

Classification of Gait Patterns in Young vs Older Adults Using Kinematic Data

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Extended Abstract

Physical impairment increases with age and is related to declines in mobility and gait. Recently, machine learning (ML) models have been used for binary classification of young and older gait patterns to increase our understanding of age-related changes in kinematics [1-3]. However, the interrelationship between age-related changes in gait mechanics and physical function remains unclear. The purpose of this study was to investigate the retrospective classification of gait patterns in young and older adults using 3D kinematic data. Gait patterns in young and older healthy adults were compared using linear and radial basis function (RBF) support vector machine (SVM) models based on kinematic features, including temporal-spatial (TS) and joint angle (JA) data. The most contributing features were then determined. Twenty young participants (10 male, 10 female, mean age 23.75±3.38 years old, mean height 1.71±0.12 m, mean weight 68.26±15.46 kg) and twenty older adults (10 male, 10 female, mean age 72.7±5.56 years old, mean height 1.67±0.09 m, mean weight 80.92±14.13 kg) participated in the study. A 12 camera Vicon T160 motion capture system (Oxford Metrics Group Ltd.), sampling at a 100Hz, was used to track the three-dimensional trajectories of 32 reflective markers placed on the participant's skin as they walked at a self-selected speed. Six force plates (Kistler Instruments, Winterthur, Switzerland) sampling at 1000 Hz were used to aid in the identification of key gait events. The features extracted from the kinematic waveforms included maximum and minimum pelvic, hip, knee and ankle angles during key gait events. The features extracted from TS data included cycle time, step length, walking velocity, single and double limb support time, time to toe-off (TO), cadence, and stride length. These kinematic features, individually and combined, served as input to a SVM classifier with linear and RBF kernels. Features extracted from the kinematic data and their combinations were used to develop support vector machine (SVM) models. ANOVA F-score analysis was used to determine the individual feature importance. Results suggest that combinations of kinematic features retrospectively classified young vs older gait patterns with an accuracy of 97.2%, which was higher than using TS or JA features alone (81.9%, 95.8%, respectively). The RBF kernel models had an overall better performance than the linear models. Additionally, through F-score ranking, we identified that pelvic kinematic features during the stance and swing phase ranked as the top four ($3.47 < \text{F-score} < 9.35$, rank = 1-4) contributors to the classification of young and older gait patterns. These results were similar to past studies that achieved classification accuracies of 75% using ANN with linear, polynomial and RBF kernels using foot clearance data [3], 91.7% by combining TS, kinematic and kinetic gait variables [4], and 90% using ANN with 3D trunk acceleration data [5]. The present study demonstrated that kinematic features, supported by ML models, can provide an accurate and interpretable classification of gait patterns in young and older adults. Further research with increased sample sizes and additional features (e.g. kinetic and EMG) is needed to validate the ML model. The application of ML models, combined with model interpretability, can facilitate an increased understanding of the

interrelationship between age-related changes in kinematics and physical function and aid in identifying optimal treatment programs to maintain independence and improved quality of life in older adults.

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