Modelling Individual Variation in Human Walking Gait Across Populations and Walking Conditions via Gait Recognition

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Summary

This study introduced a new approach to gait analysis that leverages Artificial Intelligence (AI) to explore how gait varies across individuals, groups and populations. Deep learning models were trained for person recognition using different sets of walking ground reaction force (GRF) data from around the world (N = 740 individuals, 7400 samples) and then interrogated using Explainable AI (XAI) tools. Recognition accuracy ranged from 52-100%, with factors like footwear, walking speed and body mass coalescing to define variation in GRF patterns. Models exposed to diversity during learning were highly accurate at identifying people across populations and conditions, showcasing the broad potential of force platform hardware and gait recognition software for personalised healthcare and security.

Introduction

Human walking gait is a personal story written by the body, a tool for understanding biological identity. Recent studies at the intersection of healthcare and security combined the strengths of these domains by using large walking GRF datasets in AI models for gait-based person recognition (e.g., [1]). Yet, these models were developed and evaluated on either the same individuals or the same dataset, calling into question the generality of findings across population samples and walking conditions. This study proposed a new method for force platform gait recognition to explore variation in GRF patterns across individuals, groups and datasets with different populations and walking conditions.

Methods

This study used four datasets acquired in different countries for mixed purposes: ForceID-A, AIST, Gutenberg and GaitRec (healthy subset) [1-4]. The datasets contain distinct population demographics and experimental conditions (e.g., no. sessions; footwear and speed constraints). Samples comprised GRF and center of pressure from each stance side (filtered and normalized: time – 100 frames, scale – z-score) and sample size was controlled between datasets (185 individuals × 10 samples). Various deep neural network models were implemented for gait recognition using three data configuration methods: *same-dataset* – models were trained, validated and tested on separate groups from the same dataset; *mixed-dataset* – as per same-dataset except external data was also included for model training; and *cross-dataset* – models were trained and validated on at least one dataset and then tested on a novel dataset. Predictions were generated using a difficult similarity search method to provide conservative performance estimates (measured as mean accuracy over cross-validation). Uniform Manifold Approximation and Projection (UMAP) and occlusion sensitivity analysis were used as XAI tools.

Results and Discussion

Models that learnt to distinguish between individuals from Japan or Germany (barefoot, preferred speed) were relatively ineffective at distinguishing between individuals from Austria or Australia (personal footwear, multiple speeds) (e.g., AIST → ForceID-A: 63-75%). Conversely, models that learnt to distinguish between individuals from Austria or Australia were effective at distinguishing between individuals from all four countries (e.g., ForceID-A → any: 89%+), *especially* those from Japan or Germany (e.g., ForceID-A → AIST: 99%). Overall, performance trends and XAI analyses indicated that footwear, walking speed, mass, sex, height and possibly other time-dependent factors interacted to define variation in gait at multiple levels (e.g., Figure 1).

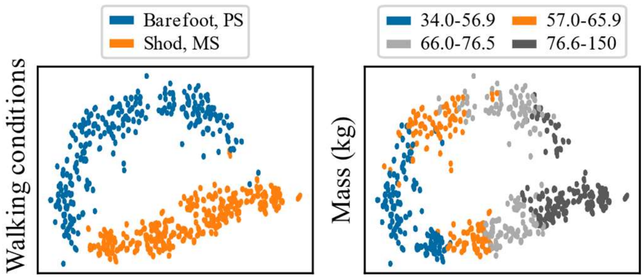

Figure 1: Example UMAP showing how gait samples (dots) from each dataset were modelled (i.e., clustered in feature space) according to walking conditions and body mass quartiles. PS = preferred speed and MS = multi-speed (slow, preferred or fast).

Conclusions

Gait recognition models trained on diverse GRF data can detect features of gait that distinguish between individuals across populations and conditions. Force platforms show substantial promise as stand-alone instruments for personalised data-driven gait analysis.

References

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