INDIVIDUAL RESPONSES TO RUNNING SHOES: AN INVESTIGATION USING UNSUPERVISED MACHINE LEARNING

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This study aimed to investigate the movement patterns of individual subjects during running across three (standardized) shod and one barefoot condition, employing t-distributed stochastic neighbor embedding (t-SNE) and k-means cluster analysis. The t-SNE analysis revealed three individual response strategies to different footwear conditions: (1) maintaining consistent ground reaction force (GRF) patterns across all conditions; (2) maintaining consistent GRF patters across two or three conditions; and (3) exhibiting changes in GRF patterns across all conditions. The cluster analysis showed that subjects were more often grouped into the same cluster when footwear conditions were more similar. The results indicate that only one group of two and one group of three subjects (out of 30 subjects) exhibited similar GRF patterns across all footwear conditions.

KEYWORDS: ground reaction force, footwear, t-SNE, k-means cluster analysis.

INTRODUCTION: A common objective in biomechanics is to suggest optimal interventions tailored to specific individuals. For instance, determining the footwear design that increases comfort, improves performance, and reduces the likelihood of injury for specific groups of individuals is a common goal. The effects of footwear design have predominantly been investigated at a collective level (i.e., group-based approach). This implies that the evaluation of footwear design effects has primarily relied on comparing average responses of groups of individuals. However, even studies involving relatively homogeneous groups, such as young, healthy male recreational runners, have shown varying responses to the same footwear design. Varying responses across individuals were reported in metabolic costs (Roy et al., 2006) and comfort perception (Kong et al., 2010), but also in biomechanical movement patterns. Bates et al. (1983) showed inter-subject variations in ground reaction force (GRF) variables in response to identical footwear designs during running.
Previous research utilized an unsupervised machine learning approach to identify clusters with distinct biomechanical movement patterns during running within a single shoe condition (Hoerzer et al., 2015). Certain clusters displayed distinct preferences to increase comfort. For example, one cluster may prefer more cushioning in the heel area, while another may need additional support in the arch area. Given the finding of distinct movement patterns unique to each combination of subject and footwear design (Horst et al., 2023), there is an emerging requirement for additional research to determine the degree to which subjects are consistently clustered across different footwear conditions.
The aim of this study was to investigate the movement patterns of individual subjects during running across three (standardized) shod and one barefoot condition. Our objective was to investigate (1) how the biomechanical running patterns of the individual subjects differ across the four footwear conditions and (2) whether clustering the running patterns of individual subjects leads to similar clusters across the four footwear conditions.

METHODS: The study involved 30 physically active male subjects (age: 20-28 years; height: 1.80-1.90 m; mass: 71.4-100.0 kg) that were free of lower extremity injuries. An extensive study description is available in Horst et al. (2023). Subjects ran at their preferred (self-selected) speed on a level 15 m runway under one barefoot and three standardized shod conditions: New Balance Minimus (neutral shoe with minimal cushioning), Adidas Adistar Boost (neutral shoe with medium cushioning), and ON Cloudsurfer (neutral shoe with medium cushioning and special outer sole). The order of footwear conditions was counterbalanced across subjects. Each subject completed running trials until ten records with foot strikes on the force plate were obtained. Three-dimensional GRFs were recorded at 1,000 Hz for one right-foot stance phase using a floor-embedded force platform (Kistler, Type 9287CA, Switzerland) located midway along the runway. The recorded GRFs were filtered using a second-order Butterworth bidirectional low-pass filter at 50 Hz. Stance phase was determined based on the filtered vertical GRF using a 10 N threshold. Each GRF signal was time-normalized to 101 data points (100% stance phase) and normalized to body weight for each footwear condition. GRF signals were normalized to each signal's maximum value across all samples, resulting in signals within the range [-1, +1]. The normalized signals were concatenated into a vector containing 303 data points prior to further analysis.

The dimensionality reduction method t-distributed stochastic neighbor embedding (t-SNE) was employed to transform the data into two-dimensional space and allow the identification of patterns and groupings within the data (Van der Maaten & Hinton, 2008). For dimensionality reduction, we utilized the entire dataset (N=1,200; 30 individuals, 4 footwear conditions, 10 trials). A grid search was performed to optimize the t-SNE-specific hyperparameter *perplexity* across the following values 5, 10, 20, 30, 40, and 50. This hyperparameter is linked to how the algorithm defines the sample neighborhoods. Lower values prioritize local structures, whereas higher values incorporate more global structures within the data.

For the exploration of clusters, we first determined a single most representative trial according to Sangeux & Polak (2015) per subject and footwear condition (N=120; 30 individuals, 4 footwear conditions). Subsequently, we applied k-means clustering to these representative trials separately for each footwear condition. Guided by Hoerzer et al. (2015), we utilized eight clusters (k=8). The clustering results for pairs of two footwear conditions were compared using the adjusted Rand index (ARI) and visually represented in the form of a matrix, illustrating which subjects are in the same clusters in the two clusterings. ARI is a measure that quantifies the similarity between two clusterings. A value of zero signifies completely dissimilar clusterings, while a value of one indicates identical clusterings. The workflow for dimensionality reduction and clustering was implemented using Python 3.11.7 and Scikit-learn (1.3.2).

RESULTS: The results of the dimensionality reduction using t-SNE are illustrated in Figure 1. The two plots reveal two influential factors on the analyzed GRF data: subject patterns on a local level and footwear condition on a more global scale.

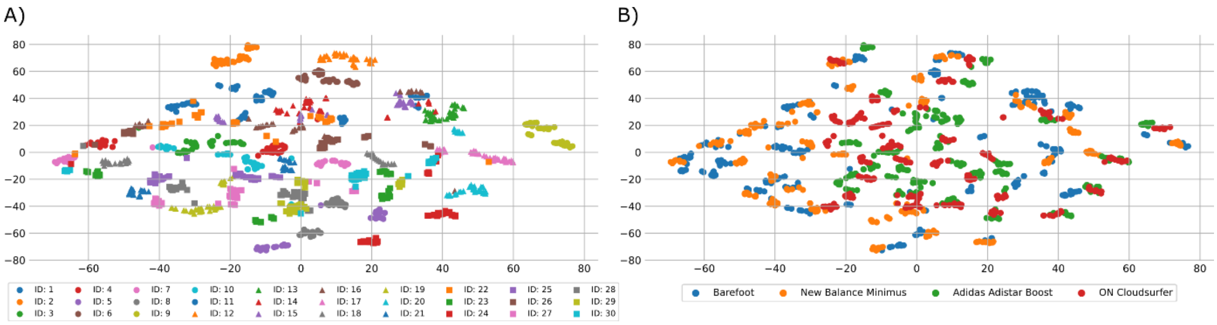

Figure 1: Visualizations of dimensionality-reduced GRF data using t-SNE. In subfigure (A), colors and markers are utilized to distinguish between the 30 subjects. In subfigure (B) colors are used to distinguish between the four footwear conditions.

Samples from the same subject tend to be grouped together when they belong to the same footwear condition. Samples from an individual subject across different footwear conditions may either form an individual group or in cases where the influence of the footwear condition strongly impacts the subject's GRF patterns, these samples may fall in a footwear condition-specific group. On a more global scale, when observing the trans-individual groups, it becomes evident that the barefoot (blue) and New Balance Minimus (orange) data group together, while the other footwear conditions (green and red) form separate groups.
The results of the pairwise comparisons of clusterings are presented in Figure 2. The highest level of overlap between clusterings was found in the comparison of the barefoot condition and the New Balance Minimus shod condition (Figure 2B), which is also evidenced by an ARI of 0.45. The other pairwise comparisons show a limited degree of overlap between the clusterings. The green cells in Figure 2 indicate that two groups of subjects (i.e., IDs 10, 27, 21 and 19, 25) are consistently part of the same cluster across all footwear conditions.

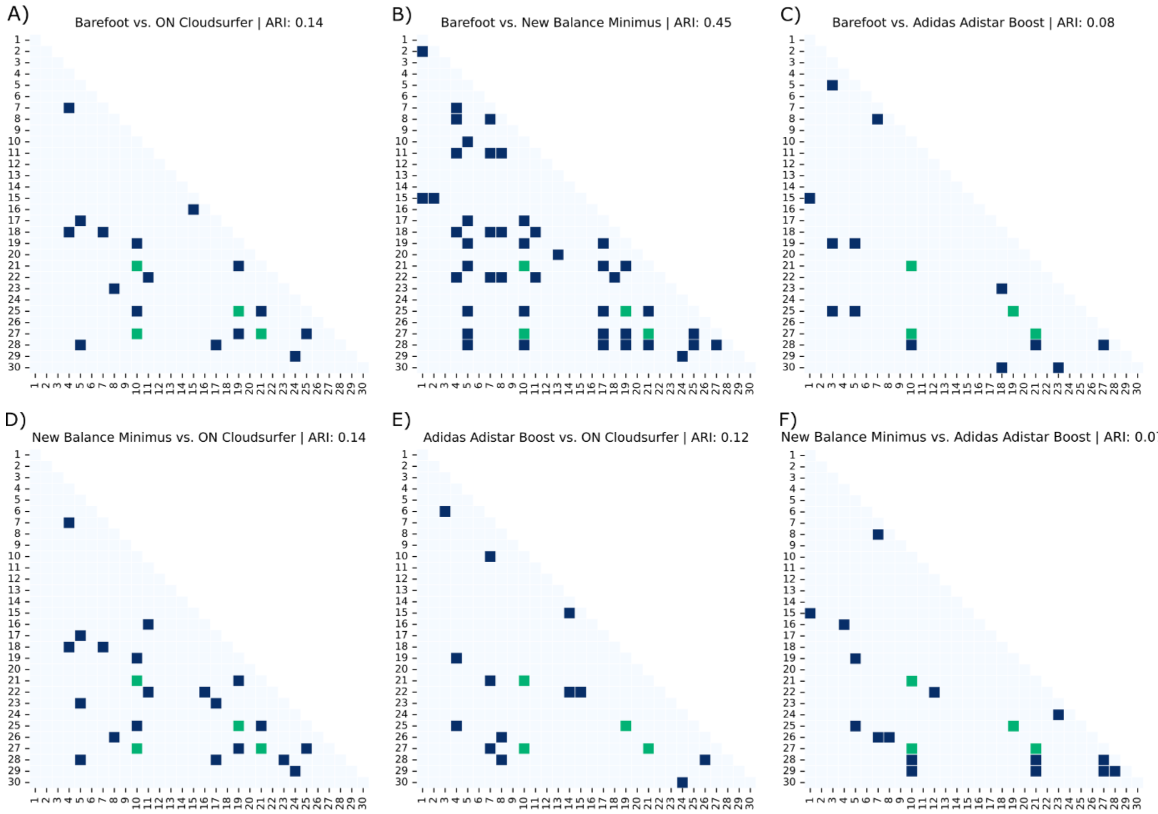

Figure 2: The matrices (A-F) depict pairwise comparisons of GRF data clusterings corresponding to the listed footwear conditions. A blue cell in the matrix indicates that the corresponding subjects are in the same cluster in both clusterings. The green cells illustrate that the corresponding subjects are in the same cluster across all footwear conditions.

DISCUSSION: The exploration of the GRF patterns of 30 subjects who ran overground in three shod and one barefoot condition revealed substantial variation in individual changes of movement patterns across the footwear conditions. Utilizing the dimensionality reduction method t-SNE uncovered three primary individual response strategies to different footwear conditions (Figure 1): (1) Some subjects exhibited a substantial degree of consistency in their GRF patterns across all four footwear conditions (e.g., IDs 2, 6, 9, 12). This suggests that the movement patterns of these subjects are less susceptible to variations in footwear. This observation aligns with previous findings that individual movement characteristics can be identified across different footwear conditions (Horst et al., 2023). (2) A significant portion of subjects maintained their GRF patterns to a considerable extent across two or three of the four footwear conditions (e.g., IDs 7, 18, 25). This suggests that the movement patterns of these subjects are affected by changes between footwear conditions. (3) Some subjects displayed significant alterations in their GRF patterns across all four footwear conditions (e.g., ID 16).

This suggests that different footwear conditions influence the movement patterns of these subjects to a high degree. These three individual response strategies to different footwear conditions indicate an eventual necessity for considering individual (biomechanical) responses to shoe design in footwear research, development, and recommendation. This poses a challenge to studying footwear effects exclusively at a collective level through a group-based approach. Our results suggest that disparities between subjects extend beyond mere changes in the direction (i.e., increase, decrease, no change) of single time-discrete variables (Bates et al., 1983). The observation that some subjects maintained consistent GRF patterns across all footwear conditions, while others undergo drastic changes between different footwear conditions, indicates varying sensitivity to footwear interventions.
The concept of functional groups aims to provide an approach (based on clusterings) to consider differing (biomechanical) responses to footwear (Nigg, 2010). The k-means clustering of GRF patterns of subjects for each footwear condition, along with the comparison of clusterings between footwear conditions (Figure 2) indicates the degree to which subjects have similar GRF patterns across different footwear conditions. The green cells in Figure 2 revealed that only five out of 30 subjects seem to have similar GRF patterns in all four footwear conditions. These findings indicate that clusters across different footwear conditions are more likely if the footwear conditions are more similar. The largest agreement in clusterings can be found between barefoot running and running with the New Balance Minimum, which is a neutral running shoe with minimal cushioning (Figure 2B). This indicates that consideration of clusters with similar movement patterns during running for the comparison of footwear designs is more likely at a micro-level (when comparing similar footwear conditions, e.g., shoes with different individual design features) than at a macro-level when comparing totally different footwear models. Further research is necessary to explore and compare different clustering methods and their respective hyperparameters. In our present study, we utilized eight clusters, following the methodology presented by Hoerzer et al. (2015). However, a side-experiment with varying numbers of clusters revealed the high sensitivity of the approach to this hyperparameter. Despite this sensitivity, the results of this side-experiment exhibited similar overall trends.

CONCLUSION: The results emphasize the individuality of biomechanical data, highlighting not only diverse responses to different footwear conditions but also distinct response strategies. We identified three response strategies and demonstrated that similar movement patterns tend to occur within similar footwear conditions. These findings confirm the importance of considering subject-specific responses to footwear.

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