Chapter 4: ***Relationship between multiscale entropy measures, accelerometry, and peak height velocity in adolescent soccer players***

Introduction

Puberty is a critical period of development characterized by rapid changes in body composition, physical attributes, and hormonal levels. These changes can significantly influence competitive performance and injury risk in adolescent athletes. In sports such as soccer, puberty-related changes can affect the biomechanics of movement, potentially leading to an increased risk of injuries (Bergeron et al., 2015; Ford, Shapiro, Myer, Van Den Bogert, & Hewett, 2010). Overuse injuries are particularly common in children and adolescents who participate in sports. These injuries occur because of repetitive submaximal loading of the musculoskeletal system, which can lead to microtrauma and eventual tissue damage (Myer et al., 2011; Valovich McLeod et al., 2011). The risk of overuse injuries is further increased during puberty, due to the rapid growth and changes in body composition that occur during this period (Ford et al., 2010; Myer, Sugimoto, Thomas, & Hewett, 2013). Current methods for tracking injury risk factors in adolescent athletes include the use of global positioning system (GPS) distances covered, center of mass (CoM) acceleration peaks, total accelerations and decelerations, etc. (Haddad, Stylianides, Djaoui, Dellal, & Chamari, 2017; Hartwig, Naughton, & Searl, 2011; Jones, Griffiths, & Mellalieu, 2017; Malone et al., 2015; McLaren et al., 2018). However, these methods provide a one-dimensional view of the biomechanical loads experienced by the athletes. Multiscale entropy (MSE) analysis is a powerful tool that allows for the examination of the complexity of biological signals over multiple temporal scales. This method has been used to analyze various biological signals, including heart rate variability and gait dynamics, providing insights into the health and function of the system under study (Bosl, Tierney, Tager-Flusberg, &

Nelson, 2011; Bravi, Longtin, & Seely, 2011; Riva, Toebes, Pijnappels, Stagni, & Van Dieën, 2013). The use of MSE analysis in the context of adolescent athletes is justified by the potential insights it can provide into how puberty-related changes affect movement patterns and injury risk. Specifically, changes in movement complexity, as measured by MSE, could be indicative of altered biomechanics and increased injury risk. Therefore, the purpose of this study is to investigate the impact of puberty on the biomechanics of movement in adolescent soccer players using MSE analysis. We hypothesize that puberty-related changes will result in altered movement complexity, as measured by MSE, and that these changes will be associated with an increased risk of injuries.

Methods

Participants

Participants were recruited via word of mouth, fliers, social media, and emails. If participants were recruited via word of mouth, flyer (Appendix D), or social media, an email containing a pre-approved email script (Appendix C) was sent to the participant's guardian to ensure they were still interested and qualified to participate in the study. 90 healthy adolescent fútbol players either pre-, mid-, or post-peak height velocity (PHV) (30 per group), between 9 and 17 years were asked to participate in the current study. Due to the paucity of literature regarding mixed-model statistical entropy comparisons, we planned for small effect sizes between groups. An a priori power analysis for a mixed model repeated measures ANOVA with an *alpha* of 0.05, a *beta* of 0.80, and effect size (*f*) of 0.20 indicated that a minimum of 66 participants (22 per group) are needed.

Each participant and their guardian provided written informed assent and consent, respectively, as well as completed the Lower Extremity Functional Scale (LEFS)(Binkley, Stratford, Lott, & Riddle, 1999) and a musculoskeletal health history questionnaire. Participants were excluded from testing if they had not been participating in club soccer training or play at least twice per week. Inclusion criteria included the following: no history of lower extremity surgical repair, no lower extremity injuries within the past six months, and no lower extremity pain on the day of testing.

Experimental Procedures

Data collections were preceded by the informed consent and assent process prior to any testing. Participants and their guardian(s) met with the primary investigator to give consent and assent before filling out the LEFS and musculoskeletal questionnaire. Height was measured via stadiometer and all other measurements were performed by the same investigator three times with the median measurement being reported. Once the investigator had obtained all IRB documents and anthropometric measurements, the participant was stratified into their experimental group. Sex-specific equations (Mirwald, Baxter-Jones, Bailey, & Beunen, 2002) utilizing standing height, seated height, leg length, and age were used to estimate the time offset (in years) of each participant from their PHV:

$$\begin{aligned}\text{Male Maturity Offset (years)} &= -9.236 + 0.0002708 \times (\text{Leg Length} \times \text{Sitting Height}) \\ &- 0.001663 \times (\text{Age} \times \text{Leg Length}) + 0.007216 \times (\text{Age} \times \text{Sitting Height}) \\ &+ 0.02292 \times ((\text{Weight}/\text{Height}) \times 100)\end{aligned} \quad \text{Eq. (10)}$$

$$\begin{aligned}\text{Female Maturity Offset (years)} &= -0.376 + 0.0001882 \times (\text{Leg Length} \times \text{Sitting Height}) \\ &+ 0.0022 \times (\text{Age} \times \text{Leg Length}) + 0.005841 \times (\text{Age} \times \text{Sitting Height}) \\ &- 0.002658 \times (\text{Age} \times \text{Weight}) + 0.07693 \times (\text{Weight}/\text{Height} \times 100)\end{aligned} \quad \text{Eq. (11)}$$

All experimental testing (see **Figure 1**) took place on an indoor, synthetic turf soccer field following a brief dynamic warm-up and each drill was completed 3 times. Participants were then fitted with small inertial measurement units (IMUs) on their distal-medial tibia just superior to the medial malleolus and data collection began with an “easy pace” jog lengthwise down the field and back. Following the jog, each subsequent drill was completed 3 times by each participant, beginning with a 40-yard (36.6 meters) dash. Then, participants completed an M-cone drill in which they sprinted and changed direction rapidly around a series of cones in both directions. Then participants completed a 5-10-5 shuffle drill where they began by straddling a central cone and then laterally shuffled between cones placed 5 meters from the middle cone. Finally, participants performed a broad jump for maximum horizontal displacement. Following the triple hop task, each participant had completed testing. The participants were then asked to complete the same experimental protocol following the end of their season (~3 months later, e.g., February through May).

Instrumentation

A fixed stadiometer and measuring tape were used to measure participant standing height and then seated height and leg length, respectively, to the nearest millimeter. An IMU with high-g accelerometer (1600 Hz; Vicon Blue Trident, Vicon Motion Systems Ltd, Oxford, UK) was used to measure 3D linear accelerations at the tibia during testing. These data were then imported into Python v3.10.4 (Python Software Foundation, Beaverton, OR, USA) computing software for subsequent data processing and analysis and R 4.2.1 (R Foundation for Statistical Computing, Vienna, AUST) for visualization. fixed stadiometer and measuring tape will be used to measure participant standing height and then seated height and leg length, respectively, to the nearest millimeter. An IMU with high-g accelerometer (1600 Hz; Vicon Blue Trident, Vicon Motion Systems Ltd, Oxford, UK) will be used to measure 3D linear accelerations at the tibia during testing. These data were then imported into Python v3.10.4 (Python Software Foundation, Beaverton, OR, USA) computing software for subsequent data processing and analysis and R 4.2.1 (R Foundation for Statistical Computing, Vienna, AUST) for visualization.

Data Reduction & Analysis

Raw data were imported from the IMU sensors for entropy analysis. The EntropyHub toolkit (Flood & Grimm, 2021) has functions native to both Python and was used to analyze the acceleration time series for each experimental task (jog, 40-yard dash, M-cone drill, 5-10-5 shuffle drill, and broad jump). For each resultant acceleration-time series, we calculated the Multiscale Entropy (MScE) of the signal (Costa, Goldberger, & Peng, 2002; McGregor, Busa, Skufca, Yaggie, & Bollt, 2009; Parshad, McGregor, Busa, Skufca, & Bollt, 2012). MScE values are unitless and used to examine signal regularity on different temporal scales by coarse-graining the original time series via:

$$y_j^{(\tau)} = \frac{1}{\tau} \sum_{i=(j-1)\tau+1}^{j\tau} x_i, \qquad 1 \leqslant j \leqslant N/\tau \qquad \text{Eq. (12)}$$

Once the time series has been "coarse-grained," Sample Entropy (SampEn) is then calculated for each new time scale:

$$\text{SampEn}\ (m, r, N) = -ln\left(\frac{A}{B}\right) \qquad \text{Eq. (13)}$$

whereby *B* and *A* are defined as the total number of template matches of length *m* and total number of forward matches of length *m+1*, respectively:

$$A = \left\{\frac{[(N-m-1)(N-m)]}{2}\right\} A^m(r),\ \ B = \left\{\frac{[(N-m-1)(N-m)]}{2}\right\} B^m(r) \qquad \text{Eq. (14)}$$

This allows for SampEn values to be plotted at each time scale and, by calculating the area under this curve, complexity index (CI) may be reported. The data cleaning and analysis process can be visualized in **Figures 4 & 5**.

Statistical Analysis

Linear mixed effects regression (LMER) was chosen for this study due to its ability to handle repeated measures and non-independence in the data. The ‘lme4’ package (Bates, Mächler, Bolker, & Walker, 2014) in R was used to conduct all LMER tests. Before conducting the analysis, the assumptions of the linear mixed model were checked (i.e., linearity, homoscedasticity (equal variances), and normality of residuals) using the R ‘performance’ package (Lüdecke, Ben-Shachar, Patil, Waggoner, & Makowski, 2021). Diagnostic plots were used to visually inspect these assumptions. Linearity was checked by plotting the residuals against the predicted values. Homoscedasticity was assessed by looking at the spread of residuals across levels of the independent variables. Normality of residuals was checked using a Q-Q plot, where the residuals are plotted against a normal distribution.

An iterative method was used to develop the LMER models, initiated with a null model and successively incorporating fixed effects until a complete model was achieved. The process began with the formation of a null model only including random effects, providing a benchmark for subsequent model performance. Subsequent to the formation of the null model, fixed effects were methodically added one at a time (PHV offset followed by sex and then testing session). With the addition of each new fixed effect, the current model was compared to its predecessor. The comparison aimed to assess the model using Akaike (AIC) and Bayesian (BIC) Information Criterion, marginal and conditional R^2, intraclass correlation coefficients (ICC), and root-mean-square error (RMSE) values as guides. The iterative process continued until all fixed effects had been integrated, thus arriving at the full model. An essential consideration throughout this process was to maintain a balance between model complexity and model fit, ensuring the final model was neither underfitted nor overfitted. This systematic, iterative approach enabled a robust and quantitative evaluation of the contribution of each fixed effect and facilitated the construction of a model that optimally represented the data.

Results

CI results parsed by drill, session, and sex can be found in **Table 1**.

Table 1. CI results

	Female		Male	
Drill	**Pre**	**Post**	**Pre**	**Post**
40yd	6.98 (0.91)	7.11 (1.03)	6.95 (1.03)	7.08 (0.96)
5-10-5	4.94 (0.82)	5.08 (0.97)	5.32 (0.9)	5.25 (0.87)
Broad	3.16 (1.28)	3.37 (1.27)	3.15 (1.28)	3.37 (1.3)
DNB	6.39 (1.31)	6.25 (1.4)	6.15 (1.43)	6.45 (1.35)
M-L	5.63 (0.94)	5.78 (0.95)	5.68 (0.84)	5.78 (1.02)
M-R	5.49 (0.93)	5.79 (0.94)	5.61 (0.92)	5.66 (0.92)

Mean (SD)

Model comparisons for CI by drill are detailed in **Tables 2-7**. Interestingly, the null LMER models, which only incorporated random effects, consistently matched the fit of the more complex models which also considered PHV, sex, and testing session. This suggests that the added fixed effects in subsequent models are not capturing the relationship with CI in this context.

Table 2. Model comparisons for 40yd dash drill

	NULL	Model 1	Model 2	Model 3
(Intercept)	6.971***	6.989***	6.952***	6.917***
	(0.079)	(0.085)	(0.123)	(0.131)
PHV		0.030	0.052	0.052
		(0.048)	(0.071)	(0.071)
SEX (Male)			0.099	0.099
SESSION (Post-season)			(0.237)	(0.237)
				0.071
SD (Intercept SUBJECT)				(0.088)
SD (Observations)	0.684	0.686	0.690	0.690
	0.641	0.641	0.641	0.642
Num.Obs.	214	214	214	214
R2 Marg.	0.000	0.003	0.004	0.005
R2 Cond.	0.532	0.535	0.539	0.538
AIC	552.2	558.1	561.0	565.3
BIC	562.3	571.6	577.8	585.5
ICC	0.5	0.5	0.5	0.5
RMSE	0.52	0.52	0.52	0.51

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3. Model comparisons for 5-10-5 drill

	NULL	Model 1	Model 2	Model 3
(Intercept)	4.946***	4.907***	4.797***	4.805***
	(0.075)	(0.080)	(0.114)	(0.122)
PHV		-0.063	0.004	0.004
		(0.045)	(0.066)	(0.066)
SEX (Male)			0.299	0.299
			(0.222)	(0.222)
SESSION (Post-season)				-0.016
				(0.089)
SD (Intercept SUBJECT)	0.625	0.621	0.617	0.616
SD (Observations)	0.640	0.640	0.640	0.643
Num.Obs.	210	210	210	210
R2 Marg.	0.000	0.014	0.026	0.026
R2 Cond.	0.489	0.492	0.496	0.492
AIC	528.9	533.3	534.7	539.7
BIC	538.9	546.7	551.4	559.8
ICC	0.5	0.5	0.5	0.5
RMSE	0.52	0.52	0.52	0.52

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4. Model results for Broad Jump drill

	NULL	Model 1	Model 2	Model 3
(Intercept)	3.162***	3.179***	3.139***	2.993***
	(0.093)	(0.099)	(0.144)	(0.160)
PHV		0.028	0.052	0.052
		(0.056)	(0.084)	(0.084)
SEX (Male)			0.109	0.109
			(0.277)	(0.277)
SESSION (Post-season)				0.291*
				(0.141)
SD (Intercept SUBJECT)	0.607	0.612	0.618	0.631
SD (Observations)	1.048	1.048	1.048	1.033
Num.Obs.	214	214	214	214
R2 Marg.	0.000	0.001	0.002	0.017
R2 Cond.	0.251	0.255	0.260	0.284
AIC	690.2	695.9	698.5	698.4
BIC	700.3	709.4	715.3	718.5
ICC	0.3	0.3	0.3	0.3
RMSE	0.94	0.93	0.93	0.91

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5. Model results for M-drill (Left)

	NULL	Model 1	Model 2	Model 3
(Intercept)	5.782***	5.771***	5.714***	5.710***
	(0.072)	(0.077)	(0.111)	(0.121)
PHV		-0.016	0.018	0.018
		(0.043)	(0.065)	(0.065)
SEX (Male)			0.154	0.154
			(0.214)	(0.214)
SESSION (Post-season)				0.008
				(0.097)
SD (Intercept SUBJECT)	0.546	0.550	0.552	0.550
SD (Observations)	0.709	0.709	0.709	0.712
Num.Obs.	214	214	214	214
R2 Marg.	0.000	0.001	0.004	0.004
R2 Cond.	0.372	0.376	0.380	0.377
AIC	552.2	558.5	561.2	566.0
BIC	562.3	571.9	578.0	586.2
ICC	0.4	0.4	0.4	0.4
RMSE	0.60	0.60	0.60	0.60

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6. Model results for M-drill (Right)

	NULL	Model 1	Model 2	Model 3
(Intercept)	5.494***	5.503***	5.481***	5.387***
	(0.071)	(0.076)	(0.110)	(0.118)
PHV		0.014	0.028	0.028
		(0.043)	(0.064)	(0.064)
SEX (Male)			0.059	0.059
			(0.212)	(0.212)
SESSION (Post-season)				0.187*
				(0.084)
SD (Intercept SUBJECT)	0.582	0.586	0.590	0.596
SD (Observations)	0.627	0.627	0.627	0.616
Num.Obs.	214	214	214	214
R2 Marg.	0.000	0.001	0.001	0.013
R2 Cond.	0.463	0.467	0.470	0.490
AIC	523.1	529.4	532.6	532.9
BIC	533.2	542.9	549.4	553.1
ICC	0.5	0.5	0.5	0.5
RMSE	0.52	0.52	0.52	0.50

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7. Model results for DNB drill

	NULL	Model 1	Model 2	Model 3
(Intercept)	6.144***	6.100***	6.255***	6.170***
	(0.110)	(0.117)	(0.172)	(0.186)
PHV		-0.069	-0.160	-0.160
		(0.066)	(0.099)	(0.099)
SEX (Male)			-0.406	-0.406
			(0.330)	(0.330)
SESSION (Post-season)				0.171
				(0.138)
SD (Intercept SUBJECT)	0.874	0.873	0.870	0.871
SD (Observations)	1.005	1.005	1.005	1.003
Num.Obs.	210	210	210	210
R2 Marg.	0.000	0.008	0.018	0.022
R2 Cond.	0.430	0.434	0.438	0.442
AIC	702.5	707.0	707.9	710.5
BIC	712.6	720.4	724.6	730.6
ICC	0.4	0.4	0.4	0.4
RMSE	0.84	0.84	0.84	0.83

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Discussion

References

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