Gait Activity Recognition Using Instrumented Shoe Insoles in Persons With and Without Multiple Sclerosis

Victor C.H. Chan[1], Matthew P. Mavor[1], Alexandre Mir-Orefice[1], Ryan B. Graham[1,2]

INTRODUCTION

- ❑ Gait quality assessments for persons with multiple sclerosis (PwMS) requires an ambulatory assessment conducted by clinicians.
  - ❑ However, clinical visits represent a barrier for PwMS, and results may not represent daily walking performance.
- ❑ Instrumented shoe insoles and machine learning (ML) can enable clinicians to unobtrusively obtain gait metrics, track progression, and perform assessments under free living conditions.
  - ❑ An important intermediary step is knowing which activity is being performed.
- ❑ ML has been widely used for activity recognition [1] and may be suitable for gait activity recognition for PwMS.

OBJECTIVE

- ❑ Develop ML models to recognize gait activities in PwMS and healthy persons (Control) using raw data obtained from commercially available instrumented shoe insoles.

METHODS

Participants

- ❑ PwMS:
  - ❑ 18 participants: 5 Male, 13 Female
  - ❑ 54.72 years (±16.85), EDSS: 3.67 (±1.71; range = 0.5-6.0)
- ❑ Control:
  - ❑ 21 participants: 11 Male, 10 Female
  - ❑ 28 years (±6.73), no pain or musculoskeletal disorders

Walking activities

- ❑ Various trials comprised of five activities performed both indoors and outdoors.
  - ❑ Stand, walk, turn, stair ascend, and stair descend.

Instrumentation

- ❑ Shoe insoles instrumented with pressure, gyroscope, and accelerometer sensors (ReGo, Germany; 50 Hz).
  - ❑ Streamed to smartphone application (Celestra Health, Canada) via Bluetooth (Figure 1).
- ❑ Xsens MVN Link motion capture suit (240 Hz).
  - ❑ Used for ground truth activity labelling.

Figure 1. Celestra Health smartphone application.

ML Model Development

- ❑ Raw data from insoles used as input (Figure 2).
  - ❑ Data from PwMS and Control were concatenated together.
  - ❑ Activities labelled using data from Xsens suit (Figure 3).
- ❑ A fully-connected artificial neural network (NN) trained using a sliding window approach [2].
  - ❑ Stochastic gradient descent was used for hyperparameter optimization.
  - ❑ NN architecture shown in Figure 4.

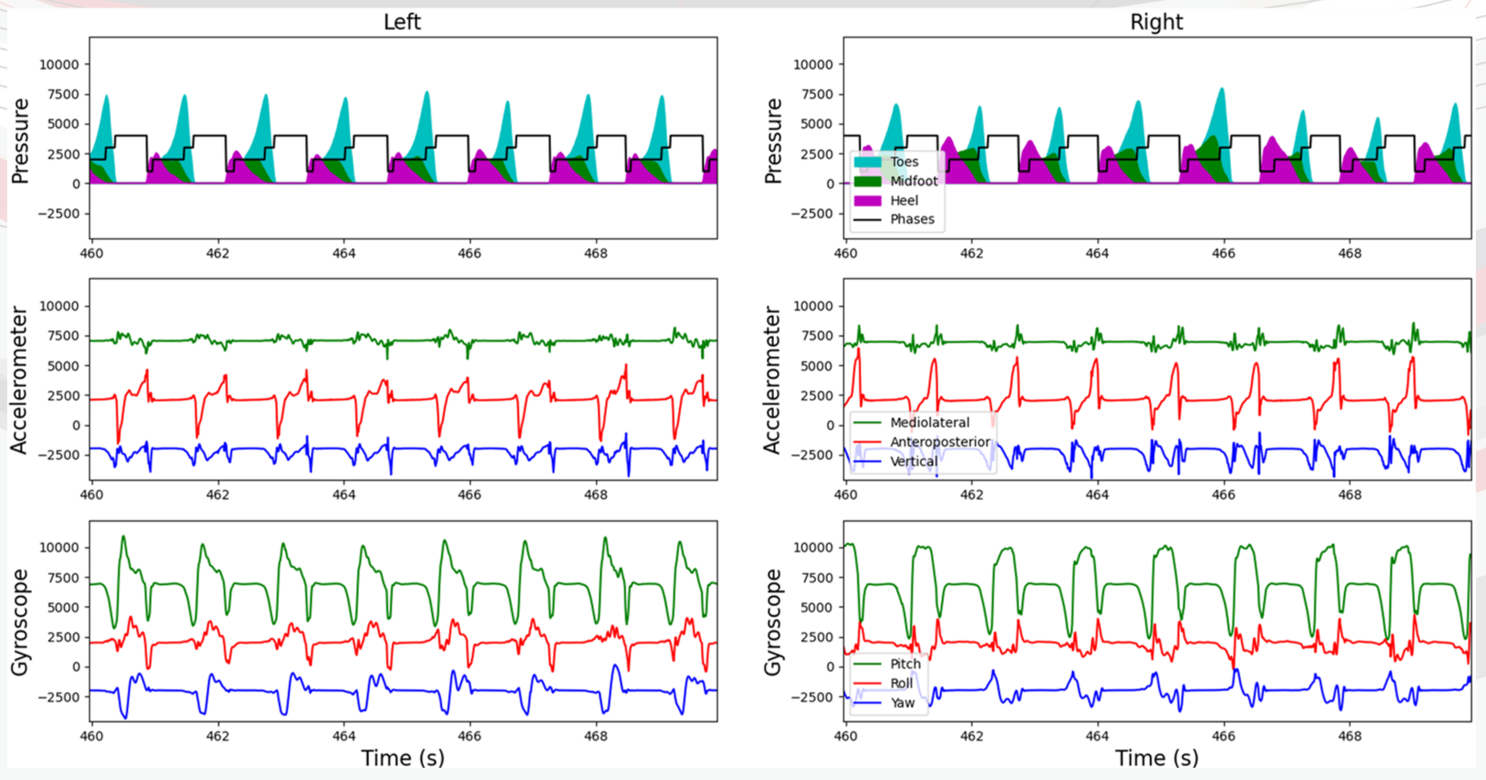

Figure 2. Sample of raw sensor data from the instrumented shoe insoles. Each insole had 16 pressure sensors, an accelerometer, and a gyroscope.

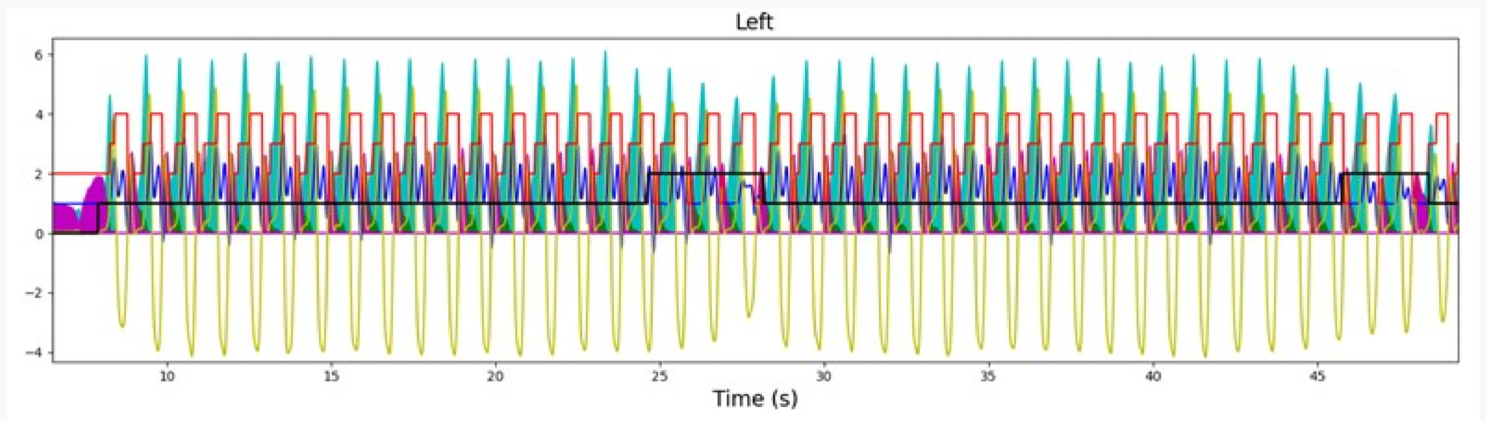

Figure 3. Example of raw sensor data labelled as stand, walk, turn, stair ascend, or stair descend. The true activities were known using the kinematic data from the Xsens suit.

METHODS (Continued)

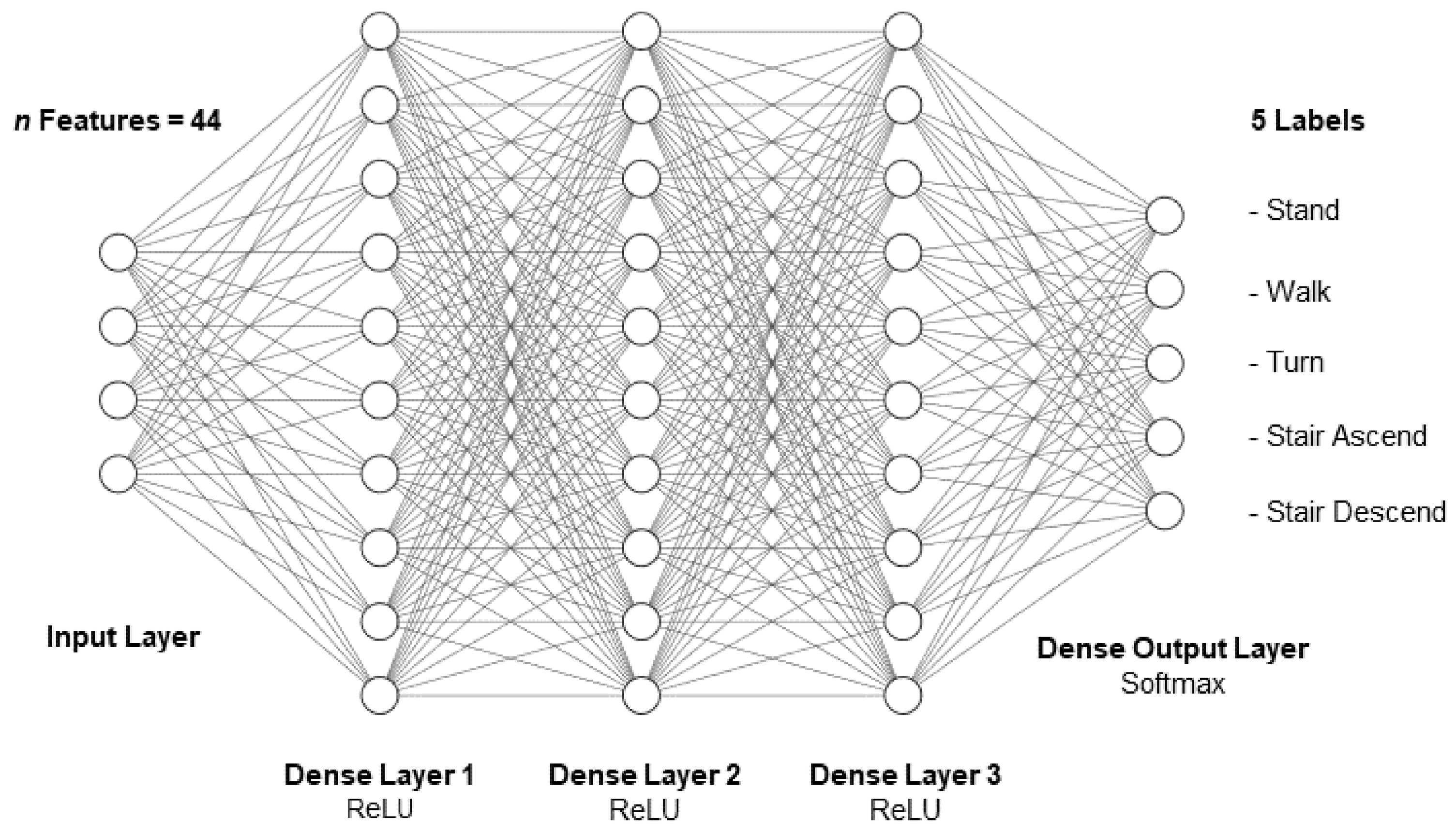

Figure 4. Architecture of the fully-connected artificial neural network. The 44 features were the 16 pressure sensors and the x, y, and x components of the accelerometer and gyroscope, for both insoles. ReLU = rectified linear unit.

ML Model Evaluation

- ❑ Hold-out testing was used to evaluate the NN.
  - ❑ All data from 1 randomly selected PwMS and Control participant used for validation and testing, each (i.e., 4 participants withheld from training) [3].
- ❑ Model performance evaluated using accuracy, loss, and weighted averaged F1-score.
- ❑ Model speed evaluated using training and prediction speed.

RESULTS

- ❑ The model achieved excellent classification performance (Table 1).
- ❑ The time to train the model was 256.04 s.
- ❑ Average time to classify 1 min of data (= 3,000 frames consisting of 44 features) from 1 person (pair of insoles) = 0.0175 s.

Table 1. Results of the hold-out testing for the fully-connected artificial neural network. The model was trained using data from both persons with multiple sclerosis and healthy persons.

Performance Metric	Score
Accuracy	94.4%
Loss	0.166
Weighted average F1-score	94.2%

DISCUSSION

- ❑ Commercially-available instrumented shoe insoles can be used to accurately identify walking activities in both PwMS and Controls in near real-time without data processing.
  - ❑ The current speed and performance of this model allows for its implementation as an intermediary step to automatically inform which algorithms to deploy to compute gait metrics relevant to clinicians and PwMS [4].
  - ❑ These, in turn, can be used to allow for remote gait assessments for PwMS.
    - Objective data can be provided to clinicians for tracking improvements or declines.
    - The burden of travelling to health professionals can be lessened for PwMS.
    - The instrumentation is accessible to PwMS.
- ❑ The large range of EDSS scores in this dataset present large kinematic variability that make activity recognition more difficult than with only healthy individuals [5].
  - ❑ Additional data will improve model performance and robustness.

Future Directions

- ❑ Analyze the trade-off between speed and performance when using processed data as inputs, such as spatiotemporal variables.

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[1]School of Human Kinetics, Faculty of Health Sciences, University of Ottawa, Ottawa, ON, Canada.
[2]Ottawa-Carleton Institute for Biomedical Engineering (OCIBME), Ottawa, ON, Canada.

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