Assessing multiple muscle activation during squat movements with different loading conditions – An EMG study

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Abstract: Surface electromyography (EMG) is a valuable tool in clinical diagnostics and research related to human neuromotor control. Non-linear analysis of EMG data can help with detection of subtle changes of control due to changes of external or internal constraints during motor tasks. However, non-linear analysis is complex and results may be difficult to interpret, particularly in clinical environments. We developed a non-linear analysis tool (SYNERGOS) that evaluates multiple muscle activation (MMA) features and provides a single value for description of activation characteristics. To investigate the responsiveness of SYNERGOS to kinetic changes during cyclic movements, 13 healthy young adults performed squat movements under different loading conditions (100%–120% of body weight). We processed EMG data to generate SYNERGOS indices and used two-way repeated measures ANOVA to determine changes of MMA in response to loading conditions during movement. SYNERGOS values were significantly different for each loading condition. We concluded that the algorithm is sensitive to kinetic changes during cyclic movements, which may have implications for applications in a variety of experimental and diagnostic settings.

Keywords: electromyography; level of determinism; multiple muscle activation; recurrence quantification analysis.

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Introduction

Human motor control is a highly complex feature of the human body, which involves a vast number of mechanisms and interactions at various levels. To study motor control at its very core, it is necessary to understand how the central nervous system (CNS) generates movement, and how multiple processes are affected by interactions with the environment or by a variety of pathologies or aging [2, 4, 5, 6, 16, 37, 40, 43].

One approach to a better understanding of motor control is based on foundations developed by researcher Nikolai Bernstein, who presented the idea that the CNS organizes the large number of degrees of freedom (DOF) associated with simple or more complex movements [14, 41, 42]. DOF is defined as the number of ways that the body can perform a vast number of translational or rotational movements. Bernstein proposed that orchestration in the neuromuscular system happens through processes that integrate co-activation of neuromuscular units in concert to reduce the number of DOFs that require independent control [5, 37–39, 44]. This multiple muscle activation (MMA), e.g.in form of modulated muscle synergies is important for natural behaviors [5, 7, 8], e.g. in postural control [38, 39].

Biological systems are explained by dynamics, which are not limited to chaos or nonlinear behaviors. This becomes crucial during analysis of physiological signals, which explains why researchers should use different approaches (linear and nonlinear) to investigate the changes in the system. It has long been postulated that physiological systems inherently depict aperiodic behaviors. The advancement in computer science and the development of a mathematical framework of nonlinear dynamics led to the application of nonlinear tools to investigate the changes in the state of the physiological systems [45]. Therefore, the variability in the systems is no longer considered a pure, random process, explaining the complexity of rhythmical processes in the system. The high sensitivity of nonlinear tools to the changes in initial conditions of physiological systems revealed a deterministic pattern in the noisy signals [1, 34]. For an objective quantification analysis of muscular activation, surface electromyography (EMG) has shown value in a large number of application areas in research and clinical settings [2, 16], e.g. in investigations related to muscular activation strategies, impact of external factors and internally generated movement goals [2]. EMG signals are collected as discrete time domain signals, and nonlinear tools are applied to investigate the evolution of this time-series. Several nonlinear tools have been employed to explain different aspects of the behavior of EMG signals and to compare the outcome with the traditional linear analysis tools [11, 13, 25, 31, 47].

With increasing knowledge regarding chaotic and stochastic components in biological systems and human motor control, it becomes obvious that traditional linear EMG tools (e.g. integrated EMG and frequency analysis) cannot assess control completely. Nonlinear analysis is more responsive regarding subtle changes in neuromuscular activation such as when facing small external changes to constraints [9–11, 13, 23, 25, 31, 47]. Despite non-linear assessment tools being valuable, it is important that data sets obtained through such tools are understandable and provide meaningful results. Especially for clinical purposes, there is a need for non-linear analysis tools that provide sensitive evaluation of neuromuscular patterns, while being straightforward and easily interpretable.

To address this issue, a computational algorithm we called “SYNERGOS” was developed, which employs established non-linear EMG analysis tools, specifically recurrence quantification analysis and measure of determinism. The computation for SYNERGOS, which has been presented in detail before [29], combines the outcome of non-linear analysis to generate a single quantity to describe MMA characteristics, whereas time-variant and time-invariant EMG signal features are assessed. To evaluate the applicability of the presented analysis tool, we utilized SYNERGOS in a variety of settings and with different healthy and patient populations. We showed that SYNERGOS is sensitive to motor control changes associated with increasing gait speed [29]. The algorithm is also sensitive to MMA changes that are present in Parkinson’s disease (PD), and to the neuromuscular modifications that are associated with specific PD medication [27]. Additionally, the method’s generalizability has been demonstrated before [28]. However, it is not yet clear if the method is sensitive to changes in muscular loading and associated neuromuscular control changes in cyclic movements. In this study, we aimed to investigate the effects of different muscular loading characteristics (100%–120% of body mass) on SYNERGOS indices in healthy younger individuals performing squats to determine if the tool is sensitive to MMA changes due to kinetic changes in cyclic movements. We hypothesized that changes would be reflected in SYNERGOS values for MMA, which would provide evidence for the value of the algorithm as a valuable neurophysiological assessment tool.

Methods

Subjects

The experiment was approved by the University of Houston Committee for the protection of human subjects (CPHS). All participants gave informed consent before participating in the study. Thirteen recreationally active individuals (five males, eight females) participated in this study. Eligibility for participation was based on the following criteria: (1) no history of neuromuscular disorders; (2) no history of traumatic or chronic injuries within the past year; (3) age range of 18 to 40 years; (4) body mass index (20–25). Prior to participation, a physical activity readiness questionnaire (PARQ) was used to determine whether there were any muscular or neural limitations that might have an influence on the outcome of the experiment.

Apparatus

All experimental trials were performed while subjects were standing on an instrumented treadmill TM-07-B (Bertec Corporation, Columbus, OH, USA). A harness system was installed in a custom-made metal frame to support subjects during squat movements. Surface EMG signals were collected using six preamplifier bipolar active electrodes (EMG preamplifier, Type No: SX230, Biometrics Ltd., Gwent, UK) with a fixed electrode distance of 20 mm placed on the rectus femoris (RF), tibialis anterior (TA), lateral gastrocnemius (GA), soleus (SO), vastus medialis (VM), and biceps femoris (BF) of the right leg, and affixed with double-sided tape and athletic wraps. Electrodes were connected to a DataLINK base-unit DLK900 of the EMG acquisition system, which was connected to a PC using a USB cable. To achieve acceptable impedance levels, the skin over the location of each electrode was shaved (if necessary) and cleaned with alcohol swabs.

EMG data were collected at 1000 Hz and passed through an amplifier with the gain set at 1000. The amplification bandwidth was 20–460 Hz (input impedance = 100 MΩ, common mode rejection ratio >96 dB (~110 dB) at 60 Hz). A zeroing reference electrode was placed above the right lateral malleolus, and was secured with elastic wrap and tape. The electrodes were not removed from the subjects until all data collection was completed.

A 12-camera motion capture device was used to collect three-dimensional kinematics data from reflective markers, which were placed on the right and left hip, knee, ankle, heel, and toe at 200 Hz (Oxford Metrics, Oxford, UK). The collected kinematics data was used to identify each squat cycle by detecting the maximum and minimum hip location (maximum flexion and extension) for each squat. A Matrix MR-500 metronome was used to help subjects to control the speed of knee extension/flexion (Quartz Inc., Mahwah, NJ, USA), and an electronic trigger was used to synchronize EMG and kinematic data.

Protocol

Upon arrival at the laboratory, participants performed 10 min of warm-up exercises, which included muscle stretching and light aerobic activities (e.g. jogging). Next, participants were trained to perform a squat motion consisting of knee flexion to 75° beginning from the anatomical position (0° corresponding to full extension) and a return to full extension. Flexion was controlled by a knee orthotic that restricted movement to 75°. Each squat lasted for approximately three seconds: 1.5 s for knee flexion and 1.5 s for knee extension (Figure 1). The subjects used a metronome to control the speed of knee extension/flexion. Prior to data collection, participants were familiarized with a weight vest used to increase muscular loading during experimental trials by having them perform two sets of five repetitions with the weight vest adding 20% to their baseline body weight. During data collection, the subjects performed a set of five squats at the assigned loading levels (100% (BW), 110% (BW + 10%), and 120% (BW + 20%) of body weight). The order of loading levels was randomized prior to data collection for each participant. After each set, participants were given a minimum of 5-min rest [18] to avoid potential effects of muscular fatigue.

Data processing

EMG and kinematic data were processed using a customized Matlab script (Mathworks, USA R2010b). The detailed specifications of each processing step are provided in the following sections.

Recurrence quantification analysis (RQA) and determinism: All EMG signals were filtered using an 8th-order zero-phase Butterworth band-pass filter with a band frequency of 10–450 Hz [32], and with no further smoothing algorithm to optimize the exposure of collected EMG signals to RQA [3, 47]. A customized Matlab script was used to generate RQA values and determinism of the EMG signals, using a RQASP program [19]. Determinism of the EMG signal is a parameter which indexes the predictability or reproducibility of the signal, or the degree to which future states in a time series rely on present and previous states, it is correlated with motor unit firing and synchronizations and can be altered by changing environmental and task-related constraints [13, 24, 25, 45].

The initial input parameters of RQA (i.e. time delay, embedding dimension, and radius) were carefully selected based on the recommended settings to minimize the effect of noise by employing mutual information and false nearest neighbor methodology [19].

To analyze the neuromuscular activities in each muscle during each squat loading condition, EMG data were clustered into five data bins [considering five squat repetitions (i.e. cycles) per squat condition] defined as the epochs of recorded data between each knee flexion and knee extension (i.e. squat cycle). The percentage of recurrence, %REC and determinism %DET of each clustered EMG signal were calculated for all muscles within each loading condition for each subject. RQA measures the time-delayed reconstructed space

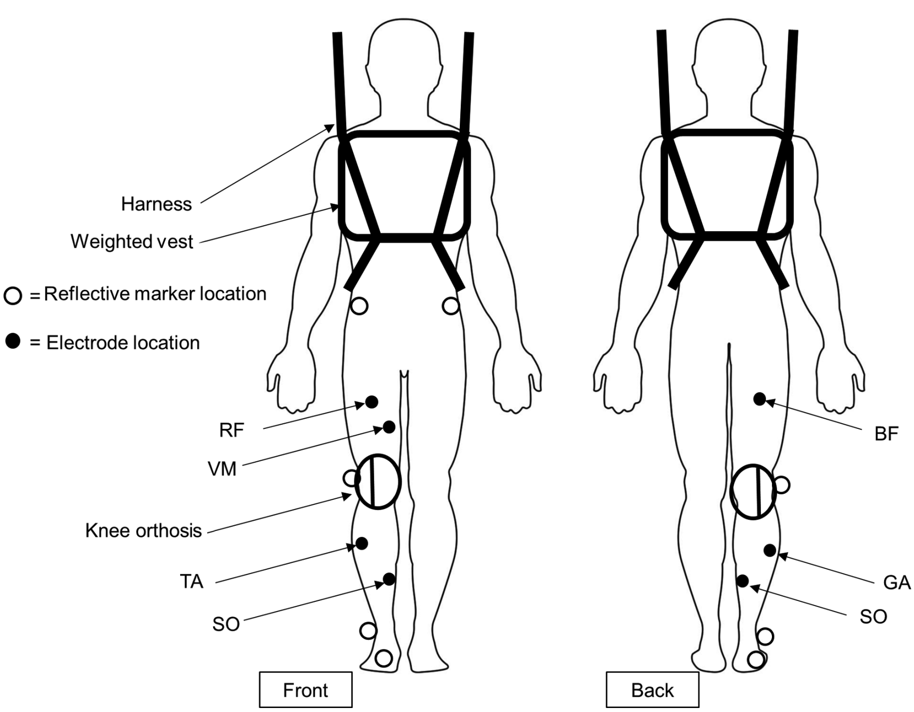

Figure 1: Schematic overview of the experimental setup including marker positions for kinematic analysis and electrode locations for measuring activity of rectus femoris (RF), vastus medialis (VM), biceps femoris (BF), tibialis anterior (TA), lateral gastrocnemius (GA), and soleus (SO).

phase of the EMG signal; therefore, several parameters were defined prior to performing the analysis. By conducting the "False Nearest Neighbor" technique, the embedding dimension was selected [21]. In addition, the time delay was assessed using the mutual information (MI) technique [15]. In the MI technique, the first local minimum of the average mutual information was used to detect the time delay. In a recent study on EMG signals collected from healthy subjects by using a similar protocol, the embedding dimension was calculated as m = 6, and the time delay was 5 ($\tau = 0.005$ s) [29]. The proximity radius was calculated as the rescaled "Maximum" unit of the distance matrix to keep the percentage of the recurring points in the recurrence plot (RP) of the signal at less than 2%, as has been recommended by previous investigations [46].

Shuffled surrogates tests: To justify the use of higher level nonlinear analysis in EMG signal analysis, shuffled surrogates testing was conducted on the EMG signals by performing 20 series of surrogate data using three algorithms. These series of surrogate data were generated for each set of muscles per each squat cycle [25, 30, 33, 36].

Signal processing

In this experiment, the SYNERGOS algorithm was used according to a specific protocol (Figure 2) to evaluate the change in the MMA due to altering load conditions during squat movements. The epochs were defined as the EMG signals calculated for each squat cycle (five squats per loading condition).

Statistical analysis

To investigate the responsiveness of SYNERGOS to detect the changes in MMA associated with altered loading condition (i.e. BW, BW + 10%, BW + 20%) and squat repetition (level 1 to 5), a two-way (repetitions by load) repeated measures analysis of variance with a significance level of $p \le 0.05$ was used. The analysis was conducted using SPSS 17.0.1 (SPSS Inc., Chicago, Illinois, USA).

The unbiased population estimate of the effect size for the main factors was calculated using the equation (1):

$$\omega = \sqrt{\frac{\left[\frac{k-1}{nk}(\mathrm{MS_M}-\mathrm{MS_R})\right]}{\mathrm{MS_R}+\frac{\mathrm{MS_{BG}}-\mathrm{MS_R}}{k}+\left[\frac{k-1}{nk}(\mathrm{MS_M}-\mathrm{MS_R})\right]}} \tag{1}$$

in which $\mathrm{MS_M}$ represents the mean square value of the effect, $\mathrm{MS_R}$ is the residual mean square value, k is the number of levels of the effect, n is the number of subjects, and $\mathrm{MS_{BG}}$ is the mean square value for the between group effects [12] .

The effect size for pairwise comparison (i.e. "r") was calculated using equation (2)

$$r = \sqrt{\frac{F(1, df_R)}{F(1, df_R) + df_R}} \tag{2}$$

in which r is the effect size and df_R refers to the degrees of freedom for the MS residual [12].

Surrogate testing

Discriminant statistics of the %DET and ApEn of the surrogate data are shown in Table 1. The results calculated for all subjects and gait cycles indicated that for all three types of surrogate tests (i.e. time shuffled, Fourier transform [FT], iterated amplitude adjusted Fourier transform [IAAFT]), the null hypotheses of equal

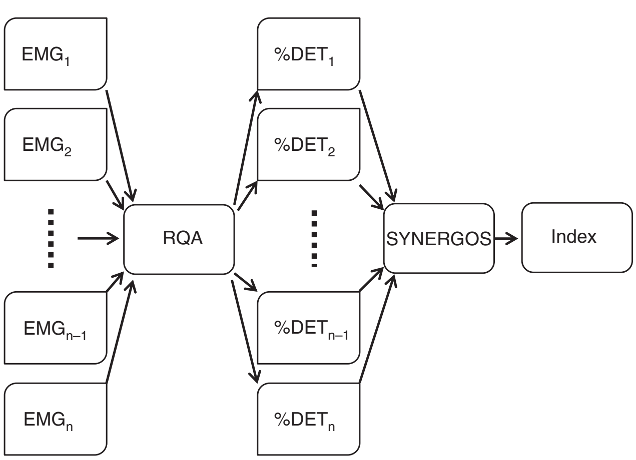

Figure 2: The schematic view of the SYNERGOS algorithm. EMG signals are analyzed using the RQA, and the output for each muscle, %DET, is imported into the SYNERGOS algorithm, which eventually provides a single scalar index representing the state of MMA (Pourmoghaddam et al., 2015)

Table 1: The values of surrogate testing for three different algorithms; . φ_{ApEn} and $\varphi_{\mathrm{\%DET}}$ represent the value of statistics calculated from ApEn and %DET of the EMG signals and surrogate data series.

		SO	GA	TA	VA	RF	BF
Time Shuffled							
φ_{ApEn}	Mean	74.41	33.28	27.62	39.12	76.91	21.85
	SD	6.37	4.74	5.30	6.13	6.85	4.42
$\varphi_{\mathrm{\%DET}}$	Mean	348.30	299.95	248.85	129.93	54.47	89.15
	SD	67.61	37.83	49.02	36.74	14.29	28.93
FT							
φ_{ApEn}	Mean	74.32	32.82	25.87	38.56	74.97	21.70
	SD	4.96	7.05	5.30	5.27	4.58	6.30
$\varphi_{\mathrm{\%DET}}$	Mean	345.20	295.15	243.93	120.37	44.59	85.06
	SD	13.47	26.88	19.72	5.72	12.35	7.51
IAAFT							
φ_{ApEn}	Mean	73.07	31.46	24.56	37.77	73.80	21.13
	SD	5.55	6.53	6.97	4.19	5.72	4.57
$\varphi_{\mathrm{\%DET}}$	Mean	340.92	286.48	238.87	110.73	43.38	83.10
	SD	4.50	10.57	16.77	11.88	6.91	6.70

[Fourier transform (FT), iterated amplitude adjusted Fourier transform (IAAFT), rectus femoris (RF), tibialis anterior (TA), lateral gastrocnemius (GA), soleus (SO), vastus medialis (VM), and biceps femoris (BF)]. The data were calculated from the EMG signals clustered by each squat cycle.

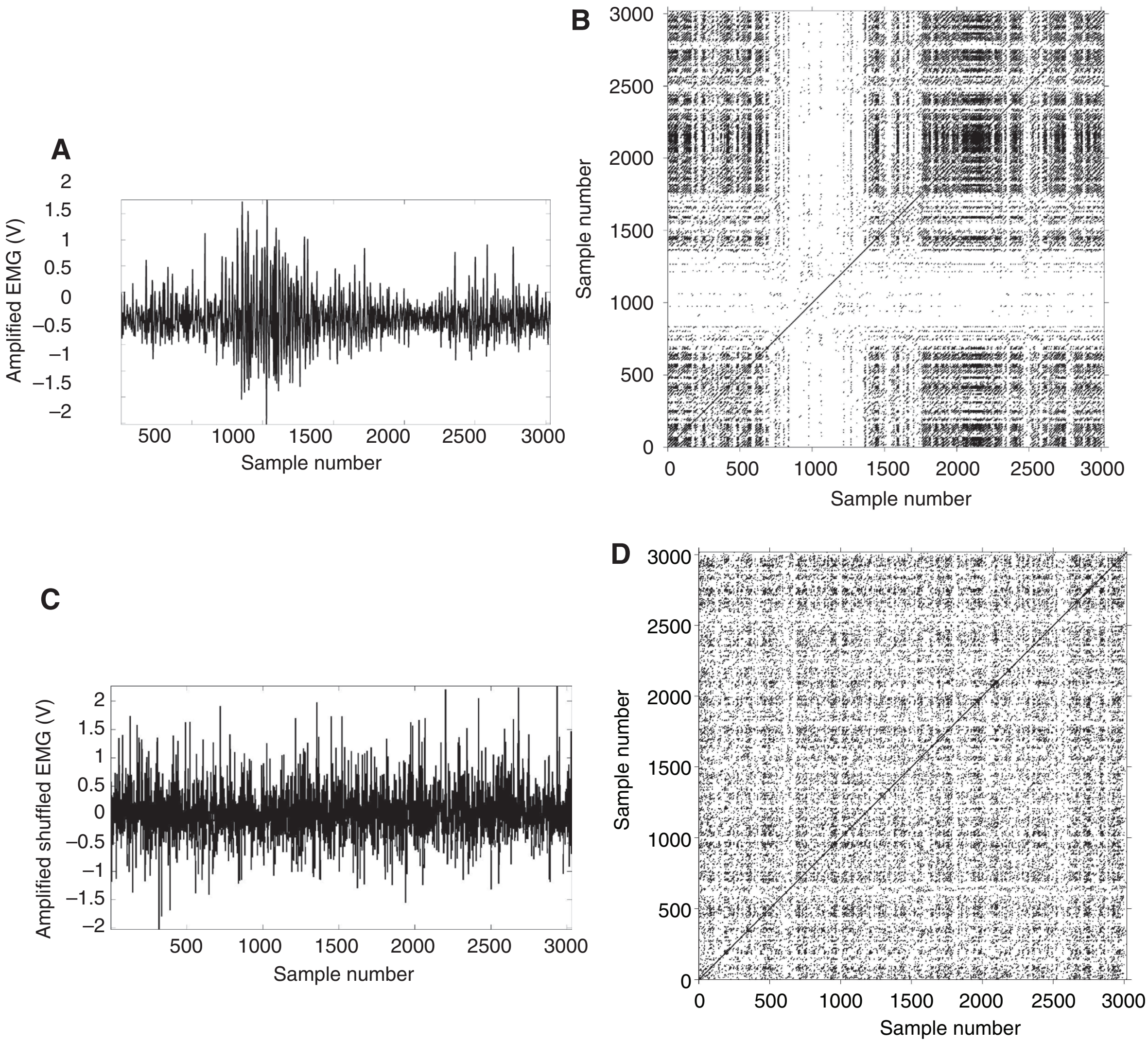

Figure 3: The neuromuscular activities of rectus femoris muscle during a squat cycle are shown by EMG activities in Figure 3A. The Recurrence plots (RP) generated based on the original data is shown in graph Figure 3B that indicates a specific pattern in the rectus femoris activity exists during a squat cycle. This pattern is depicted by several recurrent points located along particular diagonal lines which are parallel to the main diagonal line. The outcome of the RQA also verified the existence of the aforementioned pattern (%REC = 1.93; %DET = 16.86, radius = 5.2, ApEn = 0.48). The randomized shuffled data of the signal shown in Figure 3C while Figure 3D is the RP of the randomized signal which shows no significant determinism in the shuffled data. The time delayed dimensional data in RP are randomly scattered around the main diagonal line and the recurrent points are positioned along very short length. In addition, the outcome of RQA has shown significant reduction in determinism in the randomized data (%REC = 0.56, %DET = 0.01 radius = 5.2, ApEn = 1.85). The drastic drop in the determinism of the signal detected by decreasing %DET and increasing ApEn verified the nonlinear dynamics of the collected EMG signal.

or more determinism in the surrogate data were rejected ($\varphi > 2$ and $p < 5\%$). The underlying nonlinear behavior of surrogate signals was significantly different from the original EMG signals; therefore, the use of a higher-order nonlinear data analysis technique was justified.

As an example, Figure 3A depicts an EMG signal collected from the rectus femoris (RF) during a single squat cycle (one knee flexion and one knee extension). Figure 3B depicts the recurrence plot (RP) of the RF EMG activity. The deterministic pattern of EMG activity during a squat cycle is detectable by observing the recurrent points that are positioned along several parallel diagonal recurrent lines. Figure 3C represents a random shuffled signal of the EMG activity using surrogate testing algorithms. The RP of the shuffled data are presented in Figure 3D. These points do not generate long, diagonal, recurrent lines, which would indicate determinism of the signal. Therefore, no particular deterministic pattern can be recognized by observing several recurrent points scattered on the plot. The analyses of the original and surrogate signals also confirmed the results displayed in 3B and 3D. For the original signal, the %REC = 1.98; %DET = 17.47; radius = 5.2 and ApEn = 0.45, while for the surrogate data to obtain a %REC = 0.56 with the same radius of 5.2 was used and %DET = 0.01 which is significantly lower than original data.

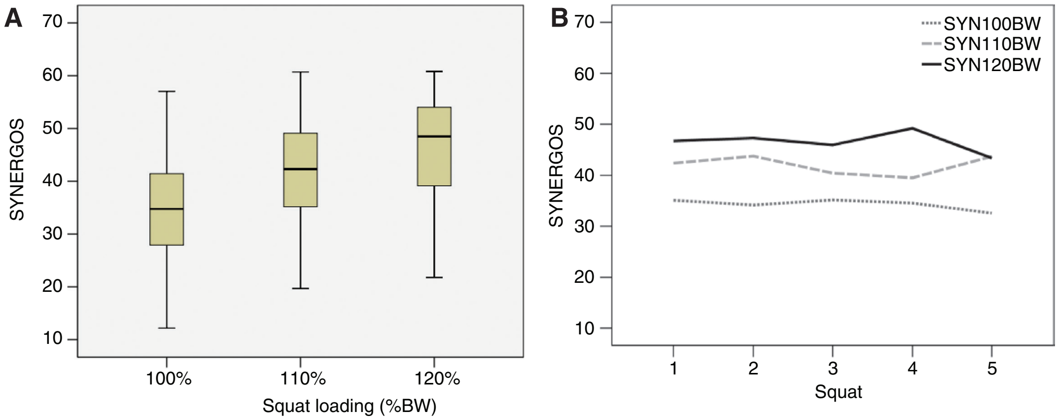

Figure 4: (A) is the box plot representation of the SYNERGOS indices, which depicts the overall SYNERGOS index increased during added weight squat performance.
(B) is the graph of the averaged value of the SYNERGOS indices for different loading and squat cycles that depicts significant increase in the SYNERGOS indices when the loading increases and shows stable repetition-to-repetition estimates of SYNERGOS within each loading condition.

Additionally, the ApEn increased to more than twice the initial value (ApEn = 1.75) in the surrogate data. The reduction in %DET and increase in ApEn indicates that the surrogate data followed a different dynamical pattern from the original EMG signal; therefore, the collected EMG signal included nonlinear behaviors (i.e. determinism), which were altered by the randomization of the original signal.

Results

The overall SYNERGOS index across all subjects and squat performances was 41.06 ± 10.93. The interaction effect between the squat cycles and loading (loading*Squat) was not significant [F(8, 96) = 1.818, p = 0.083], suggesting consistent behavior of the SYNERGOS algorithm in quantifying MMA during performance of isotonic motor tasks with different loading conditions across repetitions. This result was further verified when evaluating the similarity of the increase in SYNERGOS indices during different squat cycles when the squat loading was increased (Figure 4B). A slight decrease of the SYNERGOS index average in squat cycle 5 was not significant.

The result of the two-way repeated measures of ANOVA indicated that the SYNERGOS index was significantly responsive to the change of the squat loading condition; the increase in squat loadings was detected by a significantly higher SYNERGOS index (Figure 4A), [F(1.503, 18.37) = 29.762, ω = 0.805, p < 0.001]. Contrast analysis indicated that the SYNERGOS indices at BW + 10% was significantly higher than during the squat performance with no extra loading condition (BW) [F(1, 12) = 41.592, r = 0.88, p < 0.001]. In addition, the SYNERGOS indices were also significantly higher during BW + 20% compared to BW + 10% [F(1, 12) = 19.723, r = 0.79, p = 0.001].

Further, SYNERGOS indices were not significantly different between repetitions, averaged across load conditions [F(2.434, 29.204) = 0.595, p = 0.589].

Discussion

SYNERGOS was developed as an analysis tool to monitor the changes in MMA due to the altered environmental and task-related constraints. A pilot study had indicated that SYNERGOS was responsive to detect the subtle changes in MMA resulting from incremental changes in the kinematics of the motor performance during a treadmill walk experiment [29]. Results were confirmed in a later study that investigated the effects of medication and changing gait speed in Parkinson patients [27]. In both experiments, gait speed was increased and SYNERGOS was successful to detect the changes in the MMA. It is well established that during gait at higher speed, the ground reaction forces and muscular loading significantly increases [20]. In this experiment, the SYNERGOS algorithm was used to evaluate the state of MMA when participants performed a common isotonic exercise (i.e. squat movement). Our initial hypothesis was confirmed, since SYNERGOS showed to be sensitive to changes in isotonic loading and associated MMA characteristics. The results verified that SYNERGOS successfully detected changes in MMA due to increasing loading conditions in the squat movements. In clinical settings, altered kinetic constraints to accomplish a given task (e.g. single leg squat) have been used to assess the performance of patients [35], thus the application of SYNERGOS is justified to accompany traditional motor performance testing methods, as it is capable to monitor the changes in MMA resulted from altered kinetic conditions independent of the movement pattern.

As shown in previous investigations, increasing the squat loading was expected to result in altering neuromuscular activities, such as increasing neuromuscular activities in the quadriceps femoris in adults aged from 19 to 90 years during squat movements with increasing body weights [17]. Other investigations indicated that during squat movements, all measured muscle activities would respond to higher squat loading [22, 26]. The increase in MMA as reflected in SYNERGOS indices in the current study can be explained by the fact that the CNS employs more motor unit activation during conditions performed with higher squat loadings to ensure adequate neuromuscular compensation to provide the required energy and balance during more demanding movements over the span of the cyclic movement (i.e. squat cycle).

It should be noted as a limitation that we did not assess potential gender effects in our current study, since this was not one of our research goals. However there may be gender-specific activation pattern differences that should be taken into consideration, hence future studies including SYNERGOS to add qualitative, nonlinear analysis to traditional quantitative techniques should also employ gender effects analyses. We also observed that there were no significantly different indices across the squat motions within each loading condition, hence, SYNERGOS provided consistent results over the period of multiple squat cycles within each loading condition. The consistency of the obtained SYNERGOS indices is valuable to facilitate the use of this algorithm as a measurement tool that provides accurate assessments. The algorithm shows potential to monitor a group of muscular activities and provide a single quantity for each cycle by providing SYNERGOS indices. During clinical assessments, the response of the neuromuscular system to different loading conditions can be used as a tool for monitoring the overall health of the body. Hence, SYNERGOS may be a valuable tool, particularly in long duration data collection, as it summarizes the multiple EMG signals into a single quantity. Thus, the tool provides a representation of MMA and its non-linear components, while allowing for easier storage and interpretation of data.

Conclusions

The analysis tool presented here had shown value for investigating MMA during treadmill walking of healthy younger adults and patients before. Here, we showed that SYNERGOS as a tool to provide a single value estimate of nonlinear MMAis sensitive to the kinetic features of a movement task (squat) and associated orchestration of cyclic movements under different loading conditions. More research is needed to determine the value of SYNERGOS for clinical evaluations and research purposes.

Conflict of interest: The authors report no conflict of Interest.
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Ethical approval: Ethical approval for this study was provided by the University of Houston Committee for the protection of human subjects (CPHS).

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