CLUSTERING LONG-DISTANCE RUNNERS BASED ON THEIR TECHNIQUE AT ONE SINGLE SPEED DOES NOT GENERALISE TO MULTIPLE SPEEDS

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The aim of this study was to assess whether clustering runners based on their technique resulted in consistent group allocations across multiple speeds. Eighty-four runners (34 females) completed four 4-minute running stages at 10, 11, 12 and 13 km/h. For each stage, running technique was characterised using a set of continuous variables in the sagittal plane and discrete stride-based variables. An autoencoder neural network was used for dimensionality reduction and agglomerative hierarchical clustering was applied to identify groups of runners with a similar technique. Two clusters for each speed were selected and the clustering partitions at different incremental speeds were compared. Our results showed that partitions were inconsistent across speeds, and therefore clustering results at one single speed do not generalise to the range of speeds an athlete typically runs at. Single speed clustering may be limited to drive the design of cluster-specific running training interventions and different clustering approaches are needed to better capture runners' technique at their typical speeds.

KEY WORDS: running kinematics, unsupervised learning, machine learning.

INTRODUCTION: Running technique plays a key role in performance due to its relation to running economy, and in running injury occurrence. Multiple studies have investigated running technique and suggested most optimal movements for runners (Moore, 2016). However, contrasting findings can also be found in the literature (van Hooren et al., 2020) as running tehcnique is thought to be highly individual (Nigg 2001), making it difficult to transfer running technique research into real world training practice.

Recent studies proposed the existence of "functional groups" or clusters of runners who share some commonalities in their technique as a more effective way to group and analyse athletes. Clusters may be found based on researcher's expertise or using data-driven approaches such as unsupervised learning to minimise researcher bias. Studies using unsupervised learning have identified groups of runners who reacted in similar ways to e.g., different shoe types (Hoerzer et al., 2015) or rehabilitation programmes (Watari et al., 2018).

Unsupervised learning can also exploit multivariate datasets instead of focusing on one single variable and condition in isolation, allowing a more holistic description of an athlete's running technique and profile. This ability can help the design of cluster-specific training that may better address individual technical and strength and conditioning needs. However, current clustering studies have typically focused on one single running speed (Hoerzer et al., 2015; Watari et al., 2018). Given long distance runners may run at different speeds depending on the racing distance and change their speed within a race, understanding whether the clusters found at one single speed extend to the range of speeds an athlete typically runs becomes paramount prior to designing cluster-specific training interventions.

Thus, the purpose of this study was to cluster the same athletes based on their technique running at various speeds and to assess the consistency of the clustering partitions.

METHODS: Eighty-four runners (Table 1) were included in this study. Participants were aged between 18 and 50, free from injury in the preceding six months and had a recent race (or equivalent) 10K time under 00:57:20 for females and under 00:50:00 for males ensuring matched age-grading. All participants provided written informed consent before taking part in the study, which was approved by the Ethics Committee of the University of Bath.

Table 1. Participants' details (mean and standard deviation other than Count and age-grade).

Sex	Count	Age (yrs)	Height (m)	Mass (kg)	10K time	Age-grade (%)	LT (km/h)
Female	34	33(10)	1.66(0.05)	57(6)	42:33(04:49)	70.39	13.7(0.9)
Male	50	35(10)	1.79(0.06)	73(9.8)	39:55(03:58)	66.76	14.4(1)

Participants completed a running test to exhaustion on a treadmill at a 1% gradient. The test included 4-minute stages of constant speed running with 1-minute breaks between stages. Running speed started at 10 km/h and was increased by 1 km/h after every completed stage. Blood lactate concentration was recorded (LactatePro, Nova Biomedical, USA) after every completed stage and individuals' lactate threshold (LT) was estimated (Cheng et al., 1992). Only stages up to the first speed after LT were included in the analysis to minimise fatigue effects on running technique. All participants met this condition for the 10, 11, 12 and 13 km/h stages. A 16-camera motion capture system (Oqus, Qualisys, Sweden) was used to record the 3D trajectories of 58 retroreflective markers (200 Hz) attached to the runner's body and shoes. Marker trajectories were low-pass filtered (Butterworth, 4th order, zero-lag) with a cut off frequency of 10 Hz and used to estimate full body kinematics in Visual3D (C-Motion, Inc, Rockville, MD). Foot strike and toe off were detected (Rivadulla et al., 2021) and trials were segmented in strides from foot-strike to foot-strike. Strides were time-registered to 201 data points. Running technique was characterised by a set of eight continuous (1D) and discrete (0D) variables (Figure 1).

For each speed, an autoencoder neural network was developed to reduce the dimensionality of the data. Agglomerative hierarchical clustering was then used to discover clusters of runners using the Ward linkage criterion and the Euclidean distance as similarity metric. The algorithm starts by treating each runner as a cluster and then merges the closest pair of clusters until every runner belongs to one single cluster. The optimal number of clusters was selected based on the Silhouette score (Rousseeuw, 1987) and inspection of the dendrogram. SPM (1D) and traditional (0D) statistical tests (alpha level = 0.05) were performed to assess if the differences between clusters were statistically significant and biomechanically meaningful (greater than systematic errors). This process (Figure 1) was repeated for every speed and the resulting clustering partitions at subsequent speeds were compared using the adjusted mutual information score (AMI) (Vinh et al., 2010). AMI looks at the similarity between two clustering partitions, taking a value of 1 when the two partitions are equal and 0 when the mutual information between two partitions is equal to the expected value of two random partitions.

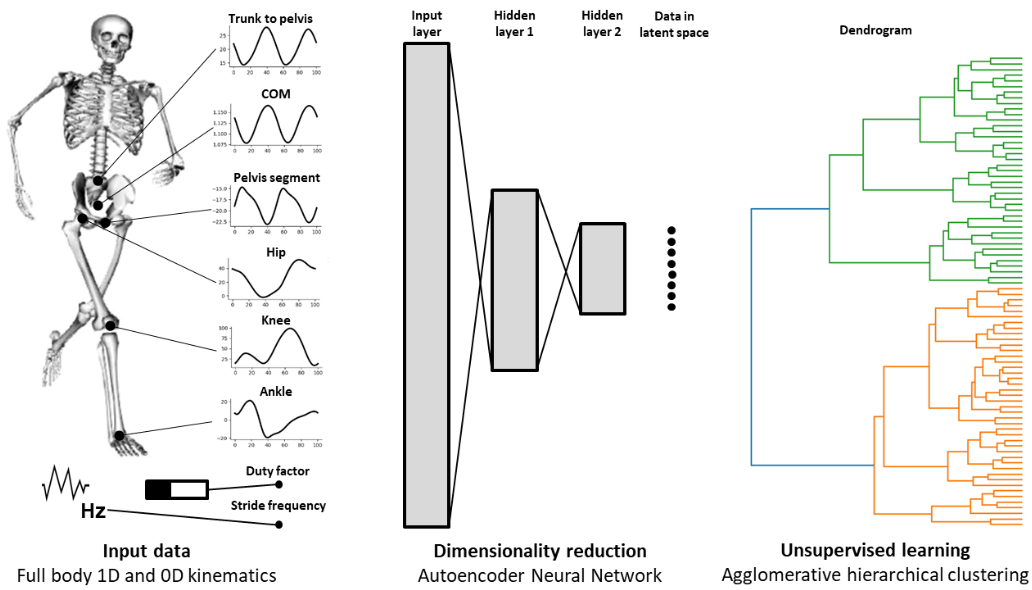

Figure 1: Data processing for each speed. The variables characterising an athlete's running technique (left) were the average vertical displacement of the centre of mass (vCOM) normalised to leg length, and the trunk to pelvis, pelvis segment, hip, knee and ankle angles in the sagittal plane (1D) during a right leg stride and the average stride frequency and duty factor (0D). These variables were concatenated in a 1x1208 array. An autoencoder (centre) was used to reduce the dimensionality of the data from a 1x1208 array to a 1x8 array. Agglomerative hierarchical clustering was then applied (right).

RESULTS: Based on the Silhouette scores, two clusters were selected for each speed (Figure 2). There were statistically significant and biomechanically meaningful differences between clusters (see Figure 3 for an example at 11 km/h). The Silhouette scores were generally low indicating low separability of the data. The AMI scores were also low, indicating poor agreement between clustering partitions of individual athletes at different speeds.

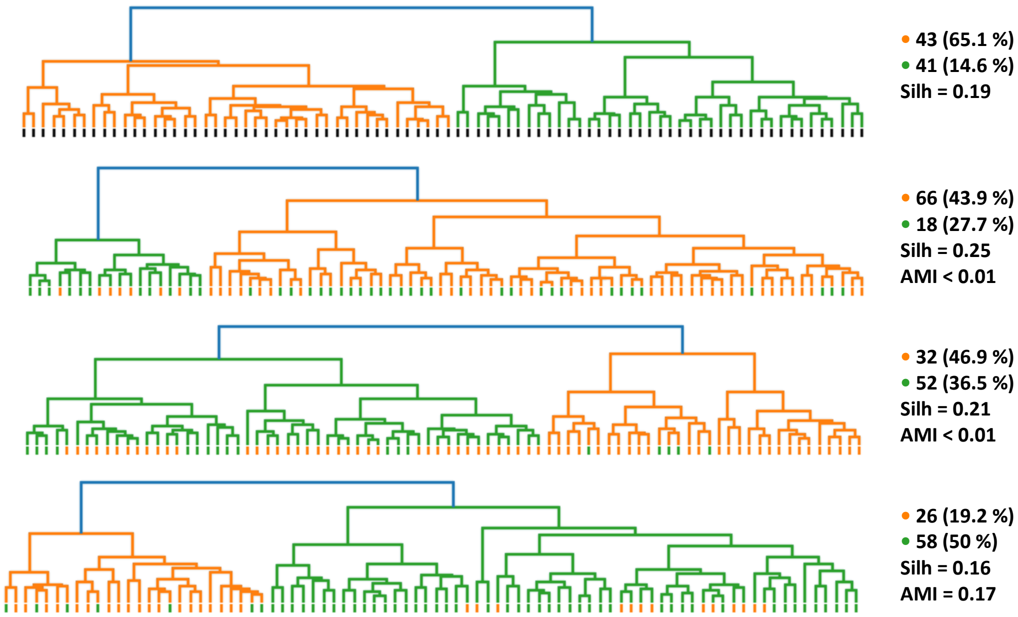

Figure 2: Dendrogram for each speed (10-13 km/h, top to bottom, respectively). To the right of each dendrogram the number of members for each cluster (and the percentage of females) and the Silhouette score (Silh) for the chosen number of clusters. Small vertical lines underneath each branch were coloured as per the cluster that participant belonged to at the previous stage and the corresponding AMI scores are reported on the right hand side.

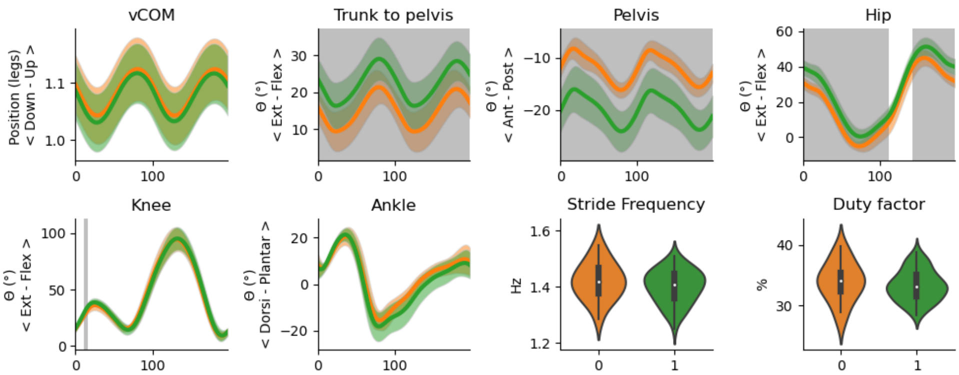

Figure 3: Cluster (green and orange) average patterns (and standard deviation clouds) for 1D variables and violin plots for 0D variables at 11 km/h. Statistically significant differences found by SPM non-parametric and 0D parametric t-tests respectively are highlighted in grey (vCOM: t* = 2.15; trunk to pelvis: t* = 2.40, p = p < 0.001 entire stride; pelvis; t* = 2.53, p < 0.001 entire stride; hip: t* = 2.74, p < 0.001 and p = 0.001 at 0-112 and 142-201 stride time, respectively; knee: t* = 3.08, p = 0.01 at 11-16 stride time; ankle: t* = 2.94; stride frequency: t = 1.26, p = 0.22 and duty factor: t = 0.91, p = 0.36).

DISCUSSION: The purpose of this study was to assess the consistency of clustering partitions of the same athletes running at different speeds. The agreement between partitions was not greater than what could be expected due to chance when comparing the clusters at 10 km/h and 11 km/h; and 11 km/h and 12 km/h and was low when comparing 12 km/h to 13 km/h. Clustering results from studies using a single speed should therefore be interpreted with caution as they might fail to generalise to the range of speeds a runner typically uses.

The selected number of clusters was low compared to previous literature (Hoerzer et al., 2015). The generally low Silhouette scores indicate low separability of the clusters and may explain the inconsistencies in cluster size and in cluster membership across speeds. Low separability of the data would suggest that, overall, athletes' running technique was not so different considering the selected variables. Indeed, even at 11 km/h, where clusters yielded the greatest separability according to the Silhouette score, the biomechanically meaningful differences between clusters were limited and mostly related to the pelvis (Figure 3).

The current results suggest that runners who react similarly to one speed may adapt to changes in speed in different ways. Clustering studies looking at one single speed (Hoerzer et al., 2015; Watari et al., 2018) may be limited in their ability to capture the full profile of runners who participate in different long-distance races in which multiple speeds are required. In future work we will aim at using methodologies that can capture runners' response to a range of speeds, as this may provide a better understanding of running technique and a more comprehensive grouping of runners.

Our selection of variables provides a holistic description of running technique, but it was limited to kinematics. Kinetic and EMG variables may have enriched the description of running technique, the dynamics and muscle coordination patterns behind it. Our choice of clustering method using Ward linkage and Euclidean distance favours spheroid clusters which may or may not suit our data well and is sensitive to outliers. More flexible density-based algorithms could be an alternative, but they require larger datasets and can also pose challenges as internal validity scores for such methods are not as well established.

CONCLUSION: Clustering runners based on their technique at different individual speeds may not lead to consistent clusters across speeds. Clustering runners at one single speed may fail at capturing the full profile of long-distance runners and therefore, might be unsuitable to drive the design of cluster-specific training interventions. Clustering approaches that can capture the range of speeds a runner might use are needed to get a more comprehensive description of running profiles that may assist the design of better targeted running training interventions.

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