

The Effect of Walking Speed on Machine-Learning Based Classification of Gait Patterns in Young and Older Adults

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Summary

Research has shown that gait speed is a reliable predictor of longevity [1]. Faster walking speeds are correlated with better health outcomes and a lower mortality risk, while slower gait speeds can indicate health issues and mobility impairments. The purpose of this study was to classify gait patterns in young and older adults across different walking speeds and identify optimal kinematic features. Gait patterns were compared using radial basis function (RBF) support vector machine (SVM) models based on temporal-spatial (TS) and joint angle (JA) data across 5 walking speeds. Top contributing features were then determined. The model resulted in classification accuracies of 96-100%. SHapley Additive exPlanations (SHAP) analysis showed age- and speed-dependent adaptations that contribute to age classification, which may be valuable for functional mobility assessments.

Introduction

Physical impairment increases with age and is related to declines in mobility and gait. Recently, machine learning (ML) models have been used for classification of young and older adult gait patterns to increase our understanding of age-related changes in kinematics [2]. However, the interrelationship between age-related changes in gait mechanics and physical function remains unclear. Few studies have examined the impact of speed-mediated effects on the classification of young and old gait patterns. Such analyses can lead to improved models of classification and increased understanding of age- and speed-mediated gait adaptations.

Methods

A total of 78 adults: 40 young adults (age=23.70±3.50 yrs; height:1.72±0.13 m; weight: 68.44±16.5 kg) and 38 older adults (age=72.70±5.71 yrs; height: 1.68±0.1 m; weight: 80.47±15.18 kg) participated in the study. A 12-camera Vicon T160 motion capture system (Oxford Metrics Group Ltd., UK) was used to track 36 retro-reflective markers placed on the skin. Six force plates (Kistler Instruments, Winterthur, Switzerland) sampling at 1000 Hz, were used to identify key gait events. Participants walked at various speeds that were post-categorized into 5 bins (very slow, slow, typical, fast, very fast). Joint angle (n=99) and temporal-spatial (n=15) features for each participant's left and right gait cycle were computed. Features extracted from the gait waveforms included max/min values, time to max/min values, and range of motion (ROM), which served as input to SVM classifier with RBF kernel. Forward feature selection was used to select the feature subset with the most accurate classification of young vs older adult gait patterns. Leave-one-out-cross-validation was performed and the mean classification

accuracy was reported. SHAP scores were used to assess feature importance.

Results and Discussion

Gait patterns in young and older adults were distinguished with high accuracy ($\geq 96\%$) across 5 walking speeds. Top speed-dependent features included time to max pelvic downward obliquity (very fast, normal speed), frontal hip ROM (fast), cycle time (slow), and ant/post trunk tilt ROM (very slow). Global feature importance using SHAP scores (Fig. 1), demonstrated distinct age-related gait adaptations at specific speeds.

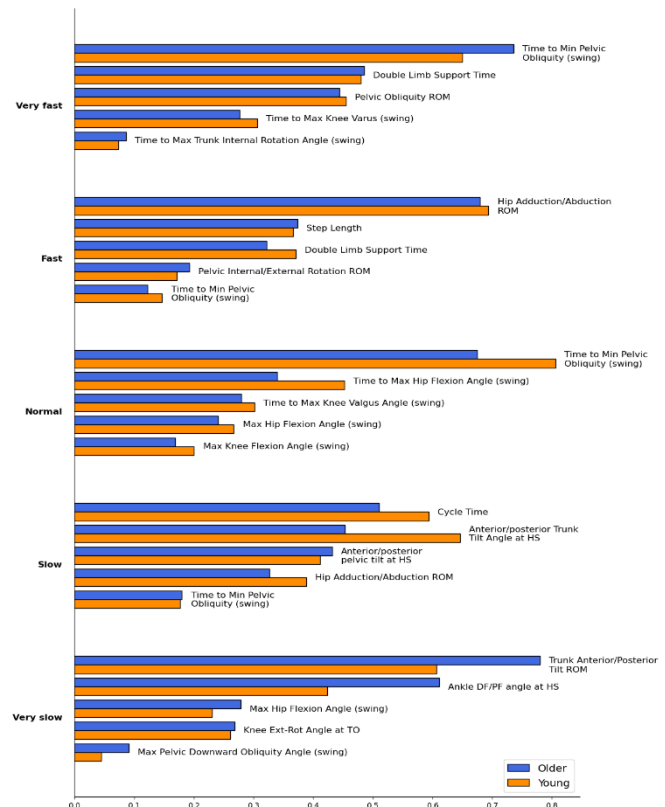


Figure 1: Global feature importance using SHAP scores

Conclusions

Results showed the impact of walking speed on the gait classification in young and older adults, emphasizing the need to consider multispeed biomechanics for improved classification accuracy and address potential biases in ML-based gait analysis.

References

- [1] Bortone I et al. (2021). *JCSM*, **12(2)**: 274-297.
- [2] Begg R et al. (2005). *J Biomech*, **38(3)**: 401-408.