MODULE 1-P2: Gait parameters and fall risk assessment among the elderly in Singapore

Kai Zhe Tan[1], Parastoo Fahimi[1], Sai G.S. Pai[1] , William R. Taylor[1,2], Navrag Singh[1,2]
[1]Singapore-ETH Centre, Future Health Technologies Programme, CREATE campus, Singapore
[2]Institute for Biomechanics, Dept. of Health Sciences and Technology, ETH Zurich, Zurich, Switzerland

1 Motivation

- A major challenge in the prevention of falls is the identification of individuals who are at risk of falling owing to an unstable gait.
- Holistic metrics that are able to comprehensively characterise locomotor patterns will allow an accurate assessment of an individual's risk of falling.

2 Aim

- Using ZurichMOVE, a wearable sensor to conduct gait assessment in clinical and community settings.
- Evaluation of dynamic stability and gait variability via biomechanical measures of foot kinematics (gait parameters) as inputs of a novel fall risk assessment tool based on machine learning.

3 Approach

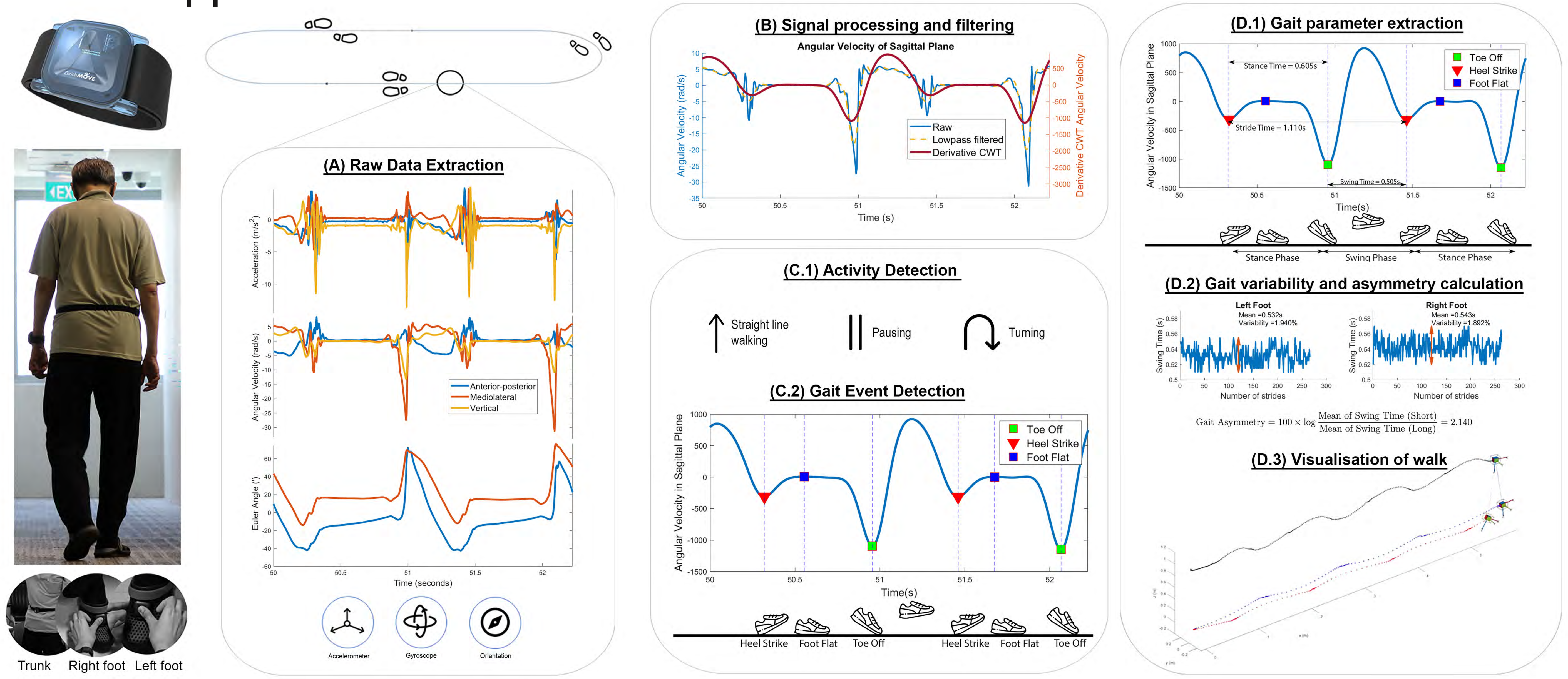

Figure 1: A 6-minute walk test is conducted on elderly participants in the PIONEER (The PopulatION HEalth and Age-Related SEnsory Decline PRofile) study cohort. Three ZurichMOVE wearable sensors are attached to the trunk, left foot and right foot to record their movement. Figure shows an excerpt of the data extraction and processing pipeline[1]: (A) the raw acceleration, angular velocity and orientation of the sensors are first extracted. (B) The raw data is filtered to eliminate inherent noise of the sensor. In this case, the angular velocity of the foot sensor in the sagittal plane is first filtered using a low pass Butterworth filter, and then smoothed by using numerical differentiation based on wavelet transform. The filtered data is used for activity detection (C.1) to segregate straight line walking, pausing and turning. (C.2) The smoothed angular velocity of the foot sensor in the sagittal plane is used for gait event detection (identifying time of heel strike, flat foot and toe off during walking). With the data segmented according to the activities, gait parameters are extracted. For example, temporal gait parameters such as stride time, swing time and stance time are extracted as illustrated in (D.1). The variability (measured by the coefficient of variation) and asymmetry[2] between the left and right foot are then computed as shown in (D.2). The movement of the feet and trunk is visualised in a 3-dimensional space as shown in (D.3).

4 Output and Outlook

- Characterise gait in different domains such as *pace, rhythm, variability, asymmetry, and postural control* (Figure 2) for **easy quality of movement interpretation** and **fall prevention intervention**.
- Build a novel **fall risk assessment tool** using machine learning for associating quality of movement with an individual's inherent risk of falling.

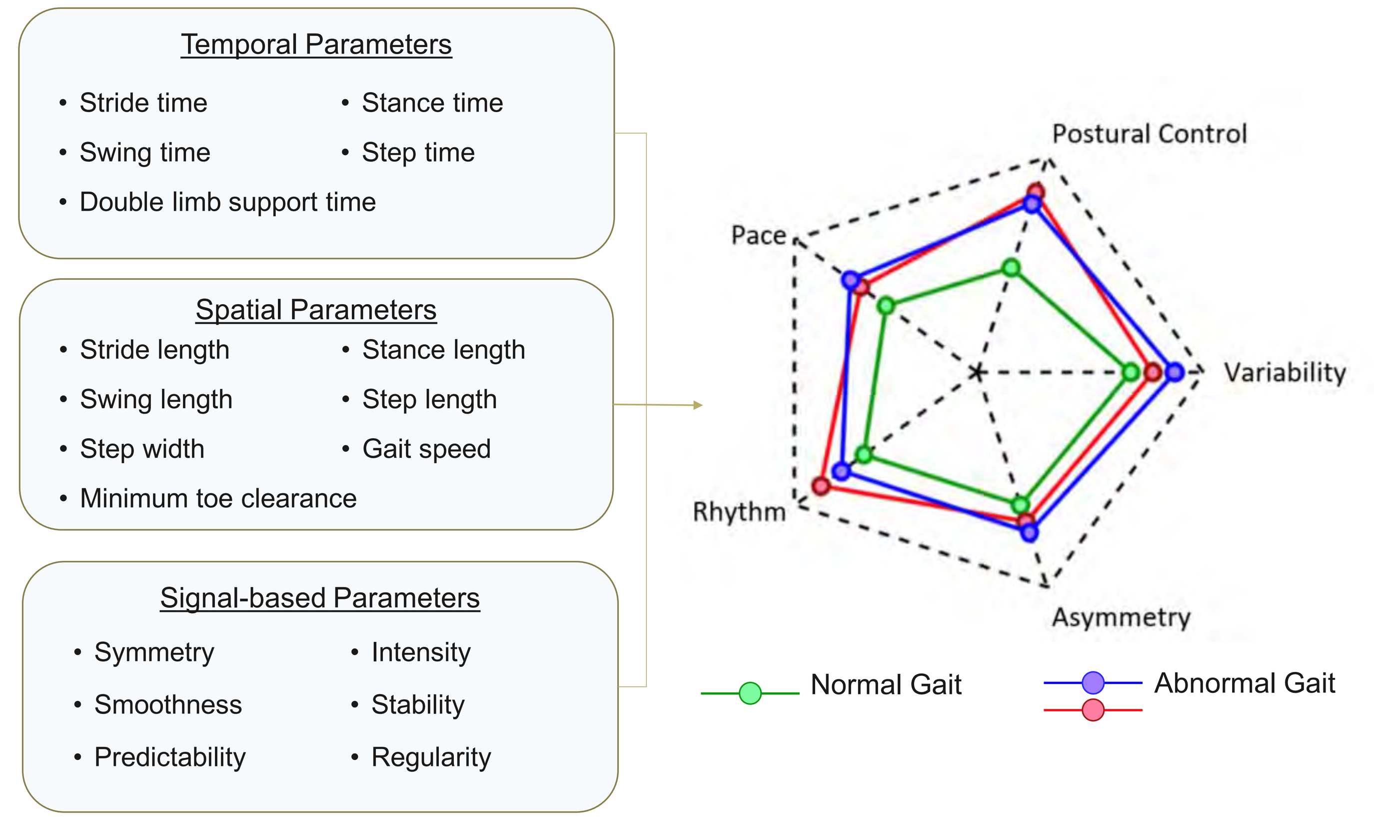

Figure 2: Characterising movement quality of elderly by classifying gait parameters into different domains such as *pace, rhythm, variability, asymmetry, and postural control*[3].

5 References

1. Renggli, D., Graf, C., Tachatos, N., Singh, et al. (2020). Wearable inertial measurement units for assessing gait in real-world environments. Frontiers in Physiology, 11.
2. Plotnik, M., Giladi, N., Hausdorff, J. M. (2007). A new measure for quantifying the bilateral coordination of human gait: Effects of aging and parkinson's disease. Experimental Brain Research, 181(4), 561-570.
3. Lord, S., Galna, B., Verghese, J., et al. (2013). Independent domains of gait in older adults and associated motor and nonmotor attributes: Validation of a factor analysis approach. J. Gerontol. A Biol. Sci., 68(7), 820.

(FHT) FUTURE HEALTH TECHNOLOGIES
(SEC) SINGAPORE-ETH CENTRE
CREATE
ETH zürich
Duke NUS Medical School
Nanyang Technological University Singapore
SingHealth
Singapore Eye Research Institute