Control Entropy of Gait: Does Running Fitness Affect Complexity Of Walking?

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ABSTRACT
Background: The purpose of this study was to determine if trained runners exhibited different complexity of walking than untrained individuals.
Methodology: Trained runners (T) and untrained controls (UT) performed two incremental walking trials that spanned 2, 4 and 6 km/h. Complexity was assessed through control entropy (CE), which was determined from high resolution accelerometry collected from the center of mass for three axes (VT, ML, AP). CE was compared between groups using a non-linear statistical approach to account for potentially non-stationary dynamical systems.
Principle Findings: Within groups, there were no significant differences in the shape of the CE response between axes in UT, but in T, AP was significantly different from VT and ML ($p < .05$). Between groups, there were no significant differences in the shape of the CE response by axis. CE was significantly lower in the VT and ML axes ($p < .05$), but CE was not different in the AP axis ($p = 0.16$).
Conclusions/Significance: These results show that T and UT individuals exhibit similar CE responses over time during incremental walking, but CE is lower in T versus UT in both the vertical and mediolateral axes. Lower CE in the T group is indicative of lower complexity, indicating that T runners are more constrained while walking than UT individuals.

Key Words: Locomotion, Nonstationarity

INTRODUCTION

Although walking is an apparently simple activity, we know that it is a complex neuromotor task (5, 21, 22). Healthy walkers can function quite well in daily society, but if gait is perturbed by disease or age, activities of daily living can be severely impaired (1, 11). Further, in the aged, falls during walking can have drastic negative consequences (8). Although there has been a great deal of interest regarding elucidating the neurological factors dictating healthy gait, there has been little attention paid to the role of cardiovascular fitness and endurance training in the process of surefootedness. Investigating the role of fitness and walking gait could add novel insight to the wealth of data regarding neurological factors and gait, and therefore, contrasting the gait characteristics of healthy and highly fit individuals is of value.

Analysis of gait has traditionally been performed using linear approaches, but recently, tools from the field of non-linear dynamical systems have become increasingly popular (5-7, 13, 22). In particular, the variability of gait has been of increasing interest. One of the ways that variability of complex systems can be assessed using a non-linear approach is through the use of entropy analysis (e.g. Approximate Entropy, Sample Entropy, etc.) (4, 5, 9, 10). Entropy measures or, “regularity statistics”, are used to determine the regularity or, conversely, the complexity of a signal (18). An example of a highly regular signal would be a perfect, noiseless sine wave that exhibits linear variability about a mean that it oscillates, but is highly regular or repeatable. This signal would be said to exhibit low entropy due to its high regularity. In contrast, a signal such as gait, which oscillates about a mean, and exhibits some linear variability, will also exhibit some non-linear irregularity or complexity, and would be said to possess higher entropy due to its greater complexity. Recently, we developed a novel approach to entropy analysis, control entropy (CE), which is well-suited to analysis of signals such as those developed under dynamic conditions such as gait (2). The use of entropy statistics, including CE, should provide us with information regarding the constraints imposed on a system. In general, we say that constrained systems exhibit regularity and correspondingly low entropy, while unconstrained systems exhibit high complexity and correspondingly high entropy (2). Using this approach, we have shown differences in constraints between axes of movement in highly trained runners using CE of high resolution accelerometry (HRA) collected during a standard treadmill running protocol (13). We have also used linear approaches to show differences in global gait characteristics between trained and untrained

Table 1. Subject characteristics: Values are mean ± SD

	Mass (kg)	Height (cm)	Age (yr)	VO2max (ml/kg/min)
Trained	65.5 ± 5.7	181.8 ± 4.1	21.4 ± 1.7	70.1 ± 6.2
Untrained	69.9 ± 11.8	177 ± 5.7	31.6 ± 9.5	49.3 ± 5.0

individuals during running using HRA (14). Using the linear and non-linear approaches, we have gained insight into the different constraints present in trained and untrained individuals while running that may be of use for the prevention and/or rehabilitation of injury.

In the case of walking, the relevance of run training status and fitness is less clear with regard to the impact on walking constraints. From our previous work examining the linear characteristics of HRA during walking, the root mean square and economy of acceleration values were not different between trained and untrained groups, but the ratio of axial acceleration to resultant scalar acceleration (ratio of acceleration) were greater in the mediolateral axis, and less in the anterior-posterior axis in trained versus untrained individuals (14). The significance of this is unclear, but non-linear entropy analysis might provide additional insight as to how these differences might be reflective of the differential constraints between groups. Therefore, the purpose of this study was to compare CE of HRA signal collected from highly trained runners and untrained individuals during a standard treadmill walking protocol. We hypothesized that increased fitness and run training status would result in reduced constraints while walking and this would be exhibited as higher CE in all axes in the trained versus untrained groups. Further, we hypothesized that since the primary constraint of walking is that imposed by gravity in the vertical plane, that CE would be lower in the vertical than either the mediolateral or anterior-posterior axes in both groups.

METHODS

Subjects

Fourteen subjects consisting of seven male NCAA Intercollegiate Division 1 distance runners (T) and seven recreationally active, college students considered untrained (UT) for running (Table 1) gave written informed consent to take part in this study, which was approved by the Eastern Michigan University College of Health and Human Services - Human Subjects Review Committee. Criteria to be considered UT was running less than four times per week and an estimated 10 km performance time of greater than 45 min.

Experimental Design

Subjects completed two continuous, incremental exercise tests on a motorized treadmill (True ZX-9, St. Louis, MO) with at least 6 days separating each trial. Exercise tests were performed while high resolution triaxial acceleromety (HRA) and open circuit spirometry was collected to determine relationships between metabolic parameters (e.g. V_E, VO_2, VCO_2) HRA, walking and running speed which are presented elsewhere (14). The subjects reported to the laboratory on the day of testing after having refrained from strenuous exercise, alcohol, and caffeine for 24 hours prior to the day of testing and having fasted for 3 hr. Trials consisted of a 2 min baseline quiet stance phase, followed by walking initially at 2 km/h, and increasing speed by 2 km/h every 2 min up to 6 km/h.

Accelerometry

The HRA device consisted of a triaxial MEMS accelerometer model ADXL210 (G-link Wireless Accelerometer Node ± 10g, Microstrain, Inc., VT). The device was mounted to a semi-rigid strap and placed, anatomically, at the intersection of the sagittal and axial planes on the posterior side of the body in line with the top of the iliac crest in order to approximate the subject's center of mass (15). It was additionally secured with elastic tape in order to remove extraneous movement of the device not associated with locomotion. Acceleration in g's was streamed in real time using telemetry to a base station at a frequency of 617 Hz.

Non-Linear Analyses

Entropy is classically defined as a measure of disorder in a system (20), in particular, computed by the coding complexity measure of Shannon entropy. However, recently a number of variants of classical entropy have become popular in the field of dynamical systems, such as sample entropy (19). In (2) we developed a regularity entropy-like statistic and called it control entropy (CE), which is designed to address the regularity/complexity of the underlying system controller. The primary merit in CE is its applicability to nonstationary time series data. This is quite relevant to real-world process, in particular dynamic gait measurements. Furthermore, it allows for the interpretation regarding the controller signal effort. The computation of CE involves the approximate entropy of variations in a signal, rather than computed directly against the signal. We thus take as input the time series data, from various subjects, measuring certain physiological properties, in this case HRA signal. We compute the CE of this time series, by computing the approximate entropy on differences, of this series. We then perform a proper orthogonal decomposition (POD) of this signal. In POD, we project the full signal onto a few dominant modes and generate graphs of these dominant modes. We then choose the first two dominant modes that are used to generate scatter plots of the data. The Karhunen-Loeve (K-L) analysis allows us to extract the dominant behavior in a CE response to determine, rigorously, if groups are behaving in a statistically similar manner. Furthermore, given these major responses, we then use a hypothesis test to enumerate the group responses. Since we are interested in quantifying differences between groups described by a projective data cloud, we choose to use the Hotellings T^2 test (12). This is a multivariate version of the student's t-test. We test the null hypothesis that the population mean vectors for the groups in question are equal, against the alternative hypothesis that they are not equal. The computations for the above-mentioned procedure were carried out in MATLAB 2009 (Mathworks, MA). We developed code to symbolize the raw data, from which the CE is calculated. This is passed into a second routine, which performs the POD, and yields the dominant modes, for runners for the groups in question. This is finally passed pair wise, into a routine that carries out the multivariate Hotelling T^2 test, yielding the statistics of interest, which enables appropriate comparison of groups. For the details of the computation of CE and POD, refer to references (2, 13).

RESULTS

Control entropy responses during treadmill walking in trained and untrained runners by axis

A comparison of results of K-L analysis of CE for accelerations between individual axes in untrained runners can be seen in Figure 1a. No significant difference was observed between axes with regard to the shape of the CE response, indicating there was no difference in the change in constraints between axes across walking speeds.

The results of K-L analysis of CE of accelerations for individual axes in trained runners can be seen in Figure 1b. Significant differences in shape of the CE response were observed between the ML (red) and AP (green) axes, whereby CE of the ML axis was initially higher during standing and the 2 km/h stage, but during the 6 km/h stage it declined below the AP axis. A significant difference in shape of the CE response was also observed between the VT (blue) and AP (green) axes. In particular, at the 6 km/h stage, a speed just below the walk to run transition (14), CE of the AP axis is highest of all axes in the trained runners, indicating high complexity and lower constraints relative to other axes.

Control entropy response of trained versus untrained runners by axis

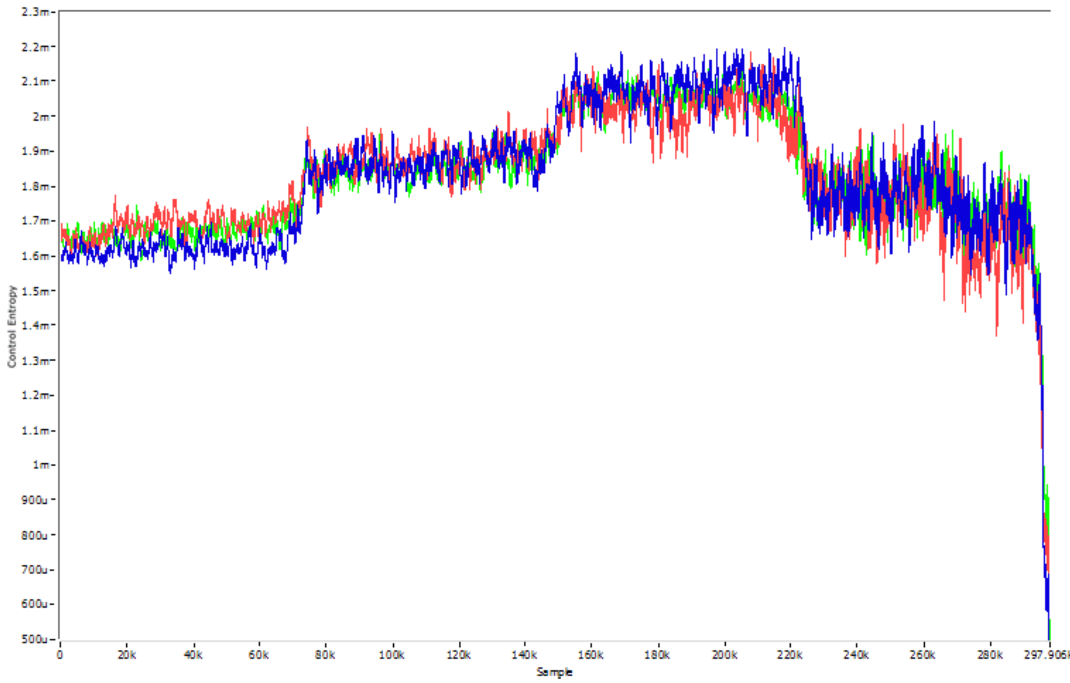
When untrained runners were compared to trained runners using the developed shape analysis, it was determined that there were no significant differences in the shape of CE responses between trained and untrained runners for the VT, ML or AP axes (Figures 2a,b, c). Although there were no significant differences of the shapes of the CE responses between groups, there were significant differences in the mean values of CE for the VT and ML axes, but not the AP between groups. Control entropy of HRA signal was higher for untrained versus trained in the VT and ML axes, indicating greater complexity and lower constraints in the untrained relative to the trained runners.

Scatter plots

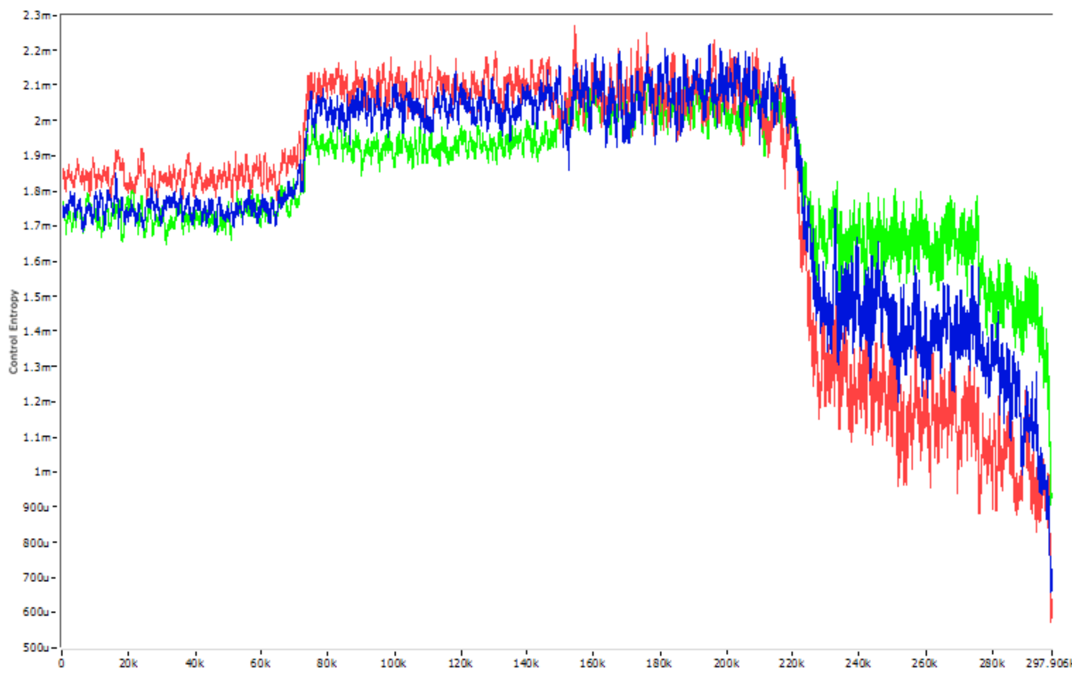
Results of scatter plots of K-L analysis for all axes can be seen in Figure 3. Apparently, in all axes, the trained (Figure 3b,d,f) and untrained runners (Figure 3a,c,e) exhibit similar scatter patterns. In the case of both groups, the scatter plots are tightly clustered. This indicates that the lack of statistical significance for the shape of the CE responses is not due to high variance of the response, and that the trained and untrained runners do indeed exhibit similar CE response patterns in all axes. We also provide figures of the scatter plots of these modes of the runners by axis. This is seen via the K-L analysis followed by the singular value decomposition. Some details behind the theory of the K-L analysis as applicable in this context are provided in the methods section. For complete details the reader is referred to (2, 17).

DISCUSSION

In this work, we tested the hypothesis that running fitness would reduce constraints of walking and this would result in greater CE of HRA signal in trained than in untrained runners. This hypothesis was not supported though, as when trained and untrained runners were compared by axis, CE was higher in the untrained in the VT and ML axes, and not significantly different in the AP axis. We also hypothesized that the constraints of walking would be greatest in the VT axis due to gravity, and this would result in lower CE in that axis compared to the ML or AP. This hypothesis was also not supported, as CE

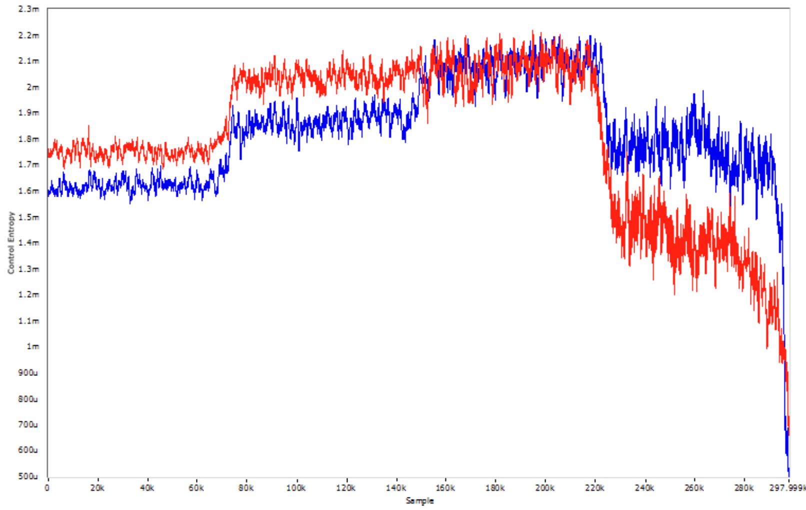


a.



b.

Figure 1. Dominant modes of control entropy responses for untrained and trained runners by axis. Control entropy (CE) of accelerations collected in high resolution at the approximate center of mass from a) untrained and b) trained runners during an incremental walking test. Karhunen-Loeve transformation was performed to generate a dominant mode for the CE response in each of three axes (vertical = blue; mediolateral = Red, anterior-posterior = green). Like symbols (*) indicate significantly different shapes of dominant modes between axes.



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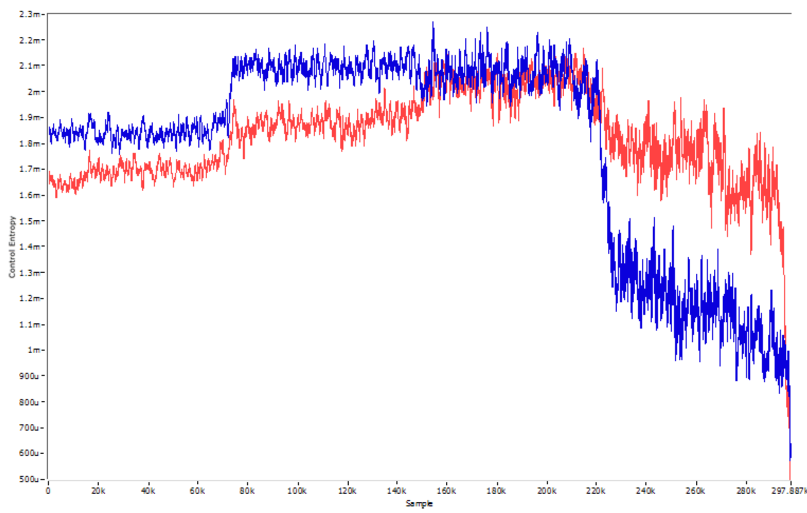

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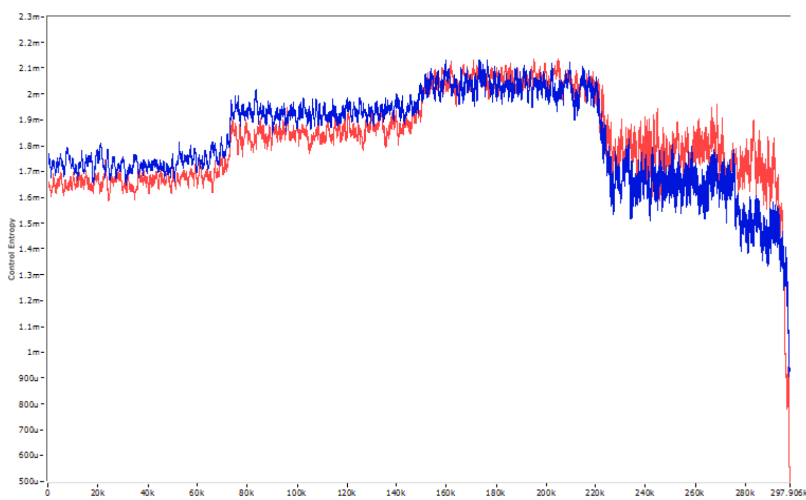

c.

Figure 2. Dominant modes of Karhunen-Loeve transformations generated from control entropy (CE) responses of accelerations. Accelerations were collected in high resolution at the approximate center of mass from trained (T) and untrained (UT) runners during an incremental test, and CE of accelerations were compared between groups for (a) vertical, (b) mediolateral, and (c) anterior-posterior axes at equivalent speeds (trained = red, untrained = blue).

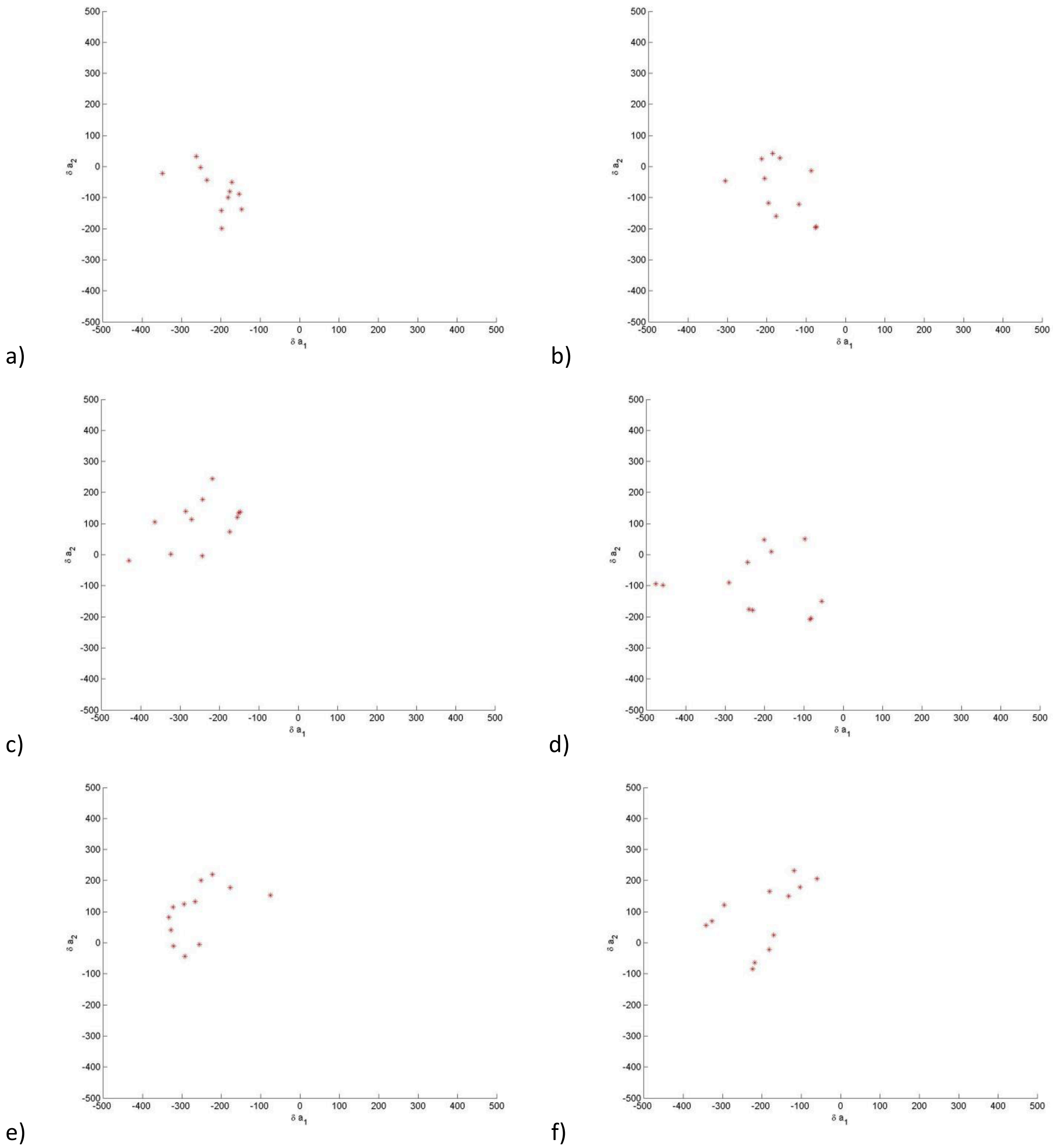

Figure 3. Scatter plots for untrained vs trained runners. Scatter plot presentation of clustering in untrained runners (left column) versus trained runners (right column) in vertical, mediolateral, and anterior posterior channels in successive rows is shown. Tight clustering within ranges is indicative of a strongly homogeneous group, here as measured within the singular value decomposition dominant modal description in the first two modes δa1 and δa2 of the CE response profile of the corresponding accelerometry axis labelled. Notice that in this presentation, it is immediately apparent that both the trained and untrained groups present a highly homogeneous resp

was not significantly different between axes in the untrained runners. In the trained runners, though, CE was indeed significantly higher in the AP axis than the VT and ML, which were not significantly different from each other.

In this approach to statistical comparison of group CE responses, we perform the K-L analysis and R-test to determine if the shape of the CE response is similar between groups. This is a critical step in non-linear analysis, because if two, non-stationary, dynamical systems are being compared, it must be assured that they are exhibiting a similar pattern of evolution over time, or statistical group comparisons may be invalid. In cases where the K-L and R-test analysis is not significantly different between groups, it is then valid to perform a simple means comparison between the two groups. In cases when the K-L analysis and R-test is significantly different, a means comparison between groups is not appropriate, or should be viewed with caution, but the difference in shapes can provide additional valuable information over and above a simple group means comparison (17).

K-L analysis was performed with the purpose of identifying common CE responses and generalizing them to the population utilized for this study. In doing so, for each axis a dominant mode was identified which exemplified the most likely common CE response for each axis. Therefore, for purposes of generalization, we will refer to the dominant mode as exemplars of a given response. In the VT axis, the shape of the CE response was not different between T and UT runners, but CE was, on average, higher in UT vs. T (Figure 2a). A similar response was observed in the ML axis, where no difference in shape of the CE response was present, but CE for the UT was higher, on average, than for T (Figure 2b). This was surprising as it was anticipated that CE would be higher in the T rather than the UT runners. A similar pattern can be seen for both the VT and ML axes whereby CE for trained is greater than untrained runners during standing and slowest walking speed (2 km/h), but for the fastest walking speed (6 km/h) CE declines precipitously, so that UT is higher than T (Figure 2a and 2b). Elsewhere, when we have compared UT and T runners while running, we observed a significant difference in the CE response in the VT axis (17). So, it may be that while walking, the constraints are not great enough to result in a different CE response by virtue of fitness in this axis. That being said, it is surprising that CE is greater in the vertical axis for UT vs. T. In particular, it is quite unexpected that CE is apparently higher while slow walking in T, but declines so that it is lower in T in the faster walking stage (6 km/h). Since we would have expected fit, trained runners to be less constrained, relative to untrained as speed increased, we anticipated results to the converse.

Control entropy can be viewed as a measure of system constraint (2), so, it is of interest that peak CE values occurred at 4 km/h in both T and UT groups (Figures 1 and 2). This was to be expected since, in healthy humans, preferred walking speed occurs at 4 km/h (1.2 m/s) (16), and constraints should minimal at preferred walking speed. At the same time, it would be expected that fit, trained individuals would be less constrained at faster walking speeds than untrained, less fit. Therefore, it is a bit perplexing that CE was lower in the T versus the UT, particularly at the fastest walking speed. Buzzi has shown though, that aged (3) and Down Syndrome patients (4) exhibit greater complexity of gait than normal controls. So, it may be that fitness and run training do not reduce the constraint of walking at fast speeds. Alternatively, and somewhat counter-intuitively, it may be that for fit, trained runners to walk at a speed (6 km/h) slightly below the run transition (8 km/h) requires a certain amount of concentration. In other words, it may take "focus" to walk at a speed fit runners could possibly run and the "awkwardness" of walking a 6 km/h may result in non-fitness related constraints which lower CE in the T individuals. Yogev-Seligman et al. have addressed the issue of executive function in gait, and have shown that complexity of gait will be reduced by adding simultaneous cognitive tasks (21, 22). It may be that the focus required to walk at a non-preferred speed without running requires increased role of executive function, which in turn results in a reduced complexity and CE.

A final alternative explanation may be that the increased constraints implied by the lower CE in trained versus untrained runners observed while walking are a result of system optimization incurred through training. In other words, since the trained runners elicit metabolic and neurological (as well as morphological) adaptations that are optimized for the task for which they train, when they locomote at speeds outside of the optimized range, constraints are greater. Whether or not this reduced complexity/increased constraint is a negative aspect of the training adaptations or simply a marker of such adaptations is difficult to ascertain. Anecdotally though, when highly trained athletes participate in activities that are outside of their primary activity, they are often susceptible to injury, and so, these results may indicate an "unhealthy" aspect of training adaptations that might otherwise be considered healthy (i.e. improved cardiovascular fitness, running prowess).

CONCLUSION

In this work we report, using control entropy, that the complexity of walking is lower in trained versus untrained runners in the vertical and mediolateral axis. This observation was unexpected and raises questions regarding the nature of adaptations that may promote optimization for running, but at the same time impose constraints while walking. It is doubtful that the lower complexity in trained runners is indicative of an unhealthy state, but may be indicative of a reduced ability to adapt to environmental conditions outside of the focused training condition.

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