Applications of Motor Variability for Assessing Repetitive Occupational Tasks

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ABSTRACT

The human body has substantial kinetic and kinematic degrees-of-freedoms, so redundant solutions are available for the central nervous system (CNS) to perform a repetitive task. Due to these redundancies, inherent variations exist in human movement, called motor variability (MV). Current evidence suggests that MV can be beneficial, and that there is an inverse association between MV and risk of injury. To better understand how the CNS manipulates MV to reduce injury risks, we investigated the effects of individual differences, task-relevant aspects, and psychological factors as modifiers of MV. Earlier work found that experienced workers adapted more stable movements than novices in repetitive lifting tasks. To expand on this, we quantified how MV differs between experienced workers and novices in different lifting conditions (i.e., lifting asymmetry and fatigue). Three different measures (cycle-to-cycle SD, sample entropy, and the goal equivalent manifold) were used to quantify MV. In a symmetric lifting task, experienced workers had more constrained movement than novices, and experienced workers exhibited more consistent behavior in the asymmetric condition. Novices constrained their movements, and could not maintain the same level of variability in the asymmetric condition. We concluded that experienced workers adapt stable or flexible strategies depending on task difficulty. In a prolonged lifting task, both groups increased their MV to adapt to fatigue; they particularly increased variability in a direction that had no effects on their main task goal. Developing fatigue also make it difficult for individuals maintain the main goal. Based on these results, we conclude that increasing variability is an adaptive strategy in response to fatigue. We also assessed variability in gait parameters to compare gait adaptability using a head-worn display (HWD) compared with head-down displays for visual information presentation. An effective strategy we observed for performing a cognitive task successfully during walking was to increase gait variability in the goal direction. In addition, we found that head-up walking had smaller effects on MV, suggesting that HWDs are a promising technology to reduce adverse events during gait (e.g., falls). In summary, these results suggest that MV can be a useful indicator for evaluating some occupational injury risks.

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GENERAL AUDIENCE ABSTRACT

Whenever an individual performs a repetitive task, we can observe variations in their movement patterns. The magnitude of these variations, which are called motor variability, may be related to the risk of injury. To better understand this relationships, we investigated how different risk factors affect the patterns of human movement. In two studies, we compared movement patterns of experienced workers and novices in a repetitive lifting task. In a simple, brief lifting task, novices had more variations in their movement patterns. However, novices did not have the same level of variation in asymmetric lifting tasks, and constrained their movement more than experienced workers. Experienced workers, though, had a similar level of variation in both simple and more difficult lifting conditions. We concluded that whether stable or flexible movement pattern are used depends on task difficulty and the level of experience. In a longer-duration lifting task, both experienced workers and novices increased variations in their movement patterns over time, and we believe that these increases were an adaptation to fatigue. In a third study, we investigated the differences between variations in walking pattern when people use different types of information display (i.e., paper, cellphone, and smart glasses). Using smart glasses had a smaller effect on movement patterns, suggesting that this technology is potentially is safer than other types of display. In summary, these results suggest that studying the variations in human movement patterns can be a useful indicator to evaluate the risk of injury.

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Chapter 1. Introduction

1.1. Significance of work-related musculoskeletal disorders (WMSDs)

WMSDs remain among the most prevalent occupational pathologies in industrialized countries (Buckle and Devereux, 2002; da Costa and Vieira, 2010). These problems have substantial adverse impacts on employers due to lost productivity (Stewart et al., 2003), the general society from high financial costs (Badley et al., 1994; Chiasson et al., 2012), and employees themselves as a result of deteriorating quality of life (Devereux et al., 1999). For example, in the US WMSDs lead to more than 600,000 workers having lost work days (da Costa and Vieira, 2010). It is also estimated that the US, Canada, and Germany respectively spent about $600 billion from 1998 to 2010 (Marucci-Wellman et al., 2015), $26 billion in 1998 (Coyte et al., 1998), and 38 billion Euros in 2002 (Thiehoff, 2002) to compensate workers' costs. It is noteworthy that these numbers are actually a small portion of actual costs (Marucci-Wellman et al., 2015), with more substantial, but less easily quantified, indirect costs related to aspects including losses of earning and productivity.

Multiple risk factors contribute to musculoskeletal disorders; among these, physical, psychological, and individual factors are main aspects 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). Psychological factors, which are related to a worker's interaction with the job environment (e.g. work-life balance, physiological demand, and job security) (Niedhammer et al., 2013), have also been

identified as common factors in developing WMSDs (Bongers et al., 2006). Individual differences also appear to be important contributing factors, including age, gender, education, life style, obesity, smoking, strength, and work history (Punnett and Wegman, 2004; Waters et al., 2007). In this research, *repetitive motion* is of particular interest as a physical risk factor, as is investigating the potential role of *work experience* as an individual difference and *mental load* as a psychological factor.

1.2. Repetitive motion and WMSD risk

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 (Bernard, 1997; Buckle and Devereux, 2002). For example, a majority (75%) of studies reviewed by Malchaire et al. (2001) and van der Windt et al. (2000) reported a significant association between repetitive motion and pain in the upper extremity and shoulder. Nordander et al. (2009) argued that there is a causal relationship between repetitive tasks and neck and shoulder injuries in many occupational settings. Several studies have also shown that repetitive lifting tasks increase the risk of low back pain (LBP) (Marras et al., 2006). More generally, Punnett and Wegman (2004) reported strong evidence confirming that repetitive motion is an important risk factor for injury in occupational tasks.

Repetitive motions are an increasing concern in occupational tasks, given that greater standardization and outsourcing has led to a decreased set of job tasks, with less task variability, and indicating that repetitive movements are often required for many contemporary occupational tasks (Srinivasan and Mathiassen, 2012). Traditionally, decreasing the similarity of repetitive work has been an important goal for preventing WMSDs. Increasing the "external variability" in

work tasks can be achieved by adding additional job duties, through work enlargement, or through task rotations or cross training. However, these approaches have not been well validated in terms of reducing WMSDs; moreover, adopting these approaches are not always feasible for employers (Srinivasan and Mathiassen, 2012). In contrast, "internal variation" is an alternative method of reducing or preventing WMSDs, which can be achieved by focusing on *motor variability*.

1.3. Potential role of motor variability in occupational risk and task performance

Bernstein (1967) noted, in classical work, that reproducing a specific movement is impossible, and there are inherently variations in movements. He conducted an experiment in which participants had to perform a repetitive hammering task, and his observations showed that trajectories of the hammer were not identical but instead there were variations in the pattern of movement. For a long time following his work, these kinds of variations in motion were ignored and treated as sensorimotor noise (Gaudez et al., 2016; Newell and Slifkin, 1998). More recently, variations in kinetic or kinematic aspects of a movement pattern are treated as an essential characteristic of motion (Newell and Corcos, 1993) and called motor variability (MV). MV is now often considered as a regulator of motion (Latash et al., 2002) to increase flexibility and adaptability (Gaudez et al., 2016). MV appears beneficial to human movement, with some evidence suggesting a potential role in *preventing musculoskeletal disorders and improving performance*. Bartlett et al. (2007), for example, emphasized the relationship between motor variability and injury risk reduction for athletes, while Moseley and Hodges (2006) reported that this connection extends even further, and suggested that increased variability leads to faster post-injury rehabilitation.

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MV has been shown to have significant relationships with precursors of injury, such as pain and fatigue (Madeleine, 2010). These associations, in turn, suggest a direction for development of preventive ergonomics methods. In one relevant report, Madeleine et al. (2008) found that acute pain led to an increase in MV, with more movement variations apparently used to find solutions to avoid pain. Their results also indicated that chronic pain was related to less movement variation: experienced butchers with pain had lower variability than a pain-free group. In another study, trunk movement variation was lower among people with LBP compared to healthy controls (van den Hoorn et al., 2012). Based on these studies, some authors have hypothesized that individuals decrease their MV to adapt to pain, and that this adaptation might lead to reduced movement boundaries (Stergiou et al., 2006). Another interesting outcome of this line of research, in the area of pain and variability, is that the movement adaptation may continue after the alleviation of pain (Sterling et al., 2001). In other words, MV among these individuals remains smaller than among healthy individuals, suggesting that individuals with pain group might learn alternative solutions that facilitate avoiding pain.

Fatigue, which is an exercise-induced reduction in muscular capability (Bigland-Ritchie et al., 1986), has an undesirable impact on tasks performance, and it may increase the risk of WMSDs (Srinivasan and Mathiassen, 2012). 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 posited 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 a higher ability to adapt with fatigue (Srinivasan and Mathiassen, 2012). As an illustration, Aune et al. (2008) found that the performance of skilled

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tennis players was maintained in the presence of fatigue, though changing MV, while novice players did not vary MV.

A number of MV related studies have focused on performance. Evidence from these indicates that when athletes have been trained the MV of controlled variables increases and at the same time performance improves (Button et al., 2003; Müller and Sternad, 2009). Mirka and Marras (1993) indicated that there are high variations in muscle activity during a repetitive lifting task, but that these variations were changed in a way that the produced external torque stayed fairly consistent. Thus, *controlled variables* (muscle activity) can have high variation even while the *performance variable* (external torque) has low variation. Gates and Dingwell (2008) found that when participants became fatigued in a repetitive sawing task they changed their movement pattern to maintain performance on the task. In summary, more variations in control variables might be beneficial to improve performance.

1.4. Methods for Quantifying MV

Characterizing or quantifying MV remains as an important challenge in the field of motor control. This challenge arises from the fact that there is an abundance of movement measures and diverse methods to quantify their variations (Stergiou, 2004). In analyses of human movement, measures are typically classified into four types: 1) performance variables, 2) kinetic and kinematic parameters, 3) muscle activation patterns, and 4) coordination (Srinivasan and Mathiassen, 2012). There are several analysis approaches available to quantify variations in these types of measures, and which fall into three classes. Traditional approaches (linear methods) are based on descriptive statistics (Stergiou, 2004), which have been used for both discrete and continuous measures. Recently, two other classes of analysis approaches have been introduced.

The first stems from chaos theory (nonlinear methods) and the second from the abundant degree-of-freedoms (DOF) available to perform an action (what Cusumano and Cesari (2006) have called "equifinality"). In the remainder of this section, these three classes of analysis approaches (i.e., linear methods, nonlinear methods, and methods based on equifinity) are described in more detail.

1.4.1. Linear methods

In biomechanical studies, measures can be discrete, such as peak trunk torque in a repetitive lifting task, or continuous, such as like trunk angle over time in the same task (Stergiou, 2004). Common approaches for quantifying discrete variables are the range, variance, standard deviation (SD), coefficient of variance, and interquartile range. While useful information can be extracted from such discrete variables, spatial and temporal features can be captured from continuous variables (Hamill et al., 2000). The mentioned approaches for discrete variables can also be used to study variability in continuous variables (Lomond and Côté, 2010, 2011). Such linear methods, though, may not be appropriate or useful for complex conditions. These methods sometimes cannot distinguish variabilities in different patterns, whereas nonlinear analysis in which relationship between outputs and inputs is not proportional, can separate them (Goldberger et al., 1988; Stergiou, 2004).

1.4.2. Nonlinear methods

Nonlinear methods have been widely used to study biological systems (Buchman et al., 2001), and recently these tools have attracted researchers' attentions in the field of human movement (Dingwell and Cusumano, 2000) for several reasons: 1) linear methods cannot give any information about the temporal variation of movement patterns (Dingwell et al., 2000; Stergiou,

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2004); 2) when using linear methods, it is assumed that each movement cycle varies randomly and independently, while a number of studies showed that these assumptions are not met (Dingwell et al., 2000; Stergiou, 2004); 3) results from linear and nonlinear tools can differ, with each one leading to a different conclusion (Dingwell et al., 2000; Lee and Nussbaum, 2013; Stergiou, 2004); and, 4) there are similarities in the complexity of human movement and physiological rhythms (Stergiou, 2004).

When using nonlinear methods, the first step is to consider the state variables (e.g., joint angles) that can describe the characteristics of a system (Kang, 2007). All of the state variables that are needed simultaneously to define a specific task (e.g., all joint angles and velocities contributing in a lifting task) form a vector space known as the *state space* (Kang, 2007; Stergiou, 2004), and assessing this can give better insight into the task (Hadadi et al., 2011; Riley et al., 1995; Salavati et al., 2009)

However, it is often not possible to track all of the state variables. An alternative is the delay-embedding method, which keeps the essential behavior of the system by copying time-delayed variables, and these state variables reconstruct the state space (Kang, 2007). For this approach, there is a need to calculate the embedding dimension (d), the minimum required variables to reconstruct state variables (Stergiou, 2004), and the time delay (τ).To estimate embedding dimension, Kennel et al. (1992) proposed the false nearest neighbors (FNN) method. There are several alternatives to estimate the time delay, including the widely used first minimum of the average mutual information (Abarbanel, 2012) and autocorrelation methods (Rosenstein et al., 1993). From the reconstructed state space, the largest Lyapunov exponent and the correlation dimension can be calculated (Stergiou, 2004).

Lyapunov Exponent:

The Lyapunov exponent (λ) quantifies the divergence rate of neighboring trajectories in state space (Wolf et al., 1985), and it is used to quantify local stability (Dingwell et al., 2000). Specifically, this measure is a tool to investigate the effects of small perturbations on state variables over time (Kang, 2007). If λ is positive, then two nearby trajectories separate or diverge over time, and the system is instable. If λ is negative, then the trajectories converge and the system is stable (Dingwell, 2006). Determining the largest λ (λ_{max}) is sufficient to quantify stability of the whole system. In fact, λ_{max} reflects the stability of the least stable variables, and if these variables are stable then the whole system is stable and vice versa (Kang, 2007). Lyapunov exponents have been used to quantify stability in many different activities, including balance (Stergiou, 2004; Tanaka and Granata, 2007), gait (Dingwell and Cusumano, 2000; Kang and Dingwell, 2008; Stergiou, 2004), and lifting tasks (Lee and Nussbaum, 2013; Tanaka and Granata, 2007). It has also been used to evaluate the effectiveness of interventions, such as exercise or rehabilitation devices (Graham et al., 2011).

Correlation Dimension

Another important nonlinear method is the Correlation Dimension (COD), which estimates the dimension of a region in state space that is occupied by a dynamical system (Buzzi et al., 2003). Periodic systems have a small integer dimension, whereas in chaotic systems the dimension is large and non-integer (Stergiou, 2004). One of the interesting applications of the COD is in field of human movement. For instance, this method has been applied to classify MV between young and older people (Buzzi et al., 2003; Dingwell et al., 2000), and postural control has been evaluated by calculating the COD of the center of pressure (COP) during quiet stance (Cignetti et al., 2011).

Entropy

Approximate Entropy (ApEn) and Sample Entropy (SaEn) can measure the uncertainty of a time series and thereby the complexity of the underlying system (Pincus, 1991; Richman and Moorman, 2000): complex systems are less predictable and have higher entropy values. ApEn and SaEn has been a popular method for characterizing MV. These methods have been used to measure the complexity of COP in young, and older individuals (Donker et al., 2007; Newell et al., 1998), and to compare patients with ACL deficient knees with healthy subjects (Georgoulis et al., 2006). In many cases such as these, linear methods were not as useful since they could not distinguish between groups (Liao et al., 2008).

Detrended fluctuation analysis

One problem with linear methods is that they only measure the average magnitude of variations, and thus cannot reveal the effects of each trial on consecutive trials (Dingwell and Cusumano, 2010). Detrended fluctuation analysis (DFA) was utilized to overcome this problem (Hausdorff et al., 1996). This method measures the correlation between successive data points within a time series, by providing a scaling exponent, alpha (α). If α is smaller than 0.5, then the time series is anti-persistence and vice versa (Cusumano and Dingwell, 2013), and smaller values of α shows that the CNS has more control on the time series. In the field of human movement, DFA has been widely utilized to quantify gait variability (Bohnsack-McLagan et al., 2015; Hausdorff et al., 1999; Hausdorff et al., 1997; Jordan and Newell, 2008; Stergiou, 2004; Terrier et al., 2005). Cusumano and Dingwell (2013), however, suggested that other method should be considered to study movement control, since DFA cannot quantify the magnitude of variability.

1.4.3. Methods based on equifinality

As mentioned above, the human body has a large number of DOFs that can be used to perform specific tasks, and a challenging question is how the CNS can overcome such kinematic redundancy (Scholz et al., 2001; Scholz and Schöner, 1999). Traditionally, optimization methods have been used to find a unique solution (Todorov and Jordan, 2002). In experimental studies, however, it has been observed that there are a set of solutions, or *manifold*, that can be used to execute a complex task (Bernstein, 1967). In fact, this solution manifold increases the system's flexibility; therefore, Latash (2008) called these variations the "principle of abundance" rather than a "problem of redundancy".

Recently, researchers have claimed that the CNS, instead of controlling every element of a system, coordinates the elements and controls global variables. This coordination is called synergy (Latash, 2008). Synergy focuses on the output of the system instead of being concerned about the contribution of each element. In other words, fluctuation in the performance of one element can be compensated by modifying another one to maintain the desired output (Latash, 2008). This feature of synergy is called "error compensation". To quantify error compensation, there are several methods including uncontrolled manifold (UCM), tolerance noise covariation (TNC), minimum intervention principle (MIP), and goal equivalent manifold (GEM).

Uncontrolled manifold

The Uncontrolled manifold approach was developed by Scholz and Schöner (1999). For quantifying variability, a basic configuration space should first be defined. For example, the space could cover all joint angles, which coordinate with each other to perform a specific task. These variables are called *elemental variables*. In the next stage, another class of variables

should be selected. It is hypothesized that these variables, called *controlled variables*, are controlled by CNS. For human movements, kinematics of the COM and end effectors are two main parameters that have been considered as controlled variables.

After selecting element and controlled variables, the state space should be divided into two orthogonal subspaces. In the first subspace, deviations of element variables do not affect the controlled variables, hence it is called the *uncontrolled space*. In the orthogonal subspace, however, variability of the element variables leads to changes in the controlled variables. If the hypothesis about controlled variables is correct, then variability in the uncontrolled subspace should be larger than the other one, and variance of the uncontrolled subspace is the magnitude of variability (Scholz and Schöner, 1999). This approach has been used to investigate MV in many different tasks, including sit-to-stand, throwing, walking, and standing (Hsu et al., 2007; Reisman et al., 2002; Robert et al., 2009; Yang and Scholz, 2005). However, it has some limitations. The UCM is based on the average behavior of the system. Each cycle of a repetitive motion has essential information, which can give a better insight about MV, yet the UCM approach cannot capture such information (Cusumano and Dingwell, 2013). In the UCM, MVs are only quantified by measuring structural variances of data, and interpretations are based on this structure. (Bohnsack, 2014). However, these kinds of interpretations may be unreliable since tasks and the data structures may not be related to each other (Cusumano and Dingwell, 2013; Valero-Cuevas et al., 2009). Finally, choosing appropriate controlled variable(s) is essential in the UCM approach; if this selection is wrong, it may lead to wrong conclusions (Bohnsack, 2014).

Tolerance Noise Covariation

TNC analysis is another method based on the task manifold (Müller and Sternad, 2009). In this approach, the combination of three goal-level costs should be optimized to minimize the variability of performance variables. The first cost is noise cost, which quantifies the effects of variability of the elemental variables on controlled variables. The second is tolerance cost, which measures the distance of the element variables from the solution manifold. The third is covariance cost, which evaluates the alignment of element variables and the solution manifold (Abe and Sternad, 2013; Müller and Sternad, 2004, 2009). This approach was used to investigate the effects of learning in throwing/reaching tasks (Abe and Sternad, 2013). However, it cannot be used for studies that include experienced participants or highly learned tasks like walking. Using TNC also requires an examination of the distribution of variability to find the controlled variables (Bohnsack, 2014).

Minimum Intervention Principle

Todorov and Jordan (2002) introduced a stochastic optimal control method to explain MV, which they called it Minimum Intervention Principle. Based on this method, a trajectory that deviates from the average trajectory will be corrected by controllers if the deviation affects task performance. Since the controller does not control the movement in task-irrelevant directions, then there is more variation in this direction. The validity of Minimum Intervention Principle validation has been evaluated in several studies (Cusumano and Dingwell, 2013; Diedrichsen, 2007; Izawa et al., 2008), but these did not consider trial-to-trial dynamics of the system (Cusumano and Dingwell, 2013). Moreover, it is essential to derive a full dynamical model of a system to use this approach.

Goal Equivalent Manifold

Cusumano and Cesari (2006) introduced a new method to quantify variability, which may not have the noted limitations of alternative methods. For this purpose, they sought an exact relation between body-goal variability and task performance, instead of focusing on finding controlled variables. They claimed that there is a goal-function, whose element variables and goal variables are related:

$$\vec{f}(\vec{x}, \vec{y}) = 0 \tag{1.1}$$

in which $\vec{x}$ is a state variable and $\vec{y}$ is a goal variable. We should notice that equation (1.1) describes a configuration that leads to a specific goal. If there is more than one solution of equation (1.2) for a fixed y, then we have a set of solutions:

$$G = \{\vec{x} | \vec{f}(\vec{x}, \vec{y}) = 0\} \tag{1.2}$$

These sets of variables for constant y which satisfy equation (1.1), are located on a manifold that is described in equation (1.2), and these do not change the task performance. Cusumano and Cesari (2006) called this manifold the GEM.

Among all of the variables on the solution manifold, some of them are more robust against external perturbations; therefore, implementation of these robust solutions have a higher priority (Cusumano and Cesari, 2006). Cusumano and Cesari (2006) used sensitivity analysis to detect these variables. After a series of mathematical calculations, it can be shown that a perturbation does not affect the final goal in the null space of equation (1.2) at a preferred joint configuration ($\vec{x}^* \in G$) and a desired goal ($\vec{y}^*$), when

$$[A]\vec{u} = 0 \tag{1.3}$$

in which $A_{ij} = \partial f_i/\partial X_i(\vec{x}^*, \vec{y}^*) = J_{ij}$ and $\vec{u}$ are perturbations. This null space is the goal equivalent subspace, and perturbations in the goal equivalent subspace plane do not cause any errors at the level of the body goal. An orthogonal plane to the goal equivalent subspace has been called a goal relevant subspace, in which perturbations in this plane make the biggest errors. The magnitude of variability can be quantified by obtaining these two planes (for more details refer to Cusumano and Cesari (2006)).

1.5. Research needs

As discussed previously, a better understanding of MV may be useful to reduce the risk of WMSDs. For example, there could be benefits of increasing "internal variations" in physical or biomechanical exposures (i.e., kinetics and kinematics) during occupational tasks (Madeleine, 2010; Srinivasan and Mathiassen, 2012). One approach is quantifying the MVs of workers performed occupational tasks, by which we may gain a better understanding of the motor control strategies that they utilize. From such knowledge, suggestions could be provided for workers to increase internal variation, such as by redesigning work stations or training to modify work styles. There may be benefits from evaluations based on a worker's MVs. Stergiou et al. (2006) hypothesized that MV associated with healthy movements should be optimal. In other words, if the observed MV is less than optimal, movements may be too rigid and vice versa. Thus, the structure of a worker's MVs could serve as an indicator future injury risk.

To achieve our long term goal, we were first interested in investigating the behavior of experienced workers, since their movements are more stable (Lee and Nussbaum, 2013) and their rate of injuries are less than among novices (Bigos et al., 1986). As such, experienced

workers might explore safer solutions in movement space. By understanding how experienced

workers regulate their movements (perhaps to avoid or minimize risk), more specific training

methods could be developed to teach novices. In the second part of the current work, we wanted

to evaluate the impacts of using a head-worn display (HWD) on MV in the work context;

applications of this technology in occupational context are expanding dramatically. Yet there are

currently no relevant safety guidelines or more generally a sufficient understanding of the impact

of combined cognitive and physical demands such as involved in HWD use for occupational

tasks.

1.5.1. Comparing MV between experienced workers and novices

There are often substantial individual differences in behaviors depending on age, gender, work

experience, etc. These individual differences lead to different movement patterns even when

performing the same task, and these differences may be associated with injury risk (Kilbom and

Persson, 1987; Madeleine et al., 2003; Srinivasan and Mathiassen, 2012). For instance, men and

women utilize different motor control strategies to perform repetitive tasks (Fedorowich et al.,

2013; Srinivasan et al., 2016b; Vafadar et al., 2015), and it has been suggested that the lower risk

of WMSDs in men might be the result of a larger variation of their movements (Vafadar et al.,

2015). Also, several groups (Hollman et al., 2007; Huxhold et al., 2006) have identified age-

related MV differences in gait and postural stability.

Another important individual difference is the level of experience in doing an occupational task.

Previous studies have reported that WMSDs were more prevalent (Bigos et al., 1986) and occur

earlier among novices (Van Nieuwenhuyse et al., 2004). Workers experienced in manual

material handling have also been found to have less stress in their back (Chany et al., 2006; Lett

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and McGill, 2006) and more stable movements (Lee and Nussbaum, 2013; Marras et al., 2006).

Muscle activities (Keir and MacDonell, 2004) and postural deviation (Gregory et al., 2009a;

Gregory et al., 2009b) are also less among experienced workers. Additionally, when novices

were trained based on MMH strategies used by experts, the loading on their back was reduced.

These results suggest that experts may develop motor control strategies which reduce the risk of

injury (Gagnon, 1997, 2003, 2005).

The level of experience, and other factors related to individual differences, may be associated

with MV. Madeleine et al. (2008) determined that experienced workers had higher motor

variability in a simulated cutting task. Lee and Nussbaum (2013) compared novices to

experienced workers during repetitive lifting tasks. They found that experienced workers were

more stable while performing the lifting tasks. Experienced workers also had higher kinematic

and kinetic measures (Lee and Nussbaum, 2012). These findings imply that increasing the

variations in biomechanical demands of a task could decrease the impact of associated risk

factors, which then has the potential to reduce injury risk. This important hypothesis needs

further investigation, since some evidence suggests that experts are exposed to a higher risk of

injuries ; further, some work did not find any difference between novices and experienced

workers (Plamondon et al., 2010).

Directly measuring the association between MV and WMSDs is challenging, as is formally

manipulating the former in a controlled study. However, as reviewed in the previous sections,

existing evidence does support an association between MV and pain, fatigue, and performance,

with the former two being potential indicators of injury risk (Srinivasan and Mathiassen, 2012).

There are a few studies (Lee and Nussbaum, 2012, 2013; Lee et al., 2014) that have investigated

how the CNS regulates movements among experts to improve performance and adapt with

fatigue, and how these regulations differ from the behaviors of novices. In these kinds of studies, though, important information that can be extracted from trial-to-trial kinematics was neglected, because the methods utilized in the studies were based on average behaviors and only few kinematics parameters were measured. To address these gaps, first we need to test which goal functions can be better reflect relevant individuals' motor control strategies, and then compare the implemented strategies among novices and experienced workers in different conditions. For this aim, the following hypotheses were tested:

Hypothesis 1: Motor control strategies of novices are different from those of experienced workers

Hypothesis 2: Individuals change their MV during a repetitive lifting/lowering task in the presence of fatigue

Hypothesis 3: Multiple measures of MV have differing sensitivity to individual (e.g., experience) and task factors (e.g., fatigue).

1.5.2. Investigating the effects of HWD on MV

A number of occupational jobs require simultaneous physical and cognitive demands (Srinivasan et al., 2016). Combat activities, use of a computer (DiDomenico and Nussbaum, 2011), assembly tasks, and order picking (Cirulis and Ginters, 2013) are several examples of such *dual task* activities. Mental loads imposed along with physical demands has been suggested as increasing the risk of WMSDs through decreased muscle endurance, delayed muscle recovery (Mehta and Agnew, 2012), increased spine loads (Davis et al., 2002), and gait variabilities (Beauchet et al., 2003). However, some other studies found inconsistent results; for instance that adding mental loads to physical tasks has no or only slight effects on muscles activities (Birch et al., 2000;

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Blangsted et al., 2004; Srinivasan et al., 2016), and even that muscle activity could decrease (Finsen et al., 2001). Different levels of physical and/or mental demands may lead to these inconsistent results (Srinivasan et al., 2016).

Augmented reality is a good example of dual-task, particularly since various industries are interested in and have begun using this technology (Van Krevelen and Poelman, 2010). Augmented reality can enhance human interaction with environments and augment human perception to perform task, or detect risk factors. There are different ways to provide Augmented reality, and among these head-worn displays (HWDs) have received recent attention for industrial applications because of features including the ability to provide visual and audio information, receive vocal commands, and enable hands-free information exchange (Yang and Choi, 2015). HWDs have been applied successfully in design, manufacturing, assembly, and logistics industries (Fallavollita et al., 2016; Fiorentino et al., 2002; Hou et al., 2013; Iben et al., 2009; Van Krevelen and Poelman, 2010). Findings of these previous studies imply that using a HWD can increase workers' performance in workstations, yet the effects of HWD use, as an additional source of mental workload, has not been fully understood. Therefore, it is necessary to investigate how HWD impacts performance of the primary task.

Smartphones, auditory devices (Van Krevelen and Poelman, 2010), and paper-based methods are widely used in industry to provide instructions and/or communicate with workers. Each of these methods likely has different impacts on workers' performance since their difficulty levels vary (Young et al., 2015). Therefore, it is of interest to investigate whether the effects of HWD (as a mental load) on performance are distinct than that of other methods. He et al. (2015) addressed this in the context of a driving task, and their results suggested that a HWD is safer than cellphones. However, no prior work addressed this question in the context of walking. Yet, one

of the most common physical activities in many industries is walking (Roffey et al., 2010), and adding mental loads to this task may increase the risk of fall/slip. For example, several studies have investigated the relationship between differing mental loads and gait performance (Amboni et al., 2013; Beauchet et al., 2005; Hausdorff et al., 2008; Hollman et al., 2007; Lindenberger et al., 2000; Schaefer et al., 2015; Verghese et al., 2007). Results of these suggest that, for some ranges of mental loading, variability in gait parameters are evident. Therefore, we wanted to know if and how using a HWD influences gait variabilities, and whether the risk of using this device was less than smartphones and paper-based methods. To address these questions, the following hypothesis were tested:

Hypothesis 1: An increase in gait variability will occur as an adaptive response when using an information display (smart glasses, cellphone, or paper-based system) while walking

Hypothesis 2: Gait performance is less adversely influenced when participants use smart glasses compared to using either a cellphone or paper-based system

Hypothesis 3: Diverse measures of MV have varying levels of sensitivity to changes induced by different dual-task conditions (information displays) in the context of gait.

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Chapter 2. Differences in motor variability between experienced workers and novices during repetitive lifting/lowering tasks

Abstract

The substantial kinematic degrees-of-freedom available in human movement lead to inherent variations in a repetitive movement, or motor variability (MV). There is growing evidence for individual differences in MV, and understanding these differences may be fruitful for understanding and controlling injuries (e.g., in the occupational domain). We investigated whether MV differs with the level of experience (novices vs. experienced workers) in the context of a repetitive box lifting/lowering task that was performed both symmetrically and asymmetrically. Kinematic MV of both whole-body center-of-mass (COM) and the box were quantified, using a linear method (standard deviation), a non-linear method (sample entropy), and the Goal Equivalent Manifold (GEM). In these lifting/lowering tasks, our results indicated that COM and the box kinematics were controlled and performance variables, respectively. There was also a direct association between these two variables, suggesting that increasing MV improves performance. Novices had higher MV in the symmetric task, with the reverse pattern found in the asymmetric task. We conclude that experienced workers may prioritize flexible or stable movement strategies based on the task conditions. Our results also support that the GEM may be a particularly useful tool for the purpose of revealing individual differences in motor control strategies (e.g., related to the level of experience).

Keywords: Motor control; experienced workers; goal equivalent manifold; sample entropy; cycle-to-cycle SD; lifting/lowering

2.1. Introduction

The human body has substantial kinematic degrees-of-freedom that can be used to perform

specific tasks, and a challenging question is how the central nervous system (CNS) can

overcome such kinematic redundancy (Scholz et al., 2001; Scholz and Schöner, 1999). Bernstein

(1967), in classical work, noted that reproducing a specific movement is impossible, and that

there are inherent variations in movements because of the available redundant solutions for

executing a complex task. These variations have been treated as an essential characteristic of

motion (Newell and Corcos, 1993) and termed motor variability (MV). MV is now often

considered as a regulator of motion (Latash et al., 2002) to increase flexibility and adaptability

(Gaudez et al., 2016); therefore, Latash (2008) called these variations the "principle of abundance" rather than a "problem of redundancy". MV appears beneficial, with some evidence suggesting a potential role in preventing musculoskeletal disorders and improving performance (Bartlett et al., 2007; Moseley and Hodges, 2006).

For example, MV is directly related with precursors of injury such as pain (Madeleine, 2010), and Madeleine et al. (2008) indicated that chronic pain was associated with less movement variation. Trunk MV was also lower among people with low back pain compared to healthy controls (van den Hoorn et al., 2012). Based on such evidence, others have hypothesized that individuals decrease MV to adapt to pain, and that this adaptation might lead to more constrained movement boundaries (Srinivasan and Mathiassen, 2012). Such adaptation also continues after pain alleviation (Sterling et al., 2001), suggesting that individuals with pain might learn alternative solutions to avoid or minimize their pain. Moreover, a number of studies have found associations between MV and performance, with evidence that the MV of controlled variables increases when athletes have been trained and performance improves (i.e., decreased variation of performance variables) simultaneously (Button et al., 2003; Müller and Sternad, 2009). In the occupational domain, Mirka and Marras (1993) found high variations in muscle activity (controlled variables) during a repetitive lifting task, but these variations changed such that the produced external torque (performance variable) stayed fairly consistent. Gates and Dingwell (2008) found that when participants became fatigued in a repetitive sawing task, their movement pattern changed to maintain performance on the task. In summary, more variations in control variables might be beneficial to improve performance.

There are often substantial individual differences in behaviors depending on age, gender, work experience, etc. These individual differences lead to different movement patterns even when

performing the same task, and these differences may be associated with injury risk (Fedorowich et al., 2013; Kilbom and Persson, 1987; Madeleine et al., 2003; Srinivasan and Mathiassen, 2012; Vafadar et al., 2015). One important individual difference, particularly in the occupational domain, is the level of experience in doing a given task, and which may be associated with MV. Madeleine and Madsen (2009), for example, determined that experienced workers had higher MV in a simulated cutting task, while Lee and Nussbaum (2013) found that experienced workers were more stable while performing a repetitive lifting/lower task. Experienced workers also had higher lumbar angular kinematics and momentum in some directions (Lee and Nussbaum, 2012). These findings imply that increasing the variation in biomechanical demands of a task could decrease the impact of associated risk factors, which in turn has the potential to reduce injury risk. This important hypothesis needs further investigation, though, especially since some evidence suggests that experts are exposed to a higher risk of injuries (Granata et al., 1999); further, some work did not find any difference between novices and experienced workers (Plamondon et al., 2010).

Characterizing or quantifying MV remains as an important challenge, arising from the fact that there are diverse methods to quantify MVs and which fall into three classes (Stergiou, 2004). Traditional approaches (linear methods) are based on descriptive statistics. The second class stems from chaos theory (nonlinear methods), with several tools presented recently in the field of human movement (see Stergiou (2004) for an overview). The third class is based on the abundant degrees-of-freedom available to perform an action, which Cusumano and Cesari (2006) termed "equifinality". There are several methods to quantify MV based on equifinality, including the uncontrolled manifold (UCM) (Scholz and Schöner, 1999; Schoner, 1995), tolerance-noise-covariation (Müller and Sternad, 2003), the minimum intervention principle (Todorov and

Jordan, 2002), and the goal equivalent manifold (Cusumano and Cesari, 2006). Among these, GEM is the only approach that can simultaneously quantify the magnitude and temporal structure of variability (Cusumano and Dingwell, 2013).

While existing evidence supports an association between MV and pain, fatigue, and performance, relatively little evidence existing regarding MV differences associated with experience in the occupational domain. Existing results are also contradictory, with some showing that novices may adapt safer strategies than experienced workers (Granata et al., 1999) and vice versa (Madeleine et al., 2008). Our first aim here was to test which kinematic parameters might better reflect relevant individual motor control strategies in the context of a common occupational task (lifting/lowering), and the second aim was to compare the implemented strategies between novices and experienced workers in different conditions. We hypothesized that motor control strategies would differ between the two groups and that multiple measures of MV would have differing sensitivity to experience level.

2.2. Methods

2.2.1. Participants and procedures

The current work was a secondary analysis of data obtained in a prior study (Lee and Nussbaum, 2012). Complete details are available in the cited report, and as such are only summarized here. Separate groups of experienced workers (EXP) and novices (NOV) were involved (five males and one female in each group), with the former group composed of individuals who had experience in occupational lifting tasks and were regularly performing such tasks. An age-matched group of NOV was selected from university students, none of whom had any experience with frequent lifting tasks. Each participant performed 40 repetitions of lifting/lowering a box

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from/to knee/elbow height. This was done both symmetrically, in the sagittal plane, and asymmetrically, with the shelf positioned 60° from the sagittal plane. Boxes were set to 10% of individual body mass, and lifting/lowering rate was controlled at 20 cycles per minute with a metronome. Participants were asked to hold the box continuously, and to use free-style lifting technique but without moving their feet. Segmental kinematics and the 3D box trajectory was tracked at 100Hz using reflective markers. Raw data were low-pass filtered (bi-directional, 2nd-order Butterworth) with a cut-off frequencies of 5 Hz. The initiation of each lifting cycle was defined at the time when BOX velocity exceeded 5% of its peak value in that cycle (Srinivasan et al., 2015).

2.2.2. Data Analysis

To quantify MV in the lifting/lowering task, several kinematic parameters could be considered. In reaching tasks, for example, variations in movement patterns of end effectors have usually been investigated (Cusumano and Cesari, 2006; Dingwell et al., 2013; Samani et al., 2015; Srinivasan et al., 2015). Here, performance of the end effector was evaluated by analyzing the BOX trajectory. Also of interest was whether the CNS might employ different strategies to control the end effector vs. body movement. MV of the whole-body center-of-mass (COM) was used to quantify the latter, since in a similar task (i.e., sit-to-stand) the COM was suggested as a parameter that the CNS controls (Scholz et al., 2001).

As noted earlier, there are three classes of methods for quantifying MV. One method was chosen from each class, and these were compared to evaluate which class might better distinguish the behaviors of EXP from NOV. Cycle-to-cycle SD (linear method), and sample entropy (SaEn, a nonlinear method: (Samani et al., 2015; Srinivasan et al., 2015)) were used, each of which has

been applied to quantify MV in pipetting tasks. In the context of MV, repetitive lifting and pipetting tasks appear similar, since in both the end effectors are considered to evaluate performance (i.e., the task involves repetitively moving a BOX vs. pipette at a constant rate between fixed origins and destinations). As discussed by Cusumano and Dingwell (2013), the GEM (method based on equifinality) may be the most appropriate method to study MV, and thus this method was used to quantify trial-to-trial MV of the lifting task. These methods are explained in more details below

Based on the work of Srinivasan et al. (2015), motor control strategies used to control the BOX and the COM can be evaluated by calculating the cycle-to-cycle SD of mean speed (V) and path (X) of the BOX and COM, as well as the duration (T) of the lifting/lowering task. We applied a method similar to that developed by Richman and Moorman (2000) to compute SaEn of the COM and BOX paths (see appendix A). To measure SaEn, we used a time series of increments, so we set time delay = 1 (Ramdani et al., 2009). Embedding dimension was also calculated using the false nearest neighbors (FNN) approach (Kennel et al., 1992), since this method is well developed and most commonly used (Samani et al., 2015).

To quantify MV using the GEM analysis, we need to define a main task goal. In the study from which the current data were obtained (Lee and Nussbaum, 2012), participants were required to maintaining pacing of the lifting task; therefore, a constant time was considered as the main goal in our GEM analysis. Expanding upon the method described by Dingwell et al. (2010) (see appendix B), the variability in each cycle can be computed in the GEM direction (δt_T) and the direction perpendicular to it (δt_P), as:

$$\begin{bmatrix} \delta t_T \\ \delta t_P \end{bmatrix} = \frac{1}{\sqrt{1+T_n}} \begin{bmatrix} 1 & T_n \\ -T_n & 1 \end{bmatrix} \begin{bmatrix} V_n - V^* \\ X_n - X^* \end{bmatrix} \qquad (2.1)$$

where X_n and V_n were obtained by normalizing path and velocity of the COM or BOX to their respective SDs; (X^*, V^*) is the mean of (X_n, V_n); and $T_n = X_n/V_n$.

To study the structure of variations, we computed the SD (σ) of both δt_T and δt_P (Cusumano and Dingwell, 2013). Similar to Decker et al. (2012), we used relative variability (i.e., $\sigma(\delta t_T/ \delta t_P)$) to compare movement flexibility between the EXP and NOV groups. If $\delta t_T/ \delta t_P > 1$, it means that participants maintained the main goal function (Decker et al., 2012). Yet, these measurements (similar to UCM analysis) only reveal the average behavior of the system. To analyze the temporal structure of our time series data (i.e., δt_T, δt_P, and $\delta t_T/ \delta t_P$), a Lag-1 autocorrelation method was used (Dingwell et al., 2013). Several studies have suggested that two consecutive cycles are highly correlated (Dingwell and Cusumano, 2010; Dingwell et al., 2013; Scheidt et al., 2001), and thus this relationship can be expressed as:

$$S_{i+1} = \lambda S_i + \xi \qquad (2.2)$$

in which S and ξ are the time series and noise, respectively. Stability and (anti)persistence of the time series can be interpreted based on the λ value ($\lambda > 0$: persistence; $\lambda < 0$: anti-persistence; $\lambda = 0$: uncorrelated) (Dingwell and Kang, 2007; Dingwell et al., 2013; Strogatz et al., 1994). In the context of motor control, a large value of λ suggests that the CNS has less control over the time series, and vice versa.

2.2.3. Statistical analyses

Effects of the level of experience (LE) and lifting-symmetry (LS) on cycle-to-cycle SD, SaEn, and GEM-based measures were assessed using separate mixed-factors analyses of variance (ANOVAs). Parametric model assumptions were assessed, and some dependent measures were transformed prior to analysis to obtain normally-distributed model residuals. Significant interaction effects were explored using simple-effects testing. In all analyses, p-values ≤ 0.05 were considered statistically significant, and summary results are presented as least-square means (95% CI). The relative sensitivity of the different measures (SD cycle-to-cycle, SaEn, and GEM method) to LE and LS were assessed via their respective effect sizes (i.e., partial eta-squared), and qualitatively interpreted based on Cohen's (1988) criteria: large if $\eta_p^2 > 0.14$, moderate if $0.01 < \eta_p^2 < 0.06$, and small if $\eta_p^2 < 0.01$.

2.3. Results

Linear measures:

Statistical results regarding cycle-to-cycle SD are summarized in Table 2.1. For this measure, only the interaction LS x LE effect on BOX kinematics was significant. Variations of the BOX path were larger in the asymmetric vs. symmetric tasks ($p=0.016$) for NOV, yet the opposite was evident among EXP (Figure 2.1, top). The same pattern was found for BOX velocity (Figure 2.1, bottom). Finally, effects of LE were approached significant on $\sigma(X_{BOX})$ for asymmetric task ($p=0.052$), and $\sigma(V_{BOX})$ for both task conditions (Figure 2.1, bottom).

Table 2.1. ANOVA results of regarding the main and interaction effects of lifting-symmetry (LS) and level of experience (LE) on cycle to cycle SD (σ) of the whole-body center-of-mass (COM), BOX, and task completion time. For the former two, results are presented for both mean speed (V) and path (X). Both p values and effects sizes (η_p^2) are provided. Bold fonts highlight significant effects.

			LS	LE	LS×LE
COM	$\sigma(V)$	p	0.759	0.820	0.071
		η_p^2	0.010	0.010	0.289
	$\sigma(X)$	p	0.647	0.303	0.124
		η_p^2	0.022	0.185	0.219
BOX	$\sigma(V)$	p	0.124	0.952	**0.002**
		η_p^2	0.220	0.001	**0.643**
	$\sigma(X)$	p	0.441	0.590	**0.008**
		η_p^2	0.060	0.0903	**0.523**
Time	$\sigma(T)$	p	0.198	0.278	0.119
		η_p^2	0.199	0.157	0.249
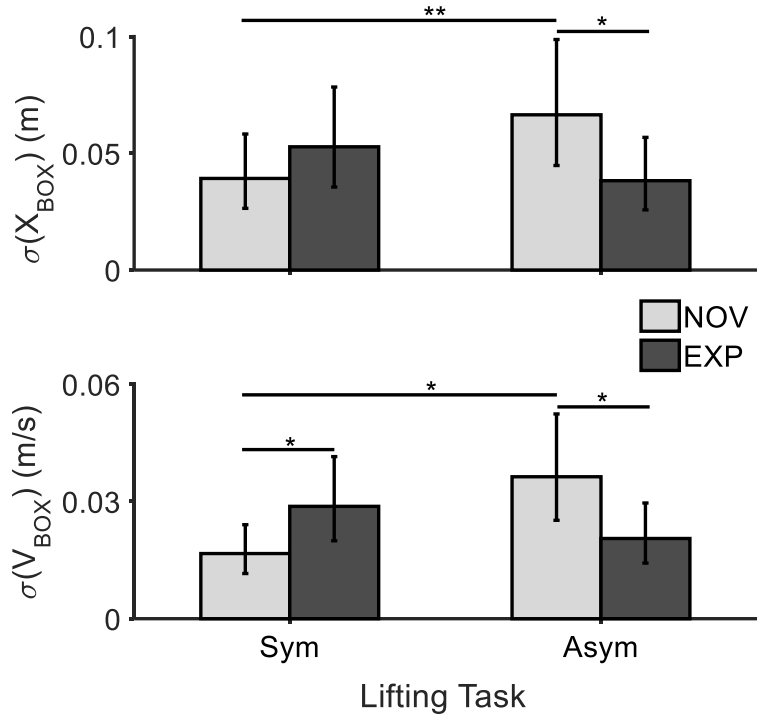
Figure 2.1: Cycle-to-cycle SD of the BOX for symmetric (Sym) and asymmetric (Asym) repetitive lifting/lowering among novices (NOV) and experienced workers (EXP). Top: variations of the BOX path. Bottom: variation of the BOX velocity. ** indicates a significant paired difference ($p < 0.05$), while * indicates a difference that approached significant ($0.05 < p < 0.06$). Error bars indicate 95% confidence intervals.

Nonlinear measures:

For the nonlinear measures, only the main effect of LE on the SaEn of x_{COM}, and x_{BOX} were

significant (Table 2.2). In both the symmetric and asymmetric conditions, SaEn(x_{COM}) and

SaEn(x_{BOX}) were higher for NOV than EXP (Figure 2.2).

Table 2.2. ANOVA results regarding the main and interaction effects of lifting-symmetry (LS) and level of experience (LE) on SaEn of the whole-body center-of-mass (COM) and the BOX. Both p values and effects sizes (η_p^2) are provided. Bold fonts highlight significant effects.

		LS	LE	LS×LE
SaEn(X_{COM})	p	0.224	**0.001**	0.178
	η_p^2	0.144	**0.908**	0.173
SaEn(X_{BOX})	p	0.914	**0.0158**	0.9393
	η_p^2	0.001	**0.601**	<0.001
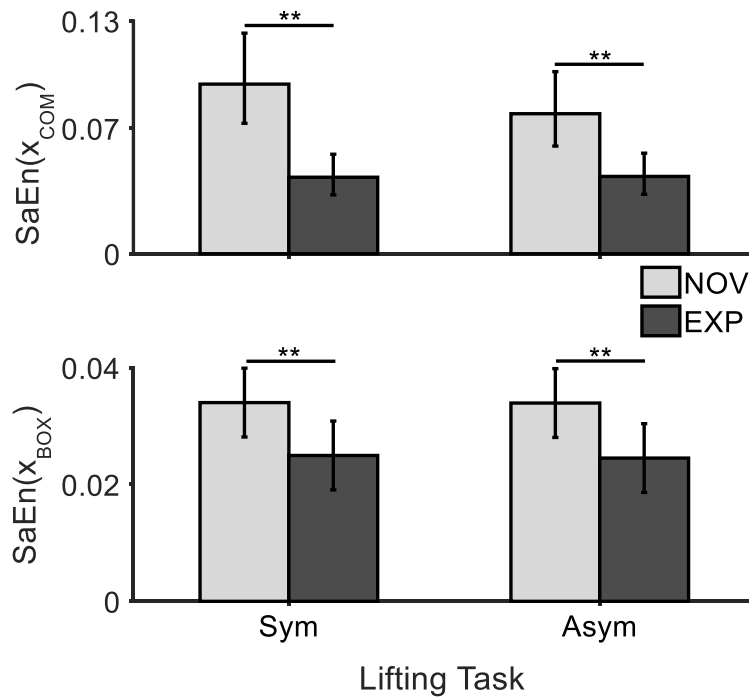
Figure 2.2: SaEn result for symmetric (Sym) and asymmetric (Aysm) repetitive lifting/lowering, among novices (NOV) and experience workers (EXP). Top: SaEn of x_{COM}. Bottom: SaEn of x_{BOX}. All paired differences between the NOV and EXP groups were statistically significant, as indicated by **. Error bars indicate 95% confidence intervals.

GEM-based measures:

Effects of LS and LE on GEM responses related to the COM are summarized in Table 2.3. There were significant LE × LS interaction effects on $\sigma(\delta t_T)$, $\sigma(\delta t_P)$, $\sigma(\delta t_T)/\sigma(\delta t_P)$ for COM, though neither of the main effects were significant for these measures. In the asymmetric condition, MV in the GEM direction was higher among EXP (Figure 2.3 top). NOV had significantly lower $\sigma(\delta t_P)$ in the symmetric vs. asymmetric conditions (Figure 2.3 middle). In the symmetric condition, EXP had significantly lower $\sigma(\delta t_T/ \delta t_P)$ (Figure 2.3 bottom). In contrast, movement variations among EXP were slightly higher in the asymmetric condition. The magnitude of relative MV among NOV significantly differed between the two asymmetry conditions (Figure 2.3 bottom). For log-1 autocorrelation outputs, only the LE main effect on $\lambda(\delta t_T)$ of COM was significant, with a higher value for NOV (LSM=0.214, CI=0.051-0.375) than EXP (LSM=0.024, CI=−0.186-0.138). In both groups and conditions, values of $\lambda(\delta t_T)$ were significantly higher than $\lambda(\delta t_P)$.

Table 2.3. ANOVA results of the GEM method for main and interaction effects of lifting-symmetric (LS) and level of experience (LE). Both p values and effects sizes (η_p^2) are provided, and bold fonts show significant effects.

			LS	LE	LS×LE
COM	$\sigma(\delta t_T)$	p	0.459	0.105	**0.013**
		η_p^2	0.056	0.287	**0.477**
	$\sigma(\delta t_P)$	p	0.299	0.268	**0.006**
		η_p^2	0.107	0.208	**0.553**
	$\sigma(\delta t_T/\delta t_P)$	p	0.267	0.190	**0.003**
		η_p^2	0.121	0.299	**0.601**
	$\lambda(\delta t_T)$	p	0.140	**0.043**	0.316
		η_p^2	0.204	**0.361**	0.100
	$\lambda(\delta t_P)$	p	0.302	0.598	0.231
		η_p^2	0.105	0.044	0.140
BOX	$\sigma(\delta t_T)$	p	0.965	0.449	0.813
		η_p^2	<0.001	0.115	0.006
	$\sigma(\delta t_P)$	p	0.602	0.503	0.287
		η_p^2	0.028	0.350	0.112
	$\sigma(\delta t_T/\delta t_P)$	p	0.880	0.464	0.983
		η_p^2	0.002	0.240	<0.001
	$\lambda(\delta t_T)$	p	0.957	0.912	0.502
		η_p^2	<0.001	0.002	0.046
	$\lambda(\delta t_P)$	p	0.259	0.972	0.789
		η_p^2	0.125	<0.001	0.007
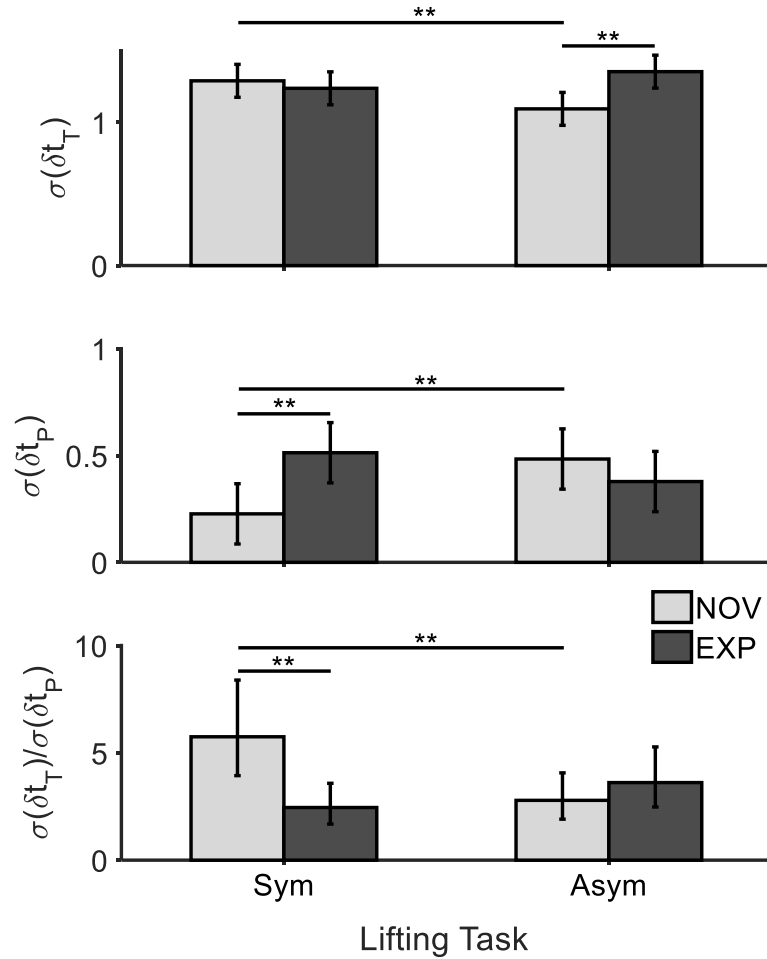
Figure 2.3: GEM result of COM for symmetric (Sym) and asymmetric (Aysm) repetitive lifting/lowering among novices (NOV) and experienced workers (EXP). Top: variability in the GEM direction. Middle: variability in the direction perpendicular to the GEM. Bottom: relative variability. ** indicates a significant difference. Error bars indicate 95% confidence intervals.

2.4. Discussion

Our first aim was to identify kinematic parameters that reflect differences between individual motor control strategies utilized by the CNS to regulate movement, in the context of a repetitive lifting/lowering task. SaEn values for the BOX were very small (Figure 2.2 bottom), indicating that variations in BOX motion were limited (Yentes et al., 2013). This suggests that the CNS employed a strategy intended to keep BOX motion fairly consistent, and by implication that BOX kinematics were *performance variables*. SaEn of the COM parameters were larger than

those for the BOX, indicating that the COM had higher movement variations than the BOX. That there were differences between GEM outcomes between NOV and EXP for the COM, and large variations in the COM motion, imply that COM kinematics are *controlled variables*. In other words, these results suggest that the CNS controlled COM parameters to regulate lifting/lowering movements (e.g., increase movement flexibility or stability), which is consistent with previous findings in a sit-to-stand task (Scholz et al., 2001; Scholz and Schöner, 1999).

We hypothesized that EXP and NOV would use different motor control strategies in lifting/lowering tasks, and our results supported this hypothesis. EXP individuals had lower relative variability ($\sigma(\delta t_T)/\sigma(\delta t_P)$) in the symmetric lifting condition, suggesting that their movements were more constrained (Decker et al., 2012). Using the same dataset, Lee and Nussbaum (2013) found that EXP individuals were more stable in the symmetric condition, based on lower Lyapunov exponents. Together, the current and earlier results imply that EXP workers constrain their movements to increase stability. These earlier authors (Lee and Nussbaum, 2012) and Granata et al. (1999) also found that peak kinetics were lower among NOV participants in symmetric lifting/lowering, which supports that a higher relative variability may lead to safer behavioral strategies. Task asymmetry was also reported to affect stability (peak lumbar momentum) among NOV participants (Granata and England, 2006; Lee and Nussbaum, 2013), but to not significantly change stability among EXP workers (Lee and Nussbaum, 2013), both of which are consistent with our results. In the asymmetric task, NOV used more constrained pattern by exerting more control of their COM (Figure 2.3, bottom). Since asymmetry can be presumed to increased task difficulty, it appears that a consistent strategy perhaps could not be used by both groups. Instead, the EXP group increased their flexibility slightly [increased $\sigma(\delta t_T)/\sigma(\delta t_P)$], which may help to decrease the risk of injury. We offer the

conjecture that EXP workers may prioritize stable patterns over flexible ones in a simple task, though this priority may change in a complex task.

In contrast to the GEM-based outcomes, SaEn results indicated that the NOV group used more flexible strategies. Larger values of SaEn indicate that movements are more complex and more flexible (Madeleine, 2010). Therefore, based on SaEn outcomes, movements of NOV were more complex than EXP (Figure 2.2), contradicting the results of Madeleine and Madsen (2009) that indicated SaEn was higher for some joints displacements in the EXP group. Our SaEn results were consistent with GEM results in the symmetric condition; however, for the asymmetric condition, these outcomes differed. We believe the divergence between SaEn and GEM outcomes is because SaEn quantifies the complexity of the whole movement without decoupling variations into "good" and "bad" directions. While some variations affected performance, others did not. GEM-based measures, on the other hand, reveal the structure of variability in both GEM and non-GEM. In the asymmetric condition, while NOV individuals had less flexible movements (Figure 2.3, bottom), they had higher $\sigma(\delta t_P)$. SaEn likely reflected variations in both the GEM direction (δt_T) and the direction perpendicular to it (δt_P), and thus SaEn results should be interpreted with some caution (i.e., they may not reflect inherent individual differences, such as between NOV and EXP).

As noted earlier, prior evidence suggests that performance variables and controlled variables are associated. Supporting this, the current GEM results for the controlled parameter (COM) and linear outcomes for the performance parameter (BOX) had a direct association (based on Figures 2.1 and 2.3). Furthermore, task performance deteriorated (more variations in BOX motion) in parallel with decreasing movement flexibility (Figures 2.1 and 2.3). It thus seems that performance was better in conditions with lower $\sigma(\delta t_P)$ (Figure 2.1 and Figure 2.3, middle). Such

an outcome is consistent with concepts underlying the UCM and GEM methods, which posit that variations in the controlled direction affect task performance (Dingwell and Cusumano, 2010; Latash et al., 2002). Compared to the GEM results, SaEn was not associated with task performance, again suggesting that GEM-based methods may better capture individual differences in motor control (e.g., related to expertise).

Our second hypothesis was also supported, in that that multiple measures of MV had differing sensitivity to group-level differences in experience. Using Cohen's (1988) criteria, effect sizes for SaEn parameters (COM and BOX), Cycle-to-cycle SD of BOX variables, and GEM outcomes for COM all had high sensitivity to the level of experience (LE) and its interactive effect with lifting symmetry. SaEn of the COM had the highest effect size for LE among all measures used. While the latter suggests SaEn might be a good candidate to explore MV differences, as mentioned earlier interpretations based on this method might be limited. While the linear method seems useful to evaluate performance, given large observed effect sizes for performance variables (BOX). GEM measures of the COM also had large effect sizes, detected group-level differences in MV structure. The Lag-1 autocorrelation method could only predict that movement was corrected more frequently in the non-relevant GEM direction, since $\lambda(\delta t_P)$ was smaller than $\lambda(\delta t_T)$ (Cusumano and Dingwell, 2013). However, significant differences were found between NOV and EXP using this method.

One limitation of this study is that the lifting task was somewhat artificial and constrained (e.g., foot placement was fixed), included only two symmetry conditions, and had a relatively small sample size. As such, we do not know whether or to what extent these results will generalize to other tasks or populations. Nor is it known whether conclusions regarding the sensitivity of different MV measures are appropriate for assessing other individual differences (e.g., related to

age). Regarding the nonlinear method, the methods employed for determining the delay time and embedding dimensions were not mathematically validated, and it is possible that the number of lifting/lowering cycles used here was insufficient to obtain reliable GEM-based measures.

Considering both the current and earlier findings, we conclude that the CNS may adopt stable lifting/lowering patterns rather than flexible movements with increased work experience or increased task difficulty. In addition, movement flexibility appears to have direct effects on task performance. While SaEn could distinguish between novice and experienced groups, its results should be interpreted with some caution. Alternatively, GEM-based measures were useful for explaining and differentiating the behaviors of novices and experienced workers.

Appendix A

The first step in applying nonlinear methods is to reconstruct the state space (Abarbanel et al., 1993; Kugiumtzis, 1996), which can be expressed as:

$$X(t) = [x(t), x(t+\tau),..., x(t+(d_E - 1)\tau)]^{'} \tag{A-1}$$

where $X(t)$ is the state vector, $x(t)$ is location (here of the BOX or COM) at time t, τ is a delay time, and d_E is an embedding dimension (d_E was 3 and 4 for the symmetric and asymmetric tasks, respectively).

Richman and Moorman (2000) introduced SaEn as a modification of approximate entropy. In their newer method, self-similar patterns are excluded (Richman and Moorman, 2000), and it was used here to measure the complexity of a time series (i.e., path of the BOX and the COM). SaEn was calculated from:

$$SaEn(m, n, N) = -\ln(\Phi^{d_E + 1}(r) / \Phi^{d_E}(r)) \tag{A-2}$$

where $\Phi^{d_E}(r)$ is the mean of $C_i^{d_E}(r) = $ (number of $X(j)$ such that $d[X(i),X(j)] < r$), tolerance r is

0.2×SD of the time series (Zhang and Zhou, 2012), and $d[X(i),X(j)]$ is the Chebyshev or

Euclidean distance.

Appendix B

In a time-based GEM analysis, any combination of path ($X(i)$) and speed ($V(i)$), in the ith cycle,

can satisfy the following goal function (Cusumano and Cesari, 2006; Dingwell et al., 2013):

$$f(X(i), V(i)) = \frac{X(i)}{V(i)} - T = 0 \tag{B-1}$$

In equation (B-1), T is duration of the lifting/lowering cycle, and it is relatively constant on

average. $X(i)$ can be several kinematic values (here, the path of the BOX and COM), and $V(i)$ is

the corresponding speed. Based on the method developed by Dingwell and Cusumano (2010),

the amount of variability in the direction of the constant time GEM (δt_T), and in the

perpendicular direction (δt_P), were calculated for each cycle. In the first step, each variable was

normalized to its SD: $X_n = X(i)/SD(X(i))$ and $V_n = V(i)/SD(V(i))$. By respectively substituting $X(i)$

and $V(i)$ in equation (B-1) with $SD(X(i))X_n$ and $SD(V(i))V_n$, the rescaled GEM is computed as:

$$\frac{X_n}{V_n} = [\frac{SD(V(i))}{SD(X(i))} \cdot T] = T_n \tag{B-2}$$

Normalizing these variables enables us to compare MV within and between subjects (Dingwell

et al., 2010). Both variables are varying around a preferred operating point, (V^*, X^*), the closest

point on the GEM to the average of (V_n, X_n). These variations can be expressed as:

$$\nabla Vn = Vn - V^{*}$$
$$\nabla Xn = Xn - X^{*}$$

(B-3)

Subsequently, equation (B-1) is linearized around (V^{*}, X^{*}) to compute δt_T and δt_P (for additional details, please refer to Dingwell et al. (2013)).

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Chapter 3. Temporal changes in motor variability during prolonged lifting/lowering and the influence of work experience

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 related to 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), as a controlled variable, and box trajectory, as a performance variable, 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.

Keywords: work-related musculoskeletal disorders; motor control; fatigue; goal equivalent manifold; experienced workers

3.1. 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 due to 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 (Müller and Sternad, 2009). It seems that the CNS can use MV to increase flexibility and adaptability of human movement (Gaudez et al., 2016); in other words, 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).

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 novice players did not vary MV.

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 both lower loads on the back (Chany et al., 2006; Lett and McGill, 2006) and more stable movements (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 the previous analysis, 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 this 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).

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 association between MV and fatigue, both of which are potential indicators of

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 presence 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.

3.2. Method

3.2.1. 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, 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). A threshold (5% of the box velocity peak value) was

used to define the initiation of each lifting/lowering cycle (Srinivasan et al., 2015).

3.2.2. Data Analysis

In our previous analysis of a repetitive lifting task (Chapter 2), we found that COM kinematics

are controlled variables. In other words, COM motions appear to be regulated by the CNS. In

contrast, BOX kinematics appeared to be performance variables. This implies that the CNS

regulates movements of the COM such that box kinematics have relatively small variations.

Therefore, we also considered 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 (nonlinear 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. (Srinivasan et al., 2015), we calculated cycle-to-cycle standard deviation (SD) of the following variables for the BOX and COM kinematics: path (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 incremental time series of COM/BOX paths. This reconstruction was done using the time delay and embedding dimension. The time delay value was set to 1, since we used the incremental time series (Ramdani et al., 2009), and the embedding dimension was calculated based on well-developed methods (i.e., the false nearest neighbors approach (Kennel et al., 1992)). Then, we calculated SaEn as follows:

$$SaEn(m,n,N) = -\ln(\Phi^{d_E + 1}(r) / \Phi^{d_E}(r)) \tag{3.1}$$

where $\Phi^{d_E}(r)$ is the mean of $C_i^{d_E}(r) =$ (number of $X(j)$ such that $d[X(i),X(j)] < r$), d_E is the embedding dimension ($d_E = 4$), $X(i)$ 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 or Euclidean 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. In an earlier chapter, we expanded on the method described by Dingwell and Cusumano (2010) to decouple movement variations of each cycle into variations in the GEM direction (δt_T) and in the direction perpendicular to the GEM direction (δt_P) (Figure 3.1). MV in the GEM direction does not affect performance variables, however variations in δt_P deteriorate task performance (Dingwell and Cusumano, 2010). Variations in each of these directions was calculated using:

$$\begin{bmatrix} \delta t_T \\ \delta t_P \end{bmatrix} = \frac{1}{\sqrt{1+T_n}} \begin{bmatrix} 1 & T_n \\ -T_n & 1 \end{bmatrix} \begin{bmatrix} V_n - V^* \\ X_n - X^* \end{bmatrix} \tag{3.2}$$

where $X_n = X(i)/SD(X(i))$ and $V_n = V(i)/SD(V(i))$ in which $X(i)$ is the path of BOX/COM 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. Also, $T_n = X_n/V_n$, and (X^*, V^*) is 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.

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). 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 (α>0.5) or anti-persistency of (α<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).
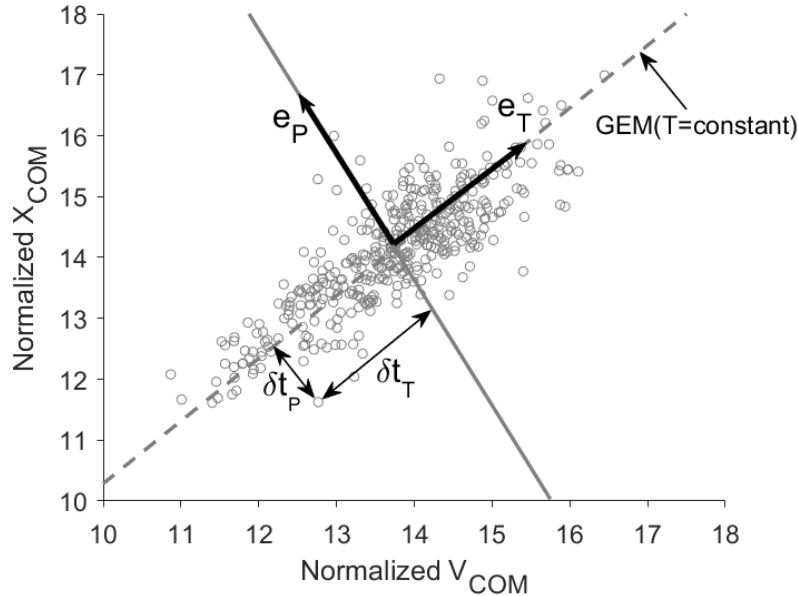
Figure 3.1: Example results using the goal equivalent manifold (GEM) method to assess movement variability in a repetitive lifting/lowering task. Each lifting/lowering cycle is analyzed to yield normalized values of the COM position (X_{com}) and velocity (V_{com}), shown as the set of 360 circles for 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).

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).

3.3. 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 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 = $\eta_p{}^2$) 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 $\eta_p{}^2 < 0.01$.

3.4. Results

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 3.1). 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 (Figure 3.2, top). Variations in timing errors also increased siginificantly from the second to the fourth time blocks (Figure 3.2, bottom).

Table 3.1. ANOVA results regarding cycle to cycle SD (σ). Both *p* values and effect sizes ($\eta_p{}^2$) 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	$\sigma(V)$	$p\ (\eta_p{}^2)$	0.258 (0.121)	0.844 (0.019)	0.543 (0.072)
	$\sigma(X)$	$p\ (\eta_p{}^2)$	**<0.001 (0.429)**	0.664 (0.044)	0.610 (0.044)
BOX	$\sigma(V)$	$p\ (\eta_p{}^2)$	0.971 (0.013)	0.422 (0.224)	0.315 (0.109)
	$\sigma(X)$	$p\ (\eta_p{}^2)$	0.182 (0.141)	0.475 (0.110)	0.243 (0.125)
Timing Errors	$\sigma(\varDelta T)$	$p\ (\eta_p{}^2)$	**0.028 (0.233)**	0.465 (0.126)	0.827 (0.036)
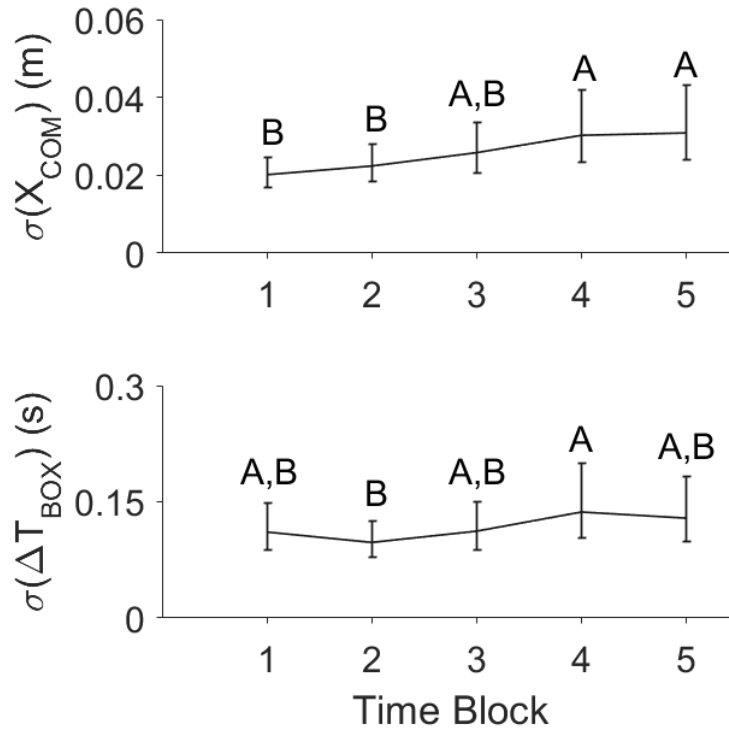
Figure 3.2: Cycle-to-cycle standard deviation of the COM path (top) and timing errors (bottom) for each of the five time blocks. Values in blocks not sharing same letters are significantly different.

SaEn results

For SaEn measures, only the main effect of LE on SaEn of the COM path was significant (Table 3.2). SaEn values of the COM path for NOV (LSM=0.162, CI=0.148-0.176) were significantly higher than for EXP (LSM=0.142, CI=0.129-0.156).

Table 3.2: 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. Significant effects are highlighted using bold font.

		LF	LE	LS×LE
SaEn(X$_{COM}$)	*p (η_p^2)*	0.400 (0.094)	**0.046 (0.565)**	0.436 (0.088)
SaEn(X$_{BOX}$)	*p (η_p^2)*	0.097 (0.174)	0.261 (0.253)	0.282 (0.116)

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 3.3). Over the five time blocks, COM variability in the GEM direction increased significantly (Figure 3.3A). The magnitude of COM deviations in the direction perpendicular to the GEM also increased from the second to the fourth time blocks (Figure 3.3B). Though only approaching significance ($p = 0.091$), COM variations in the GEM direction were 17% larger among EXP vs. NOV. While interaction effects of LE and LF on $\sigma(\delta t_T)$ for COM were not significant, paired comparison showed significant differences between the motion variations of NOV and EXP in the GEM direction 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

(Figure 3.4, top). 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 (Figure 3.3C); however, $\alpha(\delta t_P)$ increased slightly from the 1st time block (Figure 3.3D). 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.

Table 3.3. 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	$\sigma(\delta t_T)$	p (η_p^2)	**0.011 (0.272)**	0.091 (0.257)	0.195 (0.137)
	$\sigma(\delta t_P)$	p (η_p^2)	**0.024 (0.241)**	0.754 (0.014)	0.711 (0.051)
	$\alpha(\delta t_T)$	p (η_p^2)	**0.024 (0.240)**	0.771 (0.012)	0.219 (0.131)
	$\alpha(\delta t_P)$	p (η_p^2)	0.205 (0.134)	0.634 (0.026)	0.813 (0.038)
BOX	$\sigma(\delta t_T)$	p (η_p^2)	0.360 (0.101)	0.553 (0.001)	0.796 (0.040)
	$\sigma(\delta t_P)$	p (η_p^2)	0.167 (0.146)	0.452 (0.013)	0.825 (0.036)
	$\alpha(\delta t_T)$	p (η_p^2)	**0.011 (0.274)**	0.765 (0.010)	0.422 (0.090)
	$\alpha(\delta t_P)$	p (η_p^2)	0.154 (0.150)	0.668 (0.023)	0.848 (0.033)
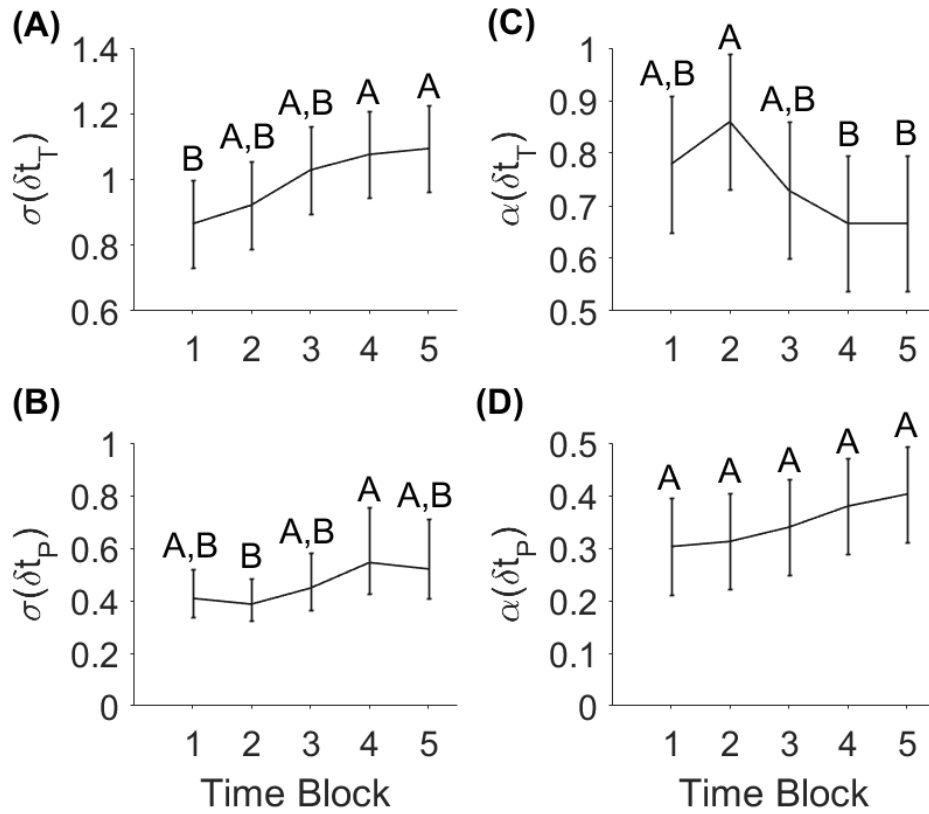
Figure 3.3: GEM-based outcomes of the COM, for each of the five time blocks. (A) magnitudes of variations in the GEM direction for the COM. (B) movement variability in the direction perpendicular to the GEM for the COM. (C) temporal variation structure in the GEM direction for the COM. (D) temporal variations in the direction perpendicular to the GEM for the COM. Results in time blocks not sharing common letters are significantly different.
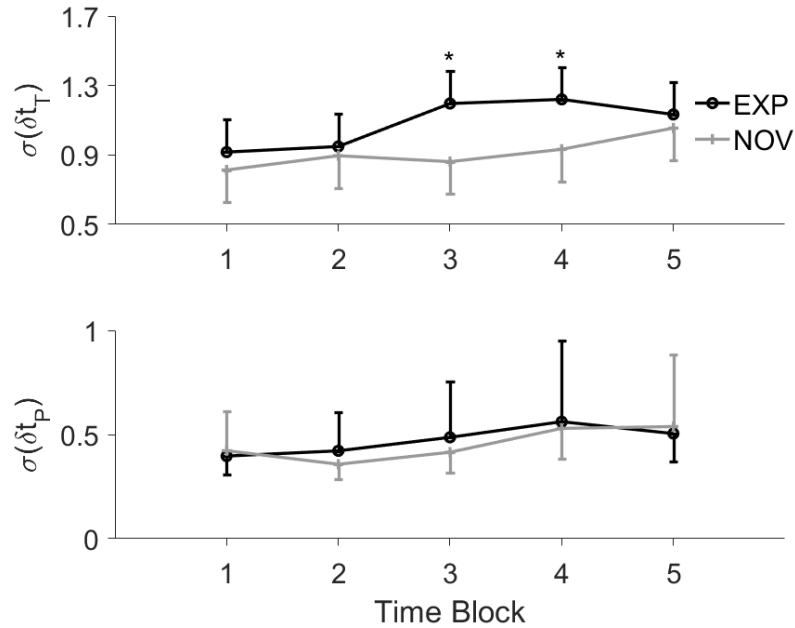
Figure 3.4: GEM-based outcomes for the COM, for each of the five time blocks. (Top) magnitudes of variations in the GEM direction. (Bottom) movement variability in the direction perpendicular to the GEM. The symbol * indicates a significant paired difference between the EXP and NOV groups.

3.5. 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 (Figure 3.2, top). This result suggests that the CNS utilized more redundant solutions to perform the lifting/lowering task as an adaptation 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 (Figure 3.3A), while variations in the other direction had a fluctuating

pattern but with a general increasing trend across the time blocks (Figure 3.3B). Effects of

fatigue on variations in the GEM-direction were more substantial than in the non-GEM-relevant

(Table 3.3). Together, these GEM outcomes imply that the CNS intended 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 trunk flexion tasks, fatigue

reduced both the capability to maintain balance (Lee et al., 2014) and dynamic stability (Granata

and Gottipati, 2008) in post-fatigue. 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 adaptation 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.

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 increased in

the non-GEM-relevant (Figure 3.3D), and indicating that participants' control over their COM

decreased in this direction with fatigue (Dingwell and Cusumano, 2010). An inverse pattern was

observed for the GEM direction (Figure 3.3C), which showed that deviations were regulated

more tightly in this direction with fatigue (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 explored the existing abundant DOFs in the GEM direction to a greater extent, 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 (Figure 3.3C). This difference suggests that the EXP group adopted 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 complex movements (Madeleine, 2010) regardless of the level of fatigue. One explanation for this inconsistency is that SaEn only could quantify variability in each lifting parameter separately, yet only emphasizing the variability of one parameter may not provide comprehensive insight about the strategy motor control utilized by the CNS (Cusumano and Dingwell, 2013). In contrast, the GEM analysis measured MV of all parameters at the same time.

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 performance variable (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 ($\sigma(\varDelta T)$) and COM variability in the non-GEM-relevant ($\sigma(\delta t_P)$) across the time blocks (Figure 3.2, bottom, and Figure 3.3B) 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 performance variable (i.e., BOX) alone could not provide any insights about potential differences in motor control strategies that are adopted by NOV vs. EXP to deal with fatigue. When using the GEM method, we thus suggest that 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. SaEn and SD of COM variations in the GEM direction (i.e., $\sigma(\delta t_T)$) also had high sensitivity to LE. While the effects of LE on SaEn values were large, we suggest that the SaEn method is less suitable for investigating MV since, as discussed above, it may lead to incorrect interpretations.

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).

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Chapter 4. Information presentation through a head-worn display ("smart glasses") has a smaller influence on the temporal structure of motor variability during dual-task gait compared to displays involving a head-down posture (paper and cellphone)

Abstract

The need to complete multiple tasks concurrently is a common occurrence both daily life and in occupational activities, which can often include simultaneous cognitive and physical demands. As one example, there is increasing availability of head-worn display (HWD) technologies that can be employed when a user is mobile (e.g., while walking). This new method of information presentation may, however, introduce risks of adverse outcomes such as a loss of gait performance. The goal of this study was thus to quantify the effects of a HWD (i.e., smart glasses) on MV during gait and to compare these effects with those of other common information displays (i.e., cellphone and paper-based system). Twenty participants completed four walking conditions, as a single task and in three dual-task conditions (three information displays). In the dual-task (DT) conditions, the information display was used to present several cognitive tasks. Three different measures were used to quantify variability in gait parameters for each walking condition (using the cycle-to-cycle standard deviation, sample entropy, and the "goal-equivalent manifold" approach). Our results indicated that participants used more adaptable gait strategies in head-up display conditions (i.e., single task and dual task with smart glasses) compared with two other head-down conditions (i.e., dual task with the paper-based system and cellphone). We conclude that the risk of an adverse gait event (e.g., a fall) in head-up walking is lower than in head-down walking, and that HWDs might help reduce the risk of such events during dual-task gait conditions.

Keywords: Motor control, Goal equivalent manifold, Sample Entropy, Cycle-to-cycle SD, Head-worn display, Head-down display, Gait

Abbreviations	
Motor variability	MV
Goal Equivalent Manifold	GEM
Preferred Walking Speed	PWS
Stride length	L_n
Stride time	T_n
Stride speed	S_n
Step length	SL_n
Step time	ST_n
Step speed	SS_n
Sample entropy	SaEn
Variations in the GEM direction	δ_T
Variations in the direction perpendicular to the GEM	δ_P
Scaling exponent	α
Stride time variability	STV

4.1. Introduction

Diverse activities impose simultaneous physical and cognitive demands (Srinivasan et al., 2016). Combat actions, use of a computer (DiDomenico and Nussbaum, 2011), and manufacturing tasks (Cirulis and Ginters, 2013) are several examples of such *dual task* activities in the occupational domain. It remains unclear, however, whether such activities impose higher risks of adverse outcomes, such as injury, as existing evidence is somewhat mixed. Mental loads imposed along with physical demands have been suggested as increasing the risk of injuries through decreased muscle endurance, delayed muscle recovery (Mehta and Agnew, 2012), increased spinal loads (Davis et al., 2002), and gait variabilities (Beauchet et al., 2003). However, other studies have found inconsistent results; for instance, adding mental loads to physical tasks have been found to have no or only slight effects on muscle activities (Birch et al., 2000; Blangsted et al., 2004; Srinivasan et al., 2016), and even decreased activity in some cases (Finsen et al., 2001). It appears that different levels of physical and/or mental demands can lead to diverse outcomes (Srinivasan et al., 2016).

Use of augmented reality is one example of a dual-task activity, and is of particular interest to us given the growing use among the general public and since various industries are interested in and have begun using this technology (Van Krevelen and Poelman, 2010). Augmented reality can enhance human interaction with environments and can augment human perception to perform tasks or detect risks. There are diverse ways to provide augmented reality, and among these head-worn displays (HWDs, including "smart glasses") have received recent attention, including for industrial applications, because of features including the ability to provide visual and audio information, to receive vocal commands, and to enable hands-free information exchange (Yang and Choi, 2015). HWDs have been applied successfully in design, manufacturing, assembly, and

logistics industries (Fallavollita et al., 2016; Fiorentino et al., 2002; Hou et al., 2013; Iben et al., 2009; Van Krevelen and Poelman, 2010). Findings of these previous studies imply that using a HWD can increase a worker's performance, yet the broader effects of HWD use, as an additional source of mental workload, has not been fully described. Therefore, we suggest there is a current need for additional investigation of the potential impacts of HWDs on performance, particular primary task performance, since there may be unintended or unexpected adverse outcomes.

Smartphones, auditory devices (Van Krevelen and Poelman, 2010), and paper-based methods are among the more widely used methods in industry to provide instructions and/or communicate with workers. Each of these methods is likely to have different impacts on workers' performance, since the required attentional demands vary. Therefore, it is of interest to investigate whether the effects of HWD use (as a mental load) on performance are distinct when compared to these other methods. He et al. (2015) addressed this issue in the context of a driving task, and their results suggested that a HWD is safer than a cellphone. However, no prior work addressed this question in the context of other common activities.

Walking is a routine and common human activity, and for many industries it is one of the most common physical activities performed (Roffey et al., 2010). While apparently a simple activity, walking is actually a complex task that is highly dependent on cognitive resources, as well as on the sensorimotor system (Decker et al., 2012). When humans perform both a cognitive task and walking simultaneously, the central nervous system (CNS) needs to allocate limited attentional resources between both tasks to complete the dual-task activity successfully. As such, variability in gait is used commonly as a proxy to indicate a decline in resources allocated towards performing the walking task (Decker et al., 2012; Woollacott and Shumway-Cook, 2002); such a decline, in turn, can be used to infer potential risks, such as a loss of balance or a fall. For

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example, several studies have investigated the relationship between differing mental loads and gait performance (Amboni et al., 2013; Beauchet et al., 2005b; Hausdorff et al., 2008; Hollman et al., 2007; Lindenberger et al., 2000; Schaefer et al., 2015; Verghese et al., 2007). Results of these suggest that, for some ranges of mental loading, variability in gait parameters are evident. We thus suggest that prior to using new devices, such as HWDs, that impose new and/or additional cognitive loads during walking tasks, it is essential to evaluate their effects to assess whether use of such devices might increase risk.

Due to the large number of degrees-of-freedom (DOFs) in the human body (Scholz et al., 2001; Scholz and Schöner, 1999), abundant solutions exist for overcoming the effect of cognitive loads on the performance of certain complex tasks, such as walking, and which lead to inherent variations in body movement (Bernstein, 1967). While these variations once were thought to be sensorimotor noise (Gaudez et al., 2016; Newell and Slifkin, 1998), they have more recently been identified as an essential movement characteristic (Newell and Corcos, 1993), and are termed motor variability (MV). One question this study poses is whether the CNS benefits from MV to successfully maintain walking adaptability in the presence of different additional sources of mental load, and whether the specific source of information presentation is influential.

Prior to exploring this question, however, an appropriate method for quantifying MV must first be determined. In the field of motor control, this remains a challenge due to the variety of methods for measuring movement variations that currently exist. Three different classes are typically used in assessing MV; linear methods, methods stemmed from chaos theory, and methods based on the numerous DOFs within the human body (Stergiou, 2004). The first class, and also the traditional approach, involves linear methods based on descriptive statistics, and has been implemented for both discrete and continuous measures. The second class, inspired by

chaos theory, incorporates nonlinear methods that have recently gained traction in the field of human movement. The final class considers the abundant DOFs accessible to execute a repetitive task, which has been termed "equifinality" (Cusumano and Cesari, 2006). Various methods have been introduced to quantify MV based on "equifinality", such as the uncontrolled manifold (Scholz and Schöner, 1999; Schoner, 1995), tolerance noise covariation (Müller and Sternad, 2009) , minimum intervention principle (Todorov and Jordan, 2002), and goal equivalent manifold (Cusumano and Cesari, 2006). Among these three classes, the GEM method is the only approach that can be employed to quantify variability the magnitude and temporal structure of the variations simultaneously (Cusumano and Dingwell, 2013).

As previously discussed, we consider it important to understand if and how using a HWD, such as smart glasses, influences gait variabilities, and whether the risk of using such a device differs from that involved when using more traditional methods (cellphones and paper-based systems). Additionally, information is needed to help identify the most appropriate method for quantifying MV, to best detect the effects of various information displays on gait performance. To address these questions, an experiment was completed to test three hypotheses. First, that an increase in gait variability will occur as an adaptive response when using an information display (smart glasses, cellphone, or paper-based system) while walking. Second, that gait performance is less adversely influenced when participants use smart glasses compared to using either a cellphone or paper-based system. Third, that diverse measures of MV have varying levels of sensitivity to changes induced by different dual-task conditions (information displays) in the context of gait.

4.2. Method

4.2.1. Participants

A total of 10 females and 10 males completed the current experiment (Table 4.1). Participants were recruited from among the local student population, and needed to meet several criteria. Our initial target population is primarily healthy young people, who are considered most likely in the near future to use HWDs on a regular basis. As such, and based on previous works (Decker et al., 2012; He et al., 2015), we limited participation to those who were 18 - 35 years old and who had no self-reported current or recent history of musculoskeletal disorders or neurologic problems. Participants were also required to have normal vision, or corrected vision with contact lenses (He et al., 2015), which was confirmed using a Snellen eye chart. We excluded participants who wore eyeglasses since it was not feasible to use smart glasses and eyeglasses at the same time. Finally, participants were required to have a cellphone or experience in using cellphones, and to be fluent in English. Prior to any data collection, participants gave written informed consent following procedures approved by the Virginia Tech Institutional Review Board (IRB # 16-420).

Table 4.1: Mean (SD) information of the study participants.

	Age (years)	Body mass (kg)	Stature (cm)
Males	23.9 (3.2)	74.75 (13.02)	176.45 (12.59)
Females	22.3 (2.5)	66.15 (13.45)	164.5 (7.61)

4.2.2. Experimental procedures

Participants completed a preliminary session and then an experimental session on a subsequent day. In the preliminary session, all experimental procedures were explained, and several anthropometric measures were obtained. Then, participant's preferred walking speed (PWS) was determined using a treadmill (h/p/cosmos gaitway® II S, KISTLER and h/p/cosmos, Nussdorf-Traunstein, Germany) and based on a well-established protocol introduced by Jordan et al. (2007). Initially, the treadmill speed was set at a low value, which was then incremented in steps of 0.1 km/h until a participant indicated that it was their preferred speed. In the next stage, the protocol started with a speed that was 1.5 km/h higher than the reported PWS, and was decremented by 0.1 km/h until the participant indicated that the speed was their preferred one. This procedure was repeated until the difference between speeds identified in the two approaches was < 0.4 km/h. We also provided sufficient time for participants to familiarize themselves with three different information displays (Figure 4.1); a paper-based system; a smart phone (iPhone 6S, Apple, Cupertino, CA); and smart glasses (Moverio BT-200, Epson). The preliminary session ended with participants walking on the treadmill while performing several cognitive tasks provided using the three display methods. These cognitive tasks were a shorter version of the tasks used during the actual experiment, as described below.

Figure 4.1: The different information displays. Left: paper-based system, middle: cellphone, Right: smart glasses.

In each of the experimental conditions described subsequently, participants were asked to perform a set of activities that involved three different cognitive tasks (Figure 4.2): 1) the Stroop test (Stroop, 1935); 2) object categorization; and 2) mental arithmetic. These three tasks were chosen to increase attentional demands in different ways and to simulate common activities that might be performed when using information technologies. For each cognitive task, participants were instructed to give as many responses as they could, and to be as accurate as possible while maintaining a comfortable pace; 5-second breaks were provided between each task. Pilot work was conducted to determine the duration of exposure periods for each task. Exposure periods during the experiment were chosen such that a majority of participants would not complete the tasks within the given periods.
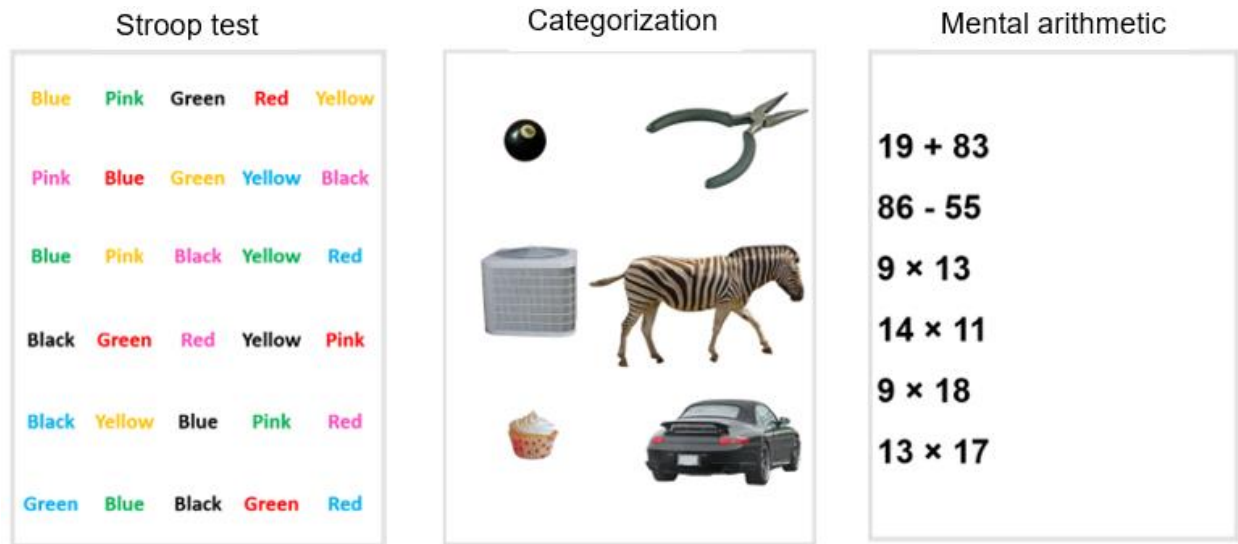
Figure 4.2: Illustrations of the three cognitive tasks.

The Stroop test involved a series of color words printed in differing colors (e.g., the word "Red" was printed in blue). For this task, the participant was asked to recite the printed colors aloud and in order, as they read a displayed list that was visible for 16 seconds. In each experimental condition, the Stroop test was given five times; each time, 30 color words were randomly chosen and positioned on the list. Randomization was constrained to six colors: blue, red, green, yellow, black, and pink. Therefore, for the 30 color words, each color appeared five times each as a word and color. For example, the word "Red" appeared in the list five times there were five words that were colored red.

The categorizing task was inspired from the Boston Naming Test (Kaplan et al., 2001), an assessment tool that measures word retrieval ability (Trebuchon-Da Fonseca et al., 2009). To implement this task, pictures were randomly selected from a database (Brodeur et al., 2014) that normalized the pictures based on category. The participant was asked to state the category (i.e., animal, tool, electronic, game, food, and vehicle) associated with each picture displayed. For each experimental condition, this task was given four times; each time, three slides were

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presented for 18 seconds with six pictures on each slide. All six categories were represented on each slide in a random order.

For the third cognitive task, a series of six arithmetic problems were presented, in increasing difficulty. The first and second problems required the addition and subtraction of two-digit numbers, respectively, with the numbers selected randomly. The remaining four problems were multiplication; to gradually increase difficulty, the first two multiplication problems involved multiplying a single digit and a two-digit number, and the final two problems involved multiplying two two-digit numbers (all numbers were randomly selected). For each experimental condition, this task (set of six problems) was presented four times, and each time participant recited the solutions aloud while the problems were displayed for 20 seconds.

In the experimental session, each participant completed one training trial and four walking trials. In the training trial, participants were asked to sit on a chair and perform the three cognitive tasks as described above (total duration ~ 5 minutes). After this, they completed four 5-minute walking trials on the treadmill, at their PWS, in each of following display conditions (Figure 4.3): 1) single-task walking (ST), with no cognitive tasks; 2) dual-task (DT) walking while completing the cognitive tasks using the paper-based system (DT-paper); 3) walking while completing the cognitive tasks using the cellphone (DT-phone); and, 4) walking while completing the cognitive tasks using the smart glasses (DT-glass). The duration of each walking condition was set to 5 minutes to ensure that sufficient data points were available for calculation of variability measures. In all conditions, a black sheet was hung from the ceiling in front of the treadmill to provide a consistent background for the participants. Confounding effects related to presentation order were minimized by counterbalancing the order of the four display conditions, using five

4×4 Latin Squares. However, the order of the cognitive tasks remained consistent with the following order: the Stroop test, categorization, and mental arithmetic.
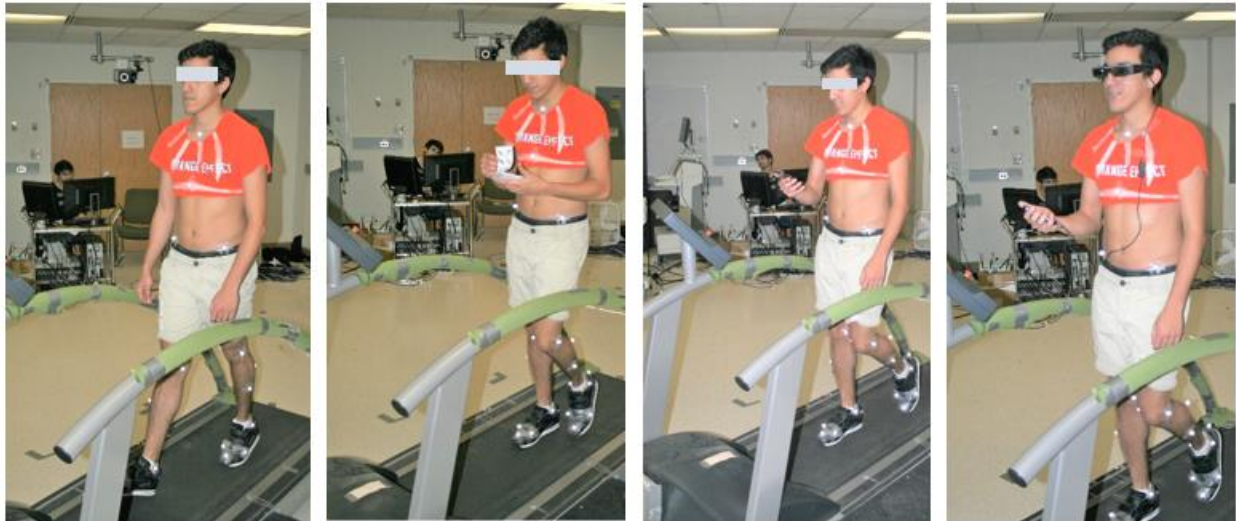
Figure 4.3: Illustration of the different walking condition. From left to right: single-task walking; dual-task walking- using the paper based system; dual-task walking using the cellphone; dual-task walking using the smart glasses.

4.2.3. Data collection and processing

Reflective markers were used to capture 3D segmental kinematics during the walking tasks. A 7-camera system (Vicon Motion System, CA, USA) tracked the marker positions at 100 Hz. These markers were placed over anatomical landmarks on the participants' lower limbs (Decker et al., 2012) and trunk. All kinematic data were processed using Vicon Nexus software and Matlab (MathWorks, Inc., Natick, MA).

After finishing each experimental condition, perceived mental workload was assessed using the NASA task load index (TLX) (Hart and Staveland, 1988). Participants also completed two questionnaires (Table 4.1), each using a five point Likert-type scale; a usability questionnaire (1=strongly disagree, 3= moderately agree, and 5=strongly agree) and a questionnaire related to eye strain and discomfort (1=none, 3=moderate, and 5=very severe). After completing all four

experimental conditions, participants were asked to rank the three different display methods (paper, cellphone, and smart glasses) in order of preference (1 = most preferred, 2 = second most preferred, 3 = least preferred), to explain their ranking, and to list perceived advantages and disadvantages for each display method.

Table 4.1. Usability metrics and associated questionnaire items

Ease of Use
1. It was useful for completing the task
2. It was simple to use
3. I was satisfied with it
4. It worked the way I wanted it to work
Discomfort
5. General discomfort
6. Headache
7. Eye Strain
8. Nausea
9. Difficulty concentrating
10. Blurred vision
11. Imbalance/Disorientation

Several measures of gait MV were derived to determine the effects of the different display types. Within each condition (i.e., 5 minutes of treadmill walking), we first calculated basic gait parameters of stride length (L_n), stride time (T_n), and stride speed (S_n) for each stride n, as well as step length (SL_n); these were obtained using raw (unfiltered) kinematic data (Bohnsack-McLagan et al., 2015). To calculate these gait parameters, we identified the times of heel strike using a common technique for treadmill walking (Zeni et al., 2008); heel contacts were identified at the maximum distance between the hip and heel markers in the anterior-posterior direction. We defined step lengths by calculating the distance between two heel markers at each heel contact event, when both feet were on the treadmill. We then added two successive step lengths to calculate stride length (Dingwell and Cusumano, 2010). Stride time was determined as the

duration between two consequetive heel contact events for the right foot. Lastly, stride speed was defined as stride length per stride time ($S_n = L_n/T_n$).

Variations in these gait parameters were quantified using a method from each of the three classes previously described (i.e. linear, nonlinear, and equifinality). First, Cycle-to-cycle SDs (σ) of the gait parameters (i.e., stride length, stride time, and stride speed) were computed as a representative linear method (Bohnsack-McLagan et al., 2015). Second, and similar to Yentes et al. (2013), sample entropy (SaEn; developed by Richman and Moorman (2000)) was used as a nonlinear method to quantify variations in SL_n, step time (ST_n; time between two successive heel contacts events), and step speed ($SS_n = SL_n/ST_n$). SaEn was used here to measure the complexity of a time series, $X(i) = X(1), X(2), ..., X(N)$, and can be calculated as follow:

$$SaEn(m, n, N) = -\ln(\Phi^{m+1}(r)/\Phi^m(r)) \tag{4.1}$$

where $\Phi^m(r)$ is the mean of C_i^m = (number of $X(j)$ such that $d[X(i),X(j)] < r$), $d[X(i),X(j)]$ is the Euclidean distance, and N is the total number of data points. We sought to quantify the MV of stride parameters; therefore, we chose $m = 2$, since this indicates the length of two steps (Yentes et al., 2013). We selected $r = 0.2 \times SD$ of the time series, as suggested by Zhang and Zhou (2012).

Third, the GEM framework was chosen from among available methods based on equifinality. Since participants walked on the treadmill at their PWS, it can be assumed the primary task goal was maintaining constant speed (v) at each stride. This can be formulated as $\langle L_n/T_n \rangle_n = v$ in which $\langle \cdot \rangle_n$ is an averaging function over n strides (Dingwell and Cusumano, 2010). For a speed-based GEM analysis, all combinations of L_n and T_n that can satisfy the goal function ($L_n/T_n = v$) describe the GEM. According to Dingwell and Cusumano (2010), after normalizing (L_n) and

time (T_n) to their SD, the magnitude of variability in the GEM direction (δ_T), and in the direction perpendicular to the GEM (δ_P), can be calculated as follows for each stride:

$$\begin{bmatrix} \delta_T \\ \delta_P \end{bmatrix} = \frac{1}{\sqrt{1+v^2}} \begin{bmatrix} 1 & v \\ -v & 1 \end{bmatrix} \begin{bmatrix} T_n' \\ L_n' \end{bmatrix} \tag{4.2}$$

For this equation, T_n' is equivalent to $T_n - T^*$, and L_n' is $L_n - L^*$. Furthermore, (T^*, L^*) is the preferred operating point in which $T^* = \langle T_n \rangle_n$ and $L^* = vT^*$. It should be noted that the goal of the task is not affected by variations in the GEM direction (δ_T), while the goal is deteriorated by variations in the other, perpendicular direction (δ_P) (Dingwell and Cusumano, 2010). The SD of variations in the GEM direction (δ_T) and the perpendicular direction (δ_P) were calculated to investigate the structure of variability that reflected the average behavior of the system (Dingwell and Cusumano, 2010). We were also interested in studying the temporal structure of the time series (i.e., δ_T and δ_P) to quantify stride-to-stride variabilities. For this, Detrended Fluctuation Analysis (DFA; see Peng et al. (1993) was used to compute the scaling exponent, α, of the time series (Dingwell and Cusumano, 2010). The derived value of α indicates whether a time series is persistent ($\alpha > 0.5$) or anti-persistent ($\alpha < 0.5$). If anti-persistent, this would indicate that participants adjusted the time series frequently to maintain the goal. Alternatively, persistent correlations would indicate non-frequent adjustments (Dingwell and Cusumano, 2010). Then, a sensitivity analysis was employed to determine the most appropriate method for distinguishing the effects of different information displays on gait parameters.

From each cognitive task, percentage of completed responses were determined (Due to the similarity between percent correct and percent completed, only the latter measure was reported). These results reflected the level of performance in each condition, and therefore were interpreted as indicating the amount of allocated resources. Mean NASA-TLX ratings were obtained using

an unweighted method (DiDomenico and Nussbaum, 2008) to assess the overall level of

perceived workload per condition. Mean responses from the usability and eye strain

questionnaires were also determined to assess ease of use and discomfort, respectively. Finally,

rankings were compiled and all open-ended question responses were summarized.

4.3. Statistical analyses

Separate analysis of variance (ANOVA: REML method) models were used to investigate the

effects of the four different display conditions (DC: three displays + none) and gender (G) on

each of the measures of gait variability (i.e., cycle-to-cycle SD, SaEn, and GEM-related

measures). Note that preliminary analyses indicate that the order of exposure to the four display

conditions did not have significant or substantial effects, so order was not included in the final

ANOVA models. Another set of ANOVA models to evaluate how the three displays (D) and

gender (G) affected cognitive performance (percentages of complete responses). In the latter

ANOVA models, order effects were significant only for one of the cognitive measures (i.e.,

responses to the Stroop test) and was included in the final model. All summary results are

reported as least square means (95% confidence intervals), and paired comparisons were done

using the Tukey HSD method (Barnette and McLean, 1998). Interaction effects were explored

using simple-effects testing. Parametric model assumptions were assessed, in and in several

cases data transformations were used to obtain normally distributed model residuals. *P*-values <

0.05 were considered statistically significant, and the sensitivity of dependent measures with

respect to DC, D, and G were assessed by calculating effect sizes (i.e., partial eta-squared = η_p^2).

We interpreted effect size qualitatively by using Cohen (1988) criteria (i.e., $\eta_p^2 > 0.14$: large

effect, $0.01 < \eta_p^2 < 0.06$: moderate effect, and $\eta_p^2 < 0.01$: small effect).

4.4. Results

Linear measures

There were significant main effects of DC on the cycle-to-cycle SD of both stride time and stride speed (Table 4.2). Stride time variations increased when participants used the paper-based system compared to the baseline (i.e., single task) condition. However, when participants used the two other displays (i.e., cellphone and smart glass), stride time variability was only affected slightly (Figure 4.4, top). Walking speed variations decreased when using each of the displays compared to the single-task condition, and this reduction was significant when participants used the cellphone (Figure 4.4, bottom).

Table 4.2. Summary of ANOVA results related to cycle-to-cycle SD (σ) outcomes. Both p values and effect sizes (η_p^2) are given for the main and interaction effects of different display conditions (DC) and gender (G), for the SD of stride length, stride time, and stride speed. Significant effects are highlighted using bold font.

		DC	G	DC×G
σ (Stride Length)	$p\ (\eta_p^2)$	0.124 (0.100)	0.806 (0.008)	0.344 (0.059)
σ (Stride time)	$p\ (\eta_p^2)$	**0.017 (0.171)**	0.793 (0.022)	0.406 (0.052)
σ (Stride speed)	$p\ (\eta_p^2)$	**0.021 (0.164)**	0.466 (0.114)	0.266 (0.070)
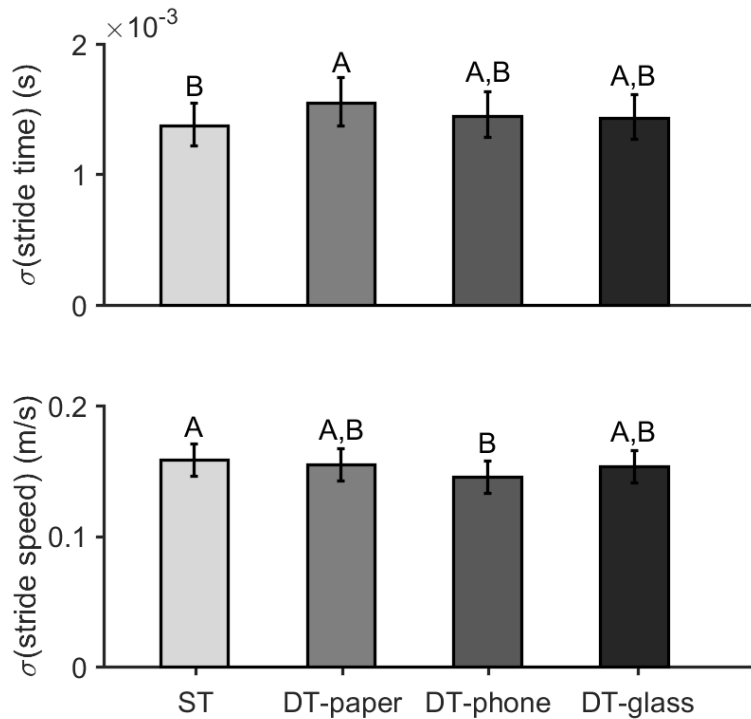
Figure 4.4: Cycle-to-cycle standard deviation (σ) of stride time (top) and stride speed (bottom) for single-task walking (ST), and for dual-task walking while using the paper-based system (DT-paper), cellphone (DT-phone), and smart glasses (DT-glass). Values in conditions not sharing same letters are significantly different.

SaEn results

For the nonlinear measure, we only observed a significant main effect of display condition on the SaEn of step length (Table 4.3). Use of the Tukey HSD procedure did not reveal any significant differences between SaEn (step length) between the four conditions. In an exploratory analysis, though, we compared mean values between display conditions using paired t tests. SaEn values of step length were significantly higher in the ST (LMS=1.993, CI=1.898-2.080) condition, compared with the DT-paper (LMS=1.918, CI=1.815-2.012; p=0.012) and DT-glass (LMS=1.919, CI=1.816-2.012; p=0.021) conditions. However, SaEn (Step Length) in the DT-phone (LMS=1.973, CI=1.876-2.062) and ST conditions were similar (p=0.51).

Table 4.3. Summary of ANOVA results related to the SaEn outcomes. Both p values and effect sizes (η_p^2) are given for the main and interaction effects of different display conditions (DC) and gender (G) for SD of stride length, stride time, and stride speed.

		DC	G	DC×G
SaEn (Step Length)	$p\ (\eta_p^2)$	**0.040 (0.141)**	0.821 (0.014)	0.578 (0.035)
SaEn (Step time)	$p\ (\eta_p^2)$	0.252 (0.072)	0.69 (0.093)	0.702 (0.026)
SaEn (Step speed)	$p\ (\eta_p^2)$	0.779 (0.020)	0.960 (<0.001)	0.456 (0.047)

GEM-based outcomes

There were significant main effects of display condition on the magnitude of MV in the GEM direction and the temporal structure of variability in the direction perpendicular to the GEM (Table 4.4). In all conditions, the magnitude of variability in the GEM direction ($\sigma(\delta_t) > 1.0$) was higher than in the non-relevant GEM direction ($\sigma(\delta_p) < 1.0$; Figure 4.5). In general, participants exhibited significantly higher variations in the GEM direction in the DT-paper (p=0.035) and DT-phone (p=0.041) conditions compared to the ST condition, while for the DT-glass condition the increase was more modest and non-significant (p=0.183; Figure 4.5, top). The gender x display condition interaction effects on $\sigma(\delta_t)$ approached significance. Simple effects testing indicated that males increased variations in the GEM direction significantly for all dual-task conditions compared to the ST, but that females had similar variations in this direction for all display conditions. In addition, magnitudes of MV in the GEM direction (i.e., $\sigma(\delta_t)$) for females were significantly (p=0.008) and slightly (p=0.11) higher in the ST and DT-paper conditions compared to the males, respectively. Values of $\sigma(\delta_t)$ were, however, similar for females and males in DT-phone and DT-glass conditions. Based on DFA analysis, the temporal

structure of variability in all of the walking conditions was persistent ($\alpha(\delta_t) > 0.5$) in the GEM

direction, and anti-persistent ($\alpha(\delta_P) < 0.5$) in the direction perpendicular to the GEM (Figure

4.6). The values of $\alpha(\delta_P)$ for the DT-paper and DT-glass conditions were significantly lower

than for ST walking ($p=0.002$ and $p=0.016$, respectively). $\alpha(\delta_P)$ values when using the DT-

glass, however, did not change significantly from the ST condition ($p=0.91$; Figure 4.6 bottom).

While the interaction effect of DC×G on $\alpha(\delta_t)$ approached significance, there was general

consistency in effects of DC for both genders.

Table 4.4. Summary of ANOVA results related to the GEM-based outcomes. Both *p*-values and effect sizes (η_p^2) are given for the main and interaction effects of different display conditions (DC) and gender (G) for SD of stride length, stride time, and stride speed. Significant effects are highlighted using bold font and effects approaching significance are italicized.

		DC	G	DC×G
$\sigma(\delta_t)$	p (η_p^2)	**0.024 (0.159)**	0.099 (0.123)	*0.075 (0.119)*
$\sigma(\delta_P)$	p (η_p^2)	0.519 (0.041)	0.140 (0.143)	0.852 (0.014)
$\alpha(\delta_t)$	p (η_p^2)	0.867 (0.013)	0.708 (0.008)	*0.058 (0.128)*
$\alpha(\delta_P)$	p (η_p^2)	**<0.001 (0.262)**	0.669 (0.011)	0.996 (0.001)
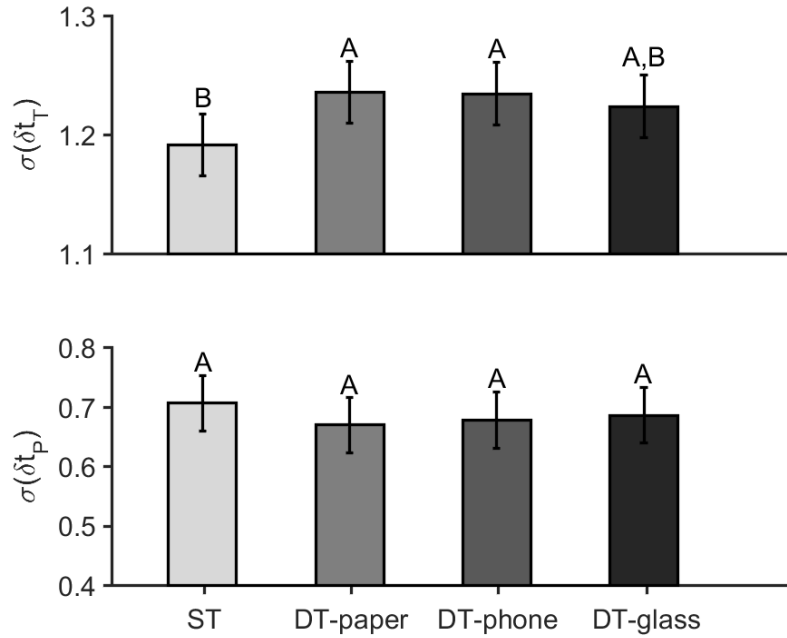
Figure 4.5: Magnitude of variability in the GEM direction (top) and in the direction perpendicular to the GEM (bottom), for single walking task (ST), dual walking task while using the paper-based system (DT-paper), dual walking task while using the cellphone (DT-phone), and dual walking task while using the smart glass (DT-glass). Values in conditions not sharing same letters are significantly different.
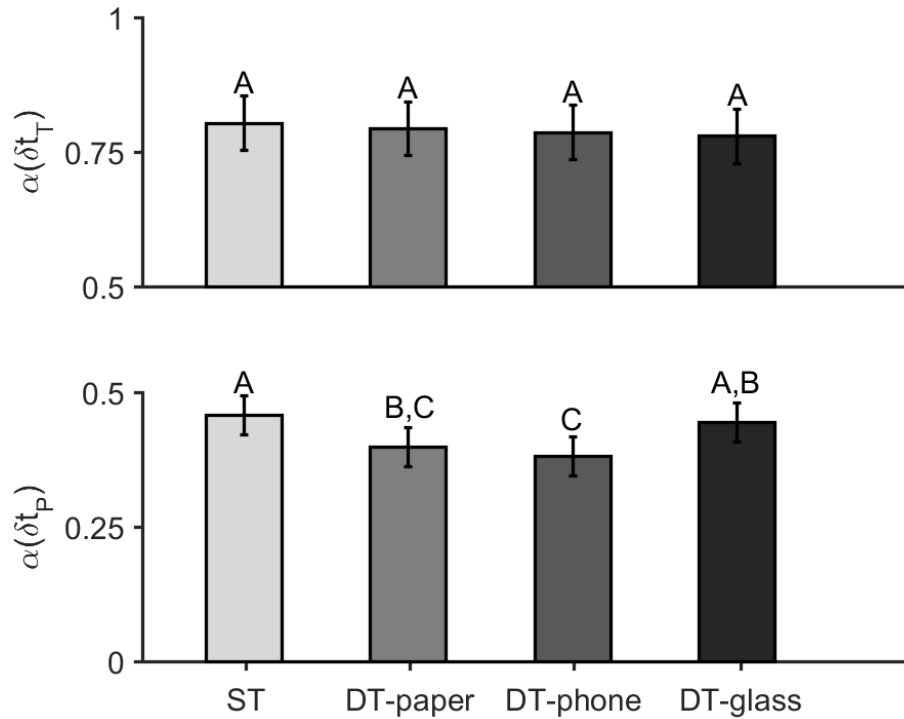
Figure 4.6: Temporal structure of variation in the GEM direction (top) and in the direction perpendicular to the GEM (bottom) for single-task walking (ST), and for dual-task walking while using the paper-based system (DT-paper), the cellphone (DT-phone), and the smart glasses (DT-glass). Values in conditions not sharing same letters are significantly different.

Cognitive performance

There were significant main effects of display type on all responses and performance measures except for NASA-TLX scores (Table 4.5). Specifically, ease of use scores were higher in the cellphone condition vs. when using the smart glasses, and the smart glasses were perceived as less comfortable than both the paper-based system and cellphone condition (Table 4.6). Further, participants performed best on the Stroop test using the paper-based system; categorizing task performance was highest when using the cellphone and lowest when using the smart glasses; and the performance in the arithmetic task was found when using the cellphone or smart glasses (Table 4.6). Rankings were significantly better for the paper-based system and cellphone, and, while non-significant, the cellphone was overall preferred more often than the paper-based

condition. Rankings were also significantly affected by a task condition x gender interaction effect (Table 4.6). Females preferred the cellphone and paper-based system equally, ranking both displays as the most preferred device to use while walking (Figure 4.8). Males preferred the cellphone more than the paper-based system or the smart glasses condition, ranking the cellphone as the most preferred device and the latter two equally as the least preferred.

Table 4.5. Summary of ANOVA results related to the cognitive load outcomes. Both *p* values and effect sizes (η_p^2) are given for the main and interaction effects of different displays conditions (D) and gender (G) for questionnaire responses and task performance. Significant effects are highlighted using bold font, and effects approaching significant are italicized.

		D	G	D×G
NASA-TLX Overall workload	$p\ (\eta_p^2)$	0.232 (0.078)	0.548 (0.104)	0.630 (0.025)
Ease of Use	$p\ (\eta_p^2)$	**0.005 (0.249)**	0.447 (0.054)	0.182 (0.105)
Discomfort	$p\ (\eta_p^2)$	**<.001 (0.586)**	**0.044 (0.465)**	**0.035 (0.181)**
Participants performance (Stroop test)	$p\ (\eta_p^2)$	**0.001 (0.283)**	*0.056 (0.792)*	0.343 (0.019)
Participants performance (categorizing task)	$p\ (\eta_p^2)$	**0.021 (0.193)**	**0.041 (0.445)**	0.627 (0.0260
Participants performance (arithmetic task)	$p\ (\eta_p^2)$	**<0.001 (0.387)**	0.137 (0.666)	0.357 (0.055)
Ranking	$p\ (\eta_p^2)$	**<0.001 (0.231)**	1 (0)	**0.038 (0.114)**

Table 4.6. Summary of ANOVA results related to the cognitive load outcomes. Both LMS values and confidence intervals (CI) are given for the main and interaction effects of different displays, for questionnaire responses and task performance. Values in conditions not sharing same letters are significantly different.

		Paper-based system	Cellphone	Smart Glasses
NASA-TLX Overall workload (0-100)	LMS	52.29	54.58	56.00
	(CI)	(45.73-58.85)[a]	(48.02-61.14)[a]	(49.44-62.56)[a]
Ease of Use (1-5)	LMS	3.70	4.06	3.28
	(CI)	(3.28-4.07)[ab]	(3.68-4.40)[a]	(2.81-3.68)[b]
Discomfort (1-5)	LMS	1.31	1.38	1.83
	(CI)	(1.19-1.47)[b]	(1.24-1.55)[b]	(1.60-2.13)[a]
Stroop test (% completed)	LMS	78.56	76.28	73.93
	(CI)	(72.31-84.78)[a]	(70.04-82.52)[ab]	(67.7-80.17)[b]
Categorizing task (% completed)	LMS	86.67	88.33	83.54
	(CI)	(82.77-90.56)[ab]	(84.43-92.23)[a]	(79.64-87.43)[b]
Arithmetic task (% completed)	LMS	71.22	75.88	78.36
	(CI)	(63.13-78.48)[b]	(68.34-82.73)[a]	(71.08-85.01)[a]
Ranking (1-3)	LMS	1.9	1.6	2.5
	(CI)	(1.58-2.22)[b]	(1.28-1.92)[b]	(2.18-2.82)[a]
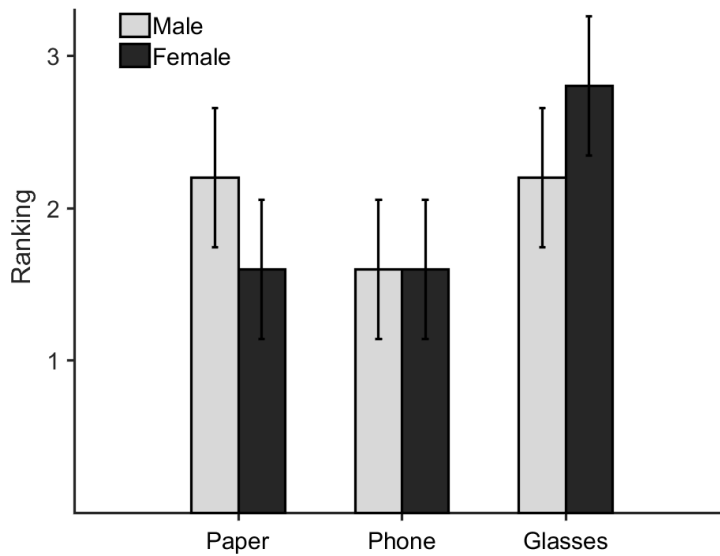
Figure 4.7: Mean preferences (rankings) of male and female participants for using different types of information display. 1= first preference, 2= second preference, and 3= least preference.

Open-ended question responses were compiled and categorized into several consistent categories – simplicity, usefulness, and comfort – and were subsequently labeled as positive or negative (summarized in Table 4.7). Participants appeared to prefer the cellphone condition overall, and the smart glass condition the least. More specifically, the cellphone condition was found to be the most simplistic condition, while participants considered the smart glasses to be the least simplistic condition. The most and least comfortable conditions were the paper-based display and smart glasses, respectively. Regarding usefulness, responses were divided evenly with the glasses condition considered as both the most and least useful.

Table 4.7. Frequency of open-ended question responses categorized by simplicity, usefulness, and comfort for each display type

Category	Response Summary	Number of Responses								
		Paper-based system			Cellphone			Smart Glasses		
		Total	Female	Male	Total	Female	Male	Total	Female	Male
Simplicity (Positive)	Images were clear and easy to see; Display was easy to use while walking	8	4	4	11	6	5	4	2	2
Simplicity (Negative)	Display was difficult to use while walking	6	3	3	4	2	2	7	4	3
Usefulness (Positive)	Display was lightweight, depth adjustable, and efficient; No glare	11	4	7	11	5	6	14	5	9
Usefulness (Negative)	Display was not stable and distracting	13	5	8	10	5	5	14	8	6
Comfort (Positive)	Display allowed for more control while walking; No eye strain	7	5	2	3	2	1	4	3	1
Comfort (Negative)	Display caused discomfort, instability, and blurred vision	7	4	3	6	2	4	13	7	6

4.5. Discussion

Our primary goal in this study was to investigate the effects of different types of information display on gait variability. Our results supported the first hypothesis. Specifically, during all three dual-task conditions (i.e., DT-paper, DT-phone, and DT-glass), most measures derived from gait parameters were affected by the additional of cognitive tasks. Participants showed higher stride time variability (STV) when they used an information display compared to the single-task condition (Figure 4.4, top). Similar to our results, in several earlier studies STV was observed to increase when participants performed attentional cognitive tasks during walking (Asai et al., 2013; Beauchet et al., 2005a; Malcolm et al., 2015). Higher STV in the DT-paper condition, relative to the other conditions, also suggests that it was the most demanding. One explanation is that during the DT-paper condition participants had to flip the pages manually; thus, participants had to allocate more cognitive resources for this condition rather than other conditions. Since STV and the risk of a fall are associated (Dubost et al., 2006), there is the implication that such a risk was elevated in all the current dual-task conditions (and especially in the DT-paper condition). In addition, stride speed variability decreased in all three dual-task conditions, with a substantial reduction in the DT-glass condition (Figure 4.4, bottom), due to increases in STV and decreased in stride length variability. Maki (1997) found that increases in stride speed variability were directly related to falling, so our results for stride speed variability may imply a decreased risk of falls in dual-task conditions. Given this apparent contradiction regarding risk, however, we suggest that sole emphasis on variability in gait parameters (i.e., stride length variability, stride time variability, and stride speed variability) provides inconsistent evidence regarding fall risk.

GEM-based analyses, in contrast, use all stepping variables simultaneously to quantify gait variability (Dingwell and Cusumano, 2010). As such, GEM-based outcomes potentially provide additional information on how the CNS regulates movement in the dual-task conditions. For all three display conditions, male participants exhibited higher MV in the GEM direction compared to the control (single task) condition, which suggests that they employed the benefits of abundant solutions (Latash, 2008) to adapt to increasing attentional demands. Females, however, did not significantly adapt their MV in either of the GEM and non-GEM-relevant directions. In the ST condition, though, females had significantly higher variations in the GEM direction than males, suggesting that females already had sufficient MV to perform the dual-task conditions successfully (i.e., without enhancing their MV). Our results, however, are inconsistent with a previous report (Decker et al., 2012) in which healthy young people performed the Boston Naming Test during walking. In this earlier study, participants had lower variations in the GEM direction and higher variations in the direction perpendicular to the GEM compared to the ST condition. Previous studies, though, have found that the effects of different types of cognitive task on gait parameters were not the same (Beauchet et al., 2005a; Schaefer et al., 2010), and that this difference may stem from each task requiring different attentional resources (Mustonen et al., 2013). Therefore, a potential explanation for the inconsistency between our results and the study of Decker et al. (2012) is that the set of cognitive tasks used here were different from their use of a single test. Based on the GEM-based analysis results, we conclude that the CNS adapts with dual-task conditions by manipulating the structure of variability (i.e., $\sigma(\delta_t)$ and $\sigma(\delta_P)$).

The three display conditions here had different effects on the temporal structure of MV. Results from DFA analysis in the non-GEM-relevant direction (i.e., $\alpha(\delta_P) < 0.5$) showed that participants tightly corrected their movements in this direction (Dingwell and Cusumano, 2010).

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Persistency of the variations (i.e., $\alpha(\delta_t) > 0.5$) in the GEM direction also indicated that these variations were only regulated loosely. More specifically, participants appeared to regulate their walking variability in the non-GEM-relevant direction more frequently during DT-paper and DT-phone conditions, in contrast to two other conditions (Figure 4.7, bottom). This behavior indicates that the CNS had to stabilize walking steps for the DT-paper and DT-phone conditions to a greater extent than in the ST and DT-Glass conditions, by maintaining GEM-based strategies more strictly (Decker et al., 2012). In the DT-paper and DT-phone conditions, participants held their heads down (Figure 4.3, middle), while in the latter two conditions they had to hold their heads up (Figure 4.3, right and left). Considering the temporal structure of variations in the non-GEM- relevant direction, and the postures adopted in each walking condition, we conclude that gait adaptability for the head-down conditions were worse than for the head-up conditions. To our knowledge, the current work is the first that has compared the effects of head-up vs. head-down postures on the variability of gait parameters. Further investigation is required, though, to determine whether the differences in temporal structure of variability for the display conditions are due to the type of information display or due to the differences in head posture. However, our results are consistent with previous findings in the context of dual-task driving; several studies have found that head-up driving tasks impairs driving performance to a lesser extent than head-down tasks (He et al., 2015; Orlosky et al., 2014; Sawyer et al., 2014).

We also evaluated different information displays from a cognitive perspective. Given the lack of substantial differences in NASA-TLX scores, the mental workload utilized with each display was considered to be similar, though display preference and task performance clearly varied. In general, participants most preferred the cellphone condition over either the paper-based system or the smart glasses. From responses to the open-ended question, participants noted that the

cellphone was the easiest to control and most familiar, yet they did not like having to look down for a long period of time or the backlight. Since performance in the categorizing task was highest when using the cellphone, this suggests that a cellphone display is preferred for pictures (vs. reading words or numbers). Crowley et al. (2016) showed that reading or texting on a cellphone significantly hinders walking performance and awareness. However, it is unknown whether altering the dual-task demands, perhaps involving looking at a picture, would have the same effect. As previously noted, different cognitive tasks may require different attentional resources (Mustonen et al., 2013). Therefore, high performance at categorization may be due to the type of attentional resources required for this task.

The second most preferred display was the paper-based system. From the responses obtained, participants considered this system to be the most comfortable, and noted that the cellphone backlight and the weight of the glasses were too uncomfortable. This is consistent with a previous report, in which participants experienced increased discomfort and eye strain when scanning text on a screen for both short and longer periods compared to scanning text on paper (Köpper et al., 2016). Further supporting these responses, Stroop test performance was higher when participants used the paper-based display, implying that tasks involving words or reading are better accomplished when using paper rather than when reading from a screen. Wright and Lickorish (1983) found similar results; scanning text, speed, and accuracy all increased when a paper-based system was used rather than a screen display. Therefore, our results suggest that increased performance in the Stroop test is correlated with comfort rather than simplicity or usefulness. The paper-based system received poor reviews regarding simplicity and usefulness, due to participants needing to flip pages.

Finally, the least preferred display was the smart glasses. From the participant responses, this condition was evenly divided between most and least useful. The negative responses regarding usefulness were focused primarily on the structure of the device rather than the display, specifically that the weight of the glasses was uncomfortable and hard to balance. Regarding display type specifically, the smart glasses were determined to be the most useful. Positive responses for usefulness suggested that participants liked the hands-free aspect of the device and the eye-level screen, which allowed participants to complete the tasks without looking down. This is consistent with a report by Liu and Wen (2004), in which head-up displays allowed for significantly faster response times, more control, and caused less mental stress, in tasks that required a quick response. Arithmetic performance here was significantly higher when using both the cellphone and smart glasses condition, and highest when using the smart glasses display. An increased performance in the arithmetic task with the smart glasses may be due to the freedom to look up in conjunction with the participant's need for extended viewing and quick response time.

Based on the above discussion, cognitive analyses did not support motor variability outcomes. In general, participants preferred to use the cellphone and paper-based system rather than the smart glasses. In contrast, gait adaptability was better for the smart glasses. One reason for the inconsistency between these results is that participants did not have adequate experience using smart glasses, which made it an uncomfortable device for them. Smart glasses are also not a well-developed technology; for example, Brusie et al. (2015) evaluated two types of smart glasses from a usability perspective, and found that both were not sufficiently mature to satisfy users. Though, there is some difficulty in interpreting our results, specifically in terms of

separating the effects of the technology itself, as an information display, from usability aspects (e.g., comfort).

As we hypothesized, there were differences in the sensitivity of several measures of variability to the use of three types of information displays. Cycle-to-cycle SD of stride time and stride speed, SaEn of step length, the magnitude of variability in the GEM direction ($\sigma(\delta_T)$), and the temporal structure of variability in the non-GEM-direction ($\alpha(\delta_P)$) all had "large" effect sizes, which implies that these measures were highly sensitive to changes that occurred due to the different walking conditions. As discussed above, separately quantifying the magnitude of variability of gait parameters (stride length, stride time, and stride speed), using cycle-to-cycle SD, cannot reveal how the CNS might employ the benefits of MV for the different walking conditions. While the linear method (i.e., cycle-to-cycle SD) was sensitive to differences between walking conditions, we conclude that it should not be used alone for studying gait variability. The values of SaEn (step length) for the ST and DT-phone conditions were higher than for DT-paper and DT-glass, indicating that gait patterns were more adaptable in the former conditions (Yentes et al., 2013). While the SaEn analysis and the GEM-based measures (i.e., $\alpha(\delta_P)$) led to contradictory interpretations, the effect size for the later measure was much higher, and validity of SaEn is questionable for a short data set (Yentes et al., 2013). Based on this, we suggest that a GEM-based analysis is the best method for evaluating effects of different information displays on gait behaviors.

Our conclusions and recommendation, though, require some cautions due to inherent study limitations. First, a relatively small number of participants were recruited. Second, there is the potential for different behaviors occurring during over-ground versus treadmill walking, though some recent evidence suggests that these differences may be minimal (Riley et al., 2007). It

remains unclear, though, regarding the extent to which the current results generalize to the use of different information displays generally, especially outside of a laboratory environment (e.g., in which diverse visual information is present in addition to the display). Third, each walking condition took five minutes; however, performing each of the cognitive tasks for five minutes was found, in pilot work, to be quite challenging (boring) for participants. We thus included all three cognitive tasks in each dual-task condition, but as a result could not investigate the effects of each cognitive task on MV and cognitive performance separately. Further investigation is thus necessary to explore how each cognitive task might influence gait variability.

In summary, gait performance was less affected by the smart glasses than when using either a paper-based or cellphone systems for information presentation, both of which required a head-down walking posture. We suggest that smart glasses are a promising technology for reducing the risk of an adverse gait event (e.g., a fall), but that this new technology may still not be matured sufficiently for implementation (e.g., into industrial environments). In addition, we found that variability in the GEM direction can be an effective solution for the CNS to adapt to challenging walking conditions, such as those that occur in dual-task conditions. Furthermore, increasing MV can potentially be a useful tool for maintaining gait performance and decreasing the risk of a fall. Finally, we used different methods for quantifying MV, and our results suggest that the GEM analysis can be a fruitful method for studying gait variability.

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Chapter 5. Conclusions

Work-related musculoskeletal disorders (WMSDs) are prevalent problems in industrialized countries, and existing research indicates that repetitive motions are strongly correlated with the development of WMSDs. Decreasing the similarity of repetitive work by using "internal variations" has been offered as a potential method for reducing or preventing WMSDs, and can be investigated by studying motor variability (MV). Understanding the association between WMSDs and MV can help to develop useful tools for providing occupational guidelines or developing interventions, and ultimately to help decrease injury risks.

5.1. MV among experienced workers and novices during repetitive lifting/lowering tasks

Previous works suggested that experienced workers may develop protective motor control strategies compared with novices. Understanding variations in the movement of experienced workers may thus be one useful approach toward decreasing worker injury risks. However, little evidence exists that has formally characterized MV differences associated with experience. Thus, we quantified how MV differs between experienced workers and novices.

In the first study (chapter 2), we compared the MV of experienced workers with novices during repetitive box lifting/lowering performed both symmetrically and asymmetrically. The Goal Equivalent Manifold (GEM), a relatively new method to quantify MV, was used to characterize the trial-to-trial kinematic MV of both the individuals and the box. The sensitivity of MV results was also compared to two other classes of relevant MV metrics, specifically cycle-to-cycle standard deviation (SD) and Sample Entropy (SaEn). As we expected, the whole-body center-of-mass (COM) and the BOX kinematics were controlled and performance variables, respectively.

The results showed that performance improved by increasing the MV of controlled variables (i.e., COM). In addition, The GEM outputs indicated that novices had more flexible movements in the symmetric task compared to experienced workers; however, they constrained their movement in the asymmetric condition. On the other hand, experienced workers exhibited consistent behaviors in both conditions, and had slightly more flexible movements in the asymmetric condition. We concluded that experienced workers prioritized movement stability in the easier task condition (i.e., symmetric condition); in contrast, movement flexibility had more priority for experienced workers in the asymmetric condition. In addition, the GEM analysis successfully revealed the differences between motor control strategies utilized in different combinations of task demands and levels of experience. Alternatively, the SaEn method was only sensitive to the level of experience, and it could potentially lead to wrong interpretations. Therefore, we concluded that the GEM analysis is a more appropriate method for studying MV.

In the second study (chapter 3), we evaluated temporal changes in MV during prolonged lifting/lowering, and we investigated whether these changes differ between experienced workers and novices. Again, we used cycle-to-cycle SD, SaEn, and GEM analysis to quantify MV of the COM as a controlled variable, and the BOX kinematics as a performance variable. MV of the COM increased for novices and experienced workers, yet variations of the COM in the GEM direction were more substantial than in the non-GEM-relevant direction. As we expected, variability of the COM in the non-GEM-relevant direction affected the task goal (i.e., maintaining a constant cycle time), and the goal was deteriorated with fatigue. By investigating the temporal structure of MV, we found that fatigue made it more difficult for the individuals to maintain the task goal. GEM analysis also revealed that the MV of experienced workers in the GEM direction was higher than for novices, especially in the middle phases of the prolonged

lifting task. From this, we concluded that movement flexibility is a protective strategy used to adapt to fatigue during a prolonged repetitive task. We also found that the linear and GEM-based methods were more sensitive to the task-relevant factor (i.e., fatigue) than the SaEn method. But, the linear method could only provide insight about average behaviors of the system, whereas the GEM-based analysis could quantify trial-to-trial variability of the system and thereby provide more information about MV. Results from the SaEn method were more sensitive to individual differences (i.e., related to task experience) than those from the GEM-based or linear methods. The SaEn method, however, quantified variability in the GEM and non-GEM-relevant directions at the same time; therefore, interpretations based on this method could be incorrect or incomplete. Based on these results, we conclude that GEM analysis is a more appropriate tool for studying the effects of task-relevant factors and the influence of individual differences on MV.

5.2. Effects of different information displays on gait variability

In modern industries, the number of tasks that require workers to perform cognitive and physical tasks simultaneously are increasing. An example of such activities is using a head-worn display (e.g., smart glasses) during walking. Current evidence suggests that performing a cognitive task during walking increases the risk of a fall; therefore, it is necessary to explore the association between the fall risk and the use existing and new technologies. Another interesting question to explore is how smart glasses impact gait performance compared to other common information displays. The goal of the third study (chapter 4) was to investigate how using smart glasses affects variability of gait parameters, and to compare these effects on gait variability with two other information displays (i.e., paper-based system and cellphone). We also wanted to explore which method is more appropriate to quantify variability in gait parameters. For this, we used the same three methods described earlier (i.e., cycle-to-cycle SD, SaEn and the GEM analysis). The

study involved four walking conditions; single walking task and three dual-task conditions. In each dual-task condition, participants were exposed to different cognitive tasks through one of the information displays. Our results suggested that the head-up display (i.e., smart glasses) had less effects on the temporal structure of variability. In contrast, though, usability results indicated that people preferred to use cellphone and paper-based systems rather than smart glasses. Based on these results, we conclude that HWD is an insufficiently mature technology, but that it is also a promising technology for reducing the risk adverse gait events (e.g., falls). In addition, we found that the GEM analysis was the most informative method for investigating the changes induced by different dual-task conditions.

5.3. Limitations and future directions

There are some notable limitations of this work that require further investigation. One limitation present in the first and second studies is that the experienced workers came from different industries; thus, their specific motor control strategies might have been developed based on their different duties and they might have had differing levels of familiarity with some of the simulated task conditions. Furthermore, only a few task conditions were included in these studies, participant movements were constrained (i.e., foot placement of the participants was fixed), and relatively few participants were recruited. As such, our results may not sufficiently capture the differences between motor control strategies of novices and experienced workers. In addition, we only quantified MV of the whole-body COM as a controlled variable, however the CNS certainly control diverse variables. Studying the variability of the other controlled variables could reveal more information regarding the motor control strategies utilized by individuals. Finally, we used a 2-dimensional GEM to measure MV, but it would interesting to quantify variability more specifically, such as separately in the anteroposterior, mediolateral, and

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longitudinal directions, to investigate whether individuals used different motor control strategies in different directions.

Results of the first two studies enhanced our knowledge of experienced workers' behavioral strategies. These results suggest that higher flexibility is a promising strategy for reducing the risk of injury, at least in the context of repetitive lifting activities. Therefore, an interesting follow up study would be to train people to increase their variability in the GEM direction, to determine if such changes are even feasible. For this, some form of biofeedback could be useful to provide the extent of MV in real time, and to ask participants to try to manipulate their variability based on the feedback.

In the third study, the walking task was simulated in a lab, yet walking in daily life or industry may be more challenging because of additional mental loads, external distractions, or uneven surfaces. Also, a treadmill was used to simulate the walking task, and some researchers argued that humans have different behaviors during over-ground versus treadmill walking. Therefore, future studies should be conducted to determine whether our interpretations are valid for overground walking and walking in industry.

5.4. Summary

In summary, the main goals of the current work were to assess repetitive occupational tasks by using a MV concept, and to investigate which method might be more appropriate for quantifying MV. In the first two studies, we quantified the differences between motor control strategies adopted by experienced workers and novices by measuring MV in different task conditions. We also addressed whether individuals used different strategies for delaying the influence of fatigue. We found that the differences between experienced workers and novices depended on task

conditions, and, for some conditions, experienced workers adapted strategies that might reduce WMSD risks. Individuals also appeared to employ the benefits of MV to reduce the risk of injury in the prolonged tasks examined. In the third study, we investigated which information displays (i.e., smart glasses, cellphone, and paper-based system) requires less attentional demands during walking by quantifying MV. We found that the risk of a loss of gait performance was less when individuals used a head-up display (i.e., smart glass) rather than the two head-down displays. In all three studies, our results showed that the GEM analysis provided additional information related to motor variability compared with other utilized measures (i.e., cycle-to-cycle SD and SaEn.