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Use of Self-Organizing Maps to Study Sex- and Speed-Dependent Changes in Running Biomechanics

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Abstract

Background

Up to 79% of runners get injured every year, with higher rates of injuries occurring in females than males. A self-organizing map (SOM) is a type of artificial neural network that can be used to inspect large datasets and study coordination patterns. The purpose of this study was to use an SOM to study the effects of sex and speed on biomechanical coordination patterns.

Method

Thirty-two healthy runners ran on an instrumented treadmill at their long slow distance speed (LSD) and at speed 30% faster (LSD + 30%). Vertical ground reaction force (vGRF), vertical tibial acceleration, step parameters, electromyograms (EMG) of six lower limb muscles, and joint angles were collected across speeds. Rate of loading (ROL), tibial impact shock (TIS), coupling angle variability (CAV) and movement pattern proportions for hip/knee sagittal and hip frontal / knee sagittal plane couplings, peak EMG, step length, step rate, and knee and ankle joint angle at initial contact were used as an input for the SOM (37 variables).

Results

The analysis identified four clusters (i.e., running patterns). While males and females showed similar distribution across clusters at LSD ($p = .36$) and at LSD + 30% ($p = .51$), females did exhibit a significant ($p = .03$) shift between clusters as the speed increased from LSD to LSD + 30% whereas males did not ($p = .17$). The shift was associated with an increase in TIS, ROL, step length, step rate, vastus lateralis EMG, hip flexion/knee extension movement pattern proportion, and a decrease in ST EMG and CAV$_{\mathrm{IC}}$ for hip sagittal/knee sagittal coupling.

Conclusion

As running speed increased there was a significant change in the coordination pattern in females, which was characterized by increases in several variables that are purported risk factors for running related injuries.

Keywords

Machine learning, Artificial neural network, Coordination, Injury, Sex differences

1. Introduction

Running is a common activity that is associated with most sports. There are about 52.3 million Americans who run on a regular basis (The Outdoor Foundation, 2017). Approximately 18 million runners participate in road races every year and about 60% of them are females (Running, 2017). Up to 79% of runners get injured every year, and the rate of injury has not changed in the past 30 years (Van Gent et al., 2007). Females may have a higher risk of developing running-related injuries (RRI), such as patellofemoral pain and tibial stress fracture than males (Taunton et al., 2002; Wright, Taylor, Ford, Siska, & Smoliga, 2015). However, there is still a lack of knowledge regarding sex-specific differences in etiology of RRI. Rate of loading (ROL) is considered one of the primary risk factors for RRI (Davis, Bowser, & Mullineaux, 2016; Zadpoor & Nikooyan, 2011). Healthy runners with high ROL had a higher risk of developing RRI compared to runners who had never been injured (Davis et al., 2016). Furthermore, a meta-analysis suggested that ROL is higher in groups who developed tibial stress fracture compared to control groups (Zadpoor & Nikooyan, 2011). In addition, tibial impact shock (TIS) also appears to be highly associated with tibial stress fracture, and may also contribute to the development of RRI (Davis, Bowser, & Mullineaux, 2010; Milner, Ferber, Pollard, Hamill, & Davis, 2006). Although previous research has not found significant sex effects for ROL or TIS, these studies all used fixed absolute speeds, which may not represent the loading environment that runners actually experience as they run most of their mileage. (Keller et al., 1996; Sinclair, Greenhalgh, Edmundson, Brooks, & Hobbs, 2012). Therefore, not much is known about sex differences at long slow distance speeds (LSD; i.e. the speed where they run most of their mileage).

Previous research that investigated lower extremity muscle activation patterns during running found no significant differences in peak EMG of the tibialis anterior or medial gastrocnemius muscles between males and females (Mero & Komi, 1987). However, during running, landing and cutting maneuvers females demonstrate lower hamstring/quadriceps muscle activation ratios than males (Malinzak, Colby, Kirkendall, Yu, & Garrett, 2001). Females typically exhibit higher quadriceps activation than males (i.e. quadriceps dominance), whereas males demonstrate higher hamstring activation compared to females (i.e. hamstring dominance). On the other hand, Chumanov and colleagues suggested that males and females demonstrated similar gluteus medius muscle activation (Chumanov, Wall-Scheffler, & Heiderscheit, 2008). However, they found that only females demonstrate greater increases in gluteus medius and vastus lateralis muscles EMG as running speed increases, which suggest an interaction effect between sex and running speed. The same authors further suggested that this increase in EMG of gluteus medius muscle may be due to the greater frontal plane motion in females during running (Chumanov et al., 2008). Again, however, these differences occurred at fixed absolute speed which may not represent the runner EMG profile as they ran most of their mileage. Therefore, there is a lack in understanding of the effect of sex and speed, and their interaction effect, on muscle activation patterns of lower extremity muscles.

Movement variability has been associated with knee pain and the risk of RRI (Hamill, van Emmerik, Heiderscheit, & Li, 1999). For example, less movement variability between the hip and knee coupling in the sagittal plane is also associated with higher impact forces during running (Wang, Gu, Wang, Siao, & Chen, 2018). Previous research on the link between movement variability and risk of musculoskeletal injury further suggests that greater task demands reduce movement variability at hip and knee joints during drop landing (Nordin and Dufek, 2016, Nordin and Dufek, 2017). These studies manipulated the landing height and load to increase the difficulty of the task and found that increasing drop height and external load may decrease movement variability, which suggests that the greater task demand may constrain lower extremities movement variability and lead to repetitive load on musculoskeletal structures. There is limited evidence, however, about the effect of task demand and movement variability during running. One recent study, which used continuous relative phase variability, suggested that movement variability in the coupling between the hip and knee in the sagittal plane decreased as running speed increased (i.e. increased task demands) (Bailey, Silvernail, Dufek, Navalta, & Mercer, 2018). However, the effect of speed on movement patterns in sagittal plane and movement variability at other planes were not investigated yet. Also, the relationship of task demand and movement variability in relation to primary risk factors for RRI (i.e., impact kinetics) is not well understood. Vector coding (VC) is a measure that uses angle-angle plot to quantify the coupling angles and movement variability between two joints or segments (Heiderscheit, Hamill, & van Emmerik, 2002; Sparrow, Donovan, Van Emmerik, & Barry, 1987). In addition, VC allows for the quantification of movement patterns based on the motion direction of two joints, which may be useful to investigate whether the dominancy of a certain movement pattern is associated with RRI risk factors such as ROL and TIS (Chang, Van Emmerik, & Hamill, 2008).

Given the large number of variables that are typically studied in biomechanics research, researchers have begun to use unsupervised learning techniques from machine learning to investigate and characterize a person's movement and coordination pattern. A self-organizing map (SOM) is a type of artificial neural network that can be used to investigate the non-linear nature of large dataset (Kohonen, 2001). SOMs can also be used to cluster and visualize large dataset and to categorize coordination patterns. SOMs have been used in many gait analysis, movement variability, and in investigating changes in coordination patterns (Bartlett, Lamb, O'Donovan, & Kennedy, 2014; Lamb, Mündermann, Bartlett, & Robins, 2011; Serrien et al., 2017). Using an SOM may be beneficial in categorizing and understanding coordination patterns during running. Given that there is a global lack of understanding about the influence of sex and running speed on impact forces, muscle activation, movement variability, and movement patterns, the purpose of this study was to use the SOM to investigate the effect of sex and speed on biomechanical coordination patterns during running. We hypothesized that as running speed increases (i.e. task demands), movement variability would decrease and impact kinetic would increase.

2. Methods

2.1. Participants

Thirty-two healthy runners participated in this study (Table 1). Participants were excluded if they had a history of lower limb surgery or musculoskeletal / neuromuscular injury that prevented them from running for three consecutive training days in the past 6 months. In addition, all runners had to run at least 10 miles per week and report no pain while running. Inclusion and exclusion criteria were self-reported by the subjects. Participants signed an informed consent document approved by local's university's review board before data collection.

Table 1. Demographic data (mean ± SD) for male and female participants.

	Males	**Females**
Age (years)	22 ± 3	22 ± 2
Weekly Mileage (miles)	33 ± 15	31 ± 16
Weight (kg)	69 ± 9	59 ± 7
Height (m)	1.76 ± 0.07	1.65 ± 0.05
LSD Speed (m/s)	3.19 ± 0.43	2.93 ± 0.42
ROL (N*kg^{-1})	213 ± 38	207 ± 43
TIS (g)	4.9 ± 1.2	5.1 ± 1.7

2.2. Data collection

Lower extremity kinematics were collected with a 14-camera motion analysis system (Vicon motion system Ltd) via twenty-three reflective markers. Markers were attached with a double sided adhesive tape (Tape2, Biopac Systems, Inc., Goleta, CA) to C7, sternum, T10, bilaterally to iliac crest, ASIS, PSIS, greater trochanters, lateral and medial epicondyles of the knee, lateral and medial malleoli of the ankle, 1st and 5th metatarsal of the foot (Geiser, O'connor, & Earl, 2010). Additionally, four rigid plates with four markers each were taped to the thigh and shank with elastic tape. Two rigid plates with three markers each were attached to the posterior side of the shoes with adhesive tape. A tri-axial accelerometer (Delsys, Natick, MA) was attached to the anteriomedial aspect of distal tibia and secured with athletic tape to reduce movement. Electromyography (EMG) sensors (Delsys, Natick, MA) were placed over the muscle belly of the gluteus medius (GM), vastus lateralis (VL), biceps femoris (BF), semitendinosus (ST), medial gastrocnemius (MG), and tibialis anterior (TA). All EMG sensors were attached to the skin parallel to the muscle fibers according to the SENIAM recommendations. The skin was shaved and cleaned with isopropyl wipes prior to the attachment of all EMG sensors.

Participants performed an 11-min running protocol on an instrumented treadmill (SciFit, Noraxon, Scottsdale, AZ). All participants started with a five-minute warm-up at their own speed. They were first asked to be at their long slow distance speed (LSD) at the end of warm-up. After two minutes of running at the LSD speed, the speed increased by 15% (LSD + 15%) for two minutes and again by an additional 15% (LSD + 30%) for another two minutes. Thirty seconds of data were collected after one minute of running at each speed. Vertical ground reaction forces (vGRF) were collected by an instrumented treadmill. Kinematic and kinetic data were collected at 100 Hz. Acceleration and EMG data were collected at 148 and 1000 Hz, respectively. Kinematic, kinetic, acceleration and EMG data were synchronously collected by Vicon Nexus 1.8.2. Kinetic data were exported from Noraxon (Noraxon, Scottsdale, AZ).

2.3. Data processing

A custom MATLAB (The Mathworks, Natick, MA, USA) program was used to filter and process kinematic and kinetic data. A fourth-order low-pass Butterworth filter was used to filter kinematic data at a cut frequency of 8 Hz. Visual3D (C-Motion, Inc., Rockville, MD) was used to process markers position data. Mid-point between medial and lateral joint markers was used to locate the knee and ankle joint center. The hip joint center was defined as 25% of the distance between both greater trochanters in the medial direction from the closest greater trochanter marker. We used joint-based coordinate system approach to calculate hip, knee and ankle joint angles (Geiser et al., 2010; Grood & Suntay, 1983). Knee and ankle joints angle and foot segment angle at initial contact was also calculated. Initial contact was defined as the point when vGRF >10 N and toe off when vGRF <10 N.

Fourth-order low-pass Butterworth filters with cut-off frequencies of 60 and 13 Hz were used to filter acceleration and kinetic data, respectively. TIS was calculated as the peak vertical tibial acceleration during the stance phase. ROL was calculated as peak derivative of the vGRF. Raw EMG signals were detrended, rectified, and filtered with a bandpass filter of 40–400 Hz. The EMG signals were normalized to the peak of muscles activity during treadmill walking at 1.16 m/s. The peak amplitude of GM, BF, ST, VL, TA, MG muscles of ten strides were extracted for analysis.

The coupling angles (CA) were calculated for the hip sagittal / knee sagittal (HSKS) and hip frontal / knee sagittal (HFKS) (Fig. 1; Eq. 1) (Hamill, Haddad, & McDermott, 2000; Sparrow et al., 1987).Y_i and x_i represent the distal and proximal joints, respectively. Where t indicates the point of time during the stride cycle or the stance cycle, and *i* = 1…, n for number of trials. CA were corrected to obtain a value between 0°-360° (Eq2). Because of the directional nature of the CA, circular statistics were used to calculate the mean CA on the horizontal axisx¯i and vertical axis ($\bar{y}i$ (Eq3 and 4) (Batschelet, 1981). The length of CA was calculated according to Eq. 5, and coupling angle variability (CAV) was calculated according to Eq. 6.

(1)

$$CA_{i,t} = tan^{-1}\left(\frac{y_{i,t+1} - y_{i,t}}{x_{i,t+1} - x_{i,t}}\right)\frac{180}{\pi}$$

(2)

$$CA = \begin{cases} \mathrm{CA} + 360\mathrm{CA} < 0 \\ \mathrm{CACA} \geq 0 \end{cases}$$

(3)

$$\bar{x}_{i,t} = \frac{1}{n}\sum_{t=1}^{n} \cos CA$$

(4)

$$\bar{y}_{i,t} = \frac{1}{n}\sum_{t=1}^{n} \sin CA$$

(5)

$$\bar{r}_{i,t} = \sqrt{\bar{x}_{i,t}^{2} + \bar{y}_{i,t}^{2}}$$

(6)

$$CAV_i = \sqrt{2.(1-\bar{r}_i)}\frac{180}{\pi}$$

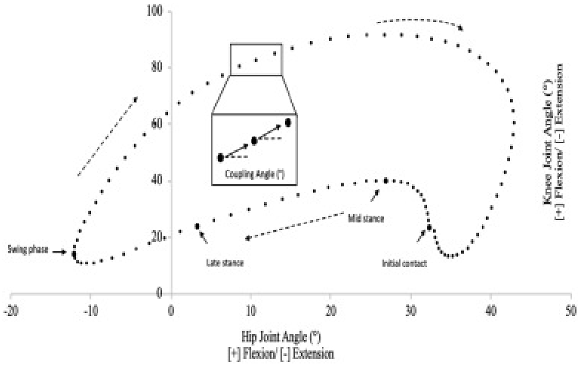

Fig. 1. Angle–angle plot of the hip and knee joints in the sagittal plane, the arrows indicate the direction from the beginning of the gait cycle to the end.

CAV was calculated over the full stride cycle (CAV_{SC}), initial contact (CAV_{IC}), mid-stance (CAV_{MS}), and late stance (CAV_{LS}) for each of the two couplings. Movement patterns were classified into one of eight distinct patterns based on the CA values (Fig. 2) (Chang et al., 2008).

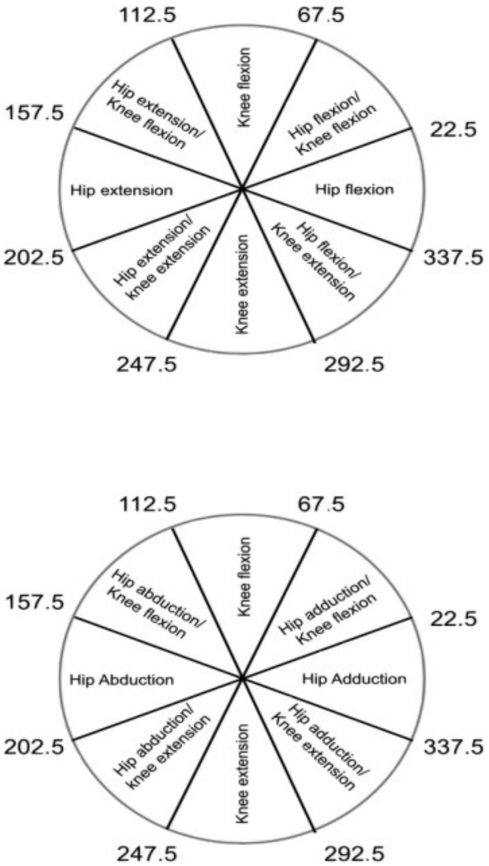

Fig. 2. Classification of movement pattern proportions for hip sagittal /knee sagittal coupling (top row) and hip frontal/knee sagittal coupling (bottom row).

Processed kinematic, kinetic, EMG, and CAV data were extracted from the first ten strides during the 30 s interval when data were collected at each running speed. The average of ten strides of each variables (i.e. discrete variables) was then calculated for LSD and LSD + 30%.

2.4. Self-organizing map

While SOM input variables may include time-series data (Bartlett et al., 2014; Lamb et al., 2011; Lamb, Bartlett, Robins, & Kennedy, 2008), the current study used discrete variables as inputs for the SOM (Hébert-Losier, Lamb, & Beaven, 2020; Serrien et al., 2017). Variables for two different speeds (i.e. LSD and LSD + 30%) from 32 participants were used. Therefore a 64*37 dataset was used as input to the SOM ([2 speeds × 32 runners] * 37 variables). The rows of this input matrix represent subject data for the two different speeds. The columns of this input matrix represent all kinematic and kinetic variables (i.e., ROL, TIS, CAV variables [CAV_{IC}, CAV_{MS}, CAV_{LS}, CAV_{SC}], eight movement patterns for each coupling, EMG peak amplitudes of GM, BF, ST, VL, TA, MG, step length, step rate, foot segment and knee joint angles at initial contact). All input variables were normalized (i.e., linearly scaled) to range between zero and one, before used as input to the SOM.

The SOM consists *m* x *n* grid of output nodes, which are connected to each input vector. Each output node has the same dimensionality as the input vectors (i.e., 1*37) but is initialized with random data. The input data are mapped onto the SOM based on the Euclidian distance between the input vector and the best matching output node. Similar input vectors are then grouped together based on a neighborhood function. The weight planes of the SOM were used to visualize the non-linear relationship between the biomechanical variables via the color gradients of the z-score color scale, and the hit histograms were used to map all trials onto the SOM. Lastly, a k-means algorithm was used to create clusters of similar groups of input vectors (i.e., individual trials) on the SOM. The SOM tool box was used to initialize and train the SOM map with MATLAB R2017b (Vesanto, Himberg, Alhoniemi, & Parhankangas, 2000). The SOM training parameters are shown in Table 2.

Table 2. SOM training parameters.

SOM parameter option	**Selected SOM parameter**
Normalization	Range (0,1)
Initialization	Linear (PCA)
Lattice	Hexagonal
Neighborhood function	Gaussian
Training algorithm	Batch
Map size	7×6
Quantization error	0.974
Topological error	0.001
Combined error	1.271

2.5. Statistical analysis of SOM

The Davis-Bouldin index was calculated to ascertain the appropriate number of clusters by calculating the lowest ratio of the average within cluster to the average between clusters (Davies & Bouldin, 1979). Individual trials were mapped onto the SOM, assigned to clusters, and used to construct contingency tables for all trials from males and females at each speed (Table 3). The contingency table can illustrate if an individual shifts between clusters and condition, because each cell shows the number of participants at each cluster for LSD and LSD + 30%. The Stuart-Maxwell Test, a non-parametric marginal homogeneity test for nominal data, was used to quantity the shift trials from males and females across clusters as running speed increased. In addition, Fisher's Exact Test was used to quantify differences in the number of trials of males and females across clusters.

Table 3. Contingency tables for males (left) and females (right) counts.

Males		**LSD + 30%**					**Females**		**LSD + 30%**				
		1	**2**	**3**	**4**	**Total**			**1**	**2**	**3**	**4**	**Total**
LSD	1	2	1	2	0	5	LSD	1	2	0	1	0	3
	2	1	1	0	3	5		2	2	1	3	3	9
	3	0	0	1	0	1		3	0	0	3	0	3
	4	0	0	0	4	4		4	0	0	0	2	2
	Total	3	2	3	7			Total	4	1	7	5	

3. Results

The Davis-Bouldin index showed a best-fit four-cluster solution for the SOM (Fig. 3). The Stuart-Maxwell Test indicated a significant difference in trial distributions between cluster for females (*p* = .03) but not for males (*p* = .17) as the speed increased from LSD to LSD + 30% (Table 3). Closer inspection of the contingency table showed that a large portion of trials from females shifted from clusters 1 and 2 to cluster 3 and 4 as the speed increased from LSD to LSD + 30%. Fisher's Exact Test indicated no significant differences in the distribution of trials across clusters for males and females at LSD (*p* = .36) and at LSD + 30% (*p* = .51) (Fig. 4, Table 4). The color gradients of the weight planes and normalized scores of each variable illustrate the biomechanical characteristics of the four clusters on the SOM (Fig. 5).

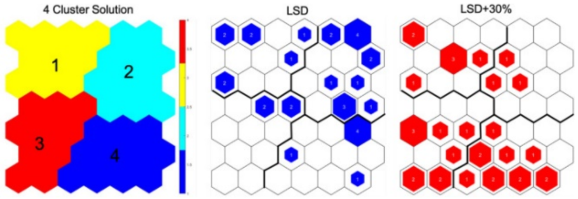

Fig. 3. SOM with the four-cluster solution (yellow = cluster 1 (top left), cyan = cluster 2 (top right), red = cluster 3 (bottom left), blue = cluster 4 (bottom right)) (left column). Hit histograms for long slow distance speed (LSD) (middle column) and LSD + 30% (right column). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

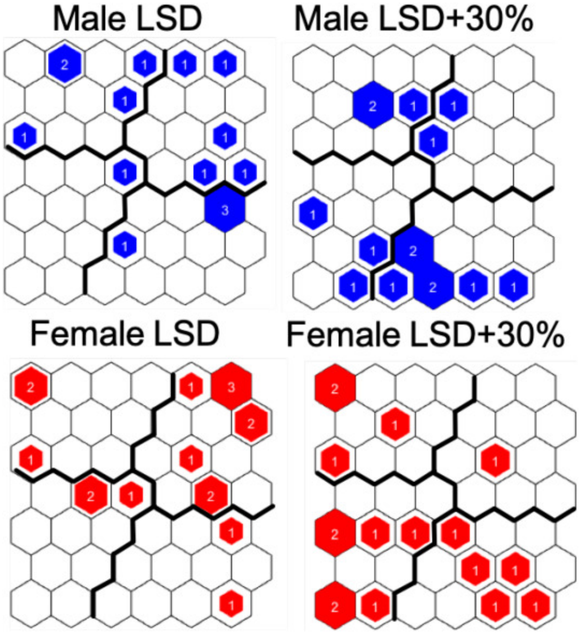

Fig. 4. Hit histograms for males (top row) and females (bottom row) at long slow distance speed (LSD) (left column) and LSD + 30% speed (right column).

Table 4. Data for Fisher's exact test for LSD and LSD + 30% speeds.

	Cluster				
Speed	**1**	**2**	**3**	**4**	**Total**
LSD					
Males	5	5	1	4	15
Females	3	9	3	2	17
Total	8	14	4	6	32
LSD + 30%					
Males	3	2	3	7	15
Females	4	1	7	5	17
Total	7	3	10	12	32

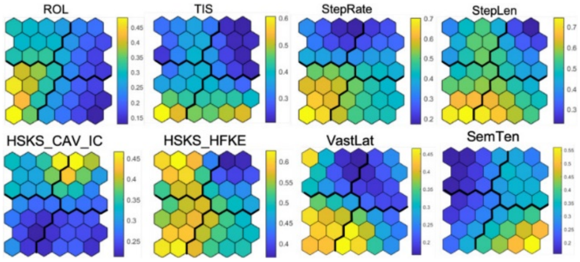

Fig. 5. Weight planes for SOM input variables. NOTE: colorbar reflects z-score for each input variable. ROL = Rate of loading, TIS = tibial impact shock, StepRate = step rate, StepLen = step length, HSKS_CAV_IC = hip sagittal/knee sagittal coupling angle variability for initial contact, HSKS = hip sagittal/knee sagittal, HFKE = hip flexion/knee extension pattern, VastLat = vastus lateralis, and SemTen = semitendinosus.

4. Discussion

The purpose of this study was to use SOM to investigate the effect of sex and speed on biomechanical coordination patterns. The k-means clustering results suggested that there were four types of coordination patterns (i.e., clusters). While the Fisher's Exact Test showed that both males and females displayed similar types of coordination patterns across speeds, the Stuart-Maxwell test indicated that females demonstrated a significant shift in coordination patterns as the speed increased from LSD to LSD + 30%. Our hypothesis, that there would be a significant change in coordination patterns as speed increased was therefore supported for female runners but not for male runners. However, there was no significant difference in coordination patterns between males and females. In addition, our hypothesis that there would be a speed-dependent reduction in movement variability, which would be associated with increases in impact kinetic, was supported for both joint couplings.

The main finding from this study was that females changed their coordination patterns as the running speed increased. During running at LSD speeds, the hit histograms showed that most trials mapped into cluster 1 and 2 (Fig. 3). However, as the speed increased to LSD + 30% the hit histograms and distributions in the contingency table showed a shifting of trials into cluster 3 and 4 (Fig. 3, Table 3). For example, at LSD speeds a total of nine female runners clustered into cluster 2, as the speed increased six subjects shifted into cluster 3 and 4, two subjects shifted into cluster 1 and only one subject remained in cluster 2. Although the speed-dependent shift between clusters was significant for females only, Fisher's Exact Test and visual inspection of the hit histograms showed that there were no clear differences in number of trials in any clusters between males and females (Fig. 4, Table 4), which may suggest that differences in coordination patterns between males and females are not well defined at either of the running speeds in this study.

The weight planes show how the z-score values of each variable mapped onto the SOM, and thus also show the relationship between variables across the four types of coordination patterns (Fig. 5). The weight plane figures help qualitatively identify the characteristic of each coordination patterns, because the separation of clusters is based on the similarity of variables within clusters and the difference of variables between clusters. For example, step rate may have a strong influence on separating cluster 3 from the other three clusters, because it has high to moderate (between ~0.5 and 1) scores values in cluster 3, whereas in other clusters the scores are moderate to low (between ~0 and ~ 0.5). Similarly, ROL may also influence the separation of cluster 3 because the weight planes show high to moderate (between ~0.3 and 1) scores values in cluster 3 but very low to moderate (between ~0 and ~ 0.3) scores in the other clusters.

Consideration of multiple variables across clusters in light of the speed-dependent changes in nominal frequency distribution provides insight into subsequent changes in coordination patterns from a multi-variate perspective. Clusters 1 and 2 were characterized by low to moderate values of step rate, ROL, TIS, and moderate to high HSKS_CAV_IC. However, cluster 1 was also characterized by low to high value of VL EMG, and moderate to high HSKS_HFKE. On the other hand, cluster 2 was characterized by low VL EMG. Visual inspection of the hit histograms for LSD and LSD + 30% supports the statistical findings and showed that there was a speed-dependent shift of trials for the majority of females into cluster 3, which was characterized by high ROL, TIS, VL EMG, step length and step rate (Fig. 5). In addition, the ST EMG and the CAV_{IC} for the hip sagittal / knee sagittal coupling in cluster 3 were relatively low, whereas movement patterns proportion of hip flexion/knee extension were high (Fig. 5). Moreover, some female runners shifted toward cluster 4, which was characterized by low ROL, moderate to low TIS, high to low VL EMG, and high to moderate ST EMG.

The biomechanical characteristics captured by cluster 3 may indicate that as speed increased, the majority of females shifted toward a coordination pattern that was characterized by higher impact kinetics, higher VL EMG, longer steps, greater step rate, greater hip flexion/knee extension proportion and lower movement variability. The speed effect on ROL and TIS in this study is consistent with previous research where ROL and TIS increased as the running speed increased (Keller et al., 1996; Sheerin, Besier, & Reid, 2018). It is likely that the speed-dependent changes in females toward higher ROL and TIS were the result of increases in step length, as suggested by previous research (Derrick, Hamill, & Caldwell, 1998; Stergiou, Bates, & Kurz, 2003). The current findings further suggest that the speed-related increase in step length may be associated with an increase in the proportion of hip flexion/knee extension movement pattern. In addition, this speed-dependent increase in ROL can be explained by the increase activation of the VL muscle activation and a decrease in ST muscle activation in cluster 3. This result is in agreement with previous research that found quadriceps dominant neuromuscular activation was associated with stiffer landings and greater impact forces. (Williams III, Davis, Scholz, Hamill, & Buchanan, 2004).

The reduction in movement variability as speed increased may occur as a result of the increase in task demands (i.e. increasing running speed). In general, as task difficulty increases, degrees of freedom decrease to simplify the task and produce controllable movement pattern. The speed-dependent reduction in movement variability is consistent with Bailey and colleagues' study in which they suggested that the variability of the continuous relative phase of the hip sagittal / knee sagittal coupling decreased as speed increased (Bailey et al., 2018). In addition, the reduction of movement variability with increases in task demand were also found in other tasks, such as drop landings (Nordin and Dufek, 2016, Nordin and Dufek, 2017). For example, one study found that the coefficient of variance of peak hip and knee sagittal plane angles during drop landing decreased as the height of drop landings increased (Nordin & Dufek, 2017). In addition, another study found that movement variability reduced as drop height and external load increased (Nordin & Dufek, 2016). The results of the current study are contrary to the results reported by (Floría, Sánchez-Sixto, Harrison, & Ferber, 2019) who reported that vector coding variability of the hip sagittal/knee sagittal plane coupling does not change as the running speed increases. This discrepancy could be explained by the percentage of the speed increase, (Floría et al., 2019) used 15% increase, in contrast to the 30% increase in the current study. Therefore, the change in movement variability may depend on the magnitude of the increase in the running speed. Given that low movement variability is associated with RRI (Hamill et al., 1999; Heiderscheit et al., 2002; Miller, Meardon, Derrick, & Gillette, 2008), consistently training at high running speed may increase that risk.

Results from the current study further suggest that the reduction in movement variability was associated with an increase in step rate. This result is in agreement with previous that found movement variability of hip sagittal / knee sagittal coupling decreased as step rate increased (Hafer, Freedman Silvernail, Hillstrom, & Boyer, 2016). These results provide interesting context for gait retraining studies that use step rate modulation to reduce impact kinetics, because these results suggest an increase in running speed and step rate reduce the flexibility of motor system and its ability to attenuate impact kinetic as observed from the speed-dependent increases in ROL and TIS. Previous research has also found a negative correlation between the movement variability of sagittal plane coupling and the first (i.e. impact) peak of the GRF (Wang et al., 2018). Combined with previous findings the results of the current study thus provide support for a link between movement variability and impact kinetics, and indicates that an optimal amount of variability is necessary to reduce the cumulative loading of tissue via mitigating the magnitudes of well-established kinetic risk factors of RRI.

One of the limitations in this study is that the order of the running speed was not randomized. This was a limitation that was necessary to implement since it would be difficult, and potentially unsafe, to achieve high running speed without first running at lower speeds. Although the current and previous research suggests that low movement variability may lead to RRI (Hamill, Haddad, Milner, & Davis, 2005; Miller et al., 2008), prospective studies are needed to investigate definitive cause and effect relationships between movement variability and overuse injuries. Further, while the results from the current study suggest that there was a significant shift toward lower movement variability as running speed increased, the likelihood of runners eliminating faster runs from their training is low and may not represent a feasible solution for decreasing the incidence of RRI. Future research should therefore focus on identifying interventions that mitigate the relevant at-risk biomechanical characteristics while running at faster than preferred speeds. Moreover, the results of the current study are based on data from healthy runners. Therefore, the results of this study may not represent the changes in coordination patterns for individuals with RRI. Further studies should include runners with RRI and investigate the effects of sex and speed on movement variability and risk factors for RRI in those populations.

5. Conclusion

The main finding of this study was that females exhibited a significant change in coordination pattern as they increased their running speeds from LSD to LSD + 30%. The coordination pattern at the faster speed was characterized by greater ROL, TIS, step rate, longer step length, and less movement variability, which collectively suggest that females may be exposed to greater risk of developing RRI if running at faster than preferred speeds. Given that eliminating speed training is likely not a feasible solution to decreasing the incidence of RRI, future research should focus on identifying interventions that mitigate the relevant at-risk biomechanical characteristics at faster than preferred speeds.

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