MULTI-MUSCLE SYNERGIES DURING LIFTING AND LOWERING TASKS: AN UNCONTROLLED MANIFOLD ANALYSIS

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In ergonomics, lifting tasks can be categorized according to their risk level of suffering work-related low back disorders (WRLBD). The aim of this study was to investigate whether trunk muscles form synergies that stabilize the time profile of selected performance variables that have been used previously to characterize the risk level for developing WRLBD. At the neuromuscular level, the spatiotemporal pattern of motoneuronal activity was quantified by applying matrix factorization algorithm with Varimax rotation. With this procedure, synergies were quantified using the framework of the UCM hypothesis. The results supported the hypothesis that trunk muscles form synergies to stabilize the time profile of variables that are being also used to characterize the risk of injury.

KEYWORDS: motor variability, ergonomics, work-related musculoskeletal disorders

INTRODUCTION: Manual material lifting and lowering tasks are the primarily risk factors for developing WRLBD (Op de Beek & Hermans, 2000). WRLBD causation is mainly based on the mechanical disruption of spinal support structures, where the integrity of the connective tissue is violated and its mechanical order perturbed due to spine loading (Marras, 2008). Spine loading is imposed by trunk muscles (co)activity in response to external loading. Therefore, the magnitude of the myoelectric (co)activity of trunk muscles during lifting and lowering tasks has been investigated extensively using Kinesiological Electromyography. On the other hand, trunk muscles stabilize the spine regarding buckling and control its movement and posture during lifting or lowering tasks. However, physical demand ergonomics assessment tools (e.g. revised lifting NIOSH equation) that are used to categorize lifting tasks according to the risk level of suffering WRLBD are built upon biomechanical, physiological, and psychological criteria. According to the US National Institute for Occupational Safety and Health (NIOSH), workers during lifting and lowering tasks have difficulties not only to control dynamic actions that result in high inertial forces but also with fast motions that limited their ability to coordinate the many trunk muscles necessary to control and stabilize the spinal column (NIOSH, 1981).

Physical demand ergonomics assessment tools take into consideration worker's biomechanics but not motor control although the common characteristics of all risk factors are their influence on trunk muscles activation patterns. Biomechanics alone cannot explain whether the natural limits of worker's motor and sense system capabilities are being reached during lifting tasks. Motor control approaches built upon systems theory of Bernstein (1967), provide quantitative tools for studying trunk muscles coordination. Thus, the notion of task-specific stability of movement and the concept of the uncontrolled manifold (UCM) (Scholz & Schöner, 1999) was applied to investigate whether trunk muscles forms synergies by reducing the variance of selected performance variables (PVs). These PVs have been used previously to characterize the risk level for the development of WRLBD (box's transversal ($\boldsymbol{\theta}$), vertical ($\boldsymbol{z}$), and radial ($\boldsymbol{\rho}$) displacement in cylindrical coordinates following Waters et al., 1993). According to the UCM, the CNS facilitates covariation in a multi-dimensional space of elemental variables (i.e., muscles) that keeps inter-trial variance primarily limited to the UCM, calculated for potentially significant performance variables. The UCM theory uses the *nullspace* formalism to analyze coordination strategies (Latash & Zatsiorsky, 2016).

METHODS: A 4^2 factorial experimental design was used to compare the synergy index in different work-design risk levels during lifting/lowering tasks (factors are, load: liquid vs. solid;

vertical distance: knee vs. hip; horizontal distance: near vs. far; asymmetry: 0º vs. 45º). The experiment was performed by randomly selecting a treatment combination, and then 14 subjects completed the box motion (weight = 67 N), which resulted in four lifting and three lowering trials for every treatment, interspersed with 5 min rest breaks between each treatment. Each trial duration was constrained at 2 sec (pace: 30 lifts per min) independently of the treatment, which was ensured by an electronic metronome. Each participant was considered a block and repeated measurements made on each block under factorial treatment structure. In total, 16 treatment combinations per block were run in a random order with 112 trials in every block (16 treatments x 7 trials per treatment). The box was defined by four markers in each corner of the frontal plane. 3D kinematics data recorded at 60 Hz (MaxPRO, Innovision Systems, Inc.) Position-time "data smoothing," derivation, and interpolation at 1 KHz was carried out by quintic splines according to the "True Predicted Mean-squared Error" criterion given the known precision of the spatial coordinates previously estimated by an uncertainty analysis (Woltring, 1986). Box's center of gravity acceleration time profile was used to define the temporal phases of the lifting and lowering tasks.

M-modes were extracted from surface EMG data from 10 trunk muscles (left and right: erector spinae, rectus abdominis, external and internal oblique and latissimus dorsi). The myoelectric signals were registered using the active sEMG sensors DE-2.3 (Delsys Inc., Boston MA) and digitized at a rate of 1 KHz using the Myomonitor IV (Delsys Inc., Boston, MA) portable EMG 16-Ch system (16 bits, range ± 5 V). Once ECG artifacts removed, the EMG signal was filtered (4^{th} - order Butterworth, 20 - 450 Hz), demeaned and stored in ASCII files. The RMS of the EMG amplitude was computed over bins of 1% of task cycle and normalized to max RMS_{EMG} for every subject and muscle and standardized to have unit variance and submitted to exploratory factor analysis with Varimax rotation where three PCs (M-modes) were retained from the correlation matrix by using principal components analysis. Linear relationships were assumed between small changes in the three M-modes and the change in the performance variable (∆PV). Except for the time profile of PVs that have been associated with the development of WRLBD, the stabilization of the COP was also investigated. The coefficients of the regression equation were arranged in a matrix that is a Jacobian matrix (**J**).

The UCM hypothesis describes a manifold in the three M-modes (PCs) subspace on which PV is reproducible from cycle to cycle. The M-modes variance that lies within the UCM subspace represents the combinations of M-modes gains that stabilize the selected PV—i.e., the stability of the performance variable. The M-modes variance that lies within an orthogonal to the UCM subspace represents the combinations of the M-modes gains that destabilize the selected PV (Latash et al., 2007). However, the same set of M-modes gains (factor scores ***F***) may be used to form different covariation patterns for various PV—i.e., the flexibility of trunk muscle activations patterns. Therefore, the synergy index for each of the PVs was computed as follows to verify whether the system comprises all the three features (sharing pattern, stability, and flexibility).

1. ***Computation of the UCM***. The null space of the **J** matrix was computed to provide the basis vectors spanning the linearized UCM. The null space of the **J** matrix consists of all vectors **x** such that **Jx** = 0. Within the 3D space of all possible vectors x, the solutions to **Jx** = 0 form a two-dimensional subspace. The two basis vectors $\boldsymbol{\varepsilon}_1$ and $\boldsymbol{\varepsilon}_2$ defining the null space were computed with the *nullspace*() function of the package **pracma** in R environment. As the M-mode space is three-dimensional (n = 3), and for the 1D performance variable d = 1 the null space is 2D (n − d = 2), the system is redundant on the task of stabilizing the performance variable.
2. ***Computation of deviation matrix***. The difference of factor score $\Delta\boldsymbol{F}$ was averaged across the trials in every time bin and the averaged vector $\overline{\Delta\boldsymbol{F}}$ was then subtracted from the vectors of the individual changes in the M-mode magnitudes
$$\Delta\boldsymbol{F}_D = \Delta\boldsymbol{F} - \overline{\Delta\boldsymbol{F}}$$
3. ***Decomposition of variability***. The component of the deviation matrix $\Delta\boldsymbol{F}_D$, which is parallel to the UCM, represents how much deviation occurs without altering the value

of the performance variable and was obtained by its orthogonal projection onto the null space. To compute the projection of the $\boldsymbol{\Delta F}_D$ onto the UCM ($\mathbf{f}_{\mathrm{UCM}}$) and the orthogonal subspace ($\mathbf{f}_{\mathrm{ORT}}$) the projection matrix **Q** for the 2D null space of R^3 spanned by the vectors $\boldsymbol{\varepsilon}_1$ and $\boldsymbol{\varepsilon}_2$ was computed.

$$\mathbf{Q} = \mathbf{A}\left(\mathbf{A}^{\mathrm{T}}\mathbf{A}\right)^{-1}\mathbf{A}^{\mathrm{T}}$$

Where $\mathbf{A} = [\boldsymbol{\varepsilon}_1, \boldsymbol{\varepsilon}_1]$. Therefore,

$$\mathbf{f}_{\mathrm{UCM}} = \mathbf{Q}\Delta\mathbf{F}_{\mathrm{D}}^{\mathrm{T}}$$
$$\mathbf{f}_{\mathrm{ORT}} = (\mathbf{I} - \mathbf{Q})\Delta\mathbf{F}_{\mathrm{D}}^{\mathrm{T}}$$

4. ***Computation of variance***. The total trial-to-trial variance V_{TOT}, as well as the variance in each of the two subspaces (V_{UCM} and V_{ORT}) normalized by the number of DOF, were calculated as

$$V_{\mathrm{TOT}} = \sigma_{\mathrm{TOT}}^2 = \frac{1}{3\,\mathrm{X}\,\mathrm{N}}\sum_{\mathrm{i}=1}^{N}\|\Delta\mathbf{F}_{\mathrm{D}}\|^2$$
$$V_{\mathrm{UCM}} = \sigma_{\mathrm{UCM}}^2 = \frac{1}{2\,\mathrm{X}\,\mathrm{N}}\sum_{\mathrm{i}=1}^{N}\|\mathbf{f}_{\mathrm{UCM}}\|^2$$
$$V_{\mathrm{ORT}} = \sigma_{\mathrm{ORT}}^2 = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{N}\|\mathbf{f}_{\mathrm{ORT}}\|^2$$

5. ***Computation of the synergy index***. A performance variable is controlled in the UCM sense when V_{UCM} is statistically higher than V_{ORT} (Latash et al., 2007). The following index was computed

$$\Delta V = \frac{V_{\mathrm{UCM}} - V_{\mathrm{ORT}}}{V_{\mathrm{TOT}}}$$

to compare synergy across subjects and treatments, which ranges between 1.5 (all variance is within UCM - a synergy) and -3 (all variance is within the orthogonal subspace - not a synergy with the current PV but probably a reflection of another synergy). A zero index means that there is not a synergy (Latash et al., 2007). For statistical analyses ΔV values were transformed into z-scores using Fisher's z-transformation adapted to the boundaries of ΔV (Verrel, 2010):

$$\Delta V_{\mathrm{Z}} = \frac{1}{2}\log\left(\frac{3 + \Delta \mathrm{V}}{1.5 - \Delta \mathrm{V}}\right)$$

To quantify if a muscle synergy is stabilizing the selected performance variables one sample student's *t-tests* were run on the transformed data to check whether synergy indices were significantly different from zero (0.5 × *log*(2)).

RESULTS AND DISCUSSION: Four temporal phases of lifting and lowering tasks were identified based on the 3D kinematics of the center of gravity of the box (lift, pull, push, deposit). Trunk M-modes stabilize the time profile of PVs that are being also used to characterize the risk level for the development of WRLBD. In particular, we have viewed M-modes as elemental variables, hypothesized that the "neural controller" acts on the M-mode subspace to formulate multi-M-mode synergies by their combination and to modulate the gain of each M-mode for stabilizing the time profile of important PVs for lifting and lowering tasks. The results revealed muscle synergies for some of the PVs that were significantly higher from zero for all phases. However, lifting and lowering tasks not presents the same synergies (Fig. 1). Temporal phases influence the synergy index, but not similar between lifting and lowering tasks. For the lifting tasks, the degree of the synergy indices decreased from lift-to-deposit phases, while for the lowering tasks there was, like in the lifting task, a decline of the level of the synergy but only from lift-to-pull or lift-to-push phases, followed by an increment of the synergy indices. Although our study does not provide specific evidence of an underlying injury mechanism related to the motor control of specific PVs, it provides support for a high injury likelihood during the lifting or lowering phases when the underlying control mechanism associated with the trunk muscle activation patterns prioritize the control of different behaviors simultaneously. For example, during the lift phase of the lifting cycle where the COP_{AP}, the *θ*, and the *z* are stabilized by trunk multi-M-mode synergies, indicating that a muscle or muscle group may acts simultaneously to accomplish different tasks. If muscle activations patterns that are underlying the switching from one task demand to the other are different, this could create a disruption of the ongoing task, and such conflict may lead to motor errors, increasing postural instability and subsequent risk for development of low back disorders (Ebenbichler et al., 2001).

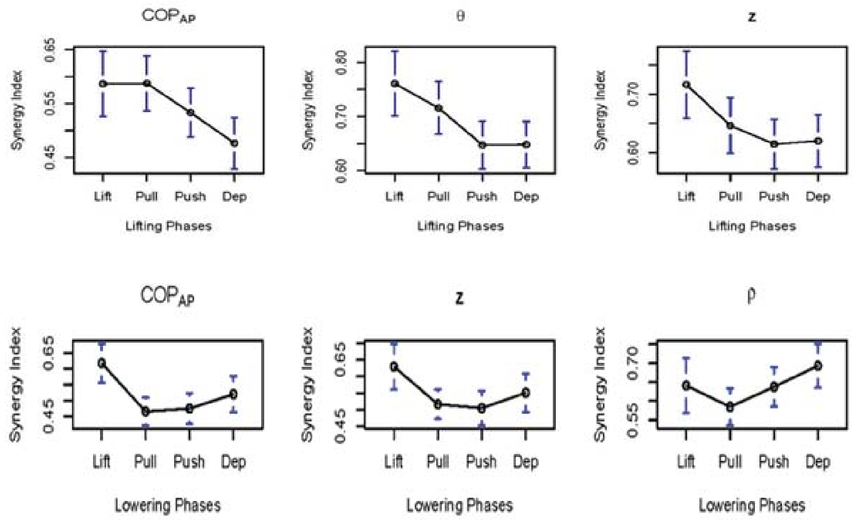

Figure 1. Synergy indices across subjects for each of the four phases within the lifting and lowering cycle. Mean values with 95% CI are shown.

CONCLUSION: Temporal phases influence the synergy index, but not similar between lifting and lowering tasks. These findings have implications for the risk assessment evaluation with multiplicative NIOSH based ergonomics tools. UCM hypothesis can provide results for inspiring new man-task-environment system interaction designs, as well as more targeted ergonomics evaluations.

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