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RESEARCH ARTICLE

Recumbent stepping has similar but simpler neural control compared to walking

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Abstract The purpose of this study was to compare muscle activation patterns and kinematics during recumbent stepping and walking to determine if recumbent stepping has a similar motor pattern as walking. We measured joint kinematics and electromyography in ten neurologically intact humans walking on a treadmill at 0 and 50% body weight support (BWS), and recumbent stepping using a commercially available exercise machine. Cross correlation of upper and lower limb electromyography patterns between conditions revealed high correlations for most muscles. A principal component analysis revealed that the first factor accounted for more muscle activation signal content during recumbent stepping (81%) than during walking (70%). This indicates that the motor pattern during walking is more complex than during stepping. Cross correlation analysis found a high correlation between factors for recumbent stepping and walking ($R = 0.54$), though not as high as the correlation between factors for walking at 0% BWS and walking at 50% BWS ($R = 0.68$). There were substantial differences in joint kinematics between walking and recumbent stepping, most notably in hip, elbow, and shoulder motions. These results suggest that although the two tasks have different kinematic patterns, recumbent stepping relies on similar neural networks as walking. Individuals with neurological impairments may be able to improve walking ability from recumbent stepping practice given similarities in neural control between the two tasks.

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Introduction

Body weight supported treadmill training is a method of gait rehabilitation that has demonstrated clinical efficacy (Hesse et al. 1994, 1995; Wernig et al. 1995, 1998, 1999; Dietz et al. 1998; Behrman and Harkema 2000). This therapy involves supporting a portion of the patient's body weight over a treadmill while therapists help to move the patient's lower limbs through normal gait kinematics. The task specific nature of this therapy increases plasticity in the spinal cord and improves functional ability. However, because the therapy requires at least two therapists and specialized equipment, it is not very accessible to patients. Researchers have been working on robotic devices

(Hesse et al. 2003; Reinkensmeyer et al. 2004) to decrease therapist labor, but the size and cost of the robotic devices also limit their implementation.

An alternative to body weight supported treadmill training is the use of exercise machines that facilitate stepping practice (Brown et al. 2005; Ferris et al. 2006). Inexpensive exercise machines that could be placed in patients' homes could drastically increase therapy intensity due to increased accessibility. Given recent findings highlighting the importance of exercise in promoting neural plasticity (Kleim et al. 2003; Vaynman and Gomez-Pinilla 2005), this would seem to be a viable option. The potential drawback to exercise machines for stepping practice is that they sacrifice some task specificity. In order to optimize neural plasticity, the practice task should be as close as possible to the goal task (Henry 1968; Edgerton et al. 1997; de Leon et al. 1998). It is not yet clear how practice performing simplified stepping motions (or cycling) would benefit functional ambulation (Brown et al. 2005).

One type of commercially available exercise machine with a simplified stepping motion is the recumbent stepper (TRS 4000, NuStep, Inc., Ann Arbor, MI) (Fig. 1). The device mechanically couples upper and lower limb motion in a normal walking phase relationship; the left arm and right leg move forward while the right arm and left leg move backward. The advantage of this device is that a patient could use his/her own arms to assist his/her legs to perform the stepping motion. Recent studies have shown that active arm exertion on a recumbent stepper facilitates lower limb muscle activation (Huang and Ferris 2004; Kao and Ferris 2005). This is likely due to neural coupling in pathways regulating arm and leg motor neurons (Dietz 2002; Zehr and Duysens 2004). An exercise intervention that capitalizes on this neural coupling between the upper and lower limbs has promise for rehabilitation. While a device such as the recumbent stepper sacrifices on task specificity, its easy accessibility could increase the intensity of therapy.

Fig. 1 Recumbent stepping machine (TRS 4000, NuStep, Inc., Ann Arbor, MI). The recumbent stepping machine is driven by pedals and handles that mechanically couple upper and lower limb motion. The left arm and right leg move forward while the right arm and left leg move backward. Both the seat and handles are adjustable to accommodate a full range of motion for participants of different sizes

An important aspect of any exercise machine designed for neurological gait rehabilitation is that it must activate similar neural pathways as walking. Recent evidence indicates that muscle activity during human locomotion is driven by relatively few neural signals (Olree and Vaughan 1995; Ivanenko et al. 2004). It is hypothesized that these basic neural signals are produced by a locomotor pattern generator and are then shaped appropriately by cortical inputs and proprioceptive feedback to regulate a number of rhythmic motor tasks (Zehr 2005). If this is accurate, then an exercise intervention that approximates a simplified stepping motion could be effective for neurological rehabilitation of gait.

The purpose of this study was to directly compare muscle activation and kinematics of walking and of recumbent stepping to assess the relative similarity in neural control between the two tasks. We studied subjects walking with and without body weight support (BWS) to determine if modifications in muscle activation amplitudes (Ferris et al. 2001) influenced our comparison between walking and recumbent stepping. We chose 50% BWS because the EMG amplitudes at that level of support are similar to recumbent stepping (Ferris et al. 2001; Huang and Ferris 2004). We hypothesized that a principal component analysis of lower limb and upper limb electromyography signals during the three conditions (recumbent stepping, walking with 0% BWS, and walking with 50% BWS) would reveal high correlations in factors. This would indicate strong similarity in neural control substrates between the three conditions (Ivanenko et al. 2004).

Materials and methods

Experimental design

Participants

Ten healthy participants (five males and five females; age range 18–27) participated in the study after providing informed written consent. The University of Michigan human subject protection office granted approval of the protocol and consent form. The study was conducted in accordance with the Declaration of Helsinki.

Body weight support

A pneumatic BWS system (Robomedica, Inc., Irvine, CA) held up a portion of the participants' body weight via a harness while they walked on a treadmill. (Biodex RTM 500, Biodex Medical Systems, Inc., Shirley, NY).

Recumbent stepping

A recumbent stepping machine (Fig. 1) was driven by pedals and handles that mechanically coupled upper and lower limb motion. The left arm and right leg move forward while the right arm and left leg move backward. Both the seat and handles are adjustable to accommodate a full range of motion for participants of different sizes. The level of resistance on the recumbent stepping machine is set using a unitless scale (values ranging from 1 to 10). The machine employs an eddy current disk break to generate the resistance. A lever on the side of the machine allows the user to adjust the resistance by moving an array of magnets closer to or farther away from a spinning conductive disc (Huang and Ferris 2004; Kao and Ferris 2005).

Protocol

The testing protocol consisted of three distinct phases. The first two phases were on the treadmill and the third phase was on the recumbent stepping machine. Each participant walked on the treadmill at three different speeds (0.5, 1.0, 1.5 m/s) with (1) 0% BWS, (2) 50% BWS, and (3) performed recumbent stepping at three different frequencies corresponding to their preferred stride frequency on the treadmill at the three different speeds. Recumbent stepping always followed treadmill walking in order to determine the appropriate recumbent stepping frequency.

On the treadmill, 20-s trials were recorded at all three speeds. The walking with 0% BWS trials were recorded first, with the three speeds randomized. The walking 50% BWS trials were then recorded, again with the three speeds randomized. We gave the participants time to practice in order to adjust to the BWS before the trials with 50% BWS were recorded.

The trials on the recumbent stepping machine were recorded last. The recumbent stepping frequency corresponding to each walking speed was determined by the time spent over ten strides. While the preferred step frequency at each speed varied from participant to participant, the average corresponding step frequencies for 0.5, 1.0, and 1.5 m/s were 71 ± 3, 101 ± 3, and 123 ± 3 steps/min (mean ± standard error of the mean, here and throughout). A metronome was used to indicate the correct stepping frequency to the participant. The participants stepped at a frequency that was within 2.5% of the desired frequency. To ensure that each participant achieved maximum EMG amplitude during recumbent stepping, we adjusted the resistance to the highest resistance at which the participant could maintain the fastest stepping frequency for 10 s. We recorded trials at that frequency corresponding to 1.5 m/s for 10 s and trials at frequencies corresponding to walking speeds of 0.5 and 1.0 m/s for 20 s. We instructed the participants to move through the full range of motion allowed by the recumbent stepping machine. Prior to collection, during practice, we adjusted the seat and handles so that the participant could most comfortably drive the machine.

Data acquisition and analysis

Goniometers

We recorded kinematic data using five electrogoniometers (Biometric Ltd., Ladysmith, VA) placed unilaterally on the left side on six of the ten participants' ankle, knee, hip, elbow, and shoulder joints. Data were not available for the other four subjects because of equipment malfunctions. The electrogoniometers were zeroed while the participants stood in a neutral position. The computer sampled electrogoniometer data at 1,000 Hz. We processed the electrogoniometer data with a second order low-pass Butterworth filter (cutoff frequency 6 Hz).

Electromyography

We recorded EMG data using surface electrodes placed unilaterally on the left side on eight lower limb muscles: soleus (SO), tibialis anterior (TA), medial gastrocnemius (MG), lateral gastrocnemius (LG), vastus medialis (VM), vastus lateralis (VL), medial hamstring (MH), and rectus femoris (RF); and four upper limb muscles: biceps brachii (BB), triceps brachii (TB), anterior deltoid (AD), and posterior deltoid (PD). We placed EMG electrodes (diameter 1.1 cm, interelectrode distance 3.5 cm) longitudinally over the belly of the muscle. For some of the smaller participants, we decreased the interelectrode distance for TA and SO in order to prevent crosstalk (Winter et al.

1994). In order to minimize mechanical artifact we secured the electrodes with tape and medical wrap.

We processed the EMG signals with a second order high-pass Butterworth filter (cutoff frequency 20 Hz). We then full wave rectified the signals and filtered them with a second order low-pass Butterworth filter (cutoff frequency 6 Hz). We defined a step cycle during walking to be left heel strike to successive left heel strike and during recumbent stepping to be left leg extension to successive left leg extension. The step cycle was determined by a footswitch that turned on at heel strike in walking and at initiation of extension in stepping. The signals were averaged over five step cycles. To quantify the level of muscle activation during walking and stepping, we calculated root-mean-square (RMS) amplitude of the filtered, rectified EMG over the period where the footswitch was on and over the period where the footswitch was off. This was done to separate the relatively quiet periods of muscle activation from their more active periods (i.e. stance and swing). We normalized EMG RMS to the value calculated for walking at 1.5 m/s for each muscle in each participant to reduce inter-subject variability (Yang and Winter 1984).

Cross correlation

A cross correlation analysis on the EMG of each muscle allowed us to measure the differences between walking and recumbent stepping. The cross correlation coefficient was calculated by

$$R_{xy}(m) = \frac{\sum_{n=0}^{N-m-1} x_{n+m} y_n}{\sqrt{\left(\sum_{n=0}^{N-m-1} x_{n+m}\right)^2} \sqrt{\left(\sum_{n=0}^{N-m-1} y_n\right)^2}} \tag{1}$$

where N is the length of the vector, and x and y represent the conditions being correlated. The correlation sequence was reported in a vector of length $2N - 1$. The phase shift was measured with the zeroth phase shift in the middle of the sequence and the phase shifts ranging from $N + 1$ to $N - 1$. Cross correlation analysis on the EMG normalized over the gait cycle to vectors of length 1,000 resulted in a correlation coefficient vector of length 1,999 for each muscle. For comparison of muscle EMG across conditions, the correlation coefficient was reported at a zero phase shift. We used $R > 0.70$ to define relatively high correlations for EMG pattern comparisons (Wren et al. 2006). There is no absolute gold standard for the correlation magnitude representing high EMG pattern correlation, but Wren et al. (2006) provide evidence from inter-subject and inter-day data collections that support 0.70 as a reasonable choice. We did not use Pearson's product–moment correlation (another form of cross correlation) because it is affected by signal amplitude. Signal amplitude is not necessarily indicative of whether the same motor neurons are being activated.

The sensitivity of cross correlation analysis (using Eq. 1) to the range of data values does not make it ideal for comparing joint angle profiles. Different joints would require different standards for high correlations and the choice of the zero angle position would greatly influence the correlation coefficients. As a result, we chose to use joint range of motion to compare joint kinematics between conditions.

Principal components analysis (PCA)

We examined the overall muscle synergy by performing a PCA that examined the phasic similarities of eight lower limb muscle EMG and four upper limb muscle EMG during gait and stepping (Ivanenko et al. 2004). The first step in performing a PCA was creating a 12×12-correlation matrix showing the linear dependence that one variable had on another. Factor scores were determined using an orthogonal varimax rotation of the eigenvectors of this matrix so that variables with similar activity were grouped together. Using the eigenvalues and eigenvectors of this matrix we described the variance of each factor. We determined the percent of total variability described by each factor by dividing its associated variance by the sum of the variances. Calculation of the total variability described by each factor revealed that in all conditions, the first four factors accounted for at least 96% of the variability. We therefore only considered the scores for the first four factors for all further analysis.

For comparison of factors across conditions, the maximum correlation coefficient and corresponding lag were reported. The first factor, the factor which described the largest percent of the variability, for both walking phases and recumbent stepping, was compared across conditions, just as the second factor, which described the second largest percent of the variability was compared across conditions and so on. A summarizing correlation coefficient for the factors was found by taking a weighted average of the maximum correlation between the first four factors based on the percent of the variance described by each of the components for walking. Because the first factor described over 65% of the variance in each of the conditions, the correlation coefficient for the first factor dominated the summarizing correlation coefficient.

For the comparison of factors, we used $R > 0.40$ to define a high correlation between conditions (Ivanenko et al. 2005). Different standards were used for defining high correlations when comparing muscle EMG patterns and factor scores because of differences in data content. Factor scores can be both positive and negative, while EMG data are only positive. This difference between the two parameters results in necessarily lower correlation coefficients when performing cross correlation analysis with Eq. 1. As with EMG patterns, there is no absolute gold standard for the correlation magnitude representing high correlation. However, the data from a range of tasks, subjects, and muscles presented by Ivanenko et al. (2005) make 0.40 a reasonable choice.

From a theoretical standpoint, we did not consider it valid to use principal component analysis on our joint kinematic data. During recumbent stepping subjects' joint motions were prescribed by the kinematic linkages of the device. As such, derivation of a reduced set of principal factors contributing to the coordination of the joints would seem to be meaningless.

Statistics

To determine the effects of speed and condition (3 speeds $\times$ 3 conditions) on the dependent variables (EMG RMS, correlation, percent of the variance explained by the factors, and range of motion) we used a repeated measures factorial ANOVA. We set the significance level to $P < 0.05$. If the ANOVA resulted in a significant effect, we used Tukey honestly significant different (THSD) tests for comparisons ($P < 0.05$).

Results

EMG pattern correlation

Visual inspection of averaged EMG data suggested a few distinct differences between the two walking conditions and recumbent stepping. Medial hamstring activation was out of phase for recumbent stepping compared to walking (Fig. 2). Soleus activation was shifted earlier in the step cycle for recumbent stepping compared to walking (Fig. 2). For the upper limb, all four muscles appeared to have fundamentally different muscle activation patterns (Fig. 3).

Cross correlation analysis of individual muscle EMG patterns between all three conditions revealed relatively high correlations ($R > 0.70$) for 7 of the 12 muscles (Fig. 4). In contrast, SO, TA, MG, LG, and the MH EMG patterns had predominantly low correlations ($R < 0.70$) between stepping and walking conditions for the three testing speeds (Fig. 4). Correlations between each of the two walking conditions and recumbent stepping were significantly lower than correlations between the two walking conditions for all muscles ($P < 0.05$) except VL ($P = 0.39$). The correlation coefficients comparing walking and recumbent stepping were lower at faster speeds for LG, RF, MH, BB, and TB ($P < 0.05$).

EMG principal components

The variance explained by the first factor and the first four factors was larger for stepping than it was for the two walking conditions ($P = 0.0001$, $P = 0.0002$, respectively) (Fig. 5). The average percent of the variance, across speeds, explained by the first factor for walking with 0% BWS, walking with 50% BWS, and recumbent stepping was 71.9 ± 2.6, 68.0 ± 2.1, and $80.5 \pm 2.3\%$, respectively. The average percent of the variance explained by the first four factors for walking with 0% BWS, walking with 50% BWS, and recumbent stepping was 97.2 ± 0.4, 97.8 ± 0.2, and $98.6 \pm 0.1\%$. The amount of the variance described by the first four factors varied with speed ($P = 0.0103$). Less of the variance was described by the first four factors for walking at 1.0 and 1.5 m/s and stepping at the corresponding frequencies than for walking at 0.5 m/s and stepping at the corresponding step frequency. Thus, faster step frequencies need more factors to describe the same variability of EMG signal content.

Factor loading revealed that the factors for the two walking conditions were weighted more heavily on leg muscle activation patterns than arm muscle activation patterns (Fig. 6). This was especially true for the first factor that explained at least 65% of the variance of the data. During both walking and recumbent stepping, upper limb muscle activation did not contribute greatly to the factors.

The factor analysis revealed that there was a relatively high correlation between factors for walking and recumbent stepping. The summarizing correlation coefficient, the weighted average correlation of factors based on the percentage of variance explained by each factor, was greater than 0.40 for recumbent stepping and walking (Table 1). However, the correlation between each of the two walking conditions and recumbent stepping was significantly lower than the correlation between the two walking conditions ($P < 0.0001$). The summarizing correlation coefficient between the factors did not vary with speed

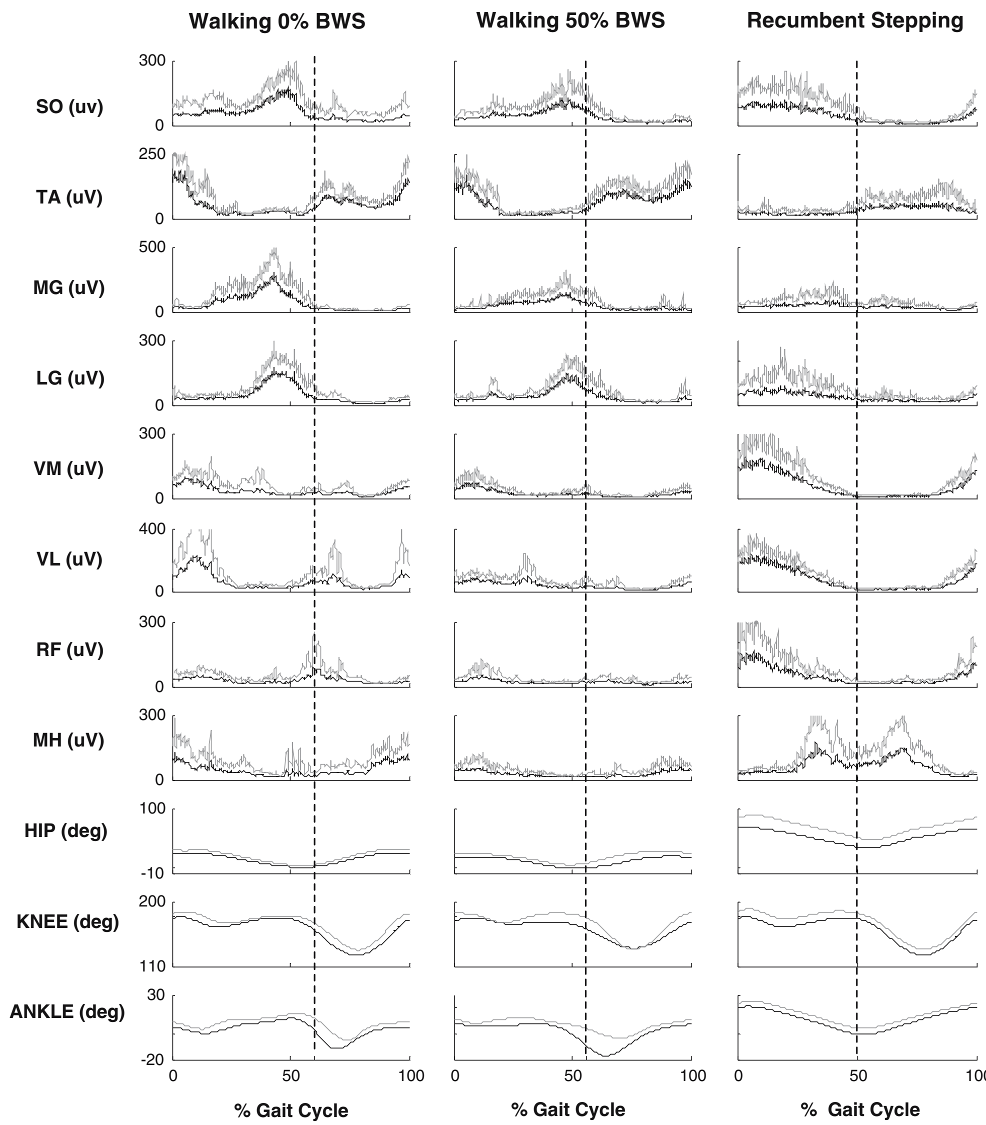


Fig. 2 Averaged rectified lower limb EMG and joint angle [soleus (*SO*), tibialis anterior (*TA*), medial gastrocnemius (*MG*), lateral gastrocnemius (*LG*), vastus medialis (*VM*), vastus lateralis (*VL*), medial hamstring (*MH*), rectus femoris (*RF*), ankle (*ANK*), knee (*KNEE*), hip (*HIP*)] walking with 0% BWS and 50% BWS at 1.5 m/s and recumbent stepping at the corresponding frequency averaged over five step cycles. The data are normalized over the gait cycle. *Dashed lines* represent the split between stance (extension) and swing (flexion) phase. *Grey traces* indicate plus one standard deviation

($P = 0.787$). The lags where the correlation was a maximum are reported in Table 2.

EMG amplitudes

There were differences in muscle activation amplitudes between walking and recumbent stepping conditions. During both stance and swing phases (corresponding to limb extension and flexion for recumbent stepping), thigh and upper limb muscle EMG RMS values were significantly lower during either walking condition than during recumbent stepping ($P < 0.0005$) (Figs. 7, 8). Leg muscle EMG RMS values were more similar across the three conditions with differences in magnitude dependent on stance or swing phase. During the stance phase (corresponding to the extension phase in recumbent stepping), TA and MG EMG RMS were lower during stepping than during walking ($P < 0.0001$). During the swing phase (corresponding to the flexion phase in recumbent stepping), SO, MG, and LG EMG RMS values were higher during stepping than during walking ($P < 0.005$).

Kinematics

Kinematic analyses revealed substantial differences between walking and recumbent stepping (Table 3). All joints except the shoulder joint had significantly different minimum and maximum joint angles for walking and recumbent stepping for the three testing speeds ($P < 0.05$). The shoulder had significantly different minimum joint angles for the two tasks ($P < 0.05$), but comparable maximum joint angles. Excursions of the hip, elbow, and shoulder were sig-

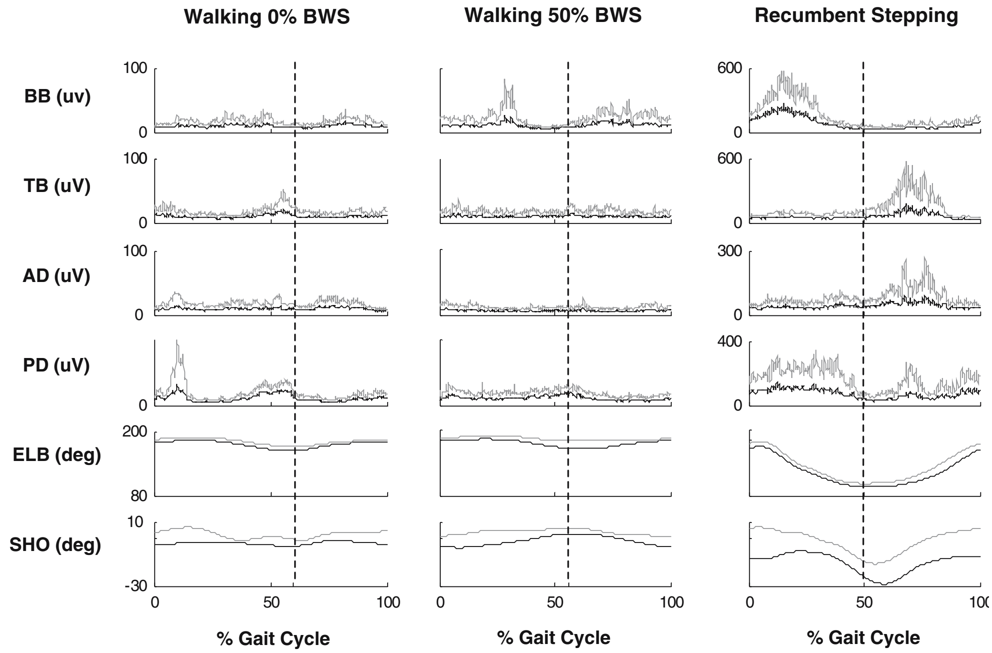


Fig. 3 Averaged rectified raw upper limb EMG and joint angle data [biceps brachii (*BB*), triceps brachii (*TB*), anterior deltoid (*AD*), posterior deltoid (*PD*), elbow (*ELB*), shoulder (*SHO*)] for walking with 0% BWS and 50% BWS at 1.5 m/s and recumbent stepping at the corresponding frequency averaged over five step cycles. The data are normalized over the gait cycle. *Dashed lines* represent the split between stance (extension) and swing (flexion) phase. *Grey traces* indicate plus one standard deviation

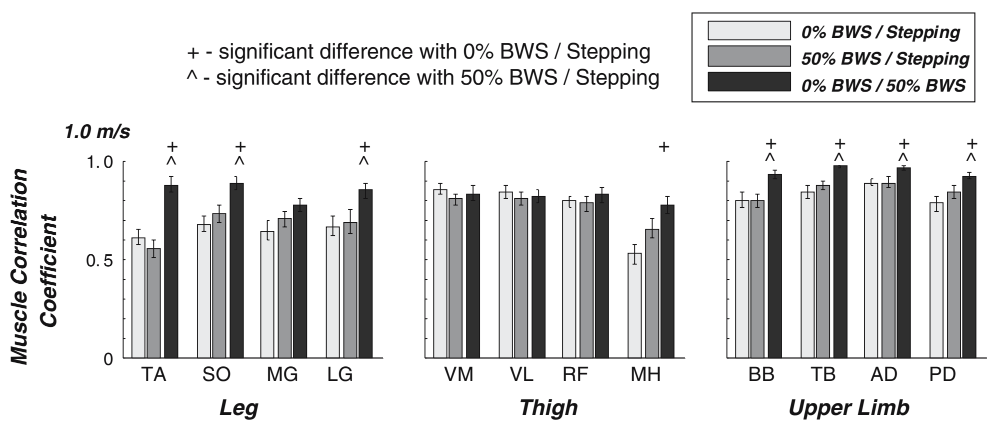


Fig. 4 Averaged ($n = 10$) correlation coefficient for muscle EMG (*TA, SO, MG, LG, VM, VL, MH, RF, BB, TB, AD, PD*) for walking at 1.0 m/s and stepping at the corresponding frequency. We reported the correlation at the zeroth lag for all three conditions (walking with 0% BWS correlated with stepping, walking with 50% BWS correlated with stepping, and walking with 0% BWS correlated with walking with 50% BWS)

nificantly less for walking than for recumbent stepping ($P < 0.05$) (Table 3). Joint ranges of motion sometimes significantly changed with speed for walking but not for recumbent stepping (Table 3). At some speeds, excursion of the knee and ankle was greater for recumbent stepping than it was for walking with 50% BWS ($P < 0.05$), but there was no significant difference between knee and ankle excursion for recumbent stepping and walking with 0% BWS ($P > 0.05$). Due to the mechanical coupling of the recumbent stepping machine, there were no significant differences in minimum, maximum, and excursion across recumbent stepping speeds ($P > 0.05$).

Discussion

The similarity in muscle activation patterns and muscle activation factors suggest that walking and recumbent stepping use similar neural substrates for control despite large differences in joint kinematics. This conclusion is based on the assumption that similarity in muscle activation patterns is indicative of similarity in neural substrates (Ivanenko et al. 2005; Cappellini et al. 2006).

We found a high correlation between the first four muscle activation factors, found by a PCA, in walking and recumbent stepping (Table 1). Summarizing cross

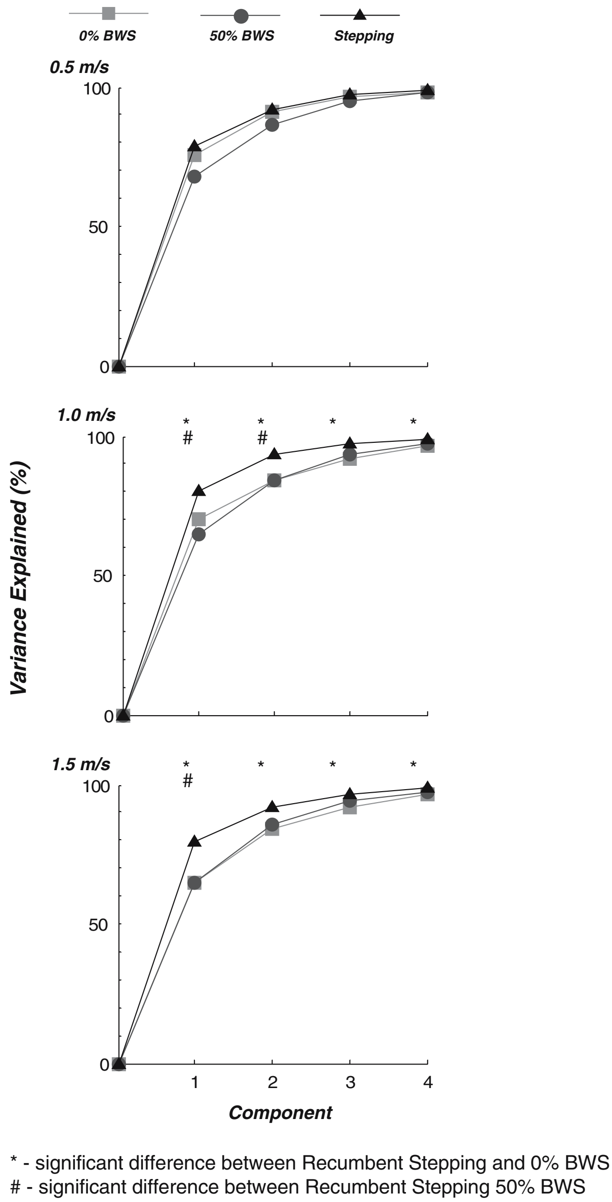


Fig. 5 The averaged (n = 10) cumulative percentage of the variance explained by each of the first four factors is shown for the three walking speeds and the corresponding stepping frequencies for each of the three conditions

correlation coefficients when comparing walking to recumbent stepping were greater than 0.40. Those factors described more than 96% of the variability of the muscle activation patterns we recorded. The similarity in the factors indicates stepping activates similar motor pathways as walking, despite temporal differences in individual muscle EMG. For comparison, Ivanenko et al. (2005) studied voluntary movements interposed with walking and found that kicking a ball while walking did not create muscle activation factors that were very different from normal walking (R > 0.40). However, when their subjects stooped during walking, muscle activation factor correlation to walking decreased to ~0.20.

When we directly compared individual muscle activation patterns for recumbent stepping and walking, we found high correlation coefficients for many of the muscles from which we recorded. All of the upper limb and thigh muscles except for the MHs had correlation coefficients above 0.70 (Fig. 4). It is important to note that magnitude of the correlation coefficients is different for rectified electromyography patterns and factors because of the different range of the signals (see Materials and methods).

The four muscles crossing the ankle (SO, MG, LG, and TA) and the MHs had correlations between walking and recumbent stepping of less than 0.70 (Fig. 4). Of these muscles, the MHs had the largest shift in timing between walking and recumbent stepping (Fig. 2). The lower correlations for the five muscles may be related to their dependence on afferent feedback for activation. Many studies have found evidence that the triceps surae muscles and the hamstrings are highly dependent on afferent mediated excitation (Duysens et al. 1998; Faist et al. 1999; Sinkjaer et al. 2000; Van De Crommert et al. 2003; Donelan and Pearson 2004; Mazzaro et al. 2005; Faist et al. 2006; Mazzaro et al. 2006). It would be instructive to know if changes in hip or knee posture during recumbent stepping could modify muscle activation patterns so that they were more similar to walking. As for the TA, there is evidence that it is more dependent on cortical activation than other lower limb muscles during walking (Capaday et al. 1999). The differences in TA muscle activation patterns between the two tasks may be related to descending signals that are modified in a task dependent manner.

Recumbent stepping appears to be a simplified version of walking. Fewer factors are required to describe the variance of the EMG data during recumbent stepping than during walking. While EMG patterns for walking at faster frequencies require more factors to describe the variability of the data, the percent of the variance described by each of the factors is constant across all three recumbent stepping frequencies. Both of these observations are likely related to the differences in afferent feedback between the two tasks. If the walking motor pattern represents a combination of cortical and spinal muscle activation overlaid with afferent mediated activation, then the recumbent stepping motor pattern will be lacking in some of the walking motor pattern complexity due to the constrained kinematics and differences in loading.

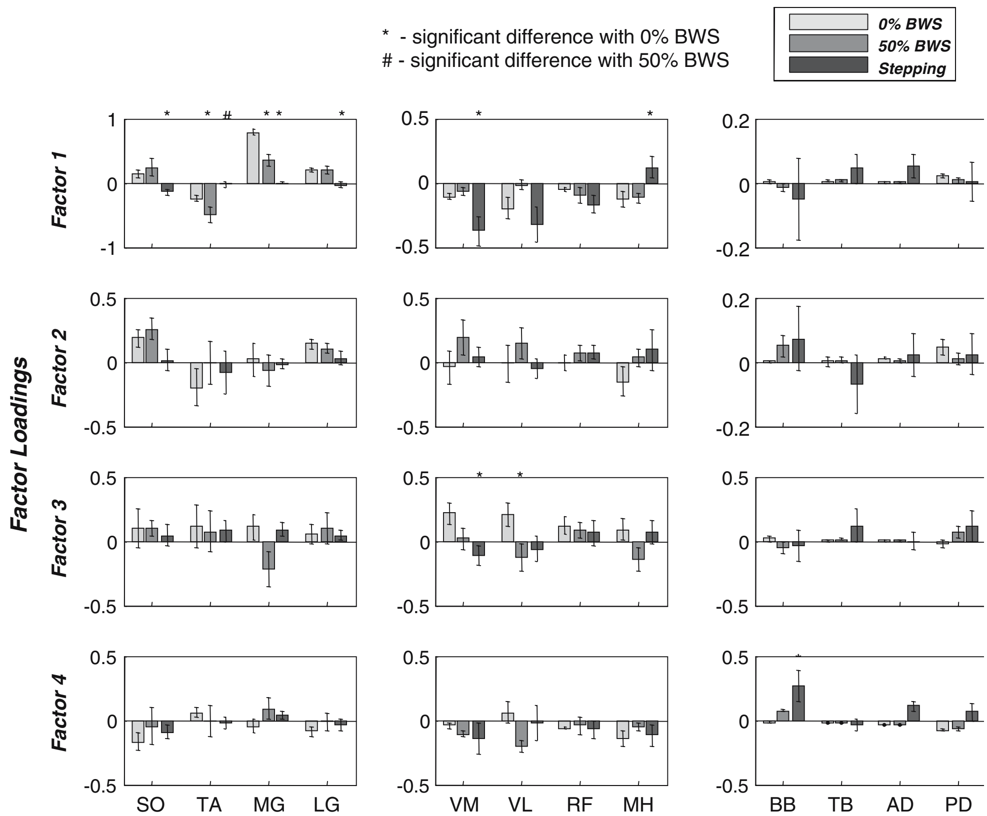


Fig. 6 The averaged (n = 10) factor loadings for the first four factors for walking at 1.0 m/s and stepping at the corresponding frequency. Note the different y-axes scales. The preponderance of loading originated from the lower limb muscles and not the upper limb muscles

Table 1 Summarizing correlation coefficients of principal components

Speed (m/s)	Summarizing correlation coefficient		
	0% body weight support (BWS)/stepping	50% BWS/stepping	0% BWS/50% BWS
0.5	0.54 ± 0.04	0.59 ± 0.04	0.66 ± 0.03
1.0	0.52 ± 0.03	0.56 ± 0.05	0.69 ± 0.03
1.5	0.56 ± 0.05	0.55 ± 0.03	0.69 ± 0.04
Overall	52 ± 0.03	56 ± 0.04	68 ± 0.03

The summarizing correlation coefficient between each of the walking phases and recumbent stepping indicated a strong correlation between the two conditions (R > 0.40), but was significantly less than the summarizing correlation coefficient between the two walking phases. The summarizing correlation coefficient was found by taking the weighted average of the correlation coefficient for the first four factors based on the percent of the variability of the muscle EMG each of the component described

Table 2 Average (n = 10) lag where the correlation coefficient of factors is at a maximum. Lag is reported as percent of the gait cycle

Correlation	Speed (m/s)	Lag			
		Factor 1	Factor 2	Factor 3	Factor 4
0% BWS/stepping	0.5	–8.5 ± 6.1	–10.9 ± 13.6	4.1 ± 3.7	22.5 ± 9.1
50% BWS/stepping		8.6 ± 10.4	10.0 ± 10.0	6.4 ± 12.7	9.7 ± 8.8
0% BWS/50% BWS		–5.6 ± 4.1	–10.6 ± 13.1	3.6 ± 15.5	2.0 ± 11.7
0% BWS/stepping	1.0	–4.0 ± 9.0	2.6 ± 8.7	–12.6 ± 12.2	–10.3 ± 7.3
50%BWS/stepping		6.2 ± 10.5	–28.4 ± 11.7	1.4 ± 6.3	14.3 ± 10.5
0% BWS/50% BWS		–7.5 ± 4.4	165 ± 99	26.0 ± 12.2	13.6 ± 13.6
0% BWS/stepping	1.5	9.4 ± 9.2	–25.2 ± 12.9	5.5 ± 12.4	–2.6 ± 13.4
50%BWS/stepping		13.7 ± 12.0	–31.0 ± 11.1	9.0 ± 9.0	30.8 ± 8.0
0% BWS/50% BWS		3.5 ± 3.9	–16.7 ± 8.7	32.6 ± 13.8	–15.7 ± 7.0

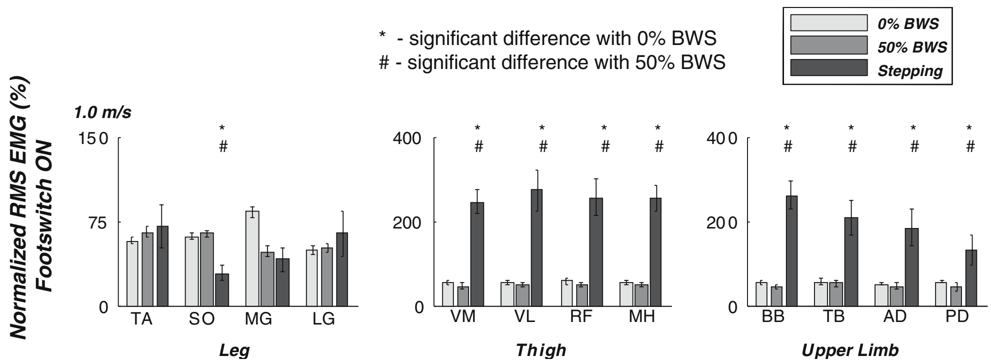
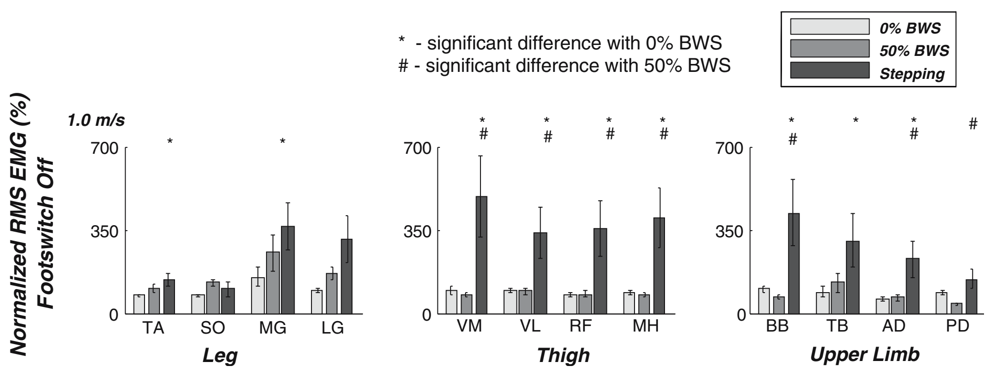


Fig. 7 Averaged root-mean-square (*RMS*) EMG during stance (extension) with standard error bars for walking at 1.0 m/s and stepping at the corresponding frequency (n = 10, normalized to normal walking at 1.5 m/s). Tibialis anterior and MG EMG RMS was significantly greater during walking than during recumbent stepping. Thigh and upper limb EMG RMS was significantly less during each of the walking conditions than during recumbent stepping

Fig. 8 Averaged RMS EMG during swing (flexion) with standard error bars for walking at 1.0 m/s and stepping at the corresponding frequency (n = 10, normalized to walking at 0% BWS at 1.5 m/s). Thigh and upper limb EMG RMS was significantly less during each of the walking conditions than during recumbent stepping



Despite the strong correlation between the motor patterns during walking and recumbent stepping, the motion of recumbent stepping is fundamentally different from walking in several aspects. First, recumbent stepping does not allow for much variability in the kinematic pattern from step to step. Each subject's kinematic patterns are defined by the position of the seat, handles, and pedals. Second, recumbent stepping generally has smaller lower limb forces than walking and recumbent steppers maintain foot-surface contact for the entire step cycle rather than in discrete bouts of the step cycle (Huang and Ferris 2004; Kao and Ferris 2005). Third, the ranges of motion of the shoulder, elbow, ankle, and hip joints are very different for the two tasks. The hip joint differences in particular could affect stepping motor patterns as hip afferents play a critical role in the neural control of walking (Grillner and Rossignol 1978; Dobkin et al. 1995; Whelan et al. 1995; Pang and Yang 2000; Lam and Pearson 2001; Knikou and Rymer 2002; Ferris et al. 2004; Steldt and Schmit 2004; McVea et al. 2005). It is likely that these kinematic differences explain the majority of the discrepancy between the motor patterns for walking and recumbent stepping.

We studied walking at both 0 and 50% BWS in order to determine if the magnitude of lower limb force influenced the similarity of muscle activation patterns between walking and recumbent stepping. We did not find any substantial differences in correlation of muscle activation patterns or factors between walking with 0% BWS and recumbent stepping and walking with 50% BWS and recumbent stepping. This was not surprising given results from Ivanenko et al. (2004) that show that BWS does not have a substantial effect on muscle activation patterns, but was helpful for confirming the conclusions in our study.

Stepping practice has been shown to facilitate gait rehabilitation after neurological injury (Hesse et al. 1994, 1995; Wernig et al. 1995, 1998, 1999; Dietz et al. 1998; Behrman and Harkema 2000). Two common ways for neurologically impaired patients to practice stepping are walking with support from parallel bars and walking with harness support on a treadmill (Dobkin et al. 2006). An alternative is for patients to practice lower limb stepping motions using a mechanical exercise machine. To be effective as a rehabilitation therapy, however, the stepping motion would have to activate the neural networks used for walking.

Table 3 Average (n = 6) joint (hip, knee, ankle, elbow, shoulder) range of motion (minimum, maximum, and excursion) ± standard error

Condition	Speed (m/s)	Minimum	Maximum	Excursion
Hip				
0% BWS	0.5	0.8 ± 1.1	18.0 ± 2.1	17.2 ± 2.8
50% BWS		–1.0 ± 2.5	12.5 ± 3.6	13.5 ± 2.1
Stepping		33.0 ± 6.4[a,b]	67.4 ± 7.6[a,b]	34.4 ± 4.9[a,b]
0% BWS	1.0	1.4 ± 0.7	22.0 ± 2.7[c]	20.6 ± 2.9
50% BWS		–1.9 ± 2.6	17.0 ± 3.3	18.8 ± 1.8
Stepping		31.5 ± 6.3[a,b]	68.4 ± 7.9[a,b]	37.0 ± 4.8[a,b]
0% BWS	1.5	–1.3 ± 1.0	24.5 ± 3.0[c,d]	25.8 ± 3.7[c,d]
50% BWS		–3.5 ± 2.4	20.1 ± 3.5[c]	23.7 ± 2.9[c]
Stepping		32.0 ± 6.0[a,b]	67.7 ± 8.2[a,b]	35.7 ± 4.7[a,b]
Knee				
0% BWS	0.5	–49.5 ± 2.6	1.3 ± 1.7	50.7 ± 3.5
50% BWS		–38.0 ± 2.5[a]	–1.8 ± 2.8	36.1 ± 2.7
Stepping		–65.9 ± 4.2[a,b]	–11.9 ± 4.4[a]	53.9 ± 6.8[b]
0% BWS	1.0	–57.1 ± 2.5[c]	2.7 ± 2.4	59.7 ± 4.3[c]
50% BWS		–47.6 ± 1.7[c]	2.4 ± 2.6[c]	49.9 ± 3.8[c]
Stepping		–66.8 ± 3.8[b]	–8.9 ± 3.1[a,b]	57.9 ± 4.9
0% BWS	1.5	–56.5 ± 2.2[c]	2.5 ± 2.5	59.0 ± 4.1[c]
50% BWS		–48.2 ± 2.3[c]	1.7 ± 2.4[c]	49.8 ± 3.8[c]
Stepping		–65.9 ± 4.2[b]	–9.1 ± 3.1[a,b]	56.8 ± 4.9
Ankle				
0% BWS	0.5	–5.6 ± 1.1	13.6 ± 1.0	19.2 ± 1.9
50% BWS		–1.9 ± 1.5	10.6 ± 2.7	12.6 ± 2.7
Stepping		0.2 ± 2.8	2.5 ± 1.5[a,b]	22.4 ± 3.4[b]
0% BWS	1.0	–10.5 ± 1.7	15.9 ± 1.4[c]	26.4 ± 1.0[c]
50% BWS		–17.2 ± 3.7[c]	8.8 ± 2.1[a]	26.0 ± 3.2[c]
Stepping		–1.6 ± 2.3[b]	21.4 ± 1.4[a,b]	23.0 ± 2.6
0% BWS	1.5	–15.5 ± 2.1[c]	13.4 ± 1.1[d]	28.8 ± 1.6[c]
50% BWS		–22.1 ± 3.9[c]	9.9 ± 1.43	32.0 ± 3.4[c]
Stepping		–1.4 ± 2.0[a,b]	21.0 ± 1.4[a,b]	22.3 ± 2.4[b]
Elbow				
0% BWS	0.5	–4.0 ± 0.6	1.2 ± 0.6	5.1 ± 0.9
50% BWS		–1.7 ± 1.4	2.6 ± 0.7	4.3 ± 1.7
Stepping		–83.8 ± 3.1[a,b]	–12.2 ± 5.6[a,b]	71.6 ± 6.7[a,b]
0% BWS	1.0	–11.3 ± 2.8[c]	1.8 ± 1.8	13.1 ± 2.4
50% BWS		–9.3 ± 3.8	2.6 ± 0.9	11.9 ± 4.5
Stepping		–85.9 ± 3.2[a,b]	–7.4 ± 4.6	78.5 ± 5.4[a,b]
0% BWS	1.5	–18.2 ± 2.8[c]	3.9 ± 1.8	22.1 ± 4.4[c,d]
50% BWS		–18.2 ± 5.0[c]	4.5 ± 1.6	22.7 ± 4.5[c,d]
Stepping		–86.0 ± 2.6[a,b]	–9.6 ± 3.8[a,b]	76.3 ± 4.5[a,b]
Shoulder				
0% BWS	0.5	–4.2 ± 0.7	0.7 ± 2.1	4.9 ± 1.6
50% BWS		–1.8 ± 2.4	2.6 ± 1.4	4.4 ± 1.5
Stepping		–28.2 ± 4.1[a,b]	–4.7 ± 4.8	23.5 ± 2.0[a,b]
0% BWS	1.0	–9.6 ± 1.5[c]	–0.4 ± 3.2	9.2 ± 4.6
50% BWS		–4.8 ± 2.9	2.3 ± 1.3	7.1 ± 1.9
Stepping		–30.1 ± 4.0[a,b]	–5.0 ± 5.0	25.1 ± 1.2[a,b]
0% BWS	1.5	–9.5 ± 0.8[c]	2.1 ± 3.1	11.6 ± 3.7[c]
50% BWS		–7.2 ± 3.3[c]	2.9 ± 1.3	10.1 ± 3.2
Stepping		–31.3 ± 4.9[a,b]	–4.8 ± 6.5	26.5 ± 1.3[a,b]

Separate ANOVAs were run to determine the significance of condition independent from changes in speed. Excursion of the hip, elbow, and shoulder were significantly less for walking than they were for recumbent stepping ($P < 0.05$). Minimum and maximum joint angles were significantly different between the two conditions for all joints except the shoulder

[a] Significant difference with 0% BWS

[b] Significant difference with 50% BWS

[c] Significant difference with 0.5 m/s

[d] Significant difference with 1.0 m/s

Recent evidence suggests that there a few basic neural signals produced by a locomotor pattern generator and shaped appropriately by cortical inputs and proprioceptive feedback to regulate a number of rhythmic motor tasks (Zehr 2005). The findings from this study suggest that similar motor patterns control walking and recumbent stepping despite the kinematic differences. It would be possible to modify the recumbent stepper or use a different machine altogether [e.g. limb-loaded cycle ergometer (Brown et al. 2005)] to make the kinematic pattern more similar to walking. However, it is important that any stepping device provides easy transfer from a wheelchair so that patients could readily use the device by themselves. There are several commercially available devices that allow patients to practice a simplified stepping motion (Hesse and Uhlenbrock 2000; Ferris et al. 2006) but patients are more likely to have access to the devices if they are low cost and are user friendly for independent exercise. Future training studies need to consider these aspects when they test the clinical efficacy of long-term stepping exercise on gait rehabilitation.

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