# Machine Learning for Assessing Weight-Shifting Rehabilitation Exercises: Data Processing and Early Modeling


**Xintong Liu**

Department of Mechanical Engineering, University of Michigan


MICHIGAN ENGINEERING SUMMER UNDERGRADUATE RESEARCH IN ENGINEERING UNIVERSITY OF MICHIGAN

MICHIGAN ENGINEERING UNIVERSITY OF MICHIGAN

## Background and Introduction

- Weight shifting (WS) is the dynamic process of transferring body weight from one area to another (**Figure 1**), and it is essential for walking, standing, and daily balance control [1].
- Impaired WS is common post-stroke and contributes to asymmetry, instability, and fall risk. Training improves postural control, balance confidence, and functional mobility [1,2].
- Physical therapists (PTs) play a pivotal role supervising and progressing WS exercises, but have limited availability. Wearable inertial measurement unit (IMU) can support PT assessments and home-based training [3].
- **Research goals:**
  - Characterize and prepare weight shifting IMU data for model training
  - Support qualitative coding of PT rationales
  - Preliminarily explore pipelines for WS machine learning models

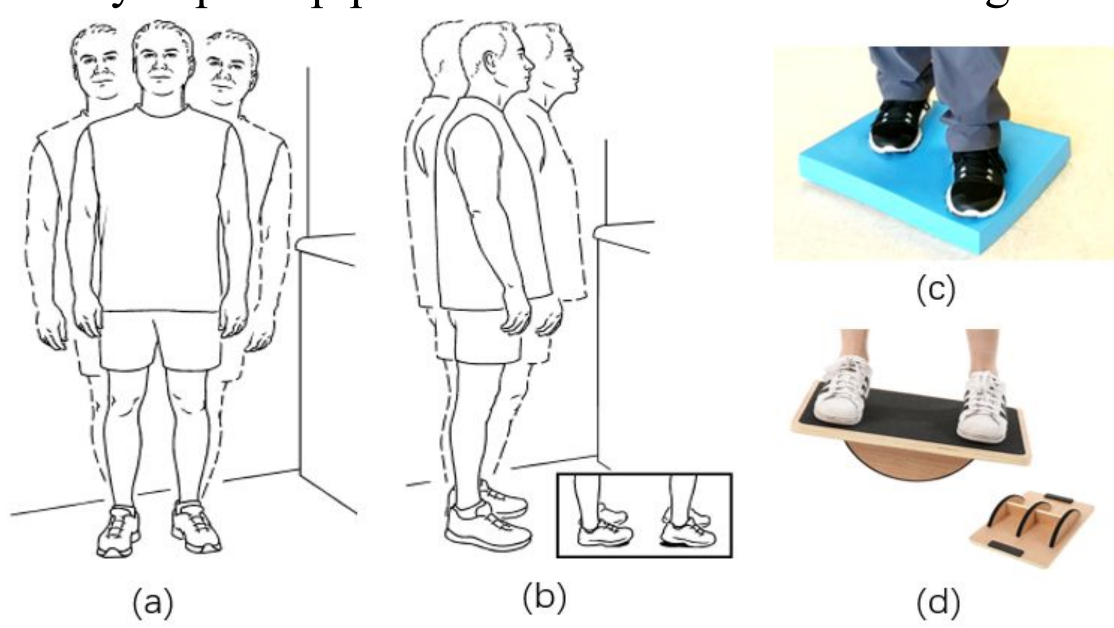

Figure 1. (a) Anterior-posterior (AP) WS, (b) medial-lateral (ML) WS on the firm surface, (c) foam surface, (d) rocker-board surface. Reference:
https://iris.hattiesburgclinic.com/patadv/exkit/Complete%20Balance%20and%20Vestibular/English/0121000300sd001m_English.html
https://iris.hattiesburgclinic.com/patadv/exkit/Complete%20Balance%20and%20Vestibular/English/0121000302sd002m_English.html

## Participants, Data, and Ratings

- **Participants:**
  - 64 adult balance exercisers (42 females, average age: 59, 25% diagnosed with balance deficits)
  - 63 Physical therapists (PTs) with an average clinical experience of 10.2 years treating balance deficits.
- **Data:** balance exercise participants performed 1–4 exercises with 3 trials per exercise and 5 weights shifts per trial with 13 synchronized IMUs. (**Figure 2**)
- **Exercise difficulty**: characterized by 1) eyes closed or open, 2) firm, foam, or rocker board surface as shown in **Figure 1**, 3) direction of weight shifts, 4) speed, and 5) maximum or medium tilts of weight shifts. The number of exercises of different directions and surfaces given different ratings are shown in **Table 3**.

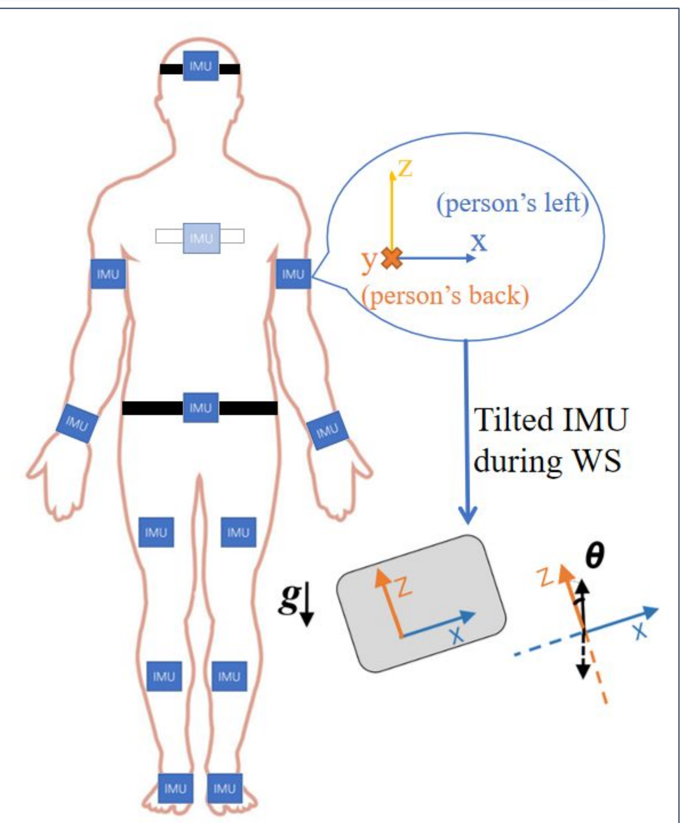


Figure 2. The placement of the 13 IMU and the uniform orientation of the sensor axes after processing.

- **Ratings**: integers from 1 (best) to 5 (worst), provided by the PT for each trial [4]. Trials without ratings have been excluded.

## IMU Data Pre-Processing

- **Data checking with visualized signals (Figure 3)**
  - Confirmed exercises were performed as expected:
    - ☒ 5WS/trial;
    - ☒ ankle driven (amplitudes of the acceleration of the dominant axis were proportional along the body)
  - Confirmed IMUs were present and oriented within the tolerance range:
    - ☒ z-acceleration were approx. +9.8 m/s^2 in value;
    - ☒ peaks and valleys were synchronized among all sensors;
    - ☒ acceleration pattern matched the directionality of the exercise
  - Confirmed step-outs were all marked:
    - ☒ Compared the denoised and original feet IMU signals, and investigated for unmarked step-outs when the denoised signal was more than 7 times smaller than the original signal.

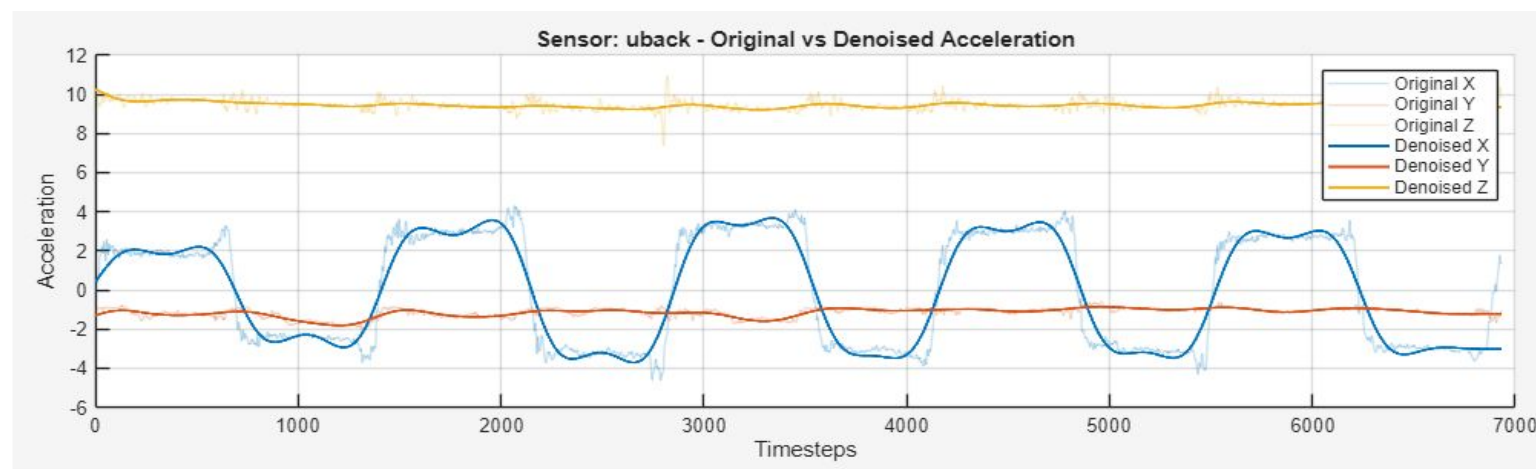


Figure 3. A sample of original and processed signals after filters were applied to remove noise of the IMU sticked to the upper back.

- **Characterization of samples**
  - Calculated max tilt angles with the denoised acceleration of the upper back IMU with the formula: $\theta = (tan^{-1}\frac{a_i}{a_z})\frac{180}{\pi}$ (**Table 2**) (where i was determined by the exercise direction)

Table 2. Typical range of motion (ROM) for ML and AP exercises performed by different participants in units of degrees, where ROM was the difference between the max tilt angles in one direction and the opposite direction along the same axis.

| | medium tilt (deg) | | max tilt (deg) | |
|---|---|---|---|---|
| | mean | std | mean | std |
| ML | 13.6 | 11.8 | 33.2 | 9 |
| AP | 12.1 | 6 | 18.7 | 9.1 |

- **Preparation for model training**
  - Stacked acceleration and angular velocity of all 13 IMUs for each timestep, and input as a matrix.
  - Zero-padded the variable length time series matrix and missing sensors to a fixed length of 17000 timesteps.
  - **Training set**: 398 trials (each as a sample); **Validation set**: 126 trials; **Test set**: 36 trials.
  - Normalized the data with z-score standardization along the axis of features among each set.

Table 3. Class distribution for the subgroups: rocker-board surface (WSR), ML, and AP exercises, where the header is the PT ratings.

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| WSR | 22 | 66 | 39 | 7 | 1 |
| ML | 163 | 126 | 47 | 12 | 6 |
| AP | 83 | 139 | 58 | 73 | 35 |

## Preliminary Model Exploration

- **Bi-directional Long Short-Term Memory (BiLSTM)**
  - A common ML model for time-series input with bi-directional time-dependence.
  - **Input**: a matrix of IMU time series data (+1st step-out timestep); **Output**: a prediction of rating; **Architecture**: **Figure 4.**
  - **Class imbalance** (as shown in **Table 3**) was handled with class weights and random minority oversampling.
  - **Metrics**: accuracy, precision, F1-score, recall, AUROC

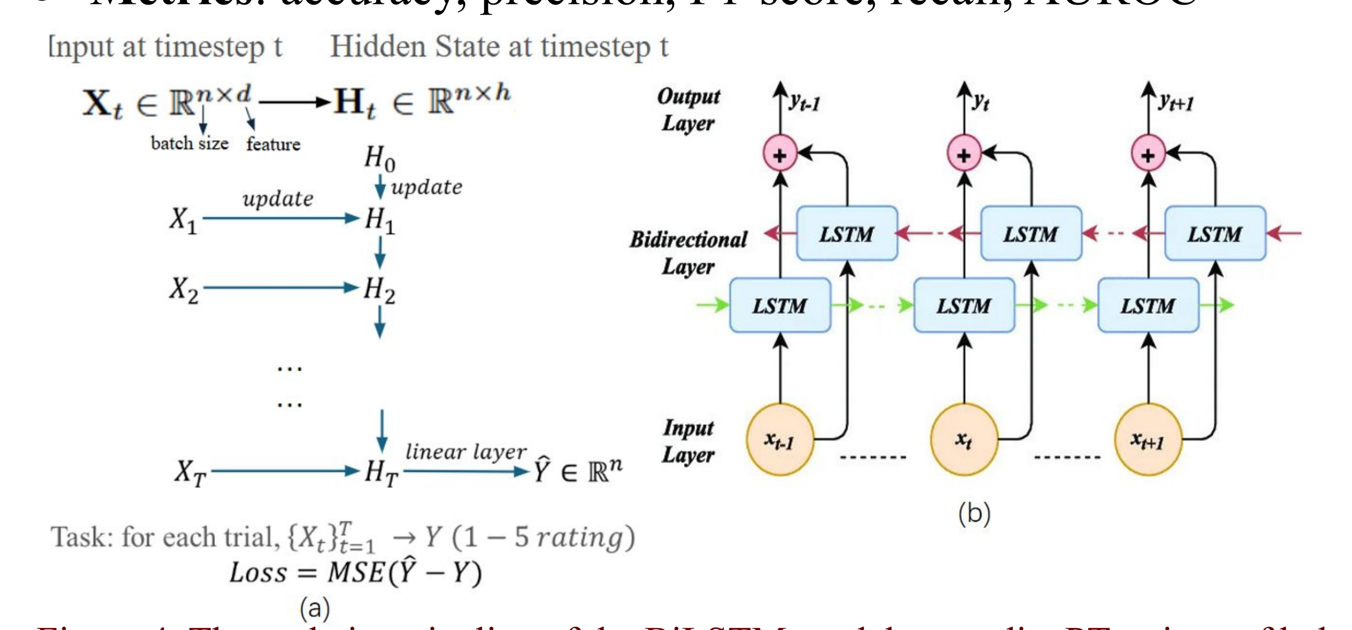


Figure 4. The updating pipeline of the BiLSTM model to predict PT ratings of balance performance in (a); The general architecture of a BiLSTM model in (b).
Reference: https://discuss.pytorch.org/t/regarding-bilstm-for-timeseries-and-input-output-tensors/173571

  - **Preliminary results:**

Table 4. Metrics results for the training and validation set, where the model integrated the 1st step-out time step into the input.

| Rating class | Training | | | | Validation | | | |
|---|---|---|---|---|---|---|---|---|
| | Accuracy | Precision | Recall | F1 | Accuracy | Precision | Recall | F1 |
| 1 | - | 0.78 | 0.86 | 0.82 | - | 0.69 | 0.48 | 0.57 |
| 2 | - | 0.73 | 0.58 | 0.65 | - | 0.35 | 0.46 | 0.40 |
| 3 | - | 0.76 | 0.90 | 0.82 | - | 0.12 | 0.22 | 0.16 |
| 4 | - | 0.98 | 0.91 | 0.94 | - | 0.12 | 0.07 | 0.09 |
| 5 | - | 1.00 | 1.00 | 1.00 | - | 1.00 | 0.20 | 0.33 |
| Overall | 0.848 | 0.850 | 0.848 | 0.846 | 0.381 | 0.459 | 0.287 | 0.310 |

  - **Discussion and Future Work:**
    - Validation results were worse than the training results → overfitting, limited by small sample size → recommend collecting more balanced data, or applying data augmentation.
    - Integrate the step-out and exercise information in the input.
    - Explore simpler architectures (e.g., logistic regression).

## Acknowledgements


This work was supported by the National Science Foundation under Grant 2125256, as well as the University of Michigan SURE Program. The author acknowledges the following mentors: Emma Nigrelli and Hongfan Chen, and the following PIs: Kathleen Sienko, Leia Stirling, Xun Huan.


## References


[1] P. V. Tsaklis, W. J. A. Grooten, and E. Franzén, "Effects of Weight-Shift Training on Balance Control and Weight Distribution in Chronic Stroke: A Pilot Study," *Topics in Stroke Rehabilitation*, vol. 19, no. 1, pp. 23–31, Jan. 2012.

[2] "NSF Award Search: Award # 2125256," *Nsf.gov*, 2021.

[3] S. Jabri, L. Spicher, W. Carender, J. Wiens, and K. H. Sienko, "Automatically Classifying Vestibular Gait Using Time-series Data from Wearable IMUs," *PubMed*, pp. 1–4, Jul. 2024.

[4]T. Bao, B. N. Klatt, S. L. Whitney, K. H. Sienko, and J. Wiens, "Automatically Evaluating Balance: A Machine Learning Approach," IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 27, no. 2, pp. 179–186, Feb. 2019