Journal of Electromyography and Kinesiology 37 (2017) 61–67

Contents lists available at ScienceDirect

Journal of Electromyography and Kinesiology

journal homepage: www.elsevier.com/locate/jelekin

Temporal changes in motor variability during prolonged lifting/lowering and the influence of work experience

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ARTICLE INFO

Keywords:
Work-related musculoskeletal disorders
Motor control
Fatigue
Goal equivalent manifold
Experienced workers

ABSTRACT

Existing research indicates that repetitive motions are strongly correlated with the development of work-related musculoskeletal disorders (WMSDs). Resulting from the redundant degrees-of-freedom in the human body, there are variations in motions that occur while performing a repetitive task. These variations are termed motor variability (MV), and may be beneficial for reducing WMSD risks. To better understand the potential role of MV in preventing injury risk, we evaluated the effects of fatigue on MV using data collected during a lab-based prolonged, repetitive lifting/lowering task. We also investigated whether experienced workers used different motor control strategies than novices to adapt to fatigue. MV of the whole-body center-of-mass (COM) and box trajectory were quantified using cycle-to-cycle standard deviation, sample entropy, and goal equivalent manifold (GEM) methods. In both groups, there were significantly increased variations of the COM with fatigue, and with a more substantial increase in a direction that did not affect task performance. Fatigue deteriorated the task goal and made it more difficult for participants to maintain their performance. Experienced workers also had higher MV than novices. Based on these results, we conclude that flexible motor control strategies are employed to reduce fatigue effects during a prolonged repetitive task.

1. Introduction

Work-related musculoskeletal disorders (WMSD) continue to be prevalent problems in industrial societies (Buckle and Devereux, 2002; da Costa and Vieira, 2010). WMSDs have substantial adverse impacts on employers, such as resulting from lost productivity (Stewart et al., 2003), on general society, such as from financial consequences (Badley et al., 1994; Chiasson et al., 2012), and on employees themselves, such as due to a deteriorating quality of life (Devereux et al., 1999). Multiple risk factors contribute to musculoskeletal disorders; among these, physical, psychological, and individual factors are the primary domains that have been associated with WMSDs (Armstrong et al., 1993; Bongers et al., 1993; David, 2005; Winkel and Mathiassen, 1994). Experimental and epidemiologic studies have shown high correlations between physical job aspects (e.g. excessive force, non-neutral posture, vibration, and repetition) and WMSDs (Chiasson et al., 2012; da Costa and Vieira, 2010; Punnett and Wegman, 2004). Jobs involving manual materials handling in particular, especially lifting/lowering tasks, have been long recognized as an important risk factor contributing WMSD risks (da Costa and Vieira, 2010). Individual differences also appear to be important contributing factors, including age, gender, education, lifestyle, obesity, smoking, strength, and work history (Punnett and Wegman, 2004; Waters et al., 2007). Here, repetitive motion (lifting/lowering) was of particular interest as a physical risk factor, as well as the potential role of work experience as an individual difference.

Repetitive motion, in the context of ergonomics, refers to performing a stereotypical or cyclic task for prolonged periods (Kilbom, 2000), and such exposures have been linked to a considerable portion of WMSDs (Malchaire et al., 2001; Marras et al., 2006; Nordander et al., 2009; Srinivasan and Mathiassen, 2012; van der Windt et al., 2000). Recently, researchers have posited that "internal variation" in human movement may be a useful method to reduce or prevent WMSDs (Srinivasan and Mathiassen, 2012). The central nervous system (CNS) has redundant solutions to execute a repetitive task because of the large number of degrees-of-freedom available for most human movements (including lifting/lowering). The existence of such kinematic redundancies leads to inherent movement variations in performing a specific task (Bernstein, 1967). Recently, workers in the field of motor control have suggested that these variations, called motor variability (MV), are an essential characteristic of the CNS (Newell and Corcos, 1993). It seems that the CNS can use MV to increase flexibility and adaptability of human movement (Gaudez et al., 2016); in other words,

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https://doi.org/10.1016/j.jelekin.2017.09.001
Received 16 March 2017; Received in revised form 9 August 2017; Accepted 8 September 2017
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the CNS can regulate movement by using MV (Latash et al., 2002). For example, there is some evidence that suggests the CNS may employ MV as a mechanism to postpone the development of fatigue during a prolonged task (Bartlett et al., 2007). However, Samani et al. (2017) found that MV did not play a substantial role in reducing fatigue development during a dynamic task.

Fatigue, which is an exercise-induced reduction in muscular capability (Bigland-Ritchie et al., 1986) typically has an adverse impact on task performance (Srinivasan and Mathiassen, 2012) and may increase the risk of WMSDs. Several studies have explored the association between MV and fatigue, and found that fatigue develops more slowly if individuals use more variation in their movement patterns (Cignetti et al., 2009; Fuller et al., 2009; Sparto et al., 1997). From such evidence, it can be speculated that individuals explore alternative movement solutions to maintain task performance and that these explorations lead to increased MV (Fuller et al., 2011). Moreover, skilled performers might have an enhanced ability to adapt with fatigue (Srinivasan and Mathiassen, 2012). As an illustration, Aune et al. (2008) found that the performance of skilled tennis players was maintained in the presence of fatigue, through changing MV, while MV was consistent among novice players.

There is an association between the level of experience (as an individual difference) and movement patterns, and these differences may lead to differences in the risk of injury (Srinivasan and Mathiassen, 2012). Previous studies have reported that WMSDs were more prevalent (Bigos et al., 1986) and occurred earlier among novices (Van Nieuwenhuyse et al., 2004), and workers experienced in manual materials handling have been found to have lower loads on the back (Chany et al., 2006; Lett and McGill, 2006). Experienced workers were also found to have more stable movements (based on Lyapunov exponents) during repetitive lifting (Lee and Nussbaum, 2013). These results suggest that experienced individuals may develop motor control strategies that reduce the risk of injury (Gagnon, 1997, 2003, 2005). Moreover, some studies have found an association between MV and the level of experience. For example, MVs were higher among experienced butchers in a cutting task (Madeleine et al., 2008). In a repetitive lifting task, Lee and Nussbaum (2012) found substantial differences in movement variations between novices and experienced workers. These authors also found that MV was directly associated with lumbar moments, implying a relationship between MV and back injury risk (Lee and Nussbaum, 2013). In a previous analysis (Sedighi, 2017), our results indicated that, in a brief, repetitive lifting/lowering task, experienced workers exhibited consistent movement behavior in both symmetric and asymmetric conditions. Novices, however, had more constrained movements in the asymmetric condition, while the movements of experienced individuals were slightly more flexible in this task.

One important challenge with investigating the association between motion variation and fatigue/work experience is in quantifying MV. This quantification proves difficult, because there are three diverse classes of methods that have been used for quantifying motion variations, and each one involves different fundamental approaches (Stergiou, 2004). For some time, many researchers have utilized the first class of methods, which are based on descriptive statistics, or *linear methods*. The second class consists of several tools from chaos theory (*nonlinear methods*), and these have been widely employed in the field of motor control to study MV. The third class, called "*equifinality*" (Cusumano and Cesari, 2006), focuses on the noted redundant degrees-of-freedom that are available for the CNS to execute a specific task. Several examples of equifinality methods are the uncontrolled manifold (UCM) (Scholz and Schöner, 1999; Schoner, 1995), tolerance noise covariation (Cusumano and Dingwell, 2013), minimum intervention principle (Todorov and Jordan, 2002), and goal equivalent manifold (GEM) (Cusumano and Cesari, 2006). It is worth noting that not all investigators agree with categorizing these methods as a subset of the equifinality class.

Directly measuring the association between MV and WMSDs is challenging, as is formally manipulating the former in a controlled study. However, as reviewed earlier, existing evidence does support an inverse association between MV and fatigue, suggesting that increased MV may decrease injury risk (Srinivasan and Mathiassen, 2012). There are a few reports (Lee et al., 2014) that have investigated how the CNS regulates movements among experienced individuals as they adapt with fatigue, and how these regulations differ from the behaviors of novices. However, important information that might existing within the trial-to-trial kinematics was neglected in these types of studies, and the methods employed were based on average behaviors and a minimal set of kinematic parameters. To address some of these limitations in existing evidence we completed work to address the following hypotheses. We first hypothesized that individuals change their MV during a repetitive lifting/lowering task in the presences of fatigue, and second that these adaptations are different between novices and experienced workers. Additionally, we assessed the sensitivity of multiple measures of MV (i.e., linear, nonlinear, and equifinality methods) with respect to the level of experience and the influence of fatigue, again in the context of a repetitive lifting/lowering task.

2. Method

2.1. Participants and procedures

For this study, data from a prior experiment (Lee et al., 2014) were used, in which 6 novices (NOV) and 6 experienced workers (EXP) participated (5 males and one female participant in each group). EXP participants were recruited from local workers, who each performed occupational lifting tasks on a regular basis. The NOV group was formed from among local university students, who were individually age-matched with the EXP group, and none of whom reported experience in repetitive lifting tasks. Participants first practiced an asymmetric (rotate 60° to the right) lifting/lowering task with a box 10 times. For each participant, box mass was adjusted to 15% of individual body mass. The horizontal location of the box (in the anterior-posterior direction), from the midpoint of the ankles at the lift origin/destination, was set to 38/69 cm. Height at the origin and destination were set to each participants' knee and elbow heights, respectively. The frequency of lifting was 30 lifting/lowering per minute, and participants used a freestyle lifting technique, but with a fixed position of their feet. Participants completed a set of 360 lifting/lowering cycles while holding the box continuously and with external pacing (via a metronome) used to control the cycle time. A 7-camera motion capture system (Nexus MX-T, VICON) was used to track 3D kinematics of the participants and the box trajectory, at a rate of 100 Hz. We low-pass filtered (bi-directional, 2nd-order Butterworth) the raw data with a cut-off frequency of 5 Hz. We determined the 3D-location of the whole-body center-of-mass (COM) for each participant using methods described by Dumas et al. (2007). Similar to Srinivasan et al. (2015), we defined the initiation of each lifting/lowering cycle by performing the following steps. First, we determined a time instance at which the box was located on the shelves while its velocity was at a minimum. In the next step, we determined the initiation of a given cycle using a threshold (3% of the peak box velocity).

2.2. Data analysis

Similar to Scholz and Schöner (1999), we considered the COM and BOX kinematics here for investigating differences between the motor control strategies utilized by EXP and NOV, specifically regarding adaptations to fatigue (i.e., over the course of the 360 lifting/lowering cycles). One aim of this study was to assess the relative sensitivity of the three classes of methods available for quantifying MV (i.e., linear, nonlinear and equifinality methods), here with respect to the level of experience and fatigue. For this, we chose one method from each of these classes to measure MV of the BOX and COM. We used cycle-to-cycle standard deviation (linear method) and sample entropy (non-linear method) for quantifying movement variations, since these methods have been widely applied in the field of motor control to quantify MV (Madeleine and Madsen, 2009; Samani et al., 2015; Srinivasan et al., 2015). The GEM method was selected among equifinality methods, since it can measure the temporal structure and magnitude of MV simultaneously (Cusumano and Dingwell, 2013).

Based on the methods implemented in a study by Srinivasan et al. (2015), we calculated cycle-to-cycle standard deviation (SD) of the following variables for the BOX and COM kinematics: path length (X), mean speed (V), and timing errors (ΔT: difference between the duration of a lifting/lowering cycle and the target cycle time). Sample entropy (SaEn) was computed (see Richman and Moorman (2000) for details) to measure complexity of the COM and BOX paths. For this, the state space was first reconstructed for the increment of COM/BOX trajectories because the original time series were highly correlated (Ramdani et al., 2009). This reconstruction was done using the time delay and embedding dimension, which were calculated based on well-developed methods, specifically autocorrelation (Rosenstein et al., 1993) and the false nearest neighbors approach (Kennel et al., 1992), respectively. To have consistent parameters across cycles and subjects, and similar to Samani et al. (2015), we first calculated the grand average of time delays over five non-overlapping time blocks (includes 72 cycles each) and participants. Time delays for the COM and the BOX time series were 310 and 360 ms, respectively. Then, a similar procedure was used to calculate the embedding dimensions (5 and 6 for the COM and the BOX time series, respectively). Then, we calculated SaEn as follow:

$$SaEn = -\ln(\Phi^{d_E+1}/\Phi^{d_E}) \tag{1}$$

where $\Phi^{d_E}(r)$ is the mean of $C_i^{d_E}(r)^{d_E}$ = (number of $X(j)$ such that $d[X(i),X(j)] < r$), d_E is the embedding dimension, $X(i)$ is reconstructed state space, r is 0.2 SD of the time series (Zhang and Zhou, 2012), and $d[X(i),X(j)]$ is the Chebyshev distance.

The GEM method was also applied to measure MV in the lifting/lowering task. Using this method, though, requires that a goal for the task is defined initially. We chose a constant cycle time as the GEM goal, since the lifting/lowering cycle time was externally paced. We expanded upon the method described by Dingwell and Cusumano (2010) to decouple movement variations between each cycle into variations in the GEM direction (δt_T) and in the direction perpendicular to the GEM direction (δt_P), as illustrated in Fig. 1. The goal of the task can be calculated by dividing the length of the COM/BOX path (X) by its corresponding velocity (V), or $T = X/V$. To compare MV between individuals in the GEM analysis, we need to normalize X and V to their standard deviations (Dingwell and Cusumano, 2010). The new goal function is thus T_n = mean (X_n/V_n), and any combination of X_n and V_n that satisfies the goal is located on the GEM (Fig. 1, solid line). Based on Fig. 1, it is clear that moving along with the GEM does not deteriorate the task goal; however, any departure from the goal line does affect the task timing. To quantify the amount of variability in the GEM and non-GEM relevant directions, we first find a preferred operating point, (V^*, X^*), a point on the GEM that has the minimum distance from the mean of (X_n, V_n) for the entire set of 360 cycles. Both variables are varying around the preferred operating point. These variations can be expressed as:

$$\begin{aligned} \nabla V_n &= V_n - V^* \\ \nabla X_n &= X_n - X^* \end{aligned} \tag{2}$$

By linearizing the above equation around (V^*, X^*), and finding its null and row space, we can compute δt_T, δt_P respectively as follows [see Cusumano and Cesari (2006) and Dingwell et al. (2013) for more details.

$$\begin{bmatrix} \delta t_T(i) \\ \delta t_P(i) \end{bmatrix} = \frac{1}{\sqrt{1+T_n}} \begin{bmatrix} 1 & T_n \\ -T_n & 1 \end{bmatrix} \begin{bmatrix} V_n(i)-V^* \\ X_n(i)-X^* \end{bmatrix} \tag{3}$$

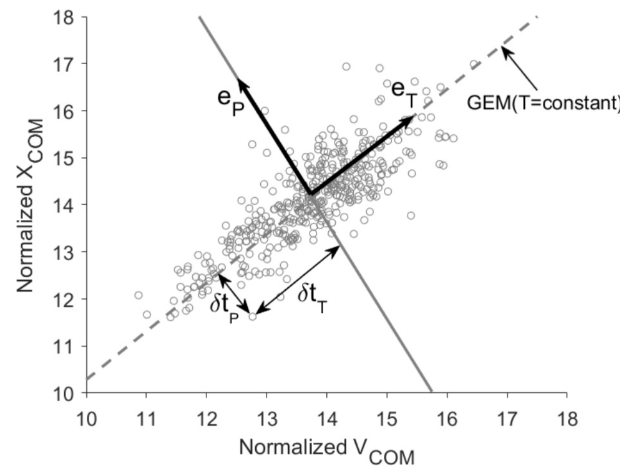

Fig. 1. Example results using the goal equivalent manifold (GEM) method to assess movement variability in a repetitive lifting/lowering task. Each lifting/lowering cycle is analyzed to yield normalized values of the COM position (X_{com}) and velocity (V_{com}), shown as the set of 360 circles for a given experimental trial. The main goal is a constant cycle time, indicated by the dashed line. Results for one lifting/lowering cycle are highlighted at the lower-left, for which δt_T is variability in the GEM direction (e_T), while δt_P is variation perpendicular to the GEM direction (e_P).

where $X_n(i) = X(i)/SD(X(i))$ and $V_n(i) = V(i)/SD(V(i))$ in which $X(i)$ is the length of the COM/BOX path at cycle i, and $V(i)$ is the corresponding speed. $SD(X(i))$ and $SD(V(i))$ are the respective standard deviations of $X(i)$ and $V(i)$ over all 360 lift/lower cycles.

As one set of measures from the GEM analysis, we computed the SD of δt_T and δt_P, which indicate the MV structure based on the average behavior of the system (Dingwell and Cusumano, 2010). We also calculated relative variability (i.e., $\sigma(\delta t_T)/\sigma(\delta t_P)$), which reflects available effective motor solutions for the CNS (Decker et al., 2012). Finally, Detrended Fluctuation Analysis (DFA; see Peng et al. (1993) (1994), and (1995)) was also used to study the temporal structure of δt_T and δt_P. DFA provides a scaling exponent, α, which indicates the persistency ($\alpha > 0.5$), anti-persistency of ($\alpha < 0.5$), or uncorrelated white noise ($\alpha = 0.5$) of a time series (here, δt_T and δt_P). Note that anti-persistency means the time series is highly correlated and suggests that the CNS corrects deviations from the GEM immediately, whereas persistency indicates that the CNS has less control over the time series and that deviations are not corrected frequently (Dingwell and Cusumano, 2010).

To derive the noted measures of MV (i.e., cycle-to-cycle SD, sample entropy, and GEM-based measures) for different levels of fatigue, five non-overlapping time blocks were considered, each including 72 lifting/lowering cycles. Then, we applied the described methods for each time block. The specific number of cycles (72) or time blocks (5, each 2.4 min.) were chosen somewhat arbitrarily, though these were found to yield observable differences over time. In addition, time blocks were desired that were longer than 2.13 min (64 cycles), since this yielded the minimum number of samples that is needed for assessing a time series using the DFA method (Delignieres et al., 2006).

2.3. Statistical analyses

Each of the outcome measures – from cycle-to-cycle SD, SaEn, and GEM analyses – were assessed using separate mixed-factor analysis of variance (ANOVA) models. In these models, the level of experience (LE) was a between-subjects factor and level of fatigue (LF, represented by the five time bocks) was a within-subjects factor. A similar approach, with the addition of direction (D), was used for comparing SD/α of variations in the GEM with that in the direction perpendicular to the GEM (i.e., δt_T and δt_P). These analyses were done with JMP (13.0.0, SAS Institute Inc., Cary, NC), using the REML method. Parametric model

Table 1
ANOVA results regarding cycle to cycle SD (σ). Both p values and effect sizes (η_p^2) are provided for the main and interaction effects of the level of fatigue (LF) and level of experience (LE) for both the SD of the path (X) and mean speed (V) of the COM and BOX, and completion time of each lowering/lifting cycle. Significant effects are highlighted using bold font.

			LF	LE	LF × LE
COM	σ(V)	p (η_p^2)	0.258 (0.121)	0.844 (0.019)	0.543 (0.072)
	σ(X)	p (η_p^2)	**< 0.001 (0.429)**	0.664 (0.044)	0.610 (0.044)
BOX	σ(V)	p (η_p^2)	0.971 (0.013)	0.422 (0.224)	0.315 (0.109)
	σ(X)	p (η_p^2)	0.182 (0.141)	0.475 (0.110)	0.243 (0.125)
Timing errors	σ(ΔT)	p (η_p^2)	**0.028 (0.233)**	0.465 (0.126)	0.827 (0.036)

assumptions were assessed, and some outcome measures were transformed prior to analysis to obtain normally-distributed residuals. Statistical significance was determined when $p < 0.05$, and summary statistics are given as least square means (95% confidence intervals). Where relevant, paired differences between time blocks were evaluated using Tukey's HSD. Effect sizes (i.e., partial eta-squared = η_p^2) for all measures were computed to assess their sensitivity to LE and LF. To interpret effect sizes qualitatively, we used Cohen's (1988) criteria, specifically that effect sizes are large if $\eta_p^2 > 0.14$, moderate if $0.01 < \eta_p^2 < 0.06$, and small if $\eta_p^2 < 0.01$.

3. Results

3.1. Cycle-to-cycle SD results

Among the main and interaction effects of LF and LE on linear outcomes, only the main effects of LF on COM path and timing error were significant (Table 1). From the second time block, variations of X_{COM} increased with time, and variations in the last two blocks were significantly larger than in the initial two time blocks (Fig. 2, top). Variations in timing errors also increased significantly from the second to the fourth time blocks (Fig. 2, bottom).

3.2. SaEn results

For SaEn measures, none of the main or interaction effects of LE and LF on SaEn of the COM/BOX path were significant (Table 2).

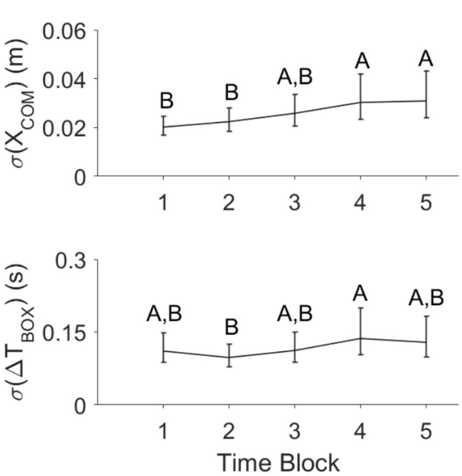

Fig. 2. Cycle-to-cycle standard deviation of the COM path (top) and timing errors (bottom) for each of the five time blocks. Values in blocks not sharing same letters are significantly different.

Table 2
ANOVA results regarding sample entropy (SaEn) measures. Both p values and effect sizes (η_p^2) are provided for the main and interaction effects of the level of fatigue (LF) and level of experience (LE) for SaEn of the COM and BOX path.

		LF	LE	LF × LE
SaEn(X_{COM})	p (η_p^2)	0.360 (0.101)	0.636 (0.032)	0.090 (0.178)
SaEn(X_{BOX})	p (η_p^2)	0.221 (0.130)	0.956 (0.001)	0.144 (0.154)

Table 3
ANOVA results related to the GEM-based method. p values and effect sizes (η_p^2) are provided for the main and interaction effects of level of fatigue (LF) and level of experience (LE) on different GEM outcomes. Significant effects are highlighted using bold font.

			LF	LE	LF × LE
COM	σ(δt_T)	p (η_p^2)	**0.011 (0.272)**	0.091 (0.257)	0.195 (0.137)
	σ(δt_P)	p (η_p^2)	**0.024 (0.241)**	0.754 (0.014)	0.711 (0.051)
	σ(δt_T)/σ(δt_P)	p (η_p^2)	0.694 (0.053)	0.094 (0.093)	0.608 (0.064)
	α(δt_T)	p (η_p^2)	**0.024 (0.240)**	0.771 (0.012)	0.219 (0.131)
	α(δt_P)	p (η_p^2)	0.205 (0.134)	0.634 (0.026)	0.813 (0.038)
BOX	σ(δt_T)	p (η_p^2)	0.360 (0.101)	0.553 (0.001)	0.796 (0.040)
	σ(δt_P)	p (η_p^2)	0.167 (0.146)	0.452 (0.013)	0.825 (0.036)
	σ(δt_T)/σ(δt_P)	p (η_p^2)	0.235 (0.127)	0.439 (0.033)	0.884 (0.028)
	α(δt_T)	p (η_p^2)	**0.011 (0.274)**	0.765 (0.010)	0.422 (0.090)
	α(δt_P)	p (η_p^2)	0.154 (0.150)	0.668 (0.023)	0.848 (0.033)

3.3. GEM-based results

In all time blocks, variations of the COM and BOX in the GEM direction were significantly higher than in the perpendicular direction ($p < 0.001$). There were several significant main effects of LF on GEM outputs, though no main effects of LE or interaction effects of LF × LE (Table 3). Over the five time blocks, COM variability in the GEM direction increased significantly (Fig. 3A). The magnitude of COM deviations in the direction perpendicular to the GEM also increased from

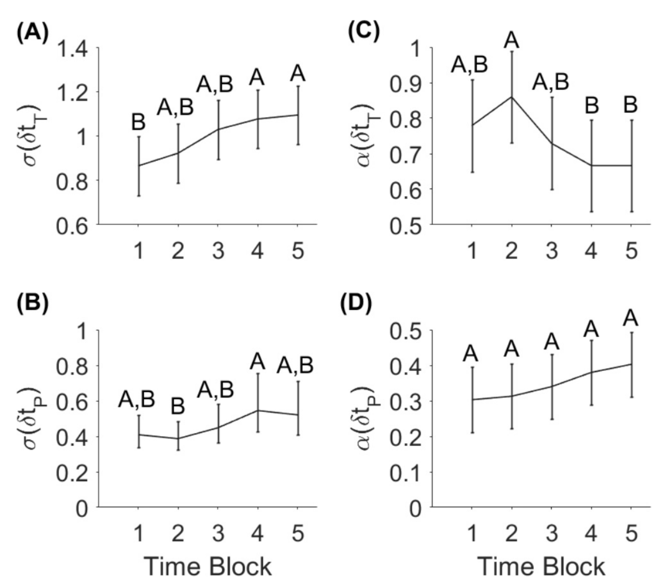

Fig. 3. GEM-based outcomes of the COM, for each of the five time blocks. (A) magnitudes of variations in the GEM direction for the COM. (B) movement variability in the direction perpendicular to the GEM for the COM. (C) temporal variation structure in the GEM direction for the COM. (D) temporal variations in the direction perpendicular to the GEM for the COM. Results in time blocks not sharing common letters are significantly different.

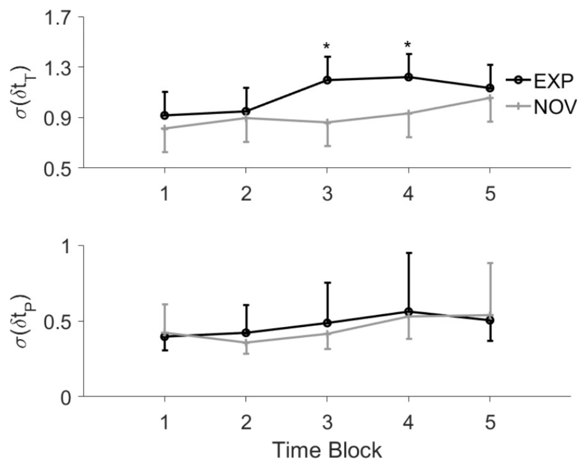

Fig. 4. GEM-based outcomes for the COM, for each of the five time blocks. (Top) magnitudes of variations in the GEM direction. (Bottom) movement variability in the direction perpendicular to the GEM. The symbol * indicates a significant paired difference between the EXP and NOV groups.

the second to the fourth time blocks (Fig. 3B). Though only approaching significance (p = 0.091), COM variations in the GEM direction were 17% larger among EXP vs. NOV. While the interaction effect of LE and LF on $\sigma(\delta t_T)$ for COM was not significant, an exploratory contrast test revealed that the main differences between the motion variations of NOV and EXP in the GEM direction occurred in two time blocks. Specifically, EXP exhibited significantly larger MV of COM in the GEM direction than NOV in the 3rd and 4th time blocks (Fig. 4, top). The value of $\sigma(\delta t_T)/\sigma(\delta t_P)$ for the COM (2.080 (1.912–2.249)) was significantly higher than for the BOX (1.443 (1.275–1.611)). In addition, DFA analyses showed that in all conditions, δt_T of the COM were persistent (i.e., $\alpha(\delta t_T) > 0.5$) while and δt_p of the COM were anti-persistent (i.e., $\alpha(\delta t_P) < 0.5$). After the 2nd time block, DFA values of δt_T for the COM decreased significantly (Fig. 3C); however, $\alpha(\delta t_P)$ increased slightly from the 1st time block (Fig. 3D). Similar patterns were observed for DFA values of δt_T and δt_p for the BOX; from the first time block, $\alpha(\delta t_T)$ declined significantly and $\alpha(\delta t_P)$ increased slightly.

4. Discussion

We hypothesized that fatigue will affect an individuals' MV, and our results confirmed this hypothesis. Participants had changes in the kinematics of their COM across the time blocks (note that fatigue developed gradually over the time blocks). More specifically, variability of the COM in terms of cycle-to-cycle SD increased over the successive time blocks (Fig. 2, top). This result suggests that the CNS utilized more redundant solutions to perform the lifting/lowering task as an adaption to fatigue. Similarly, Fuller et al. (2011) found a positive association between MV of the COM and fatigue in a reaching task. Use of a GEM-based analyses decoupled variations of the COM into the GEM and non-GEM-relevant directions (i.e., the direction perpendicular to the GEM). Variations in the GEM direction increased continuously with developing fatigue (Fig. 3A), while variations in the other direction had a fluctuating pattern but with a general increasing trend across the time blocks (Fig. 3B). Although the D × LF interaction effect was not significant, based on the effect size analysis the influence of fatigue on variations in the GEM-direction were more substantial than in the non-GEM-relevant (Table 3). Together, these GEM outcomes suggest that the CNS may intend to use kinematic redundancies in the GEM direction, since variations in this direction did not deteriorate achieving the task goal (Cusumano and Cesari, 2006; Dingwell and Cusumano, 2010; Latash et al., 2002). Previous studies have reported that, in repetitive lifting and trunk flexion tasks, fatigue reduced both the capability to maintain balance (Lee et al., 2014) and dynamic stability (Granata and Gottipati, 2008). Based on these two earlier studies, and our current results, we conclude that the CNS may prioritize movement flexibility (i.e., higher MV) rather than movement stability in the presence of (or as an adaption to) fatigue. It is worth mentioning that we calculated relative variability (i.e., $\sigma(\delta t_T)/\sigma(\delta t_P)$), which reflects available effective motor solutions for the CNS (Decker et al., 2012). Our results indicated that the extent to which effective motor solutions were available was consistent across the time blocks. Based on the SaEn outcomes, movement complexity also did not change with developing fatigue. These results suggest that a similar amount of motor solutions were available for the CNS in each of the time blocks, and that the human body can only manipulate variability in the GEM and non-GEM-relevant directions.

DFA analyses also confirmed that a constant time was the task goal. In the non-GEM-relevant direction, variations were anti-persistent (i.e., $\alpha < 0.5$), implying that the CNS tightly regulated COM movements in this direction (Dingwell and Cusumano, 2010). On the other hand, deviations in the GEM direction were not tightly controlled, since they were persistent (i.e., $\alpha > 0.5$). Lifting-induced fatigue influenced the DFA scale values (α), such that they moved toward 0.5 (Fig. 3C and D), and shows that the time series in both directions converged to uncorrelated white noise (Dingwell and Cusumano, 2010). These findings regarding DFA analysis outcomes imply that maintaining/achieving the time goal became more challenging for the CNS with increasing fatigue.

GEM-based results weakly supported that the level of experience influences MV in the current task investigated. Based on the GEM outcomes, the EXP group, to some extent, explored more abundant DOF in the GEM direction, as reflected in the larger variations observed in this direction. Consistent with a previous study, from which the current data were obtained (Lee et al., 2014), both groups had similar kinematic behaviors at the beginning and end of the task. However, differences in MV structures between the two groups were observed midway between the second and final time block (Fig. 3C). This difference suggests that the EXP group adapted a more flexible strategy than NOV after fatigue developed, but that they could not maintain this distinct strategy for the entire task duration. However, SaEn outcomes contradicted the GEM-based results. SaEn values for NOV individuals were larger than for EXP. This indicates that NOV had more flexible movements (Madeleine, 2010) regardless of the level of fatigue. One explanation for this inconsistency is that GEM analyses decoupled variability in two directions (i.e., GEM and non-relevant GEM directions), and MV was quantified in each direction separately. In contrast, SaEn quantified MV in both directions concurrently.

Overall, the participants were able to maintain consistent BOX movements even in the presence of fatigue. For example, fatigue did not influence the cycle-to-cycle SD of the end effector (i.e., BOX) kinematics. Similar results regarding the consistency of performance with fatigue were reported for both a pointing task (Emery and Côté, 2012) and a sawing task (Cowley et al., 2014; Gates and Dingwell, 2008). Our results suggest that the strategy used for regulating the COM (i.e., increasing flexibility) minimized the effects of induced fatigue on participants' performance. Qualitatively, the pattern of varying timing errors ($\sigma(\Delta T)$) and COM variability in the non-GEM-relevant ($\sigma(\delta t_P)$) across the time blocks (Fig. 2, bottom, and Fig. 3B) were the same. Consistent with the GEM concept (Dingwell and Cusumano, 2010), we conclude that the task goal was deteriorated with fatigue since we observed changes in COM variations in the non-GEM-relevant direction. In contrast to the earlier UCM method, Cusumano and Dingwell (2013) suggested that it is not necessary to define controlled variables in advance to quantify MV with GEM analyses. Our results indicated that quantifying MV of the BOX alone could not provide any insights about potential differences in motor control strategies that are adapted by NOV vs. EXP to deal with fatigue. Further, the COM had more relative variability (i.e., $\sigma(\delta t_T)/\sigma(\delta t_P)$) compared with the BOX, which indicates that the CNS sought mainly to maintain the GEM for the COM (Decker et al., 2012; Scholz and Schöner, 1999). Based on these results, we thus suggest that when using the GEM method, there may still be a need to determine controlled variables that can reflect the behavior of the CNS.

As we hypothesized, the different MV measures had differing sensitivity to the level of fatigue (LF) and level of experience (LE). Based on effect sizes, fatigue had the largest effect on cycle-to-cycle SD of the COM path. Also, most of the GEM outcomes for COM were highly sensitive to LF. From this sensitivity analysis, it seems that GEM and cycle-to-cycle SD methods are appropriate for investigating the effects of fatigue. SD of COM variations in the GEM direction (i.e., $\sigma(\delta t_T)$) also had high sensitivity to LE; therefore, this measure appears useful to identify difference in movement patterns between NOV and EXP workers. It is worth noting, though, that effect sizes for the SaEn analysis were very small, and it thus seems that this method is not useful to reveal the effects of LF and LE on MV for tasks such as those examined here.

Some limitations in this study are notable. For example, participants were not allowed to move their feet during the experiment, there were relatively few participants, and a single relatively simplistic task was investigated. As such, it is unclear whether these results can be generalized to other conditions and populations. In addition, the autocorrelation and the false nearest neighbor approaches, which were used to calculate parameters needed for the SaEn method, have not been validated.

A better understanding of MV may be useful for the control of WMSDs. By understanding how NOV and EXP regulate their movements (perhaps to avoid or minimize risk), suggestions could be provided to workers to increase internal variation, potentially by redesigning work stations or via training to modify work styles. Based on the current study of a prolonged repetitive lifting tasks, we conclude that the CNS adapts a strategy to increase MV in a direction that does not affect task performance. Also, it seems that individuals can develop more flexible movements through experience. While this latter conclusion may suggest value in encouraging workers to increase their internal variability, such as strategy is not necessarily safe and requires further investigation. Selecting an appropriate method for measuring MV is challenging, and multiple approaches have been described. Based on our results, GEM analysis appears to be a useful tool for investigating the effects of both task-relevant factors (e.g., lifting asymmetric and fatigue) and the influence of individual differences (e.g., related to task experience).

Acknowledgment

The first author was supported under a pre-doctoral training program grant from the Centers for Disease Control and Prevention (T03 OH008613). The contents of this paper are solely the responsibility of the authors, and do not necessarily represent the official views of the Centers for Disease Control and Prevention or the Department of Health and Human Services.

Conflict of interest

The authors declare no conflict of interest.

Financial disclosure

The authors have no financial relationships with other persons or organizations that might have inappropriately influenced our work presented in this manuscript.

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