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CLASSIFICATION OF HETEROGENEOUS RUNNING POPULATIONS USING A TRI-AXIAL ACCELEROMETER

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INTRODUCTION

The tri-axial accelerometer (AC) is quickly becoming ubiquitous in the analysis of human movement and has the potential to become a valuable tool in the assessment of gait patterns. Previous research has shown that accelerations measured at the centre of mass are effective in discriminating between healthy and pathological walking patterns [1]. Furthermore, novel time-frequency analyses (e.g., wavelet decomposition) of AC signals have been successful in classifying varying types of activities (e.g., walking, running, stair climbing) [2]. These findings demonstrate a potential application for ACs in assessing various running patterns, including those that may lead to an injury.

Accurately detecting injurious running patterns is a challenging task requiring a more complete understanding of the AC's capabilities and covariates (e.g., gait speed, body mass) in a heterogeneous population. Therefore, the purpose of this study was to test the ability of a single AC to discriminate between two highly heterogeneous cohorts of athletes. Specifically, we hypothesized that a wavelet decomposition of the centre of mass accelerations can correctly classify the running patterns of two populations and that this classification is influenced by gait speed and body mass.

METHODS

Fourteen female competitive soccer (CS) players (age: 19.2 ± 1.2 yrs) and 16 female recreational marathon (RM) runners (age: 46.6 ± 7.9 yrs) participated in the study. All subjects were free of injury for at least 3 months prior to testing and provided written informed consent.

A single AC (G-Link Wireless Accelerometer Node ± 10g, Microstrain Inc., VT) sampling at 617 Hz was securely mounted to the subjects' lower back (L3 vertebra). Subjects ran on an instrumented treadmill (Bertec, Columbus, OH) at a self-selected pace for 2 minutes to acclimatize to the treadmill before 15 seconds of AC data were collected.

A discrete wavelet transformation, similar to that used by Preece [2], was applied to accelerations in all axes following an attitude-correction [3]. The transformation involved a five level wavelet decomposition using a Daubechies 2 wavelet mother. This procedure decomposed the original signal by iteratively removing high frequency components using a bandpass filter with a passband of $f_{max}/2$, f_{max}. The end result was five levels of decreasing frequency ranges extracted from the original signal, and a sixth level consisting of the remaining lowest frequency accelerations.

The Root Mean Square (RMS) of each decomposition level was calculated for a total of 18 variables (3 coordinate axes * 6 decomposition levels). This computation is commonly used as a quantification of the overall magnitude of acceleration in a signal, and therefore represents the magnitude of accelerations for each frequency band and coordinate axis. The RMS of the vertical (V) accelerations were defined as V_1, V_2, V_3, V_4, V_5 and V_A; with V_1–V_5 representing the RMS in the highest to lowest frequency bands, and V_A representing the RMS of the remainder signal. Similar annotation was used for the anterio-posterior (AP) and medio-lateral (ML) acceleration signals.

To determine the classification accuracy of the dependent variables, a step-wise discriminant analysis was used (Model 1). Group differences were tested on all dependent variables (independent t-tests; alpha = 0.05) and those variables demonstrating a significant difference between CS and RM were entered into the discriminant analysis. The step-wise discriminant analysis then determined a combination of these variables which optimally classified data into one of the two groups. A leave-one-out cross validation technique was used to measure the classification ability of the model. Two additional discriminant analyses were completed with dependent variables normalized for gait speed (Model 2), as well as gait speed and body mass (Model 3) to address the potential influence of these covariates.

RESULTS AND DISCUSSION

Body mass (CS: 60.4 ± 8.8 kgs; RM: 70.6 ± 12.9 kgs; p-value = 0.018) and gait speed (CS: 2.42 ± 0.13 m/s; RM: 2.26 ± 0.23 m/s; p-value = 0.032) were significantly different between groups and controlled for in Model 2 and Model 3. Means (± SD) for the dependent variables are presented in Table 1. Model 1 found a single discriminant function using V_A and ML_2 as predictors. This function significantly differentiated groups, $\Lambda = 0.57$, $X^2(2) = 14.15$, $p = 0.001$, explaining 43.2% of the variance and correctly classifying 78.6% of the cases. Model 2 used only ML_1 as the predictor to significantly differentiate groups, $\Lambda = 0.73$, $X^2(1) = 8.15$, $p = 0.004$, explaining 27.4% of the variance and correctly classifying 75.9% of the cases. Model 3 used V_A and ML_2 as predictors to significantly differentiate groups, $\Lambda = 0.71$, $X^2(2) = 8.97$, $p = 0.011$, explaining 29.2% of the variance and correctly classifying 73.3% of the cases (Figure 1).

Table 1: Means ± SD of dependent variables in CS and RM groups, before controlling for gait speed and/or body mass.

	CS	RM
V_A	5.729 ± 0.373	5.329 ± 0561[1,3]
V_5	1.456 ± 0.433	1.554 ± 0.424
V_4	0.597 ± 0.221	0.745 ± 0.286[2]
V_3	0.189 ± 0.074	0.272 ± 0.134[1,2]
V_2	0.047 ± 0.020	0.075 ± 0.042[1,2]
V_1	0.013 ± 0.005	0.019 ± 0.010[2,3]
ML_A	1.633 ± 0.486	1.721 ± 0.455
ML_5	1.255 ± 0.401	1.138 ± 0.248
ML_4	0.492 ± 0.135	0.573 ± 0.228
ML_3	0.145 ± 0.053	0.195 ± 0.086[2]
ML_2	0.033 ± 0.011	0.053 ± 0.024[1,2,3]
ML_1	0.010 ± 0.003	0.014 ± 0.005[1,2,3]
AP_A	1.799 ± 0.225	1.885 ± 0.447[2]
AP_5	1.208 ± 0.367	1.475 ± 0.492
AP_4	0.557 ± 0.139	0.706 ± 0.248[2]
AP_3	0.188 ± 0.062	0.242 ± 0.103[2]
AP_2	0.044 ± 0.013	0.062 ± 0.029[2]
AP_1	0.011 ± 0.003	0.015 ± 0.006[2]

[1] $p < 0.05$ Model 1
[2] $p < 0.05$ Model 2
[3] $p < 0.05$ Model 3

The primary findings of the study were; (i) a single waist-mounted AC can successfully discriminate between two heterogeneous populations, (ii) gait speed and body mass are important covariates for gait research using ACs, and (iii) high frequency ML and low frequency V accelerations were the most effective predictors.

The results show a single-waist mounted AC, combined with a wavelet decomposition analysis, can accurately classify running patterns from two heterogeneous populations. The classification accuracies of the current study ranged from 73-78%, which are in agreement with previous research using similar methodology [2]. The addition of a lower limb sensor has been shown to increase classification accuracies to nearly 90% [2]. Therefore, supplementing the current analysis with a lower limb AC may lead to an increase in the classification ability in various populations of runners.

The classification accuracy and the variance explained were reduced when normalized by gait speed and body mass in Models 2 and 3 (Figure 1). This finding suggests that some of the variance in the dependent variables of Model 1 was related to the effects of gait speed and body mass. Research has consistently shown that RMS accelerations are highly dependent on gait speed, and that faster running is associated with larger accelerations and therefore a larger RMS [4]. While no research has directly addressed the effect of body mass on accelerations during running, the current findings suggest that controlling or subject-matching based on both gait speed and body mass may be important to ensure the accuracy of gait classification across populations.

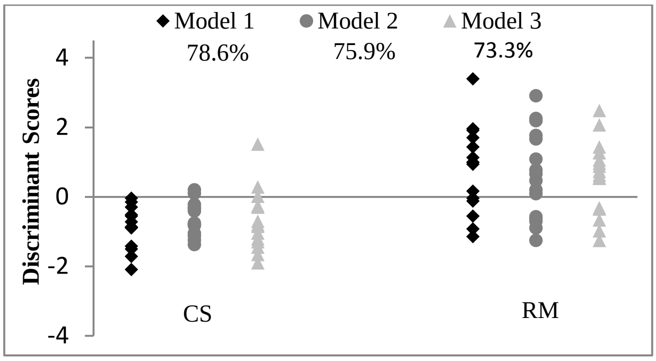

Figure 1: Classification accuracy and discriminant scores of subjects for each model.

The most effective predictors in the models involved high frequency ML accelerations and low frequency V accelerations. Either ML_1 or ML_2 was used in every model, and results showed RM runners had more high frequency ML accelerations than the CS group. These high frequency accelerations are likely due to ground reaction force vibrations at impact and are potentially related to injury [5]. V_A was a predictor in both Models 1 and 3, but unlike all other variables with significant differences V_A was larger in the CS. Given the importance of both high and low frequency accelerations, it is recommended to use ACs at high sampling rates to collect multiple frequency bands of acceleration during running.

CONCLUSIONS

A single AC was effective in classifying gait from a heterogeneous population of female marathon runners and competitive soccer players, with both gait speed and body mass influencing classification accuracy. These findings support the possibility that wavelet decomposition of gait accelerations may be used to discriminate between individuals in terms of their potential for injury. However further research is required.

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