ARE THERE COORDINATION INSTABILITIES IN THE WALK-TO-RUN TRANSITION? A CASE STUDY USING SELF-ORGANISING MAPS

Roger Bartlett, David O'Donovan, Gavin Kennedy and Rupinder Saini

School of Physical Education, University of Otago, Dunedin, New Zealand

This study investigated multi-dimensional coordination instabilities in the transition between walking and running for a 26 year old female runner using self-organising maps (SOMs). We found different multi-dimensional coordination patterns for walking and running using the output from SOMs as stride trajectories on U-matrices and attractor diagrams. In the second experimental procedure, the participant showed clear transient multi-stability, or instability, at 8.2 km/h in the transition region for decreasing but not for increasing speeds; this is unlikely to be general across runners. She also showed increased multi-dimensional coordination variability around the transition region. SOMs provide us with a tool to study multi-dimensional coordination and to reduce its complexity to relatively simple map outputs.

KEY WORDS: attractor diagrams, multi-dimensional coordination, SOMS.

INTRODUCTION: The transition from walking to running and vice versa has often been studied. Coordination patterns have most frequently been analysed using relative phase between two joint angles designated as being important to the movement pattern. Some authors (e.g. Diedrich & Warren, 1995) have noted an increase in movement or coordination variability as the transition from one form of gait to another is approached. However, coordination in walking and running is multi-dimensional, involving the joints of all extremities as well as the trunk and head in all three cardinal planes. Such multi-dimensional coordination has rarely been studied, largely because of the few tools available. Self-organising maps (SOMs, a type of artificial neural network) are a tool for reducing high-dimension datasets, such as those produced when investigating human motion using three-dimensional motion-capture systems. The non-linear properties of SOM analysis reduce redundancies in datasets and enable high-dimensional data to be mapped onto low-dimensional output maps for interpretation (Lamb, Bartlett & Robins, 2011). Of particular use and importance is that topological relationships in the original dataset are preserved by the SOM procedure. For a more comprehensive explanation of using and interpreting SOMs in human movement studies see Lamb et al. (2011).
We hypothesized that the SOM analysis would show an increased multi-dimensional coordination variability towards the gait transition region, in confirmation of previous findings. We also hypothesized that the SOM would enable us to identify attractor diagrams (as in Lamb et al., 2011) and that there would be separate attractors for walking and running, with possible multiple basins of attraction in the transition region. Attractor diagrams for walking and running have not previously been produced from experimental data. As the transition from walking to running occurs frequently in sport, this research is very sport relevant.

METHODS: The participant in this case study was a 26 year old female who was a regular runner, running at least 3-4 times a week and competing in short and middle distance club events at weekends. Ethical clearance already existed for this type of study, through a three-year course approval. The rigid-body model that we used consisted of 15 segments (head, thorax, humerus [L & R], forearm [L & R], hand [L & R], pelvis, thigh [L & R], shank [L & R], and foot [L & R]. Sixty three retro-reflective markers (15 mm and 10 mm in diameter) were used to define segments and local joint coordinate systems. Joint centres were mostly located at the midpoint of a line joining lateral and medial markers; for example, the elbow joint was calculated at 50% of the distance between markers on the lateral and medial epicondyles. Glenohumeral and hip joint centres were estimated by calculation of the pivot point of the instantaneous helical axes method, the preferred method as it is more accurate than regression analysis. This calculation was performed in Visual3D (C-Motion Inc., Germantown, MD) on functional range of motion trials for each arm and leg using the built-in functional joint processing option. The right-handed orthogonal system defines the vertical or longitudinal axis as Z; the anteroposterior axis as Y; and the mediolateral axis as X; these axes represent axial rotations (Z); ab-adduction (Y); and flexion-extension (X) at most joints. All rotation orders were represented by Cardan sequences (e.g. X-Y-Z, Z-X-Y).

A ten-camera three-dimensional motion analysis system (Vicon, Oxford, UK) sampling at 200 Hz captured the positions of markers. A standard wand calibration procedure was followed, based on manufacturer guidelines. Assessment of camera residuals (reconstruction accuracy) took place and if any camera had residuals >1.0 mm, the calibration was repeated until a satisfactory residual (<1.0 mm) was achieved. Data were collected at the University of Otago, School of Physical Education Biomechanics Laboratory. On arrival the participant was briefed on experimental procedures and gave informed consent to participate. Retro-reflective markers were applied and calibration trials conducted. A static calibration was taken with all markers affixed and in the data capture space. Dynamic range of motion trials were then performed in which the participant actively moved her shoulder, elbow, wrist, hip, knee, and ankle joints through full ranges of motion to enable calculation of functional joint centres.

The first (steady state) procedure began with a six minute warm-up, during which the participant identified her preferred walking and running speeds on a level treadmill. The speed at which the walk-to-run transition occurred was also identified. Based on this range of speeds, eighteen speeds were selected from 2.5 to 16.0 km/h. The transition region was bordered by speeds of 7.5 km/h, and 8.0 km/h. The trial order was randomised to minimise any step-wise practice effects. For each trial the participant was given a one-minute familiarisation before data capture began. Twenty to twenty-five strides at each speed were collected, with ten strides being randomly selected for further analysis in post-processing. Between trials the participant was given one minute of recovery time to minimise the potential effect of fatigue. In the second (transient) procedure, on a separate day, the participant walked or ran at speeds from 6.2 to 9.2 km/h in 0.2 km/h steps with the belt speed increasing and then decreasing. Data were collected for 30 s immediately after the belt had reached the new speed.

After testing, motion capture data were reconstructed and cleaned using Vicon Nexus software. Each trial was visually inspected for correct marker labelling and trajectory gaps. Any gaps were reconstructed with cubic spline or pattern (symmetric alternative marker) interpolation. Cleaned, unfiltered data were then exported for further modelling in Visual 3D. Local segment coordinate systems were established, and functional joint centres and joint angles were calculated before angle data were exported for further processing, such as key event identification, using custom Matlab (Mathworks, Natick, MA) routines. Analysis of residuals informed the use of a fourth-order zero-lag Butterworth low-pass filter with a 10 Hz cut-off frequency. Key foot events (toe-off and heel strike) were identified in Matlab by finding local minima in the vertical spatial position of foot markers at the calcaneus and on the shoe above the head of the second metatarsal. After event identification and visual inspection, trials were trimmed to individual strides, beginning and ending at right toe-off. Angular velocities were calculated using differentiation of joint angle data. Individual strides were saved for later input into the Self-Organising Map (SOM) procedure. Strides were range-normalised to maximum and minimum values of + and -1 respectively for angle data, and +1 or -1 for angular velocity data, before being time normalised to 100 data points in both instances. A SOM (see Lamb et al., 2011 for further details) was trained for each of the experimental procedures using all of the normalised data for all angles and angular velocities for each speed, for ten random strides for the first procedure and for the first twenty strides for the second. The output was visualised as a two- or three-dimensional U-matrix, which shows weight differences between regions of the output map (for brevity and because they are difficult to interpret when not in colour, these are not included here; for examples for the golf chip shot, see Lamb et al., 2011). More importantly for the purposes of this communication, the outputs from the first SOM were then used to train a second SOM, the output from which (as in Lamb et al., 2011) was in the form of an attractor diagram (Figures 1 and 2).

RESULTS: The participant walked fluently at speeds up to and including 7.5 km/h and ran fluently at all speeds at and above 8.0 km/h in the first (steady state) procedure. The attractor diagrams at each speed all showed a single basin of attraction, those for walking and running occupied different regions of the SOM output, one being a mirror image about the vertical axis of the other (Figure 1).

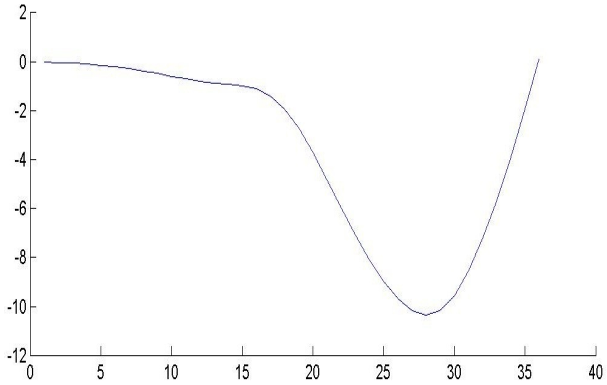

Figure 1: Basins of attraction for (left) walking at 5.1 km/h and (right) running at 12.6 km/h. The horizontal axis is the node index and the vertical axis is the relative frequency of activated nodes on the second SOM.

In the second (transient) procedure, the same result was found for increasing speed; however, for decreasing speed at 8.2 km/h instability - or multi-stability - was evident in the form of several shallow basins of attraction (Figure 2, left). At the next speed down, 8.0 km/h, two basins of attraction were evident, but now both in the walking region of the attractor diagram (Figure 2, right), but unlike the single basin of attraction at the same speed for the first procedure (Figure 1, left).

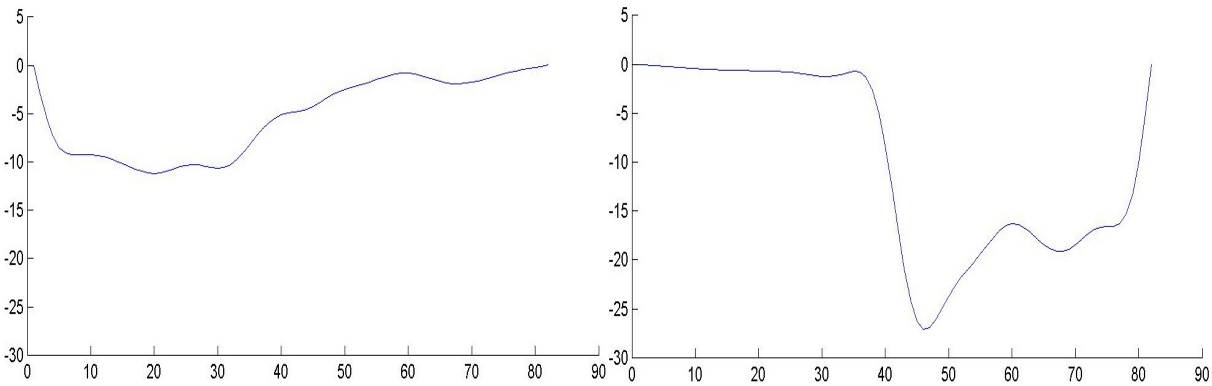

Figure 2: Basins of attraction for decreasing belt speed at 8.2 km/h (L) and 8.0 km/h (R).

Multi-dimensional coordination variability between strides – expressed as weight differences in the SOM trajectories - was high at slow walking speeds, decreased at faster walking speeds, increased towards and through the transition from walking to running and decreased again as the running speed increased; this was true for both experimental procedures (Table 1 is for the first procedure).

Table 1: Total trajectory variability at various gait speeds.

Speed km/h	2.5	3.6	4.3	5.1	6.0	7.0	7.5	8.0	8.4	10.0	11.0	12.0	12.6	13.2	14.0	15.0	16.0
Variability	4.3	4.6	3.5	2.8	2.8	3.6	3.6	4.5	4.4	3.4	3.1	3.2	3.1	2.5	2.8	2.6	2.5

DISCUSSION: The participant in this study was able to transition smoothly from a multi-dimensional walking coordination pattern to a running pattern with no instabilities evident in the first (steady state) procedure and in the second (transient) procedure when the treadmill belt speed increased but with instabilities at 8.2 km/h in her transition region when the belt speed decreased in the second procedure. The participant was uncertain whether to run or walk at that speed. The instability was transient – in the second procedure; when allowed time to adjust to new belt speeds in the first procedure, the participant walked or ran fluently at all belt speeds. Two golfers in the study of Lamb et al. (2011) showed a complex transition between coordination patterns when chipping distance increased as they changed from a short to a long chipping pattern, with one clearly showing multi-stability or instability; no instabilities were shown by their other two golfers. In the light of those findings, we might expect that other runners would demonstrate different patterns of multi-dimensional stability – or instability - from those of the runner in this study.
The finding for multi-dimensional coordination variability between strides - it was high at slow walking speeds, decreased at faster walking speeds, increased towards and through the transition from walking to running and decreased again as the running speed increased - supports previous research that has reported an increase in two-joint coordination variability around the transition from walking to running. The large coordination variabilities that were evident at slow walking speeds in our study may well have been due to the participant's unfamiliarity with walking at those speeds. We also found that sagittal plane variables only were not able to demonstrate these results clearly and that a combination of angles and angular velocities gave a much clearer picture than angles or angular velocities alone. This could throw some doubt on the results of studies of the walk-to-run transition that have used sagittal plane variables only or focused only on joint angles.

CONCLUSION: This study clearly showed different multi-dimensional coordination patterns for walking and running using the output from SOMs in the form of attractor diagrams. In the second experimental procedure, the participant in this study showed transient multi-stability or instability at 8.2 km/h - in the transition region - for decreasing but not for increasing belt speeds; this is unlikely to be general across runners. She also showed increased multi-dimensional coordination variability around the transition region, which agreed with findings from previous studies. Self-organising maps provide us with a tool to study multi-dimensional coordination – which is what all sports movements essentially involve – and to reduce its complexity to relatively simple map outputs. Furthermore, SOMs enable us to visualise attractor diagrams, and basins of attraction, from real multi-dimensional time series data rather than from theoretical reasoning, as has often been the case previously.

REFERENCES:

Diedrich, F. J. & Warren, W. H. (1995). Why change gaits? The dynamics of the walk-to-run transition. *Journal of Experimental Psychology: Human Perception and Performance*, 21, 182-202.

Lamb, P. A., Bartlett, R. M. & Robins, A. (2011). Artificial neural networks for analysing inter-limb coordination: The golf chip shot. *Human Movement Science*, 30, 1129-1143.