GAIT PHASE IDENTIFICATION BASED ON IMU READOUTS USING THREE GRADIENT-BOOSTED MODELS

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Introduction

Inertial measurement units (IMU) have enabled quantitative gait analysis to characterize normal/altered gaits of young and elderly individuals and those with disabilities in the natural environment. Most current gait phase identification and temporal event detection methods using IMU readouts suffer from at least one of the following drawbacks [1]: (1) dependency on the morphology of the time series, making them dependent on the ground conditions; (2) lack of sensitivity and precision, making them impractical for real-time applications such as assistive and rehabilitative devices and active exoskeletons; and (3) lack of generalizability and reliability, making them unsuitable for unseen data. By combing and strengthening the implemented decision trees, gradient boosted methods (GBM) can be used in classification problems with high performance in real-time. Therefore, this study aimed to compare the performance of three GBMs in gait phase identification and interpret the feature importance produced by the models' outputs.

Methods

The dataset used for this study contained IMU readouts obtained from seven able-bodied participants (26 ± 3 years old, 72 ± 13 kg, 177 ± 6 cm) during four gait modalities: oval-shaped walking over ground and walking, running, and inclined walking over the treadmill. Additionally, the readouts from two pressure insoles were used as references to identify gait phases.

The dataset was split into training and test sets using the leave-one-out cross-validation approach. Seven-fold cross-validation was implemented with one participant's readouts in the test set and the rest in training set in each fold. XGBoost [2], LightGBM [3], and CatBoost [4] models were fed with the raw IMU readouts labelled either stance or swing according to the reference pressure insole using the threshold of 10N.

Results

In total, 649,814 time-instants were labelled as swing (238,330 instants) or stance (411,484 instants) using the reference method. The average precision of 85%, 87%, and 83%, sensitivity of 91%, 92%, and 91%, accuracy of 85%, 87%, and 83%, and F1 Score of 88%, 90%, and 87% were obtained by XGBoost, LightGBM, and CatBoost models, respectively, to identify gait phases (Table 1).

It was observed that foot angular velocity in the sagittal plane had the highest contributions, among other kinematics time series, as an input to the models. In XGBoost and CatBoost models, foot vertical acceleration had the second highest contribution. Figure 1 shows the contribution of IMU readouts (acceleration and angular velocities presented in the anatomical frames) in the three models.

Performance	XGBoost	LightGBM	CatBoost
Precision	85 ± 4	87 ± 4	83 ± 4
Sensitivity	91 ± 2	92 ± 2	91 ± 2
Accuracy	85 ± 3	87 ± 4	83 ± 4
F1 Score	88 ± 3	90 ± 3	87 ± 3

Table 1: GBMs performance expressed in percentage in predicting the gait phases using leave-one-out cross-validation approach.

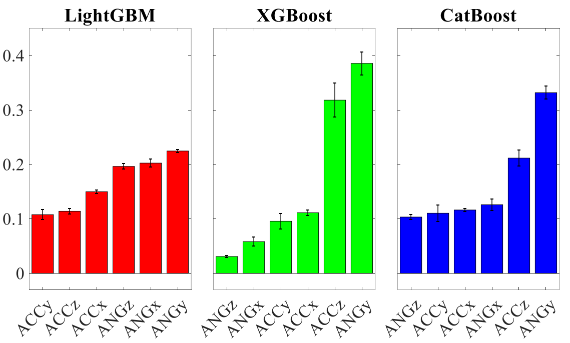

Figure 1: GBMs feature importance where ACC and ANG stand for foot acceleration and angular velocity, respectively, presented in foot anatomical frames (x: anterior-posterior direction or frontal plane, y: medial-lateral direction or sagittal plane, and z: superior-inferior directions or horizontal plane).

Discussion

Gait phases were predicted with high sensitivity (> 91%) and specificity (> 83%) as well as high accuracy (> 83%) using XGBoost, LightGBM, and CatBoost models. Among these models, LightGBM marginally outperformed the other two in identifying gait phases and spread the contributions over all the features (i.e., IMU readouts). Conversely, the contribution of the two most significant features in the XGBoost and CatBoost models was higher than the other features. This interpretation is concurrent with the other morphology-based temporal event detection methods using IMU readouts and distinguishes these GBMs from conventional neural networks. Finally, by increasing the number of participants, their sexual diversity, the gait patterns, and the activity type, gradient-boosted methods can be trained and employed in a comprehensive model for real-time gait analysis appropriate for diverse therapeutic applications.

References

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2. Chen et al, ACM SIGKDD, 785-904, 2016.
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4. Prokhorenkova et al, NIPS, 2018.