

Preliminary evaluation of ear-level gait and postural stability monitoring technology

Justin R. Burwinkel, Au.D., Eitamar Tripto, M.S., Etti Barel, M.S., Roy Rozenman, B.Sc.

Presented at the Annual meeting of the American Academy of Audiology, Seattle, WA, April 2023



Hear better. Live better.

INTRODUCTION

Hearing aids are among the few wearable devices that can be worn comfortably and unobtrusively for extended periods of time. Recently, motion sensors have been embedded into commercially-available hearing aids for the purposes of helping the wearer to track their daily physical activity and to automatically send notifications to caregivers should the hearing aid wearer sustain a fall^{1,2}.

Wearable motion sensor data may also become useful for the prevention of future falls. For example, instrumented falls risk screening tasks have previously employed machine learning to differentiate fallers and non-fallers^{3,4}. Additionally, data from home-based walking tasks and passive activity monitors have both been used to yield clinically accurate and meaningful insights regarding a wearer's functional capacity⁵. It has been postulated that sensors embedded in hearing aids could be leveraged to identify potential fallers from non-fallers and prompt interventions.

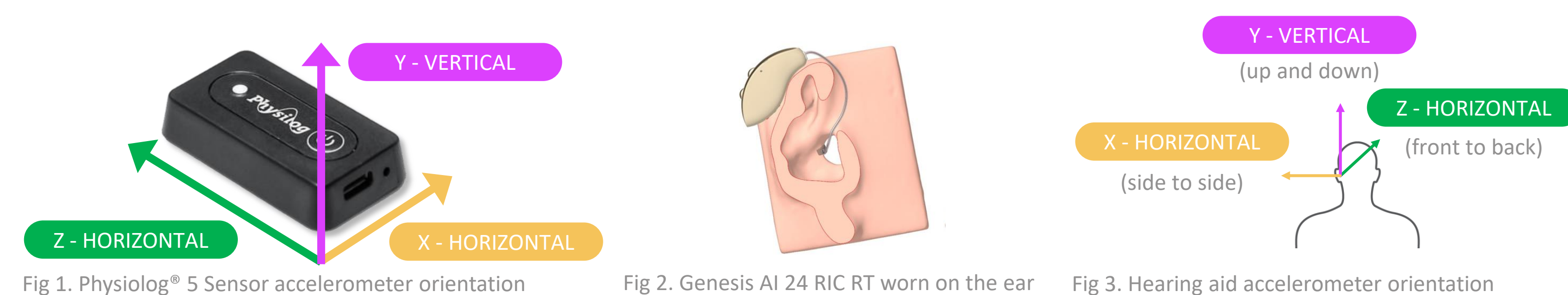
As a result, several prototype hearing aid applications have been developed to evaluate gait patterns and autonomously score several falls risk screening tests. An independent investigation recently found that the hearing aid application scored structured falls risk screening tests similarly to trained clinical observers⁶. However, passive monitoring during typical daily activities may be less burdensome for the wearer and allow for greater granularity in assessing chronic data. This poster discusses the development process and presents an initial feasibility assessment for using ear-level motion sensor data to assess specific gait pattern signatures during periods of hearing-aid users' free walking.

METHODS

PARTICIPANT GROUPS

- Young adults with normal hearing (n=20), Average age: 32 years
- Older adults with hearing impairment (n=10), PTA: 51 dBHL, Age: 65-88 years

MOTION SENSOR TRAINING DATA COLLECTION



- Participants provided researcher-observed, self-selected gait speed samples while wearing motion sensors and walking on hard-surface walkways
 - Bipedal shoe-worn Gait Up Physiolog[®] 5 sensors stored 6-axis accelerometer and gyroscope, barometric, and temperature data to their internal storage
 - Binaural hearing aids with embedded inertial measurement units (IMUs) wirelessly streamed 6-axis accelerometer and gyroscope data to a tablet for storage
- The Older adults group completed the CDC's 12-item "Stay Independent" falls risk assessment questionnaire and completed gait, strength, and balance tests

METHODS (CONT.)

GROUND-TRUTH GAIT ANALYSIS

- Video recordings served as a visual reference for analyzing the bouts of walking
- Gait Up Lab software⁷ and its algorithmic codebase were used to generate cycle-by-cycle calculations of 46 spatio-temporal metrics of gait

MACHINE-LEARNING ALGORITHM TRAINING

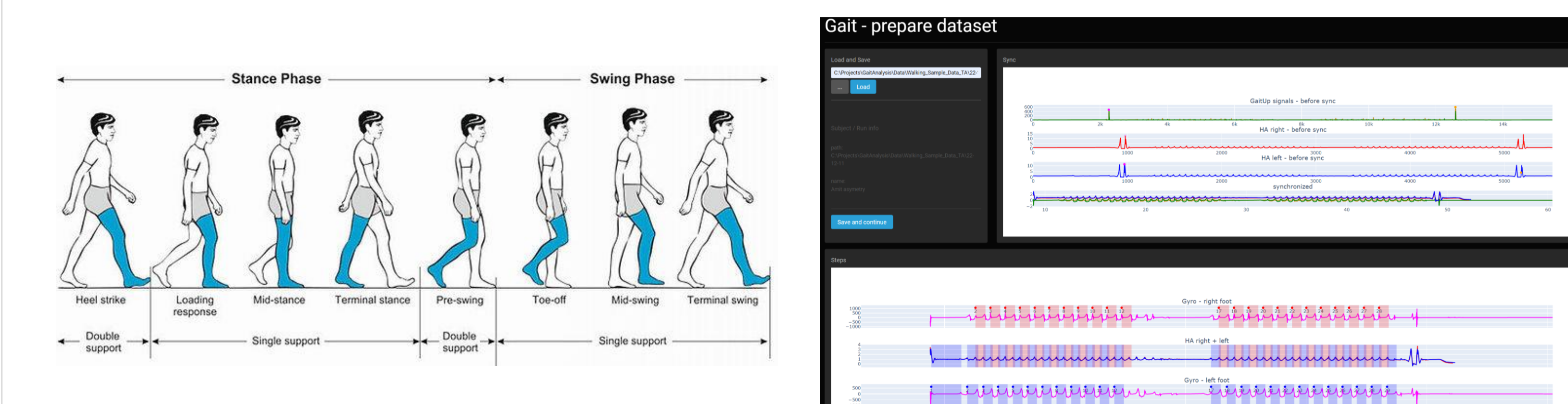


Fig 4. "Phases of the normal gait cycle" by Pirker & Katzenschlager is licensed under CC BY 4: <http://creativecommons.org/licenses/by/4.0/>

Fig 5. Screen capture of the custom software tool that was developed to align and label synchronous motion sensors' data for machine-learning algorithm training

A custom PC-based software (Figure 5) was developed to align synchronous motion sensor data across all recording devices, display ground-truth calculations derived from the Gait Up Lab software/gait analysis algorithms for the foot-worn motion sensor data, and allow the researcher to manually review the reference labels.

The algorithm consists of a neural network inputting full strides (i.e., right-heel strike to next right-heel strike) and outputting the right and left toe-off event markers. The network was trained using cross-validating methodology where training was conducted repeatedly on data from 2/3 of all the subjects and then validated on the remaining 1/3 for each fold. The machine-learning training process was repeated until peak performance was achieved.

RESULTS

The unique morphology of a walking stride allows for the detection of the heel strike at the peak of y-axis acceleration signal (marked by ★) and the x-axis provides useful information about the toe-off timing (marked by ▲). The morphology of a typical adult shows symmetrical "W" or "M" shaped pattern, depending on the foot leading the stride of interest.

Metrics for gait symmetry and double support time can be derived from the accurate detection of heel-strikes and toe-offs. Figure 6 is an illustrative example of three strides, as measured from a right-side hearing aid that was being worn by a typical young adult subject, during a bout of free walking. Older adults and individuals with balance difficulties tend to display altered gait patterns with increased sway and bipedal floor contact time.

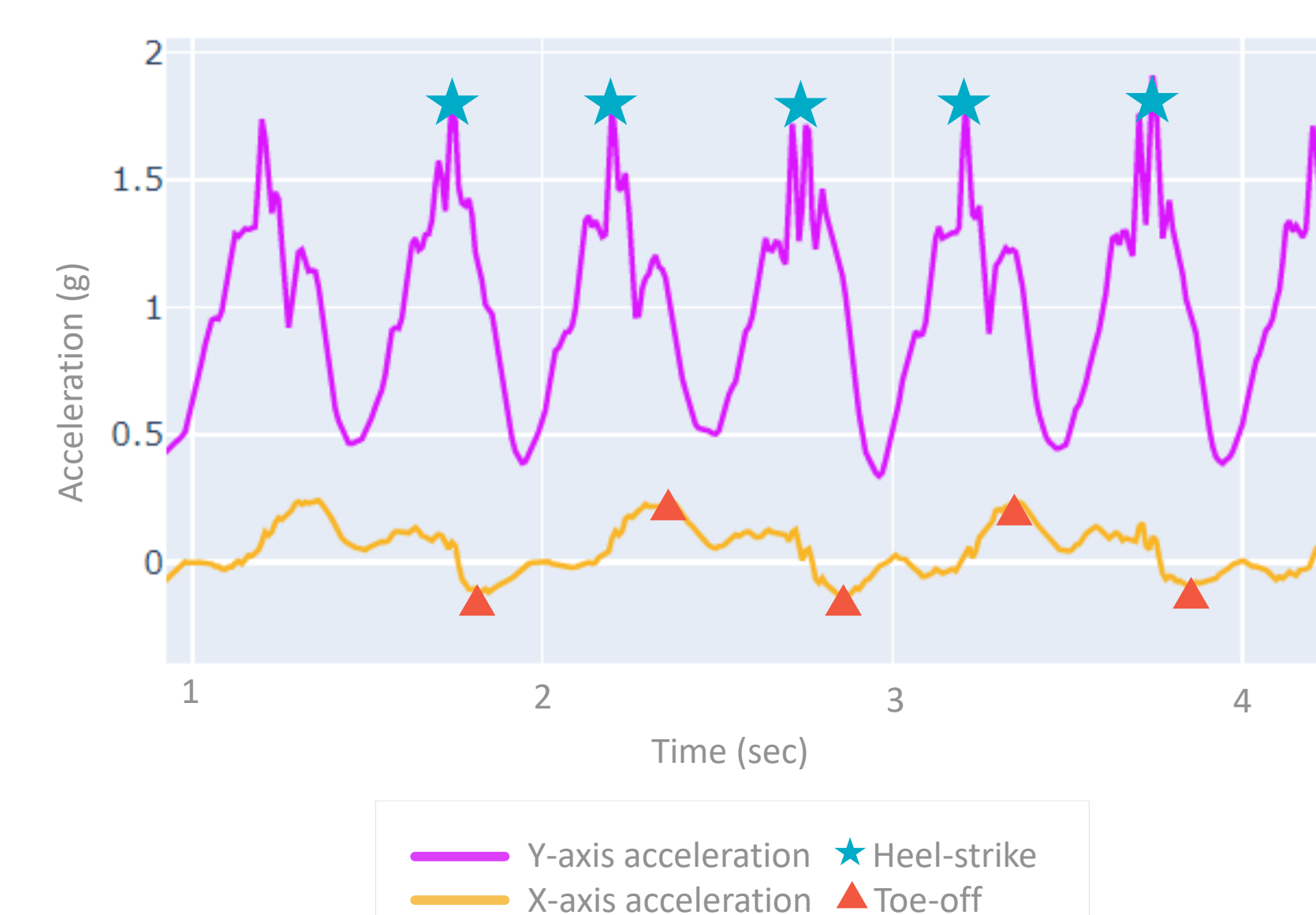


Fig 6. Analysis of ear-level motion sensor data was processed with the machine-learning algorithm, which provided automated detection and labeling of heel-strike and toe-off events.

RESULTS (CONT.)

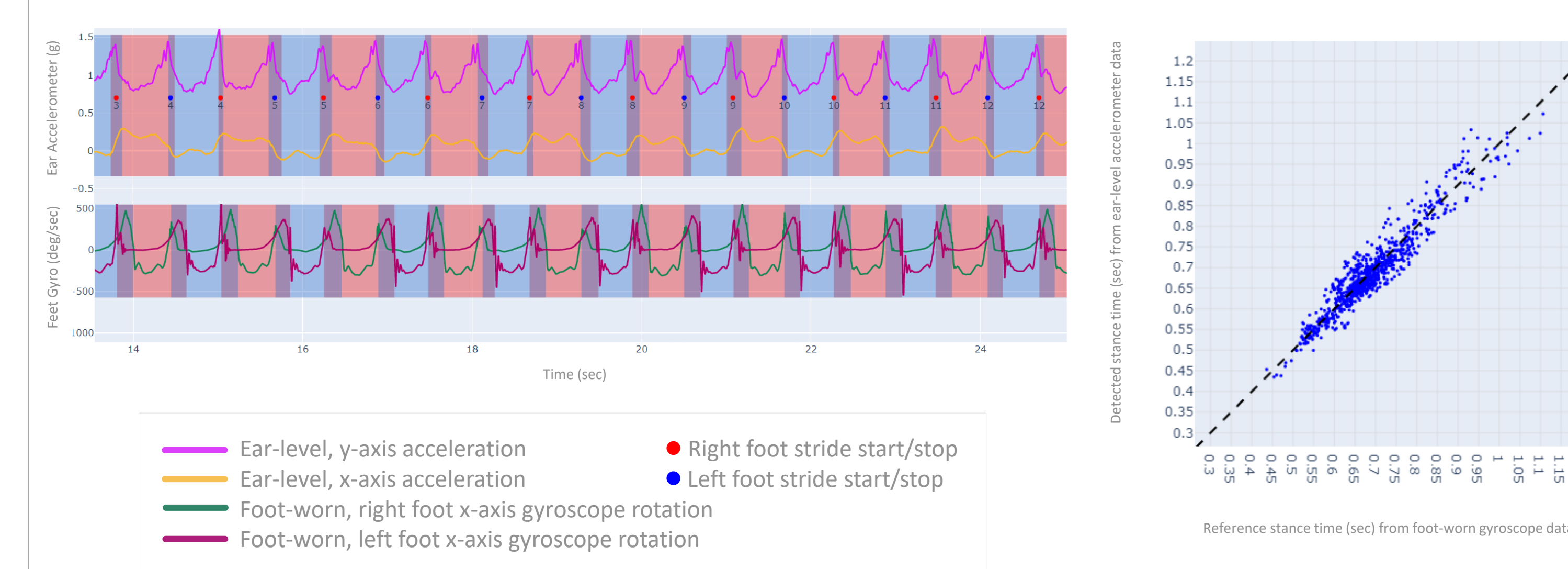


Fig 7. Synchronous raw motion sensor data from ear-level accelerometer and foot-worn gyroscope is shown with sided leg support and double stance phases identified.

Fig 8. The stance time detected by the machine-learning algorithm based on ear-level accelerometer data (y-axis) compared to the reference stance time derived from foot-worn gyroscopes (x-axis).

Figure 7 shows the heel-strikes and toe-offs detected when processing raw motion signals from both ear-level and foot-worn sensors. The performance of the ear-level machine-learning algorithm was characterized by comparing its output to that provided by the ground-truth foot-worn motion sensor analysis software and algorithm codebase for approximately 1,000 samples of walking strides at participants' self-selected walking speed. The comparisons shown in Figure 8 demonstrated 87% agreement for the calculation of stance time (i.e., heel-strike until toe-off) within a tolerance of 50 msec.

DISCUSSION

- Analysis of the accelerometer signals from the ear-level motion sensors embedded in the hearing aid, shows that heel-strike and toe-off events can be readily identified on the y- and x-axis respectively.
- Comparisons between the ear-level motion sensor analysis demonstrated good agreement with the ground-truth foot-worn motion sensor analysis for self-selected walking speeds.
- These results suggest that hearing aids have the potential to help measure relevant metrics of a wearer's gait and help identify individuals at risk for falling and monitor for changes in status.

REFERENCES

1. Burwinkel, J.R., Xu, B. & Crukley, J. Preliminary Examination of the Accuracy of a Fall Detection Device Embedded into Hearing Instruments. *Journal of the American Academy of Audiology* **31**, 393-403 (2020).
2. Rahme, M., Folkeard, P. & Scollie, S. Evaluating the Accuracy of Step Tracking and Fall Detection in the Starkey Livio Artificial Intelligence Hearing Aids: A Pilot Study. *Am J Audiol* **30**, 182-189 (2021).
3. Howcroft, J., Lemaire, E. D. & Kofman, J. Wearable-Sensor-Based Classification Models of Faller Status in Older Adults. *PLOS ONE* **11**, e0153240 (2016).
4. Zakaria, N. A., Kuwae, Y., Tamura, T., Minato, K. & Kanaya, S. Quantitative analysis of fall risk using TUG test. *Computer Methods in Biomechanics and Biomedical Engineering* **18**, 426-437 (2015).
5. Rens, N. et al. Activity data from wearables as an indicator of functional capacity in patients with cardiovascular disease. *PLOS ONE* **16**, e0247834 (2021).
6. Griswold, B. et al. Use of hearing aids with embedded inertial sensors and artificial intelligence to identify patients at risk for falling. (2023). Presented at the annual meeting of the American Balance Society, Scottsdale, AZ.
7. Gait Up SA. (2017). Gait Up Lab Software (Version 1.1.1) [Software].