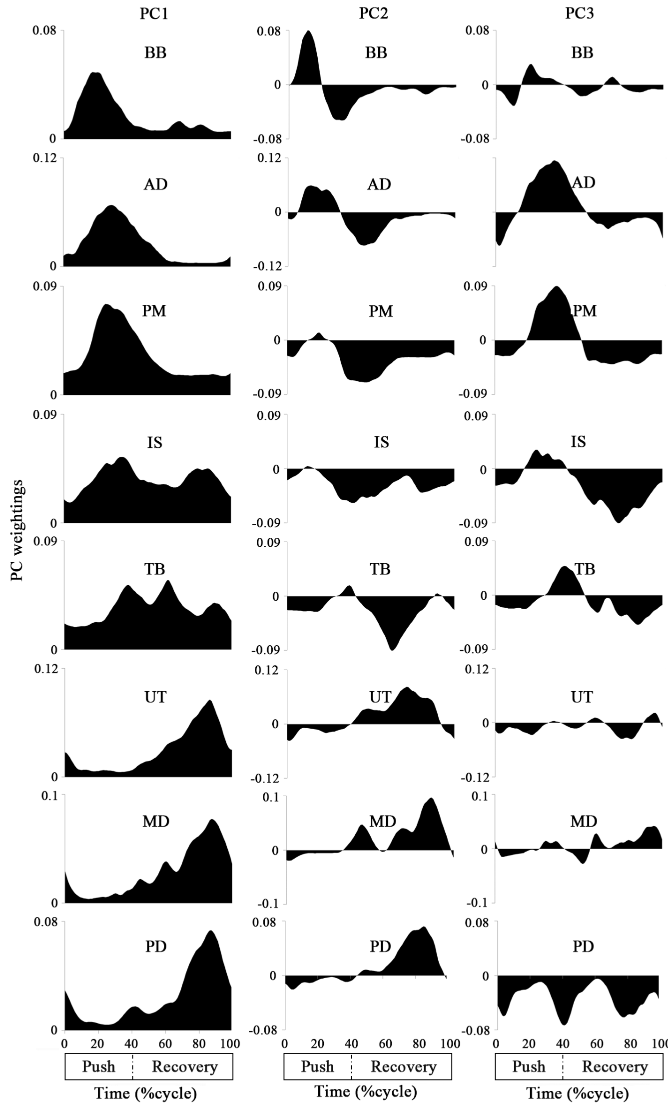

Fig. 1. The weightings of PC1, PC2, and PC3. PC1 explains 42.1% of the overall coordination patterns. PC2 and PC3 explain 9.3% and 5.1% of the overall coordination patterns respectively. The time base of the propulsion cycle was normalized to 100%, the push phase beginning and ending with the contact between hand and handrim.

TABLE III
THE FIRST 5 PC LOADING SCORES OF DIFFERENT STATES OF FATIGUE AND % WEIGHTS. DATA ARE REPORTED AS MEAN (SD)

PC	Non-fatigued	Transition to fatigue	Fatigued	% signal explained by PC
PC1	7.0(4.3)*	19.2 (6.9)*	27.8 (8.3)*	42.1%
PC2	3.4(3.8)	3.4 (9.5)	-5.5 (11.6)	9.3%
PC3	-1.5 (1.2)	-3.6 (6.3)*	2.6 (10.0)*	5.1%
PC4	2.2 (1.7)	2.1 (4.2)	-0.8 (10.9)	4.7%
PC5	0.5 (2.1)	-1.0 (5.2)	-1.2 (8.4)	3.3%

**p* < 0.05, analysis of covariance

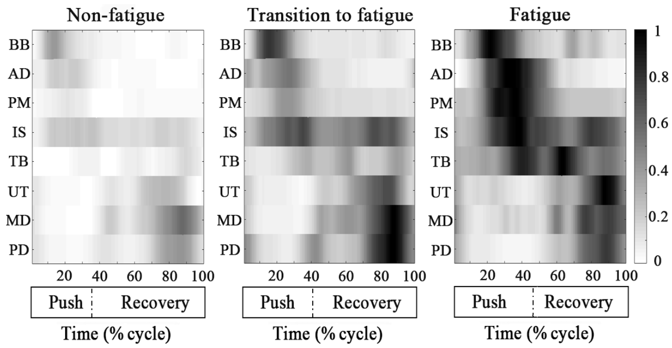

Fig. 2. Reconstructed EMG intensity at non-fatigue, transition to fatigue, and fatigue states from the tested 8 muscles. EMG intensity scales are normalized to maximum intensity for each muscle in the range of [0, 1] where the gray scale map represents the intensity of the EMG signal. The time base of the propulsion cycle was normalized to 100%, the push phase beginning and ending with the contact between hand and handrim.

for the effect of the ergometer workload. However, the covariate, the ergometer workload, was significantly related to the PC2 loading scores, $F(1, 23) = 7.0$, $p = 0.015$. PC3 explains 5% of the signal. ANCOVA shows that there is a significant effect of the fatigue level on the PC3 loading scores after controlling for the effect of increasing work load, $F(2, 23) = 3.5$, $p < 0.05$. The ergometer workload as covariate was not significantly related to the PC3 loading scores, $F(1, 23) = 4.0$, $p > 0.05$. Planned contrasts revealed a significant difference in PC3 loading scores between the "transition to fatigue" and the fatigued state.

PCA decomposes EMG coordination patterns across shoulder joints into a small set of basic patterns that capture the most relevant features of the original EMG coordination patterns such that the original patterns could be reconstructed from the compressed representation. The EMG coordination patterns were reconstructed from the sum of the products of the PC weightings (Fig.1) and their loading scores for each propulsion cycle (Table III), using the first 10 PCs (more than 75% of the signals), that describe the major features of the coordination. For each state of fatigue, the EMG coordination patterns from 8 muscles are depicted in Figure 2.

V. Discussion

The present study examined the muscle coordination and propulsion biomechanics of individuals with SCI using their own wheelchairs during an incremental test to volitional exhaustion. The purpose was to detect the possible changes in muscle coordination patterns during a wheelchair incremental exercise performed until task failure. Through wavelet and PCA, we were able to identify how muscle coordination patterns vary over time during the wheelchair incremental exercise test.

Several studies have examined the effects of fatigue on wheelchair propulsion with different fatigue testing approaches. Rodgers *et al.* used a graded exercise test, progressively adding resistance to induce volitional exhaustion [10]. Rice *et al.* employed a constant velocity test during an extended period of propulsion [29]. Keyser *et al.* used the wheelchair ergometer power output corresponding to 75% peak VO_2 as the sustained intensity for the fatiguing test [30]. We adopted the incremental wheelchair exercise test protocol that progressively increases ergometer workload to cause volitional exhaustion, where participants were stopped when they could no longer maintain the target velocity. By tracking oxygen uptake and sEMG recording during the incremental test, we were able to determine three levels of fatigue (non-fatigue, transition-to-fatigue, and fatigue) and quantify how muscle coordination changes over time. In order to control the effect of the progressively increased workload during the incremental test, we used the analysis of covariance to determine the effect of fatigue level on EMG, kinetic and oxygen uptake variables with ergometer workload as covariate because the ergometer workload is linearly related to the level of the fatigue. Therefore, the effect of the fatigue level can be examined after controlling for the effect of a progressively increased ergometer workload.

The ANCOVA results were not significant for the kinetic variables, heart rate and energy expenditure, which indicates no significant effects of fatigue level on these variables after controlling for the effect of increased ergometer workloads. Our previous constant velocity mild fatigue study also did not find significant changes of the kinetic variables during prolonged periods of propulsion at two different speeds [7]. In the present study, the peak F_{tot}, push phase (%), and energy expenditure were significantly related to the increased ergometer workload. The increase of peak force, push phase (%), and energy expenditure are necessary to provide a higher power output during the incremental wheelchair test. Rodgers *et al.* observed increased peak handrim forces occurring with fatigue during their graded exercise test [10]. Rice et al found that experienced wheelchair users did not significantly change their peak resultant force over time, but they increased the amount of time on the handrim during an extended period of propulsion [29].

PCA was used in the present study to quantify differences in muscle coordination patterns and thus determine how different levels of fatigue affect movement strategies. Different coordination patterns are represented by the relative loading scores of the different components coupled to their weightings. The ANCOVA shows that there is a significant effect of fatigue levels on the PC1 loading scores after controlling for the effect of the increasing work load. The higher PC1 loading scores are associated with higher muscle activities, and PC1 loading scores increased significantly over time (non-fatigue, transition-to-fatigue, and fatigue). This is consistent with the findings of previous studies that the EMG activity of the main shoulder muscles increased over time during wheelchair fatiguing tests. Bernasconi et al observed that sEMG from four shoulder muscles increased progressively during a six minute strenuous wheelchair exercise at constant workload [6]. One of our previous studies also showed a progressive increase of EMG intensity from eight shoulder muscles during constant velocity prolonged propulsion at two different speeds [7].

There was no significant effect of fatigue levels on PC2 loading scores after controlling for the effect of ergometer workload. The ergometer workload as covariate was significantly related to the PC2 loading scores. PC2 shows relatively more activity in the push muscles (BB, AD, PM) in the late push phase at the fatigued state. The increase of muscle activity might reflect the considerably greater propulsive force delivered by the push muscles towards the end of the push phase. The increase of ergometer resistance mimics the upward propulsion on a ramp. The coordination patterns represented by PC2 were similar to the muscle activity reported in previous studies, which suggested more EMG activity of push muscles in the push phase and less EMG activity of the recovery muscles during wheelchair incline propulsion [31].

There was a significant effect of the fatigue level on the PC3 loading scores after controlling for the effect of increasing workload. The covariate ergometer workload was not significantly related to the PC3 loading scores. PC3 thus proves fatigue to have dominant effect on muscle coordination patterns rather than the increased ergometer workload. PC3 weightings of the push muscles are positive in the middle of the push phase to its end (20-50% cycle) (Figure 2), with positive PC3 loading scores at the fatigued state (Table III), which shows that towards the end of the incremental exercise test, when muscles are fully fatigued, a significant increase in EMG activity occurs in the muscles responsible for propulsive force generation, AD and PM, and also in the IS and TB, responsible for glenohumeral joint stability. Conversely, PC3 weightings of the recovery muscle, PD, are negative during the recovery phase (40-100% cycle), with positive loading scores in the fatigued state, which shows a relative decrease in EMG activity in the recovery muscle. The relatively increased activity of the push muscles and relatively decreased activity of the recovery muscles may indicate muscle imbalance when muscles are fully fatigued at the end of the incremental exercise test. Previous fatigue studies suggest that a possible strategy to counteract the effects of fatigue is to modify muscle coordination by a redistribution of muscle activity levels among muscles and/or changes in muscle activity profiles [32], [33].

For the transition to fatigue state, PC3 weightings of both push muscles and the recovery muscles are negative in the push/recovery transitions (0-20% cycle and 40-60% cycle), coupled with negative loading scores, which implies muscle co-activation of the push muscles and recovery muscles. Co-activation has been observed as a strategy used to stiffen the joint and enhance stability [34], [35]. Our results suggest that when muscles are beginning to fatigue, co-activation of the shoulder joint's AD and PD muscles during the early push phase and transitions (push to recovery and recovery to push) may increase shoulder stiffness to accommodate potential balance concerns (Figure 2).

A. Study Limitations

Since the model of fatigue in the present study is based solely on incremental exercise test during wheelchair propulsion, our results may not be applicable to other fatigue models. More studies are needed to investigate fatigue under different circumstances, such as high intensity fatigue tests under a constant workload or prolonged mild fatigue tests.

EMG signals were normalized to maximum activities measured during the wheelchair incremental exercise test. Such a normalization approach was beneficial in assessing the distribution of EMG across the propulsion cycle and modulation of activity levels under increasing workloads and fatigue. However in using this normalization approach, we could not place activity levels in relation to isometric maximum voluntary contraction (iMVC).

Although PCA showed significant changes in the muscle coordination patterns associated with progressing muscle fatigue, the difficulty of PCA was that attaching a physical/clinical meaning to the PCs. As the order of the PCs increases, it becomes more difficult to explain.

VI. Conclusion

EMG signals were first decomposed by a well-defined wavelet analysis, which allowed us to identify the timing and level of individual muscle activity during each propulsion cycle, and then PCA analysis was used to capture the most relevant features of the coordination patterns associated with muscle fatigue in the present study. Compared to the traditional EMG profile of timing and amplitude of individual muscles, PCA resolved functional PCs associated with changes of coordination patterns that were not detectable using the traditional EMG statistics. We were able to capture and quantify a more global effect of fatigue on the muscle coordination patterns during fatiguing wheelchair propulsion. The ANCOVA shows significant effects of fatigue level on PC3 loading scores after controlling for the effect of a progressively increasing work load. PC3 reflects the most dominant fatigue effect in muscle coordination patterns which are not affected by the increased ergometer workload. PC3 is associated with relatively increased activity of push muscles and relatively decreased activity of recovery muscles, which may indicate muscle imbalance when muscles are fully fatigued at the end of the incremental exercise test. Co-activation of AD and PD was also identified by PC3 when muscles are beginning to fatigue.

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