Comparative Analysis of Gait Characteristics in Different BMI Categories Using IMU Sensors

Shuban M S
SENSE
Vellore Institute of Technology, Chennai
Chennai, India
shuban.ms2021@vitstudent.ac.in

Jervis Francis Lopes
SENSE
Vellore Institute of Technology, Chennai
Chennai, India
jervisfrancis.lopes2021@vitstudent.ac.in

Dr. Vijayarajan R
CHAIR
Vellore Institute of Technology, Chennai
Chennai, India
vijayarajan.r@vit.ac.in

***Abstract*—The primary aim of this study was to classify individuals into three categories—underweight, normal weight, and overweight—based on BMI and data collected from IMU sensors. Using Xsense MTw Awinda IMU sensors, data was gathered from participants as they walked up and down stairs. The sensors were placed on the tail bone, knees, and upper parts of the feet. The data was analyzed using three clustering algorithms: K-means, agglomerative, and spectral clustering. Participants were initially classified into three BMI-based categories and later classified using height and weight independently to create three distinct classes.**

Key findings revealed that, in some cases, the classification based solely on weight produced more accurate results compared to using BMI. Among the clustering methods, agglomerative clustering consistently outperformed K-means and spectral clustering in most scenarios. The study concluded that there is a slight but notable relationship between an individual's weight and the movement of their knees and feet. Future research may expand on these findings by incorporating additional factors beyond height and weight to enhance the accuracy and applicability of gait analysis using IMU sensors.

***Index Terms*—Gait Analysis, Xsense MTw Awinda, IMU Sensors, Movement Analysis, Wearable Sensors**

I. Introduction

Gait analysis, the systematic study of human walking patterns.In the broader context of this study, we aim to explore the potential relationship between gait characteristics, as captured by Inertial Measurement Unit (IMU) sensors, and the propensity for health problems associated with being overweight.

IMU sensors are increasingly favored in gait analysis [1] [2] due to their numerous advantages. These sensors are portable, non-invasive, and capable of providing real-time data. They offer a detailed capture of 3D movement, which is crucial for accurately assessing gait patterns. For this study, we utilized the Xsense MTw Awinda Research Bundle [3] [4], known for its excellent range, connectivity, and long battery life of up to six hours. The bundle includes six MTw Awinda Wireless 3DOF Motion Trackers, a recording and docking station, a receiving dongle, a full body strap set, an MTw Software Development Kit, and a convenient suitcase. These features, combined with the system's automatic calibration, ensure reliable and precise data collection.

Despite the advancements in gait analysis, current methods still face several challenges. One significant gap is the reliance on BMI as a sole indicator of health. Additionally, many existing studies do not explore the isolated effects of height and weight on gait characteristics.

This study addresses these gaps by investigating the relationship between IMU sensor data and BMI, height, and weight, and classifying participants into underweight, normal weight, and overweight categories. We employed K-means, agglomerative clustering, and spectral clustering algorithms to analyze the data and determine the most effective method for classification. Our findings suggest that weight may be a more reliable predictor of gait characteristics than BMI.

II. Literature Review

A. Gait Analysis and Health Implications

Gait analysis is crucial in health, rehabilitation, and sports for diagnosing, monitoring, and treating various conditions. Studying gait characteristics in overweight and obese populations helps understand the potential health issues related to altered walking patterns.

B. Use of IMU Sensors in Gait Analysis

IMU sensors are favored for their portability, non-invasiveness, and real-time 3D movement data. The Xsense MTw Awinda Research Bundle, with its excellent range, connectivity, and automatic calibration, is particularly effective for capturing detailed gait data.

C. Relationship Between BMI and Gait

Research shows that higher BMI is linked to altered gait patterns, such as slower walking speed and reduced stride length [5]. These changes are crucial for understanding the impact of additional body mass on movement.

D. Gait Parameters and Machine Learning

Most studies focus on specific parameters like roll, pitch, yaw, or acceleration in the three axes. Existing papers use supervised learning methods like logistic regression model on normalized gait cycle data [6], and they achieved a classification accuracy of 92% and identified a significant negative correlation (-0.66) between BMI and cadence.

E. Gaps in Current Research

Existing studies often limit their focus to specific parameters or small datasets, missing the full variability in gait patterns [7]. The integration of IMU data with traditional health metrics, especially in real-world settings, remains underexplored.

III. Methodology

A. BMI and ground truth dataset

This study involved 37 male participants all aged between 20 and 22 years. Participant's height and weight were recorded to calculate their BMI, which was used to categorize them into 3 classes underweight, normal weight, and overweight. The height and weight were then used to make three more classes like the BMI class which were the height class, weight class and the combination of the height and weight class. These were created using unsupervised learning methods while the BMI was calculated using the formula.

$$\text{BMI} = \frac{\text{weight (kg)}}{\text{height (m)}^2} \tag{1}$$

To maintain uniformity after the calculation of the BMI classes (1) the participants were divided using the following labels:

- The **underweight** class had **11** people, assigned label of **0**.
- The **normal weight** class had **21** people, assigned label of **1**.
- The **overweight** class had **5** people, assigned label of **2**.

The classes obtained from height, weight and a combination of height and weight using un-supervised learning [8] algorithms were also labeled using the above method where the maximum number of points under a class were labeled as **1**, the second highest labeled as **0** and the one with least data points as **2**.

This consisted and made up our BMI dataset which was later used to calculate accuracy and validate the IMU classes, acting like our ground truth. This dataset consisted of 14 columns, 2 of which were height and weight, 1 calculated BMI using the formula mentioned above (1), one was the ID to specify each person's corresponding IMU data with ascent and descent data recorded. The rest are the labels of the dataset, 9 of them calculated from three un-supervised learning algorithms:

- **K-means Clustering** - `height_and_weight_kmeans`, `height_kmeans`, `weight_kmeans`.
- **Agglomerative Clustering** - `height_and_weight_agglomerative`, `height_agglomerative`, `weight_agglomerative`.
- **Spectral Clustering** - `height_and_weight_spectral`, `height_spectral`, `weight_spectral`.

The naming was done by selecting the columns used in the clustering algorithm and then separated by the underscore the name of the clustering algorithm.

B. Sensors and their placement

The Xsense MTw Awinda Research Bundle had 6 sensors out of which we used 5 of them along with some velcro straps. The participants were asked to remove their shoes and two of the sensors were strapped to their feet, two of the sensors were fit to their knees on the front and the last sensor was placed on the backside of the hip near the tail bone. To avoid confusion we labeled each sensor with a unique code and used the respective sensor each time at the same exact place to get uniform results.

The sensors and their codes along with the place they were used as follows:

- **1FF:** Right Knee
- **1FD:** Left Knee
- **204:** Right Foot
- **17D:** Left Foot
- **200:** Tail bone

Fig. 1. IMU Sensors with labeled codes.

The sensors once fit were auto calibrated by the software and were ready to record the data by the participant performing certain activity in this case climbing up and down the flight of stairs.

C. Data collection and cleaning

The preferred activity to record data was to ask the participants to climb stairs, the software was used to connect to the sensors wirelessly and began recording data. They would climb 13 steps of stairs after we click record and once they reach the top we would click stop and then 5 text files would be generated of the IMU data recorded from the 5 sensors. These text files for individual sensors contained basic IMU data like acceleration, gyroscopic data and velocity in the 3 axes also containing columns of roll, pitch and yaw. Once these files were created they would then walk down repeating the process finally creating 10 files for a single person, 5 for ascent and 5 for descent. These files were appropriately named with codes and had a relation to the person this was from.

This process was repeated for all 37 participants and all the text data files were saved in different folders for ascent and descent. Python scripts were written to condense and join all the data from the text files into a single DataFrame and to avoid errors we included two new columns for a Sensor and an ID. The sensor column denotes which sensors data is this and the ID is for which person from the BMI table.

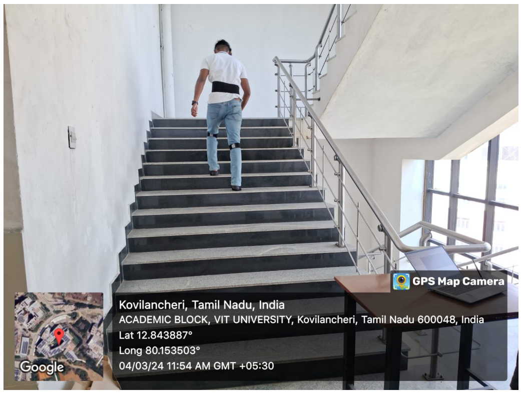

Fig. 2. Walking up the flight of stairs.

Fig. 3. Walking down the flight of stairs.

The new merged DataFrame with all the files was then cleaned to extract the features from the data. IMU data when recorded is usually time-series data so we need to extract a single value from it to apply the clustering algorithms to the dataset. There were 5 methods selected for feature extraction they were:

1) Mean:

$$\text{Mean} = \bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{2}$$

2) Median:

$$\text{Median} = \begin{cases} x_{\left(\frac{n+1}{2}\right)} & \text{if } n \text{ is odd} \\ \frac{1}{2}\left(x_{\left(\frac{n}{2}\right)} + x_{\left(\frac{n}{2}+1\right)}\right) & \text{if } n \text{ is even} \end{cases} \tag{3}$$

3) Mode:

$$\text{Mode} = \arg\max_{x_i} f(x_i) \tag{4}$$

4) Interquartile Range:

$$\text{IQR} = Q_3 - Q_1 \tag{5}$$

5) Fast-Fourier Transform:

$$\text{FFT}(x) = X_k = \sum_{n=0}^{N-1} x_n e^{-i2\pi kn/N} \quad \text{for} \quad k = 0, 1, \ldots, N-1 \tag{6}$$

On both the Ascent and Descent datasets these methods were applied to decompose and extract a single dimensional feature from each column so we can apply the clustering algorithms. Helper functions were written for the IQR (5) [9] and FFT (6) [10] methods, while for the statistical values inbuilt functions from numpy were used.

D. Clustering algorithms

Once we had the smaller datasets of decomposed values we then applied the three clustering algorithms to them to label each data point. The algorithms used were K-means [11], agglomerative clustering [12] and spectral clustering [13].

Python scripts were used along with the inbuilt models from sklearn module, each model was declared without tweaking a lot of parameters

We have three classes from the BMI table so we ensure each clustering algorithm had `n_clusters = 3` and `random_state = 0` to ensure reproducibility of results, after clustering the IMU dataset had three label columns for each of the three clustering algorithms applied and made sure that each of those labels in the columns matched with the classes used in the BMI dataset to maintain uniformity.

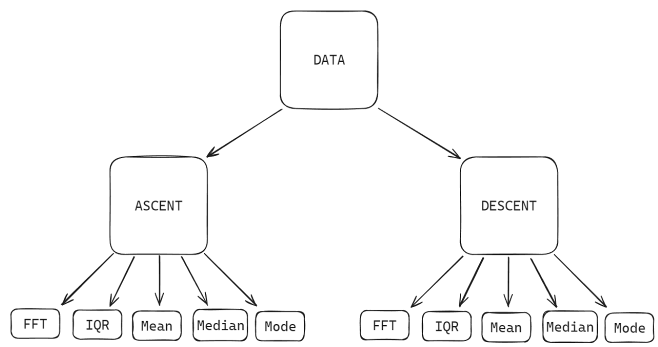

Fig. 4. Split of our datasets.

At the end of the data cleaning and applying the algorithms we were left with 10 sub-datasets as shown in Fig. 4. with all the predictive labels and the ground truth labels. This was then used to calculate accuracy using the models mentioned above, the results are presented in the next section.

IV. Results and Discussion

Now we present the results of our clustering models applied to the ten datasets derived from the original IMU data. The datasets were categorized into ascent and descent data, further processed using five different methods (2) (3) (4) (5) (6). We discuss the performance of the models in terms of accuracy and analyze the implications of the results.

A. Ascent

During the ascent phase, BMI emerged as a strong predictor across various feature sets, with notable accuracies of up to 45.41% using the IQR feature and 43.78% using the Mean feature with Kmeans clustering. This suggests that BMI effectively captures the body characteristics relevant to climbing

TABLE I
ACCURACY RESULTS FOR ASCENT

Ground Label	Predictive Label	FFT	IQR	Mean	Median	Mode
Height_and_weight_kmeans	Kmeans	29.73%	31.35%	33.51%	31.89%	38.38%
Height_kmeans	Kmeans	38.38%	36.22%	38.92%	38.92%	41.62%
Weight_kmeans	Kmeans	29.73%	31.35%	33.51%	31.89%	38.38%
BMI	Kmeans	42.16%	45.41%	43.78%	41.08%	38.92%
Height_and_weight_agglomerative	Agglomerative	31.35%	34.05%	34.59%	37.84%	39.46%
Height_agglomerative	Agglomerative	43.24%	31.89%	31.35%	38.92%	40.54%
Weight_agglomerative	Agglomerative	31.35%	34.05%	34.59%	37.84%	39.46%
BMI	Agglomerative	43.24%	40.00%	41.08%	37.30%	39.46%
Height_and_weight_spectral	Spectral	39.46%	38.92%	36.22%	40.00%	43.78%
Height_spectral	Spectral	35.14%	39.46%	34.05%	34.05%	35.68%
Weight_spectral	Spectral	35.14%	34.05%	35.14%	34.05%	40.54%
BMI	Spectral	36.76%	32.97%	33.51%	36.76%	40.00%

TABLE II
ACCURACY RESULTS FOR DESCENT

Ground Label	Predictive Label	FFT	IQR	Mean	Median	Mode
Height_and_weight_kmeans	Kmeans	42.16%	43.24%	40.54%	42.16%	32.43%
Height_kmeans	Kmeans	37.30%	40.00%	37.30%	37.84%	37.30%
Weight_kmeans	Kmeans	42.16%	43.24%	40.54%	42.16%	32.43%
BMI	Kmeans	40.00%	43.78%	42.16%	42.70%	42.70%
Height_and_weight_agglomerative	Agglomerative	41.62%	43.24%	38.92%	45.41%	35.14%
Height_agglomerative	Agglomerative	40.00%	44.86%	43.78%	43.24%	39.46%
Weight_agglomerative	Agglomerative	41.62%	43.24%	38.92%	45.41%	35.14%
BMI	Agglomerative	37.30%	40.00%	36.22%	44.32%	40.54%
Height_and_weight_spectral	Spectral	41.08%	38.38%	40.54%	37.84%	35.14%
Height_spectral	Spectral	32.97%	44.32%	44.32%	40.00%	36.76%
Weight_spectral	Spectral	40.54%	31.35%	29.73%	35.68%	36.22%
BMI	Spectral	38.38%	38.92%	38.38%	40.54%	41.08%

stairs. Agglomerative clustering also performed well with height, reaching a top accuracy of 43.24% with FFT, indicating its sensitivity to structural variations in the data. Spectral clustering showed the best results with the Height_and_weight feature set, particularly using the Mode, achieving an accuracy of 43.78%. This indicates that the method effectively captures non-linear relationships in ascent patterns.

B. Descent

In the descent phase, Kmeans clustering showed significant accuracy with the Height_and_weight feature set, particularly with FFT and Median, achieving up to 43.24% accuracy. This indicates that height and weight combined provide a robust measure for classification during descent. BMI also demonstrated strong performance, especially in IQR and Mode, reaching 42.70%. The descent's bio-mechanical demands appear to favor the comprehensive nature of BMI.

Agglomerative clustering performed well with height and weight combinations, achieving 45.41% accuracy with Median. Spectral clustering displayed high accuracy using the Height feature with IQR and Mean, both reaching 44.32%. This suggests that spectral clustering effectively captures the subtle variations in gait that occur during descent.

V. CONCLUSION AND FUTURE SCOPE

This study examined the effectiveness of clustering algorithms like Kmeans, Agglomerative, and Spectral clustering in classifying gait patterns using features such as FFT, IQR, Mean, Median, and Mode. BMI emerged as a key feature, often providing higher classification accuracy than height and weight alone. Kmeans performed consistently well with BMI data, while Spectral clustering excelled at capturing non-linear relationships.

To enhance the study's findings, future research should consider:

1) **Incorporating Additional Features**: Including factors like age, gender, and stride length could provide a more comprehensive understanding of gait patterns and improve classification accuracy.
2) **Expanding the Dataset**: A larger, more diverse sample, including older adults, would enhance model generalization and reliability.
3) **Exploring Advanced Algorithms**: Implementing neural networks or ensemble methods may capture more complex relationships in gait data.

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