

Dynamics of modular neuromotor control of walking and running during single and dual task conditions.

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Abstract

The aim of the study was to determine the stability and complexity of muscle synergies to provide insight to the neural control of gait stability in walking and running and when performing a concurrent cognitive dual task. Eighteen healthy young adults performed walking and running at preferred speeds and 120% of preferred speeds in single and dual task conditions. Muscle synergies were determined from the activity of 9 trunk and leg muscles and centre of mass (COM) motion was recorded with an inertial measurement unit. Local dynamic stability, complexity and width of synergies, and stability and complexity of COM motion were determined, in addition to the cross sample entropy to determine the coupling between COM motion and muscle synergies. Increasing locomotion speed increased complexity and decreased stability of COM motion with a concurrent decrease in synergy complexity and stability but with no change in synergy width. The coupling of COM motion and muscle synergies also increased with increasing speed. Vertical COM motion was more complex and less stable but with no change in anterior-posterior or medio-lateral directions in dual task locomotion. Muscle synergies were also more stable in dual task conditions. These findings indicate that changes in neuromotor dynamics may underpin reported changes in COM local stability during gait as the neural commands responsible for generating the movement are altered in response to increasing task demands. Increased cognitive demands lead to more stable neuromotor commands possibly to maintain local stability of COM motion in the anterior-posterior and medio-lateral directions.

Keywords

Gait; Electromyography; Muscle Synergy; Complexity; Local dynamic stability

Introduction

Muscle synergies represent the activation of a group of muscles by spinal circuits modulated by supraspinal commands (Bizzi and Cheung, 2013), with individual muscles within a synergy also demonstrating similar time-frequency characteristics of their activity (Frère, 2017).

Muscle synergies reduce dimensionality of neuromotor control associated with the vast number of degrees of freedom resulting from the number of combinations of muscle activations and joint motions possible for each movement (Bizzi and Cheung, 2013). Each synergy recruits multiple muscles and a single muscle can be present in multiple synergies (Wojtara et al., 2014) allowing for the flexible production of movements in response to variable task constraints (Santuz et al., 2018).

The production and control of voluntary movements requires the integration of activity in multiple areas of the motor cortices such as the primary motor cortex and pre-motor area, supplementary motor area and cingulate motor area (Cheung et al., 2009; Rathelot and Strick, 2009) and the integration of sensory information. This complex system presents significant non-linear output; small perturbations to initial conditions can generate large variations in the system output (i.e. neuromotor commands). Several studies have previously utilised a variety of methods to measure the stability of muscle synergies in response to different task conditions in an attempt to understand central nervous system (CNS) control strategies (Cheung et al., 2009; Suzuki et al., 2014; Wojtara et al., 2014; Kibushi et al., 2018; Santuz et al., 2020). Recently, utilising non-linear methods such as the maximum Lyapunov exponent, the local dynamic stability of muscle synergies has been demonstrated to decrease with increasing walking speed (Kibushi et al., 2018). Conversely, it has been found that synergies were more stable, wider and less complex in running compared to walking and when gait was perturbed (Santuz et al., 2020), suggesting the CNS alters the dynamics of modular neural commands in response to changing task conditions.

Similarly, non-linear methods to determine local dynamic stability and complexity of movement have been employed to understand the control dynamics of common tasks such as walking (e.g. England and Granata, 2007; Bruijn et al., 2009b; Suzuki et al., 2014; Walsh et al., 2018; Walsh and Taylor, 2019; Caronni et al., 2020; Magnani et al., 2020). Since human gait requires executive and automated control processes (Hamacher et al., 2015) previous

studies have employed dual task paradigms to examine the dynamic nature of neural control by manipulating the available cognitive resources (e.g. Bruijn et al., 2009a; Patel et al., 2014; Magnani et al., 2017) demonstrating that performing cognitive dual tasks while walking results in more complex (Magnani et al., 2017) and less stable (Bruijn et al., 2009b; Magnani et al., 2017) gait as the increased cognitive demand interferes with the normal supraspinal neuromotor control processes. It is possible that changes in stability and complexity of motion during gait result from changes in the stability or complexity of the neuromotor output (i.e. muscle synergies) due to the cognitive motor interference, however, this has not been studied.

The purpose of this study is to investigate the effects of increasing task demands on the neural dynamics of motor control during walking and running by employing preferred and faster than preferred speeds and cognitive dual task conditions. To the authors knowledge this study will be the first to directly examine the effects of cognitive dual tasking during locomotion on the stability and complexity of neuromotor output in the form of muscle synergies. It was hypothesised that as task difficulty increased with increasing speed from walking to running, at faster than preferred speeds, and in dual task conditions muscle synergies and centre of mass (COM) motion would become less stable and more complex, and that the width of muscle synergies, i.e. the width of synergy activity peaks, would increase. In addition, it was hypothesised that the coupling between COM motion and muscle synergies would increase with speed as the neuromotor control requirements increased but would decrease in dual task conditions as available cognitive resources are reduced. Further, it was hypothesised that speed effects on muscle synergy and centre of mass dynamics would be greater in dual task conditions than single task conditions as the additional mechanical task demands interact with the greater cognitive demands.

Experimental Procedures

Participants

Eighteen physically active adults free from neurological conditions and injury (females: n=9, age: 27±9 years, height: 1.70±0.11 m, mass: 69.4±15.0 kg; males: n=9, age 31±4 years, height 1.80±0.08 m, mass 77.5±7.9 kg) volunteered to participate in this study. Participants were made aware of the purpose of the study and gave written informed consent before

commencing any study procedures. The study was conducted in accordance with the Declaration of Helsinki.

Procedures

Participants attended a single visit during which all data collection procedures were completed. Before commencing data collection trials 5-minute periods of familiarisation with treadmill walking and running were performed. During familiarisation periods self-selected preferred walking (PWS) and running (PRS) speeds were determined. To determine self-selected speeds participants increased treadmill speed until they reached a perceived comfortable speed, treadmill speed was then increased and participants were asked to decrease treadmill speed until they reached a perceived comfortable speed. The average of the 2 speeds was taken as the preferred speed. Participants were blinded to treadmill speed at all times.

Following familiarisation, participants performed 3-minute walking and running trials at PWS and PRS respectively and at 120% of the preferred speeds (PWS₁₂₀ and PRS₁₂₀). For each of the 4 speeds trials were completed under single (ST) and dual task (DT) conditions. Participants therefore completed a total of 8 trials with 2 minutes of rest provided between each trial, the time for each trial was started once the treadmill reached the target speed. The order which trials were completed was randomised.

During the DT trials participants were asked to count backwards out loud in 7s from a randomly generated 3 digit number. A new 3 digit number was presented at the start of each minute of the 3 minute trial. The starting numbers were presented for 2 seconds on a TV screen positioned 2 m in front of the treadmill at eye level.

Electromyographic (EMG) muscle activity was recorded using wireless EMG sensors with a 1 cm interelectrode distance at 1000 Hz (Avanti wireless system, Delsys Inc., Natick, MA, USA) from the dominant side Erector Spinae (ES), Rectus Abdominis (RA), Rectus Femoris (RF), Vastus Medialis (VM), Biceps Femoris (BF), Semitendinosus (ST) Soleus (SOL), Gastrocnemius Medialis (GM) and Tibialis Anterior (TA). Muscles of the lower limb responsible for body support, propulsion and limb progression were included, similarly to previous studies

investigating muscle synergies of gait. Unlike previous studies, muscles of the trunk (i.e. ES and RA) were also included. Previous studies have not included activity of ES and RA to study the muscle synergies of gait, however, given the role of these muscles in trunk support and stability of the COM it was deemed relevant to include these muscles to address the specific aims of this study. Electrodes were placed according to the SENIAM guidelines (Hermens et al., 1999), prior to attachment the electrode sites were shaved and cleaned using an alcohol wipe. 9-axis inertial measurement unit (IMU) data were recorded synchronously with EMG data by an integrated IMU from the ES EMG sensor. A 9-axis IMU (LPMS-B2, Life Performance Research, Tokyo, Japan) was also attached over the L5 vertebrae to measure the movements of the COM recording at 100 Hz. The LPMS-B2 IMU was used to measure COM motion due its lighter mass and smaller depth making it less susceptible to movement artefacts.

Gait stability and complexity

All data analysed by custom written MATLAB (R2016b, Mathworks Inc., Natick MA, USA) scripts. Initial contact events were determined from the anterior-posterior (AP) acceleration of the IMU placed over L5 which was filtered twice separately with 20 Hz and 2 Hz cut-off frequencies using 2nd order dual-pass Butterworth filters. Initial contacts were determined as the points of the peaks in the 20 Hz filtered signal which immediately precede positive to negative zero-crossings in the 2 Hz filtered signal (McCamley et al., 2012). The middle 120 gait cycles were then separated for the AP, medio-lateral (ML) and vertical (VT) acceleration signals and the data were interpolated to 12000 data points for each direction (Raffalt et al., 2019).

From the interpolated COM acceleration signals the maximum Lyapunov exponent (MLE_{COM}) using the Rosenstein algorithm (Rosenstein et al., 1993) and the fractal dimension (HFD_{COM}) using Higuchi's algorithm (Higuchi, 1988) were calculated separately for each direction. The MLE of a signal represents its local dynamic stability in the presence of small perturbations as the exponential rate of convergence or divergence of neighbouring trajectories in state space. Larger values of MLE represent a lower dynamic stability. The HFD of a signal represents the complexity, or irregularity, of that signal. A fractal dimension of 1 represents a signal with no complexity and a value of 2 represents a signal with maximum complexity.

For the calculation of MLE_{COM} the state space of each acceleration signal was determined using the delay embedding method. The appropriate embedding dimension and time delay were determined using the false nearest neighbour and average mutual information algorithms. An embedding dimension of 6 was appropriate for each direction for both walking and running trials and for walking trials delays of 9, 11 and 8 and for running trials delays of 7, 10 and 9 were used for the AP, ML and VT directions respectively.

The nearest neighbour for each point in the state space was found as the points with the smallest Euclidean distance. Nearest neighbours with a temporal separation of less than the mean period of the signal were ignored (Rosenstein et al., 1993). The Euclidean distance of each pair of neighbours was followed for the length of the signal creating as many divergence curves as there were points in the state space. The MLE_{COM} was determined from the log average divergence curve as the slope of the linear period from the first point to the duration of 1 step (0.5 strides).

To calculate the HFD_{COM} for each direction the interpolated acceleration signals were divided into k new time series with initial value $x(m,k)$ where m is the initial point which ranges from 1 to k and k is the delay interval which ranged from 2 to k_{max} . The length of each new time series with total points N is calculated as:

$$L_m(k) = \sum_{i=1}^{\lfloor \frac{N-m}{k} \rfloor} |x(m+ik) - x(m+(i-1)k)| \frac{(N-1)}{\lfloor \frac{N-m}{k} \rfloor k}$$

For every value of k the average length of the reconstructed time series is calculated and the HFD_{COM} was determined as the slope of the plot of $\ln(L(k))$ vs. $\ln(1/k)$. The value of k_{max} was determined separately for each direction by iteratively calculating HFD with increasing values of k_{max} . The point at which the plot of HFD vs. k_{max} plateaued was chosen as the k_{max} value. For walking trials k_{max} values of 64, 55 and 61 were chosen and for running trials values of 42, 49 and 43 were chosen for AP, ML and VT as the average for all trials in each direction.

EMG processing and muscle synergy extraction

The process of identifying heel strikes was repeated with the EMG synchronised onboard IMU of the ES EMG sensor. The accuracy of ipsilateral and contralateral initial contact events when compared to the L5 located IMU was confirmed in pilot testing. Once initial contact events were detected the EMG data for all muscles representing the middle 30 strides of each trial was extracted and were bandpass filtered using a 2nd order dual-pass Butterworth filter with 50 and 450 Hz cut-off frequencies. Bandpass filtered data were demeaned, full wave rectified and lowpass filtered with a 2nd order dual-pass Butterworth filter with a 15 Hz cut-off frequency to create the linear envelope for each muscle. The envelope of each muscle was normalised to the maximum value for each muscle in each trial. The normalised data for each stride was then interpolated to 200 data points and the interpolated data for all 30 strides were concatenated.

Muscle synergies were then extracted using non-negative matrix factorisation (NMF), the 30 strides of normalised, interpolated data were concatenated into a 9 x 6000 matrix (9 muscles x 6000 data points). EMG data were factorised into synergy motor primitives, C , with dimensions $r \times n$ where r is the number of synergies and n is the number of data points, and synergy muscle weights, W , with dimensions $m \times r$ where m is the number of muscles, such that $EMG = W \times C + error$, error is the difference between the original EMG data and the reconstructed EMG data. Example muscle weights (W) and motor primitives (C) for a representative trial of ST PWS are shown in Figure 1. Synergy weights and primitives were calculated by NMF, a total of 1000 iterations were performed with 50 replicates, 1×10^{-4} convergence threshold and 1×10^{-6} threshold for completion (Shuman et al., 2017). Synergy factorisation was repeated successively for the number of synergies from 1 to 8 with randomised initial W and C matrices for each repetition to avoid local minima (Santuz et al., 2020). To determine the number of synergies used in the subsequent analysis for each trial and participant the variance accounted for (VAF) by the EMG data reconstructed (EMG_r) from the W and C vectors for each of the 8 synergies was calculated. The number of synergies required was calculated on an individual trial basis as the minimum number of synergies needed to achieve a VAF of $\geq 90\%$ (Gui and Zhang, 2016; Shuman et al., 2017; Kim et al., 2018). The VAF was calculated as:

$$VAF = 1 - \frac{(EMG_r - EMG)^2}{EMG^2}$$

For running trials the average number of synergies required was 6.2 ± 1.4 and the average number of synergies required for walking trials was 5.4 ± 0.8 .

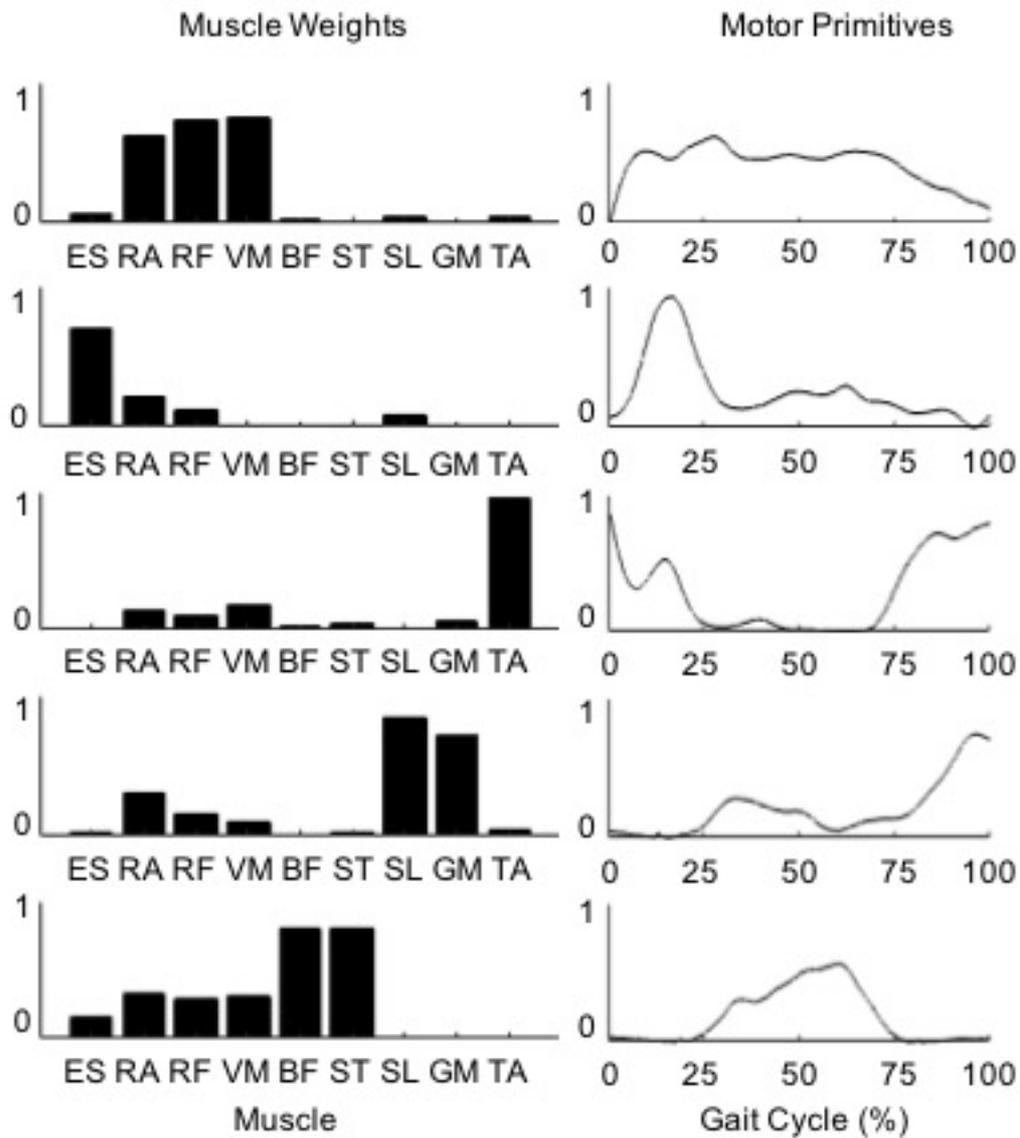


Figure 1. Representative muscle weights and motor primitives during single task preferred speed walking for a trial with five synergies calculated by non-negative matrix factorisation.

Muscle synergy width, stability and complexity

From the extracted motor primitives the full width at half maximum (FWHM) was calculated. As has been previously recommended the FWHM was determined only for fundamental (single peak) synergies, due to a lack of consensus for the interpretation of combined (multiple peaks) synergies (Santuz et al., 2020). The identification of fundamental synergies was completed manually for each trial. After subtracting the minimum primitive value from each value the FWHM was calculated as the number of points with a magnitude greater than half the maximum value. FWHM calculation was performed for each cycle and separately for each synergy then averaged for all synergies to produce a single value per trial.

The local dynamic stability of the motor primitives was determined by the MLE (MLE_{SYN}) which has been previously applied to determine the stability of muscle synergies (Kibushi et al., 2018; Santuz et al., 2020). To avoid the need to determine appropriate embedding dimension and delay factors for the creation of the state space used to calculate the MLE, it was determined that the space of interest had a dimension equal to the number of synergies determined by the NMF (Santuz et al., 2020). Therefore, the n-dimensional synergy measurements were used instead of a reconstructed state space (Sauer et al., 1991), for example, for a trial where the EMG data is factorised into 5 synergies the MLE_{SYN} would be calculated from the 5 motor primitives. Before calculation of the MLE_{SYN} each primitive was scaled to have unit variance by subtracting the mean and dividing by the standard deviation. MLE_{SYN} was then calculated in the same manner as for the COM acceleration data, however, a minimum temporal separation for nearest neighbours of 100 data points was applied ensuring that neighbours were found on different steps. The slope of the logarithmic divergence curve was determined from the first 4 points to calculate the MLE_{SYN} for the trial.

The complexity of muscle synergies was calculated using HFD (HFD_{SYN}) as described previously, using k_{max} values of 204 and 196 for walking and running trials respectively. HFD_{SYN} was calculated separately for each synergy and then averaged to produce a single value for each trial.

Coupling of synergy and COM motion complexity

To determine the coupling between muscle synergy and COM motion complexity the cross sample Entropy (XSampEn) was calculated separately for each muscle synergy and each COM motion direction combination. The XSampEn was calculated between the motor primitives of length 6000 points per synergy, representing the data for 30 strides, and the acceleration data of the same 30 strides. The acceleration data was interpolated to 6000 data points as the calculation of XSampEn requires each time series to have the same length. The process for calculating XSampEn has been described in detail previously (e.g. Liu et al., 2015; McCamley et al., 2017). Briefly, before calculating the XSampEn the data were normalised to have 0 mean and standard deviation of 1. For the input parameters m and r and the normalised synergy time series $x(i)$ and normalised acceleration time series $y(i)(1 \leq i \leq N)$, where N is the number of samples, the vectors X_i^m and Y_j^m , representing m consecutive x and y values respectively, were created:

$$\begin{aligned} X_i^m &= \{x(i), x(i+1), \dots, x(i+m-1)\} \\ Y_j^m &= \{y(j), y(j+1), \dots, y(j+m-1)\} \\ 1 &\leq i, j \leq N - m \end{aligned}$$

The distance between X_i^m and Y_j^m , determined as the maximum absolute difference, was calculated as:

$$d_{i,j}^m = d[X_i^m, Y_j^m] = \max_{k=0}^{m-1} |x(i+k) - y(j+k)|$$

For each X_i^m , set $B_i^m(r)$ is denoted as $(N-m)^{-1}$ multiplied by the number of Y_j^m ($1 \leq j \leq N - m$) that meet the criteria $d_{i,j}^m \leq r$ and set $A_i^m(r)$ is denoted as $(N-m)^{-1}$ multiplied by the number of Y_j^{m+1} ($1 \leq j \leq N - m$) that meet the criteria $d_{i,j}^{m+1} \leq r$. The XSampEn is then determined as:

$$XSampEn(m, r, N) = -\ln \left(\frac{\sum_{i=1}^{N-m} A_i^m(r)}{\sum_{i=1}^{N-m} B_i^m(r)} \right)$$

Values of $m=3$ and $r=0.25$ were used based on previous recommendations for biological signals (McCamley et al., 2017). Higher values of XSampEn represent less closely coupled signals. Therefore, a lower XSampEn in this study will demonstrate a greater degree of coupling between the complexity of muscle synergies and COM motion.

Statistics

Data were tested for normality using the Shapiro-Wilk test. To test the effects of locomotion speed (PWS, PWS₁₂₀, PRS, PRS₁₂₀) and cognitive task condition (ST, DT) on gait dynamics variables, muscle synergy dynamics variables and XSampEn 4x2 two-way repeated measures ANOVA were performed. For main effects and interactions which violated the assumption of sphericity the Greenhouse-Geisser correction of the degrees of freedom was performed. For significant main effects of speed pairwise comparisons with a Bonferroni correction were performed. For all main and interaction effects the partial eta squared (η_p^2) effect size was calculated, values of 0.01, 0.06 and 0.14 represent small, moderate and large effects, respectively. For all tests the level of significance was $p < 0.05$. All statistical analysis was performed using SPSS (v26, IBM Corp., NY USA).

Results

Gait dynamics

All results for COM gait dynamics are shown in Figure 2. There were significant effects for speed on the HFD_{COM} in the AP ($F(1.9,32.6) = 47.3$, $p < 0.001$, $\eta_p^2 = 0.74$), ML ($F(1.2,21.1) = 43.0$, $p < 0.001$, $\eta_p^2 = 0.72$) and VT ($F(1.6,27.3) = 48.8$, $p < 0.001$, $\eta_p^2 = 0.74$) directions. HFD_{COM} AP was greater in PRS (PWS: $p < 0.001$, PWS₁₂₀: $p < 0.001$) and PRS₁₂₀ (PWS: $p < 0.001$, PWS₁₂₀: $p < 0.001$) than PWS and PWS₁₂₀ but there was no difference between PWS and PWS₁₂₀ or between PRS and PRS₁₂₀. HFD_{COM} ML was greater in PRS (PWS: $p < 0.001$, PWS₁₂₀: $p < 0.001$) and PRS₁₂₀ (PWS: $p < 0.001$, PWS₁₂₀: $p < 0.001$) than PWS and PWS₁₂₀ and greater in PWS₁₂₀ than PWS ($p = 0.001$) but there was no difference between PRS and PRS₁₂₀. HFD_{COM} VT was greater in PRS (PWS: $p < 0.001$, PWS₁₂₀: $p < 0.001$) and PRS₁₂₀ (PWS: $p < 0.001$, PWS₁₂₀: $p < 0.001$) than PWS and PWS₁₂₀ but there was no difference between PWS and PWS₁₂₀ or between PRS and PRS₁₂₀. There was no effect of cognitive task condition on

HFD_{COM} AP or ML, however, VT was greater in DT than ST ($F(1,17) = 5.6, p = 0.029, \eta_p^2 = 0.25$). There were no significant interactions for HFD_{COM} in any direction.

There was also a significant effect of speed on the MLE_{COM} in the AP ($F(1.4,23.1) = 49.7, p < 0.001, \eta_p^2 = 0.75$), ML ($F(1.5,25.0) = 20.4, p < 0.001, \eta_p^2 = 0.55$) and VT ($F(1.6,26.6) = 154.3, p < 0.001, \eta_p^2 = 0.90$) directions. MLE_{COM} AP was greater in PRS (PWS: $p < 0.001, PWS_{120}$: $p < 0.001$) and PRS₁₂₀ (PWS: $p < 0.001, PWS_{120}$: $p < 0.001$) than PWS and PWS₁₂₀ but there was no difference between PWS and PWS₁₂₀ or between PRS and PRS₁₂₀. MLE_{COM} ML was greater in PRS (PWS: $p = 0.049, PWS_{120}$: $p < 0.001$) and PRS₁₂₀ (PWS: $p = 0.042, PWS_{120}$: $p < 0.001$) than PWS and PWS₁₂₀ and greater in PWS than PWS₁₂₀ ($p = 0.001$) but there was no difference between PRS and PRS₁₂₀. MLE_{COM} VT was greater in PRS (PWS: $p < 0.001, PWS_{120}$: $p < 0.001$) and PRS₁₂₀ (PWS: $p < 0.001, PWS_{120}$: $p < 0.001$) than PWS and PWS₁₂₀ and greater in PWS than PWS₁₂₀ ($p = 0.007$) but there was no difference between PRS and PRS₁₂₀. There was no effect of cognitive task condition on MLE_{COM} AP or ML, however, VT was greater in DT than ST ($F(1,17) = 6.1, p = 0.024, \eta_p^2 = 0.27$). There were significant interaction effects for MLE_{COM} AP ($F(2.5,41.9) = 20.2, p < 0.001, \eta_p^2 = 0.54$), ML ($F(2.4,41.2) = 17.3, p < 0.001, \eta_p^2 = 0.50$) and VT ($F(2.3,38.4) = 16.6, p < 0.001, \eta_p^2 = 0.50$) with the effect of speed being greater in DT condition than ST for all directions.

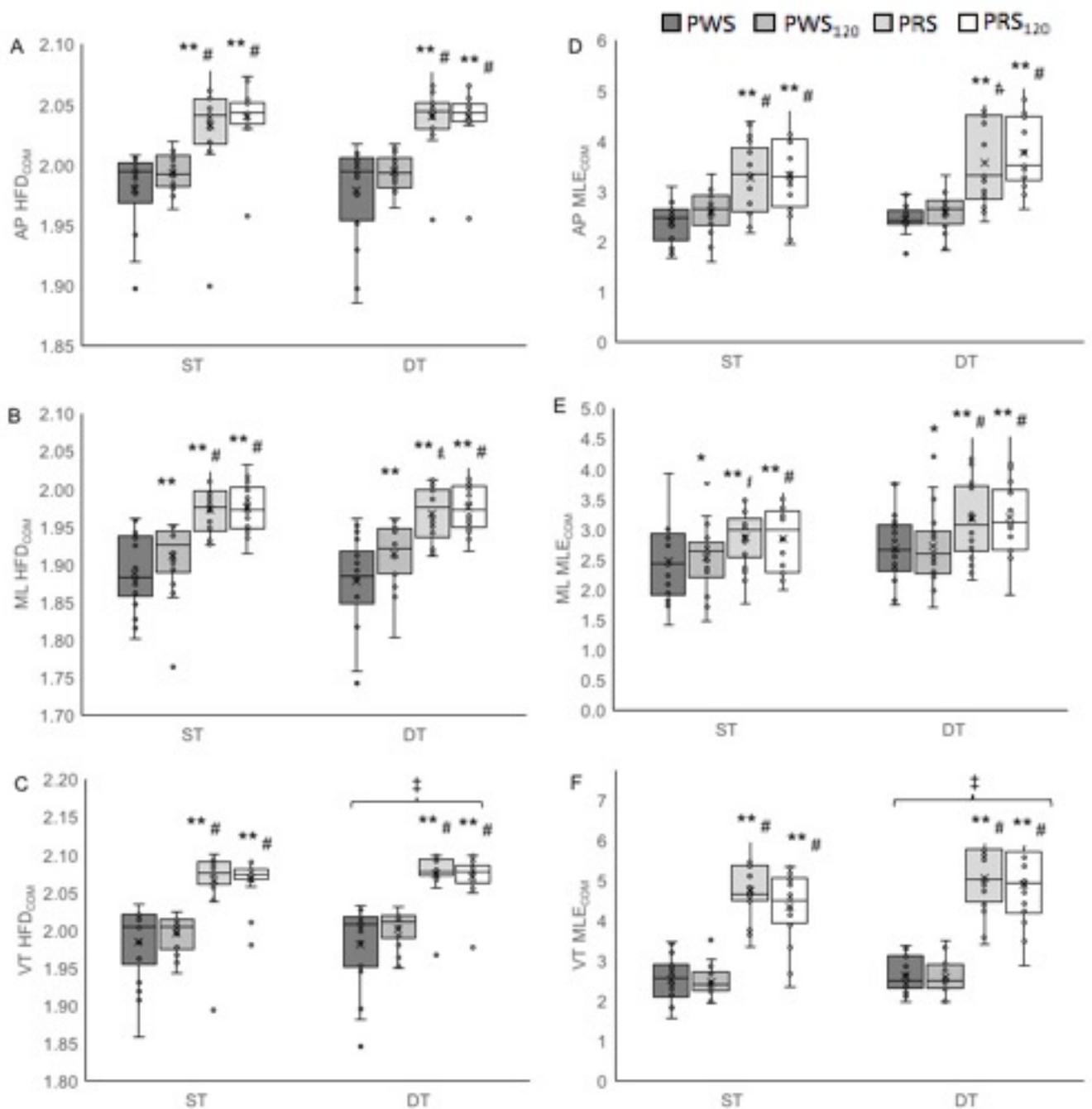


Figure 2. Box plots for fractal dimension calculated for centre of mass motion (HFD_{COM}) in the A) AP, B) ML and C) VT directions, maximum Lyapunov exponents for centre of mass motion (MLE_{COM}) in the D) AP, E) ML and F) VT directions in single task (ST) and dual task (DT) conditions for all speeds. The mean of each variable for each speed x dual task condition combination is represented by an X.

* significantly lower than PWS, ** significantly greater than PWS, # significantly greater than PWS₁₂₀, † significantly greater than ST

Muscle synergy dynamics

All results for muscle synergy dynamics are shown in Figure 3. There was a significant effect of speed on HFD_{SYN} ($F(1.6,27.6) = 24.9$, $p < 0.001$, $\eta_p^2 = 0.59$). HFD_{SYN} was lower in PWS_{120} ($p < 0.001$), PRS ($p < 0.001$) and PRS_{120} ($p < 0.001$) than PWS but there was no difference between PWS_{120} , PRS and PRS_{120} . There was also no effect of condition or interaction for HFD_{SYN} .

A significant effect of speed on MLE_{SYN} ($F(1.4,27.6) = 156.7$, $p < 0.001$, $\eta_p^2 = 0.90$) was also present. MLE_{SYN} was greater in PRS (PWS: $p < 0.001$, PWS_{120} : $p < 0.001$) and PRS_{120} (PWS: $p < 0.001$, PWS_{120} : $p < 0.001$) than PWS and PWS_{120} and greater in PWS_{120} than PWS ($p = 0.001$) but there was no difference between PRS and PRS_{120} . MLE_{SYN} was also greater in ST than DT conditions ($F(1,17) = 6.6$, $p = 0.20$, $\eta_p^2 = 0.28$).

Significant effects of speed were also found for FWHM ($F(2.2,38.0) = 3.7$, $p = 0.031$, $\eta_p^2 = 0.18$), however, there were no significant Bonferroni corrected pairwise comparisons and also no main effect of condition or interaction effects for FWHM.

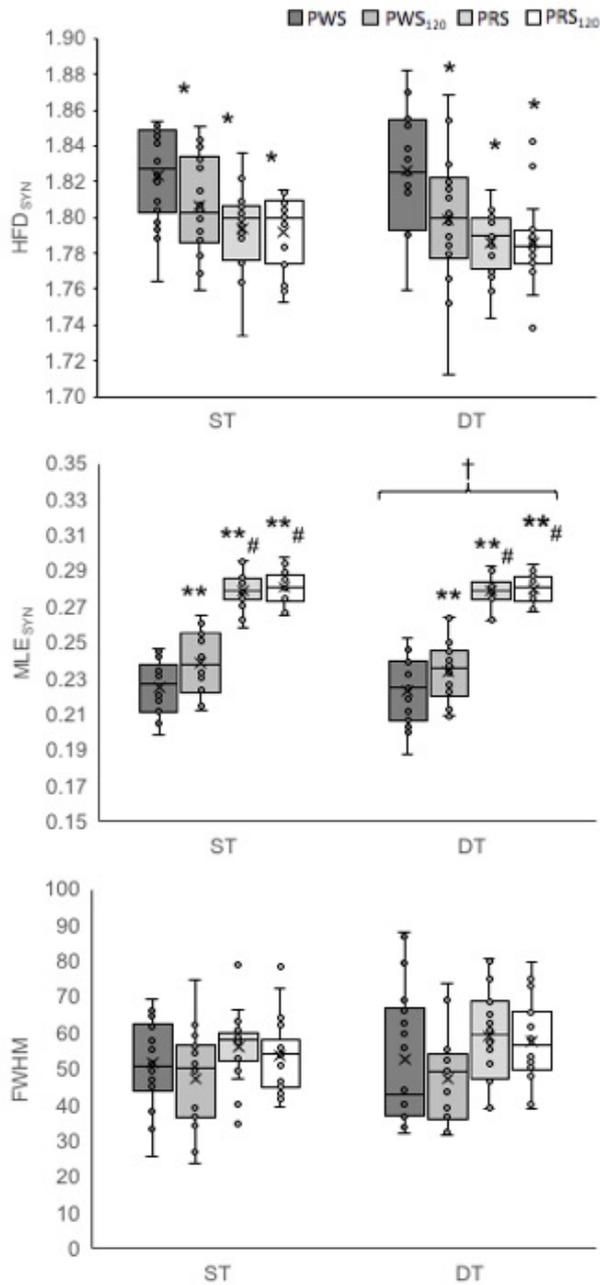


Figure 3. Box plots for A) the fractal dimension calculated for muscle synergies (HFD_{SYN}), B) the maximum Lyapunov exponent for muscle synergies (MLE_{SYN}) and C) the full width at half maximum of muscle synergies (FWHM) in single task (ST) and dual task (DT) conditions for all speeds. The mean of each variable for each speed x dual task condition combination is represented by an X.

* significantly lower than PWS, ** significantly greater than PWS, # significantly greater than PWS_{120} , † significantly lower than ST

Coupling of COM motion and muscle synergies

All results for XSampEn are shown in Figure 4. There was a significant effect of speed on XSampEn ($F_{1,4,23,3} = 25.79$, $p < 0.01$, $\eta_p^2 = 0.59$). XSampEn was lower in all conditions compared to PWS (PWS₁₂₀: $p = 0.001$, PRS: $p < 0.001$, PRS₁₂₀: $p < 0.001$) and in PRS ($p = 0.008$) and PRS₁₂₀ ($p = 0.037$) compared to PWS₁₂₀ but there was no difference between PRS and PRS₁₂₀. There was also no effect of DT condition or interaction effects for XSampEn.

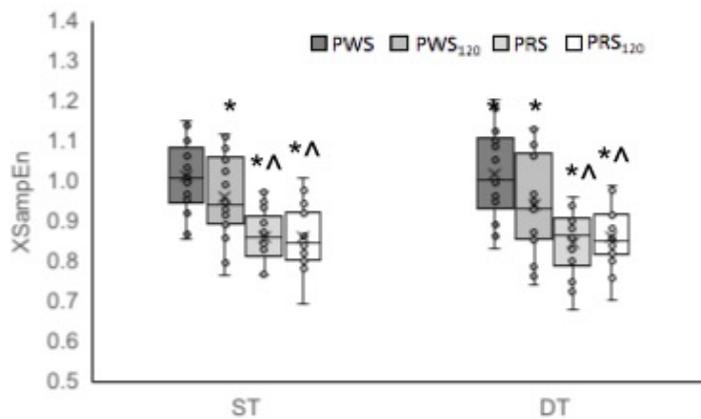


Figure 4. Box plot for the cross sample entropy (XSampEn) of centre of mass motion and muscle synergies) in single task (ST) and dual task (DT) conditions for all speeds. The mean of each variable for each speed x dual task condition combination is represented by an X.

* significantly lower than PWS, ^ indicates significantly lower than PWS₁₂₀

Discussion

The purpose of this study was to determine the effects of speed and cognitive dual tasking on the dynamic stability and complexity of muscle synergies and COM motion during walking and running. It was found that synergies became less complex and stable at faster locomotion speeds compared to PWS. The stability of COM motion also decreased, however, the complexity of COM motion was greater in running than walking conditions. Dual tasking reduced the stability of COM motion but with a concurrent increase in stability of muscle synergies.

The increase in complexity and decreased local stability of COM motion with increasing locomotion speed are in agreement with previous findings indicating that the added

neuromotor challenge of faster speeds leads to less stable more complex gait (England and Granata, 2007; Mehdizadeh et al., 2014; Acasio et al., 2018; Walsh and Taylor, 2019). In addition, the decrease in local dynamic stability (i.e. increased MLE_{SYN}) with increasing locomotion speed, from PWS to PWS_{120} and in running compared to walking, for MLE_{SYN} reported in this study are in agreement with previous findings (Kibushi et al., 2018), despite the large degree of inter-subject variability demonstrated in the present study. However, in opposition to the present and previous findings it has also been reported that synergy stability increased in running compared to walking (Santuz et al., 2020). Furthermore, the present study found no effect on FWHM which has previously been demonstrated to increase with increasing speed and task difficulty (Santuz et al., 2020). These discrepancies could be the result of experimental differences, for example in this study self-selected speeds were used as the baseline speeds, whereas, Santuz et al., (2020) utilised fixed speeds for all participants. These studies also utilised different muscles in the calculation of synergies with the current study including trunk muscles in addition to leg muscles and fewer leg muscles than previously reported (Santuz et al., 2020).

The present study also found that synergy complexity was greater in PWS than all faster speeds, in agreement with previous findings (Santuz et al., 2020). It has been suggested that the requirements for greater force production in faster locomotion speeds may result in more unstable synergy activations (Kibushi et al., 2018) and that lower synergy complexity may be associated with the response of a robust motor control system during gait in more challenging tasks, e.g. walking vs. running (Santuz et al., 2020). Therefore, the changes in COM complexity and stability as a result of speed are likely a reflection of changes in the dynamics of synergy activation in response to greater neuromotor challenge. This notion is supported by the finding that the coupling between COM motion and muscle synergies was increased with increasing locomotion speed. A possible interpretation for this finding is that the greater coupling is representative of increased supra-spinal activity (Harada et al., 2009) and sensory feedback (Yokoyama et al., 2017) required at higher locomotion speeds.

The findings of the present study also provide some support for the notion of cognitive motor interference on walking and running, with increases in VT HFD_{COM} and MLE_{COM} during DT compared to ST, indicating greater complexity and lower stability in DT. These findings

are in agreement with previous studies reporting decreased stability in cognitive and motor dual tasks (Magnani et al., 2017) and those reporting changes in spatio-temporal variables such as decreased gait speed (Patel et al., 2014) and step length (Caramia et al., 2017), increased step width and step width variability (Magnani et al., 2017) in young healthy adults. The increased complexity and decreased stability reported for VT suggest that active control or constraint of COM motion was reduced in this direction (Dingwell and Marin, 2006; Acasio et al., 2018; Walsh and Taylor, 2019) resulting in greater instability. However, the lack of effect of DT in the AP and ML directions suggests these directions were more tightly controlled, or less effected, under DT conditions. This may be because a loss of local dynamic stability in these directions is arguably a greater risk for a loss of global stability than the VT direction. It should also be noted that these variables demonstrated smaller effect sizes for DT than for speed effects and demonstrated relatively large inter-subject variability in AP and ML HFD_{COM} of walking trials and MLE_{COM} of running trials, providing an alternative explanation for these findings.

The current study extends our understanding of the effect of cognitive motor interference by demonstrating an increase in the stability of muscle synergies in DT. The locomotor muscle synergies are encoded in the spinal interneuron circuits, however, the activity of these circuits is modulated by supraspinal commands (Cheung et al., 2009; Bizzi and Cheung, 2013). It is therefore reasonable to interpret the changes in MLE_{SYN} to be a result of changes in the descending supraspinal commands. It has been proposed that gait is controlled by two cortical networks; a direct pathway incorporating the primary motor cortex, cerebellum and spinal cord, responsible for automatic gait control, and an indirect pathway additionally incorporating the prefrontal cortex and premotor area, responsible for additional executive control processes (la Fougère et al., 2010; Zwergal et al., 2012; Hamacher et al., 2015; Al-Yahya et al., 2019). Since DT increases prefrontal cortex activation (Hamacher et al., 2015; Al-Yahya et al., 2019) the increased stability of muscle synergies may be a CNS compensation to minimise the impact of cognitive interference on movement stability. This finding may explain why no effect of DT was found on the HFD_{COM} or MLE_{COM} in the AP and ML directions, as the CNS prioritised the stability of gait in these directions. Interestingly, contrary to the hypothesised decrease in COM motion-synergy coupling, dual tasking had no effect on the coupling. This may further explain why no change was found in

the HFD_{COM} or MLE_{COM} in the AP and ML directions. It is also possible that the selected DT was not sufficiently challenging for the population of young, healthy adults used in this study and the redistribution of cognitive resources had no effect on the COM motion-muscle synergy coupling.

There are limitations of the present study that should be considered. Firstly, only healthy, young adults were included in the study. It is therefore likely that the CNS of these participants were capable of accommodating the combined challenge of increasing locomotion speed and DT without a large decrement to movement stability, interpretation of the results of this study should therefore be limited to healthy individuals. Future research should examine the changes in neuromotor control stability in participants with lower neuromuscular capacity such as frail older adults, or individuals with neurological disorders. Secondly, the present study utilised a cognitive DT to induce the desired demand on the CNS, however, it may be considered that a task requiring both cognitive and motor resources would have greater impact on neuromotor command stability. However, the solely cognitive task was selected for this study to avoid significant cross-talk between motor tasks in the motor cortices to allow the study of increased cognitive demand on gait. It is also important to consider that the rate at which participants completed the cognitive dual task, i.e. backwards counting, was not controlled. It is therefore feasible that as task complexity increased with increasing speed, participants simplified the cognitive task by slowing down the rate of backwards counting. This may explain the small dual task effects reported. Finally, the inclusion of additional muscles responsible for locomotion would allow further insight into the locomotor muscle synergies of interest. Unlike many studies investigating muscle synergies of gait, the present study included activity of the ES and RA due to the role these muscles play in controlling the position and stability of the COM. Qualitatively, these muscles contribute to a number of synergies (e.g. Figure 1) indicating the relevance of their inclusion when studying the role of neuromotor stability in movement stability during gait.

In conclusion, this study confirmed previous studies findings that increasing locomotion speed increases gait complexity and reduces dynamic stability. However, the findings of this study extend our understanding of changes in gait stability by demonstrating that the

stability and complexity of muscle synergies decreased with increasing speed suggesting changes in neuromotor dynamics contribute to changes in local stability of COM motion. It was also demonstrated that the coupling between COM motion and muscle synergies increased with increasing speed. Furthermore, this study demonstrated reduced stability and increased complexity of VT COM motion in DT than ST conditions and provided a novel insight into the neural control of gait during cognitive motor interference by demonstrating that DT conditions increase the stability of muscle synergies, possibly as a compensatory mechanism to preserve the local stability of AP and ML motion.

Declarations of Interest: None

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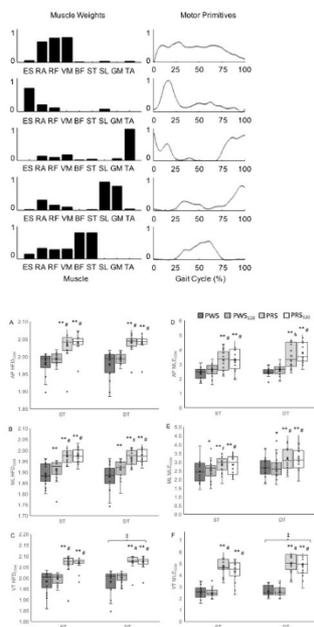
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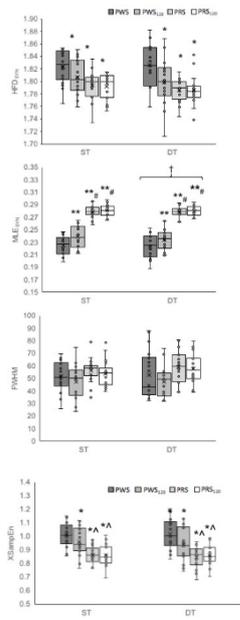
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Highlights

- Muscle synergy stability was greater in dual task conditions than single task.
- Increasing locomotion speed decreased muscle synergy stability and complexity.
- Centre of mass motion became less stable and more complex with increasing speed.
- Vertical centre of mass motion was more complex and less stable in dual tasking.
- Neuromotor (synergy) stability likely moderates changes in gait local stability.