A Machine Learning Approach to Real-Time Gait Analysis with 3D Augmented Reality Body Tracking

Introduction

Background
- Accurate **classification of gait phases** is essential in addressing one of the major challenges faced by stroke patients and elders, the decrease in gait velocity [1, 2].
- While **marker-based** gait analysis is considered the gold standard, it has its limitations, such as time-consuming marker placement, skin marker occlusions, and the need for controlled laboratory settings [3].
- Study on **markerless gait analysis** has been on the rise, where depth sensors [4], RGB cameras [5], and wearable sensors [6] have shown great promise.
- The **Microsoft Azure Kinect** has surfaced as a possible low-cost alternative for its similar depth capture and human body tracking ability [7, 8].
- The gait phases are determined based on the gait cycle established by Perry, a widely recognized framework [9] (refer to figure 1).
- There is still limited implementation of markerless gait analysis in real-world and real-time applications.

Objective
- Our aim is to develop a **rehabilitation** tool that assists **stroke patients and elderly** individuals with gait disorders in gait training. The tool utilizes real-time gait analysis using **3D augmented reality** body tracking with the help of a Microsoft Azure Kinect camera.
- Different **machine learning** models are implemented to conduct **real-time gait phase classification**.

Methods

Data Collection Procedure
- **Two Azure Kinect cameras** (Camera A and Camera B) connected to a single computer in addition to one treadmill. (Figure 2)
- Two healthy and injury-free adults (aged 22 to 26, 1 male and 1 female) participated in the data collection process.
- Participants were instructed to walk on the treadmill at a speed of 2km/h for a duration of 120 seconds
- Three types of joint angles were opted for analysis (Figure 3): **hip angle, knee angle,** and **ankle angle** and determined from Equation 1.

$$\cos\alpha = \frac{v_1 \cdot v_2}{\|v_1\|\,\|v_2\|}$$

Equation 1.

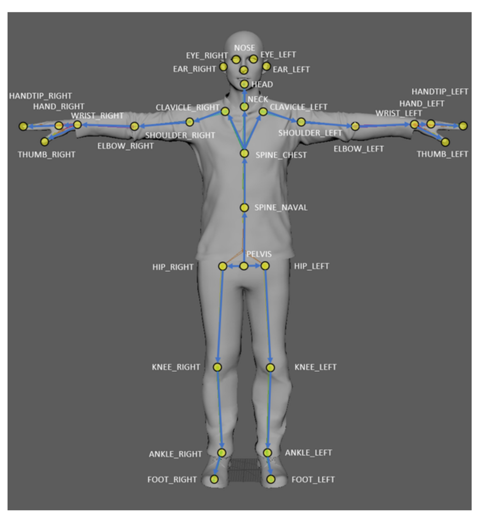


Figure 3 - Azure Kinect Body Tracking Map

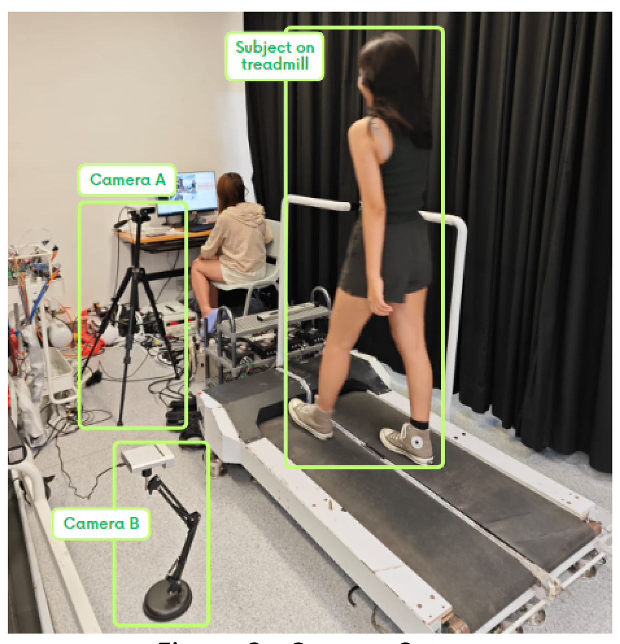


Figure 2 - Camera Setup

Machine Learning Models & Gait Classification
- Knn classifier vs Decision Tree, Random Forest
- **Number of neighbors**: 15, considers the 15 closest data points.
- **Weighting scheme**: 'distance', where closer neighbors have a higher influence on the classification decision.
- **Distance metric**: 'minkowski', a generalized distance metric that includes Euclidean distance as a special case. The Minkowski distance with a parameter of 2 corresponds to the Euclidean distance.

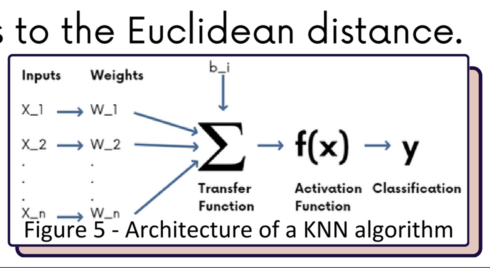


Figure 5 - Architecture of a KNN algorithm

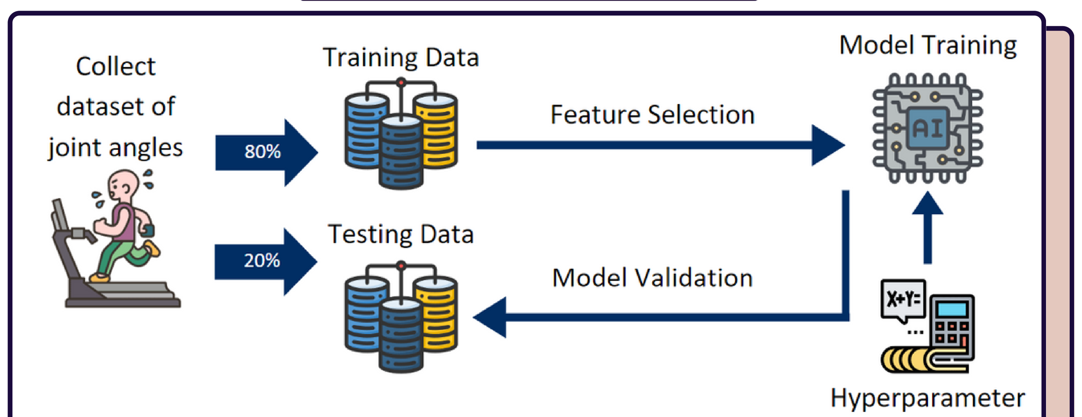
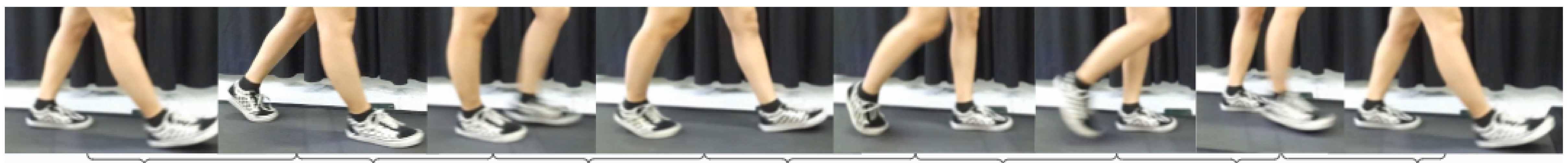


Fig4 - Model Training Procedure



Loading Response	Midstance	Terminal Stance	Pre-Swing	Initial Swing	Mid Swing	Terminal Swing
Begins with initial floor contact and continues until the other foot is lifted for swing.	Begins as the other foot is lifted and continues until body weight is aligned over the forefoot.	Begins with heel rise and continues until the other foot strikes the ground.	Begins with initial contact of the opposite limb and ends with ipsilateral toe-off.	Begins with lift of the foot from the floor and ends when the swinging foot is opposite the stance foot.	Begins as the swinging limb is opposite the stance limb and ends when the swinging limb is forward and the tibia is vertical.	Begins with a vertical tibia and ends when the foot strikes the floor.

Figure 1 - Gait Cycle Defined by Perry [9]

Results

Lower Limb Joint Angles

Figure 6 shows the collected hip, knee, and ankle angles across one gait cycle.

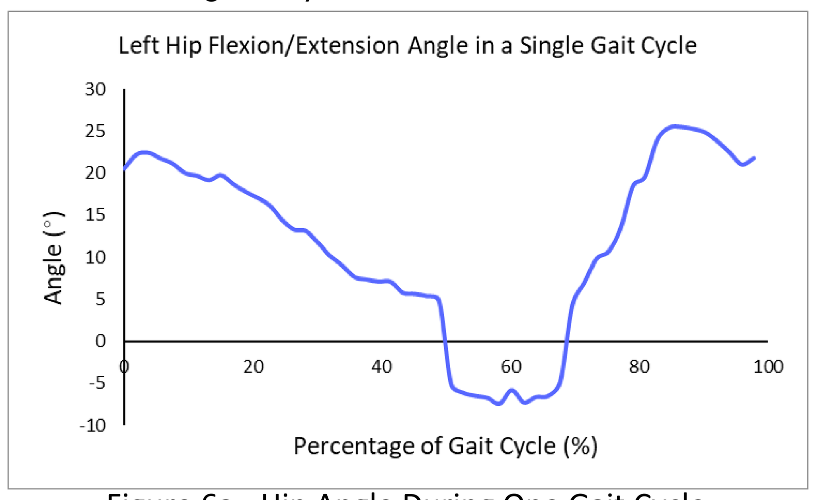


Figure 6a - Hip Angle During One Gait Cycle

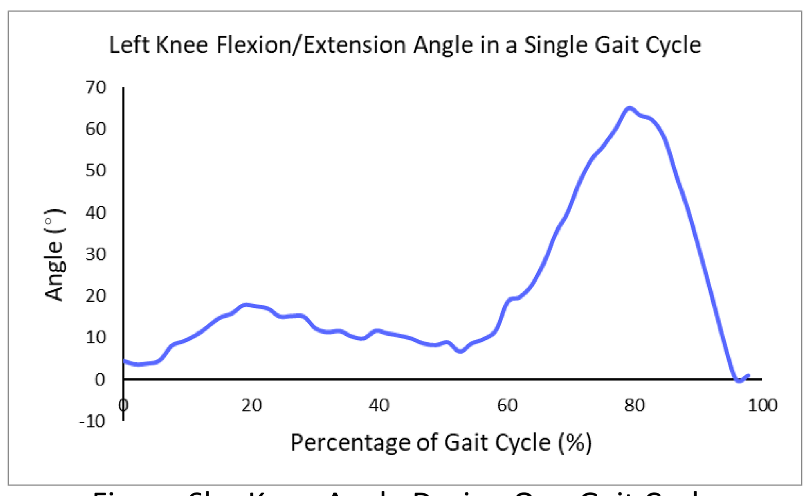


Figure 6b - Knee Angle During One Gait Cycle

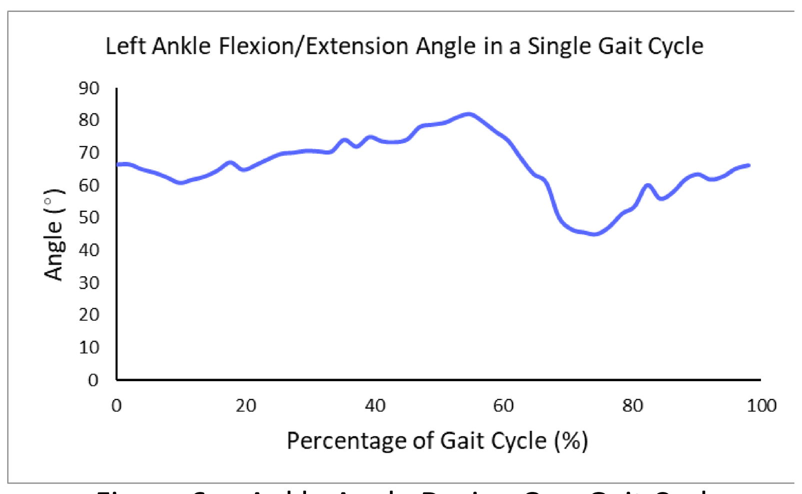


Figure 6c - Ankle Angle During One Gait Cycle

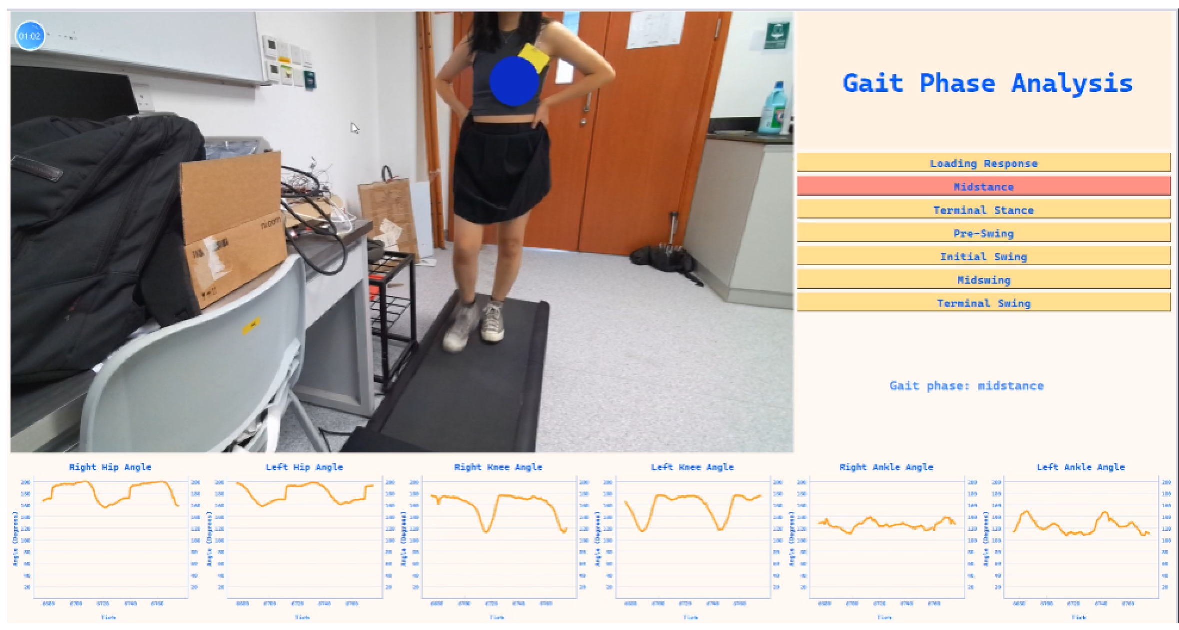


Figure 9 - Gait Phase Analysis Program User Interface

Figure 7 shows the average range of motion for the hip, knee, and ankle joints for both the female and male subject.

Joint ROM	Hip Flexion/Extension ROM (°)	Knee Flexion/Extension ROM (°)	Ankle Flexion/Extension ROM (°)
Female	51.40	69.78	57.70
Male	37.20	65.16	39.11

Figure 7- Range of Motion for each Joint Angle

Figure 8 shows the test accuracy for the machine learning models that were explored.

Model	KNN	Decision Tree	Random Forest
Test Accuracy	91.1420%	86.8228%	90.4832%

Figure 8 - Performance of Different Classifiers

Discussion

Lower Limb Joint Angle Discussions
- The consistency in joint angles could provide reasonable results for knee angles while hip and ankle results have varied accuracy.
- **Hip flexion/extension angles**
  - The trend followed by the hip flexion/extension angles are consistent with previous findings [10].
  - A steep jump in angle can be seen at the 0 degrees boundary, likely caused by hip abduction movement resulting in inaccurate angle calculations.
  - An additional projection of the knee to hip vector onto the sagittal plane can be implemented.
- **Knee flexion/extension angles**
  - The joint angle cycles appear to be consistent with past studies [10], which greatly strengthens the confidence in using the Azure Kinect for capturing knee angles.
- **Ankle flexion/extension angles**
  - There is instability and shakiness when tracking the ankle joint, possibly caused by the obstruction of joints.
  - It may be advisable to explore alternative methods such as utilizing foot pressure data.

Machine Learning Model Discussions

Data Constraints
- The dataset consists of data of two individuals walking. This limited sample size may not fully capture the variability in gait patterns across different individuals, ages, and health conditions.
- The data was recorded using a Kinect Azure depth camera, which is sensitive to changes in lighting and angle.
- The joint angle data was obtained by calculating joint positions from 3D body tracking data, which may introduce noise and occlusions.

Model Drawbacks
- The k-NN classifier can be computationally expensivefor large dataset as it requires computing the distance between the input data point and every training sample in the feature space.
- The k-NN classifier is sensitive to the choice of distance metric and the value of k, which can affect the classification accuracy.
- The k-NN classifier can be affected by the presence of noisy or irrelevant features in the dataset, which can lead to overfitting or reduced classification accuracy.

Significane of Findings
- The real-time capabilities of our approach, enabled by the Microsoft Azure Kinect camera and machine learning techniques, offer the potential for continuous monitoring and intervention during daily activities.
- Validates the effectiveness and comparability of a machine learning model based on the Azure Kinect camera's joint angle data alone. This approach offers non-invasive, cost-effective, and convenient gait analysis, eliminating the need for additional sensors or markers.

Future Direction

- **An additional body tracking camera** can added by having one camera positioned facing the left side and another facing the right side of the body.
- **The use of foot pressure** as an additional feature for predicting gait analysis instead of relying soley on ankle joint information.
- **More complex models**: use CNNs, SVMs, ANNs, GMMs, HMMs, or LSTMs could potentially improve the accuracy and scalability by learning more informative and robust features from the raw 3D body tracking data or by modeling temporal dependencies and transitions between gait phases.
- **Larger and more diverse datasets**: could help validate the findings and investigate the generalizability of the approach across different populations and conditions.

References

[1] Goldie, Patricia A., et al. "Gait After Stroke: Initial Deficit and Changes in Temporal Patterns for Each Gait Phase." Archives of Physical Medicine and Rehabilitation, vol. 82, no. 8, Elsevier BV, Aug. 2001, pp. 1057–65. https://doi.org/10.1053/apmr.2001.25085.

[2] Cruz-Jimenez, Maricarmen. "Normal Changes in Gait and Mobility Problems in the Elderly." Physical Medicine and Rehabilitation Clinics of North America, vol. 28, no. 4, Elsevier BV, Nov. 2017, pp. 713–25. https://doi.org/10.1016/j.pmr.2017.06.005.

[3] Moro, Matteo, et al. "Markerless Vs. Marker-Based Gait Analysis: A Proof of Concept Study." Sensors, vol. 22, no. 5, Multidisciplinary Digital Publishing Institute, Mar. 2022, p. 2011. https://doi.org/10.3390/s22052011.

[4] Dubois, Amandine, and François Charpillet. "A Gait Analysis Method Based on a Depth Camera for Fall Prevention." IEEE, Aug. 2014, https://doi.org/10.1109/embc.2014.6944627.

[5] Gu, Xiao, et al. "Markerless Gait Analysis Based on a Single RGB Camera." IEEE, Mar. 2018, https://doi.org/10.1109/bsn.2018.8329654.

[6] Saboor, Abdul, et al. "Latest Research Trends in Gait Analysis Using Wearable Sensors and Machine Learning: A Systematic Review." IEEE Access, vol. 8, Institute of Electrical and Electronics Engineers, Jan. 2020, pp. 167830–64. https://doi.org/10.1109/access.2020.3022818.

[7] Y. Ma, B. Sheng, R. Hart and Y. Zhang, "The validity of a dual Azure Kinect-based motion capture system for gait analysis: a preliminary study," 2020 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC), Auckland, New Zealand, 2020, pp. 1201-1206.

[8] Y. Zeng, L. Wu and D. Xie, "Gait Analysis based on Azure Kinect 3D Human Skeleton," 2021 International Conference on Computer Information Science and Artificial Intelligence (CISAI), Kunming, China, 2021, pp. 1059-1062, doi: 10.1109/CISAI54367.2021.00212.

[9] Perry, Jacquelin, and Judith M. Burnfield. Gait Analysis: Normal and Pathological Function. Slack, 2010.

[10] Xu, Xu, et al. "Accuracy of the Microsoft KinectTM for Measuring Gait Parameters during Treadmill Walking." Gait & Posture, vol. 42, no. 2, May 2015, pp. 145–151, https://doi.org/10.1016/j.gaitpost.2015.05.002.

Acknowledgements

This research was completed under the supervision of Professor Raymond Tong and his research team at CUHK BME lab.