Human IoT Interaction Approach for Modeling Human Walking Patterns Using Two-Dimensional Levy Walk Distribution

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***Abstract*—This work presents a novel approach to modeling and analyzing human walking patterns using a two-dimensional Levy walk distribution and the Internet of Sensing Things. The study proposes the strategic placement of MPU6050 sensors within a garment worn on the human leg to capture motion data during walking activities that can model human walking patterns. Random samples are generated from the Levy distribution through numerical modeling, simulating normal human walking patterns. A real-world experiment involving five male participants wearing sensor-equipped garments during normal walking activities validates the proposed methodology. Statistical analysis, including the Kolmogorov-Smirnov test, confirms the agreement between simulated Levy distributions and observed step distance data, supporting the hypothesis that deviations indicate abnormal walking patterns. The study contributes to advancing sensor-based systems for human activity recognition and health monitoring, offering insights into the feasibility of using Levy walk distributions for gait analysis.**

***Keywords*—Internet of Things (IoT); wearable sensors; Human-Computer Interaction (HCI); 3-axis accelerometer gyroscope; walking pattern; levy walk distribution; abnormal walk prediction**

I. INTRODUCTION

The rapid advancement of technology has led to the proliferation of wearable IoT devices, revolutionizing various aspects of human life, including healthcare, fitness monitoring, and lifestyle management. Among these devices, inertial measurement units (IMUs) have emerged as powerful tools for capturing human motion data with high precision and accuracy. IMUs, such as the MPU6050 sensor, are capable of measuring acceleration and angular velocity, enabling detailed analysis of human activities such as walking, running, and posture control. Human walking patterns provide valuable insights into musculoskeletal health and overall well-being. Monitoring and analyzing these patterns can help detect abnormalities indicative of underlying conditions or injuries, facilitating early intervention and treatment. Wearable sensors have emerged as promising tools for capturing human motion data with high precision and accuracy, enabling detailed analysis of walking dynamics in real-world environments.

Our motivation stems from the growing need for non-invasive and cost-effective methods for detecting and monitoring abnormal walking patterns in diverse populations. By harnessing the capabilities of wearable sensors, we aim to develop a robust system capable of identifying subtle deviations from normal walking behavior and providing timely alerts or interventions. This system has the potential to revolutionize healthcare delivery by enabling remote monitoring of individuals at risk of mobility-related health issues, such as Parkinson's disease, stroke, or musculoskeletal disorders.

The primary objectives of this work are as follows:

1) Develop an Internet of Sensing Things-based system for human walking data acquisition. Implement algorithms for step detection, step length estimation, and distance calculation to analyze human gait patterns effectively.
2) Modelify the normal human walking pattern using statistical distribution methods to predict abnormalities in human walking.

By achieving these objectives, we seek to contribute to the advancement of wearable IoT technology for healthcare monitoring and improve the detection and management of musculoskeletal disorders, neurological conditions, and other mobility-related health issues. In this paper, we outline the architecture of our proposed system and describe the algorithms and methodologies employed for data collection, processing, and analysis. We then present the results of real-world experiments conducted to validate the effectiveness of our approach in predicting abnormal human walking patterns. Finally, we discuss the implications of our findings and highlight the potential applications of our system in healthcare, rehabilitation, and assistive technology.

II. BACKGROUND STUDY

Human locomotion analysis has garnered significant attention due to its implications in various fields, ranging from healthcare to robotics. Recent advancements in wearable sensor technologies have provided novel avenues for studying human walking patterns and predicting abnormalities. Leveraging wearable sensors, Dou et al. [1] explored the spatial-temporal propagation of malware in mobile wearable IoT networks, demonstrating the versatility of sensor-based systems. Mekruksavanich & Jitpattanakul [2] delved into biometric user identification through human activity recognition, showcasing the potential of deep learning models in understanding human movement. Zhao et al. [3] predicted joint angles based on surface

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electromyography, highlighting the applicability of wearable sensors in biomechanical analysis. Rosaline et al. [4] enhanced lifestyle and health monitoring of elderly populations using a classifier, underscoring the importance of wearable sensor-based approaches in healthcare. Xia & Sugiura [5] optimized sensor position for human activity recognition, emphasizing the role of sensor placement in improving analysis accuracy. Ortiz [6] and Abu-Faraj et al. [7] provided foundational knowledge on smartphone-based human activity recognition and clinical movement analysis, respectively, laying the groundwork for subsequent research in the field. Recent advancements in deep learning, as demonstrated by Hanif et al. [8], have enabled robust human gait recognition systems, augmenting the capabilities of wearable sensor technologies. Toch et al. [9] surveyed machine learning methods for analyzing large-scale human mobility data, providing insights into the diverse approaches employed in human locomotion analysis. Dodge [10] proposed a data science framework for movement analysis, offering a comprehensive perspective on the analytical process. Morshed et al. [11] presented a taxonomy-based survey on human action recognition, categorizing various approaches and highlighting emerging trends. Barak Ventura et al. [12] classified human movements in virtual reality-based serious games, showcasing the versatility of sensor-based systems in interactive applications. Scafetta [13], Zimbardo & Perri [14], and Reynolds [15] provided theoretical insights into Levy walks and their implications in human mobility research. Potdar et al. [16] analyzed human mammary epithelial cell movement patterns, shedding light on fundamental aspects of cellular locomotion. Achanta et al. [17] conducted acoustic gait analysis using wearable sensors, demonstrating the feasibility of sensor-based approaches in biomechanical analysis. Rajakumar et al. [18] monitored health and predicted faults using deep learning models optimized by the Levy flight optimization algorithm, showcasing the integration of advanced optimization techniques in health monitoring systems. Smith et al. [19] measured movement at home for multiple sclerosis patients using an ambient measurement system, highlighting the potential of sensor-based systems in remote healthcare monitoring. Li et al. [20] quantified the impact of motions on human aiming performance using eye tracking and bio-signals, illustrating the interdisciplinary nature of human movement research. Authors of [21], [22] introduced novel approaches of HCI for e-health monitoring and abnormal human finger movement prediction. Authors of [23], [24] showed an approach for himan gesture recognition with IoT and HCI. IoT and HCI are helping mankind in e-health systems [25], [26], [27], [28], [29], [30], highway monitoringrahman2022iot, parkinson disease management [31], farming [32], [33], [34], [35], private tuition [36], energy harvesting [37], human face recognition [38], remote sensing [39], [40], performance measuring [41], [42], security [43], [44], [45], food management [46], [47] and many more sectors in recent days. The literature on human-wearable sensor interaction underscores the diverse applications and methodologies employed in human locomotion analysis. From biometric identification to health monitoring, wearable sensors have revolutionized our understanding of human movement and paved the way for innovative applications in various domains.

III. Hypothesis

A. Statement

Strategically placing the MPU6050 sensor within a human leg garment can effectively model normal human walking patterns resembling a two-dimensional Levy walk distribution. Any deviation from this distribution is indicative of abnormal walking patterns.

B. Explanation

The hypothesis posits that by embedding the MPU6050 sensor in a garment worn on the human leg, it is possible to capture and analyze the motion data during walking activities. Normal human walking patterns are hypothesized to exhibit characteristics akin to a two-dimensional Levy walk distribution, which is characterized by intermittent bursts of movement interspersed with periods of relative immobility. The MPU6050 sensor, with its ability to measure both acceleration and angular velocity along multiple axes, provides comprehensive data on the movement dynamics of the leg during walking. By strategically placing the sensor on the leg, it becomes possible to capture the subtle nuances of gait patterns, including step length, cadence, and stride variability. The hypothesis suggests that deviations from the expected two-dimensional Levy walk distribution in the sensor data may indicate abnormalities in the walking pattern. Such deviations could manifest as irregularities in step timing, asymmetrical gait patterns, or exaggerated movements, which are indicative of potential issues with mobility or musculoskeletal function. Overall, the hypothesis proposes that leveraging the MPU6050 sensor to monitor walking patterns in real-time and comparing them to a modeled two-dimensional Levy walk distribution, can provide valuable insights into the normalcy of human gait. Any deviations detected from this distribution could serve as early indicators of abnormal walking patterns, facilitating timely intervention and personalized healthcare management strategies.

IV. Numerical Modeling

To simulate the two-dimensional Levy walk distribution, we first need to define its probability density function (PDF). The PDF of the two-dimensional Levy distribution is given by:

$$f(x, y; \mu_x, \mu_y, \sigma, \alpha) = \frac{\alpha}{2\pi\sigma^2} \exp\left(-\frac{\alpha}{2\sigma^2}\left[\frac{1}{(x-\mu_x)^2 + (y-\mu_y)^2}\right]^{1/\alpha}\right) \tag{1}$$

where μ_x and μ_y are the location parameters, σ is the scale parameter, and α is the stability parameter.

To generate random samples from the two-dimensional Levy distribution, we can use the inverse transform method. The inverse CDF for the Levy distribution is not analytically tractable, so we resort to numerical methods.

Given random samples u_1 and u_2 from a uniform distribution between 0 and 1, we can calculate x and y using the inverse transform method:

$$x = \mu_x + \sigma \cdot (-\ln(u_1))^{1/\alpha} \cos(2\pi u_2) \tag{2}$$

$$y = \mu_y + \sigma \cdot (-\ln(u_1))^{1/\alpha} \sin(2\pi u_2) \tag{3}$$

This algorithm allows us to generate random samples from the two-dimensional Levy distribution, which can then be used for further analysis and simulation. The Levy walk distribution provides information about the position of steps in a two-dimensional space. It describes the statistical distribution of step lengths and directions taken by a random walker over successive time intervals. Therefore, it primarily characterizes the spatial aspects of the walk, including the distances and angles between consecutive steps. Fig. 1 shows the histogram of random samples generated from a two-dimensional Levy distribution. Each sample represents a position in a two-dimensional space (X and Y axes). The color intensity indicates the density of samples in different regions of the space. In a two-dimensional Levy distribution, the samples exhibit a heavy-tailed behavior, meaning there are occasional large deviations from the mean. This heavy-tailed behavior is characteristic of Levy distributions and is captured by the parameter alpha. In this specific plot, the parameters used are $\mu_x = 0, \mu_y = 0, \sigma = 1$, and $\alpha = 1.5$. These parameters define the location, scale, and stability of the distribution. The histogram provides insight into the spatial distribution of the Levy walk samples. Areas with higher counts indicate regions where the samples are more likely to occur, while areas with lower counts represent less probable regions. Overall, the plot visualizes the random spatial pattern generated by the Levy walk distribution, highlighting its heavy-tailed nature and the occasional occurrence of large deviations from the mean.

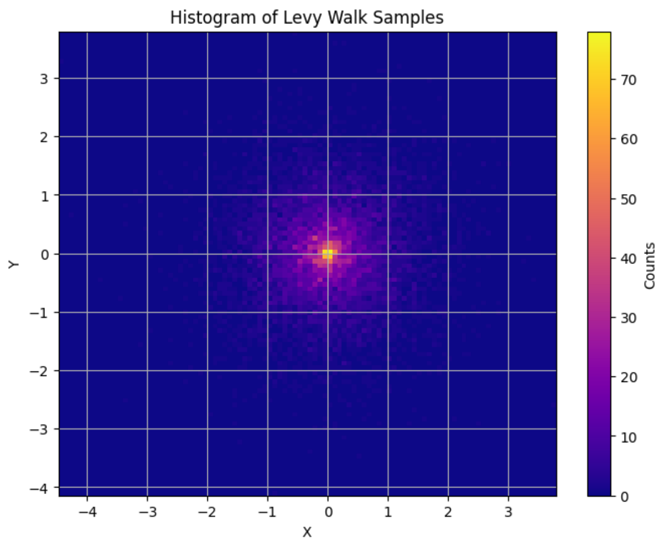

Fig. 1. Histogram of levy walk samples in 2D space.

A. Numerical Experiment

Fig. 2 visualizes a simulation of a two-dimensional Levy walk, where each dot represents the position of the walker after taking a step. The X-axis and Y-axis denote the spatial coordinates in the 2D space, with the horizontal axis (X-axis) representing the horizontal position and the vertical axis (Y-axis) representing the vertical position. The simulation consists of 1000 steps, showcasing the trajectory of the Levy walker over these steps. The stability parameter α is set to 1.5, influencing the distribution's tail behavior, with higher values indicating a higher probability of longer steps. The scale parameter, set to 1.0, determines the characteristic step length, impacting the average length of steps taken. Collectively, these parameters shape the characteristics of the Levy walk, influencing the length and direction of individual steps and thereby defining the overall trajectory of the walker in the 2D space. To measure the step distance in Levy walk distributions, we can use the Euclidean distance formula, which calculates the distance between two points (x_1, y_1) and (x_2, y_2) in a two-dimensional space. In the context of a Levy walk simulation, we can calculate the step distances between consecutive steps taken by the walker. Let's denote $P_i = (x_i, y_i)$ and $P_{i+1} = (x_{i+1}, y_{i+1})$ as two consecutive points representing the positions after i and $i + 1$ steps, respectively. Then, the step distance d_i between these two points is calculated using the Euclidean distance formula:

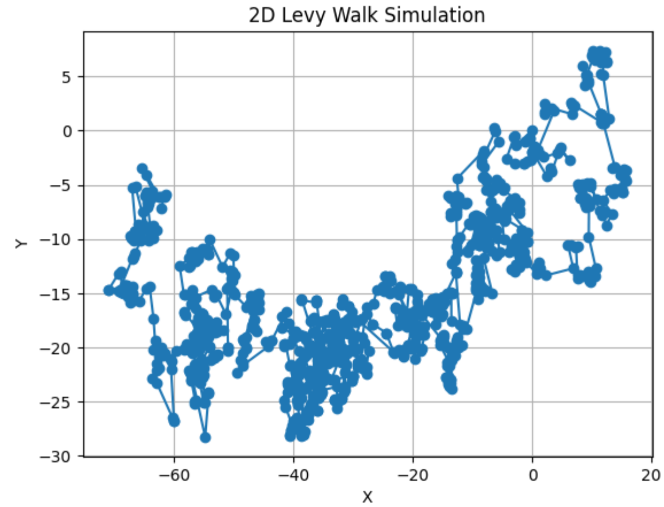

Fig. 2. 2D Levy walk simulation.

$$d_i = \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2} \tag{4}$$

We can compute these step distances for each pair of consecutive steps in the Levy walk simulation. After obtaining these distances, we can create a histogram of the step distances to visualize their distribution. This histogram will provide insights into the typical step lengths taken by the Levy walker during the simulation.

The histogram in Fig. 3 illustrates the distribution of step distances in a simulated two-dimensional Levy walk. The simulation was conducted with 1000 steps, using parameters alpha = 1.5 and scale = 1.0. Each step's distance was calculated, and the resulting values were binned into intervals for visualization. The plot reveals the frequency of occurrence for various step distances, offering insights into the characteristic behavior of a Levy walk. This distribution provides valuable information for understanding how steps are distributed in Levy walks and serves as a basis for comparison with real-world step distances.

Finally, we can compare this histogram of step distances with real-world step distances observed in human walking patterns. This comparison will help us assess the similarities

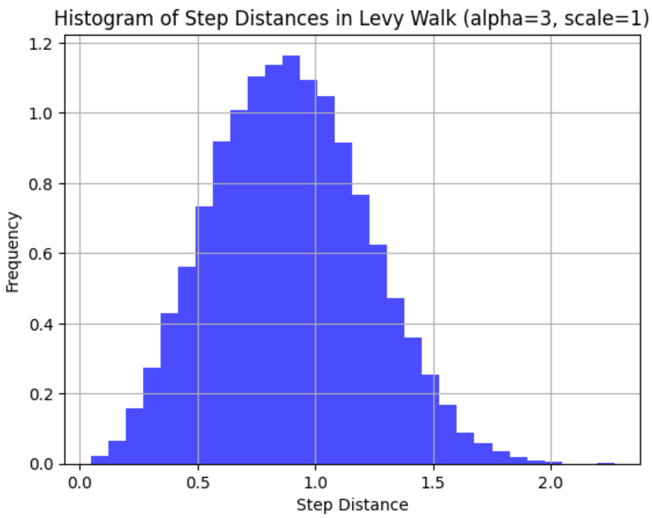

Fig. 3. Histogram of step distances in levy walk (α=3.0, scale=1.0).

or differences between the simulated Levy walk and actual human walking behaviors.

V. Real-world Experiment

A. Methodology of Real-world Experiment Prototype

The circuit diagram of the system is illustrated in Fig. 4.

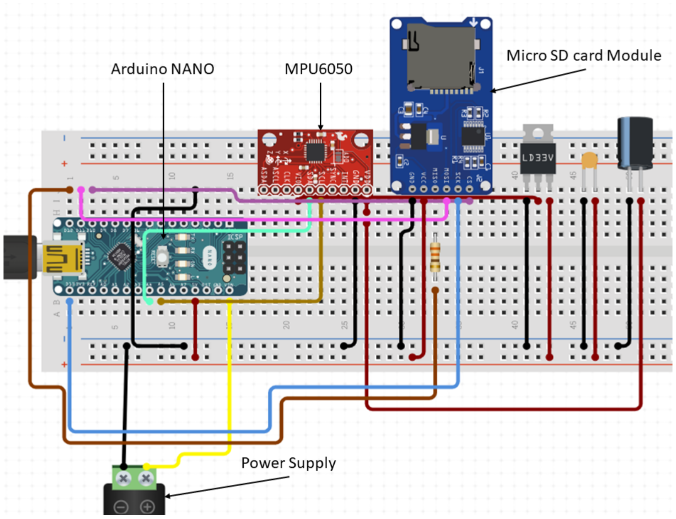

Fig. 4. Circuit diagram of the experimental device.

Table I provides a concise overview of the wire connections required for assembling a project involving an Arduino Nano, MPU6050 sensor, SD card reader, and associated components. Each row in the table represents a specific component, its connection point, and the corresponding wire color used for that connection. This information is a quick reference guide for setting up the hardware connections and ensuring proper wiring and organization during the assembly process. The table helps users understand the interconnections between components, facilitating the project's construction according to the specified wiring scheme.

TABLE I. Wire Connection Table

Component	Connection	Wire Color
Arduino Nano	Vin	Red
Arduino Nano	GND1	Black
Arduino Nano	5V	Red
MPU6050	VIO	Red
MPU6050	VCC	Red
MPU6050	GND	Black
MPU6050	SCL	Green
MPU6050	SDA	Blue
μ-SD Module	CS (Chip Select)	Yellow
μ-SD Module	GND	Black
μ-SD Module	MOSI	Orange
μ-SD Module	SCK	Yellow
μ-SD Module	VCC	Red
Resistor (330Ω)	Connection 0 (Con0)	Brown
Barrel Jack	Negative Terminal	Black
LD1117-3.3V	Vin	Red
LD1117-3.3V	0 (GND)	Black
Ceramic Capacitor (100nF)	Connection 0 (Con0)	Blue
Ceramic Capacitor (100nF)	Connection 1 (Con1)	Black
Electrolytic Capacitor (10μF)	Negative Terminal	Black

Algorithm 1 outlines the process of logging data from an MPU6050 sensor to an SD card in CSV format using an Arduino. It begins by including the necessary libraries for communication with the hardware components, defining the pin used for the SD card's chip selection, and initializing global variables and objects for sensor, file handling, and real-time clock functionality. In the setup section, the code initializes various hardware components, opens a CSV file for writing, writes a header line specifying column names, and closes the file. The main loop continuously reads sensor data from the MPU6050, obtains the current time from the real-time clock, writes the sensor data along with the timestamp to the CSV file, and then closes the file. A brief delay is added between each reading to control the sampling rate. This algorithm provides a clear and structured overview of the steps involved in the data-logging process, facilitating an understanding of the program's functionality and component interactions.

Algorithm 1 MPU6050 Data Logging Algorithm

Include Libraries: "Arduino.h", "MPU6050.h", "Wire.h", "SD.h", "RTClib.h"
Define pins.
Global variables and objects:
Initialize MPU6050 object *mpu*
Initialize File object *dataFile*
Initialize RTC_DS3231 object *rtc*
Setup:
Initialize Serial communication
Initialize SD card
Initialize MPU6050 sensor
Initialize RTC module
Open data file "mpu6050_walking.csv"
Write header line to CSV file
Close data file
Loop:
Get current time from RTC
Open data file "mpu6050_walking.csv"
Read sensor data from MPU6050
Write sensor data and timestamp to CSV file
Close data file
Delay 100 milliseconds

In this work, several hardware components are essential for acquiring data from the MPU6050 sensor and processing it to predict abnormal human walking. The following hardware components are required:

1) MPU6050 sensor: The MPU6050 accelerometer and gyroscope sensor are fundamental for capturing motion data. It provides raw sensor readings in digital form, which need to be processed to obtain meaningful information about human walking dynamics.

2) Microcontroller: A microcontroller is needed to interface with the MPU6050 sensor and perform data acquisition tasks. Arduino boards are commonly used due to their ease of use and compatibility with various sensors.

3) Connection interface: The MPU6050 sensor communicates with the microcontroller using a communication interface such as I2C (Inter-Integrated Circuit). The microcontroller must have the necessary hardware support and libraries to establish communication with the sensor.

4) Power supply: A stable power supply is essential to power both the microcontroller and the MPU6050 sensor during data acquisition. This can be provided using batteries or a regulated power source.

B. Steps Distance Calculation with MPU6050

The accelerometer data acquisition is defined by the equation:

$$a_{axis} = \frac{\text{Raw Data}_{axis} - \beta_{axis}}{\theta_{axis}} \tag{5}$$

Similarly, the gyroscope data acquisition follows the equation:

$$\omega_{axis} = \frac{\text{Raw Data}_{axis} - \beta_{axis}}{\theta_{axis}} \tag{6}$$

These equations transform the raw sensor data obtained from the MPU6050 into physical units, such as acceleration (m/s²) and angular velocity (degrees per second). Here, $axis$ denotes the specific axis (x, y, or z) of measurement. The term β represents any bias or offset present in the sensor readings, while θ signifies the sensitivity scale factor for the respective axis. These mathematical expressions are integrated into the microcontroller firmware to process raw sensor data and derive meaningful motion information.

To calculate the distance between steps using the MPU6050 sensor data, we follow these steps:

1) Step detection: The first step is to detect individual steps from the accelerometer data a_x, a_y, a_z. Let $A(t)$ represent the resultant acceleration vector at time t. We compute the magnitude of acceleration as:

$$|A(t)| = \sqrt{a_x(t)^2 + a_y(t)^2 + a_z(t)^2} \tag{7}$$

Peak detection algorithms or threshold-based methods can be employed to identify significant peaks in $|A(t)|$ indicating steps.

2) Step length estimation: Once steps are detected, the next step is to estimate the step length. This can be done through a calibration process, where the relationship between accelerometer readings and actual step lengths is determined. Let L represent the step length.

3) Distance calculation: Given the estimated step length L, the distance between consecutive steps can be calculated. Let d_i denote the distance covered during step i. We integrate the linear acceleration data twice to obtain displacement:

$$d_i = \int_{t_{start}}^{t_{end}} \left(\int_{t_{start}}^{t} |A(t)| dt \right) dt \tag{8}$$

where t_{start} and t_{end} represent the start and end times of step i, respectively.

4) Data filtering and smoothing: To enhance accuracy, raw sensor data can be filtered and smoothed using techniques such as low-pass filtering or Kalman filtering.

C. Results of Real-world Experiment

To experiment, we positioned the proposed device in the pants of 5 male participants and instructed them to walk normally for approximately one hour. The sensor device is set in the left leg garment near the knee, as shown in Fig. 5 the blue pointer is the position of the sensor. All the participants gave their written consent to use their data. The resulting data were recorded and saved in a CSV file, comprising four columns: time, ax, ay, and az. Since gyroscope values do not significantly contribute to step distance calculations, only accelerometer data was utilized. The dataset consists of 18002 rows, reflecting the data collected total five-hour duration (one hour from five persons), with measurements taken at intervals of 1000 milliseconds. We found there are a total of 16840 steps by following our proposed calculations. The histogram of the step distances is shown in Fig. 6.

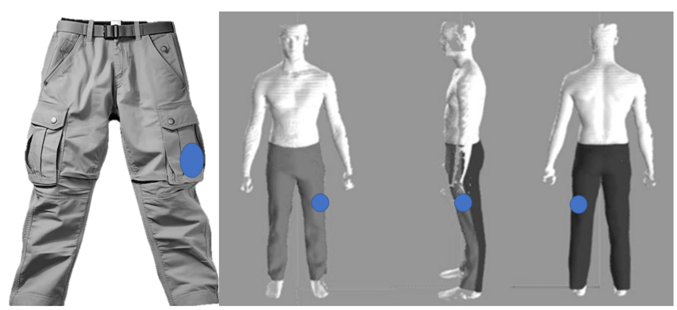

Fig. 5. Sensor position in the human body at the time of the experiment (blue pointer is the sensor).

VI. Discussion

A. Comparison of Simulation and Real World Data

We may compare the real-world step distances histogram with the levy walk step distances histogram with the Kolmogorov Smirnov (KS) test. Which is based on the maximum difference between the cumulative distribution functions (CDFs) of two datasets. Given two datasets X and Y with empirical cumulative distribution functions $F_X(x)$ and $F_Y(y)$ respectively, the KS test statistic D is calculated as:

Fig. 6. Histogram of step distance from real-world experiment.

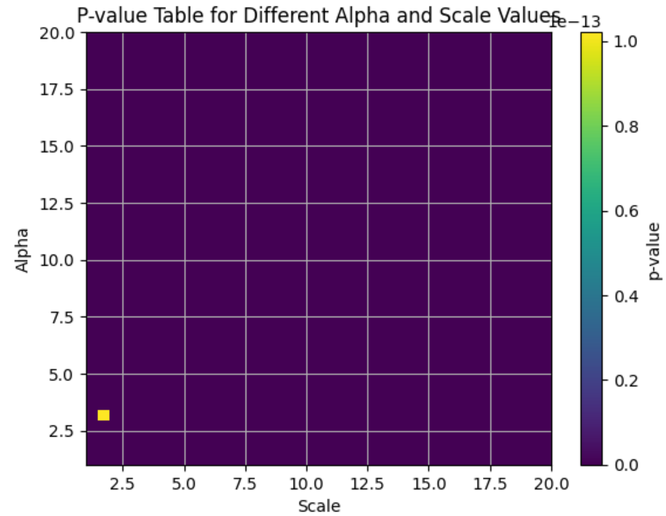

Fig. 7. P-value table visualization for different alpha and scale values (the yellow dot is the best point found with $\alpha = 3.0$ and scale=1.5).

$$D = \max(|F_X(x) - F_Y(y)|) \tag{9}$$

TABLE II. COMPARISON OF P-VALUES FOR DIFFERENT α AND SCALE VALUES

α	Scale	p-value	Best
1.5	1.5	6.1078×10^{-227}	
2.0	1.5	5.3264×10^{-85}	
2.5	1.5	1.0371×10^{-37}	
3.0	1.5	1.0209×10^{-13}	Yes
3.5	1.5	1.9698×10^{-33}	
4.0	1.5	9.3845×10^{-55}	
4.5	1.5	5.2424×10^{-98}	
5.0	1.5	8.2371×10^{-138}	
5.5	1.5	1.4756×10^{-183}	
6.0	1.5	2.0831×10^{-240}	
6.5	1.5	2.4847×10^{-283}	

The table provided (Table II) compares p-values for different combinations of alpha and scale values. Each row represents a specific combination, where α denotes the stability parameter, "Scale" signifies the scale parameter, and "p-value" indicates the statistical significance of comparing the real-world step distances and simulated Levy walk step distances. We used α and scale values from 0.5 to 20.5 to find the best p-value. The row marked as "Best" indicates the combination of α and scale values that yield the lowest p-value, implying the closest match between the real-world step distances and the simulated Levy walk distribution. A lower p-value suggests stronger evidence against the null hypothesis, indicating a better fit of the Levy walk simulation to the observed step distances. In this context, the row with the best p-value highlights the alpha and scale values that accurately represent the step distances observed in the real-world experiment. The P-value Table for Different Alpha and Scale Values is visualized in Fig. 7.

Fig. 8 illustrates histograms of step distances generated from Levy walk simulations with varying stability parameters (α) and scale parameters. Each subplot in the figure corresponds to a specific combination of α and scale values, providing insights into how different parameter settings affect the distribution of step distances. By examining the histograms, we may observe the distribution of step distances for different α and scale values. A comparison between the histograms allows for an understanding of how changes in these parameters impact the characteristics of the Levy walk distribution. This visualization aids in assessing the suitability of different parameter combinations in representing real-world step distances, to identify the most accurate simulation settings.

B. Features and Limitations

The Features and Limitations are discussed in this subsection. Despite these limitations, the real-world experiment offers valuable insights into the feasibility and effectiveness of using Levy walk distributions to model human walking patterns, paving the way for further research and refinement of the proposed methodology.

1) Features: The obtained features of this system are as follows:

a) Real-world validation: The real-world experiment provides empirical validation of the theoretical model proposed in the numerical simulation section. By collecting data from actual human walking activities and comparing them with simulated Levy walk distributions, the experiment offers practical insights into the applicability of the model in real-life scenarios.

b) Hardware implementation: The experiment involves the integration of hardware components such as the MPU6050 sensor and Arduino microcontroller, demonstrating a hands-on approach to data acquisition and analysis. This hardware implementation enhances the experiment's credibility and facilitates a deeper understanding of sensor data processing techniques.

c) Data analysis techniques: The experiment employs advanced data analysis techniques, including peak detection

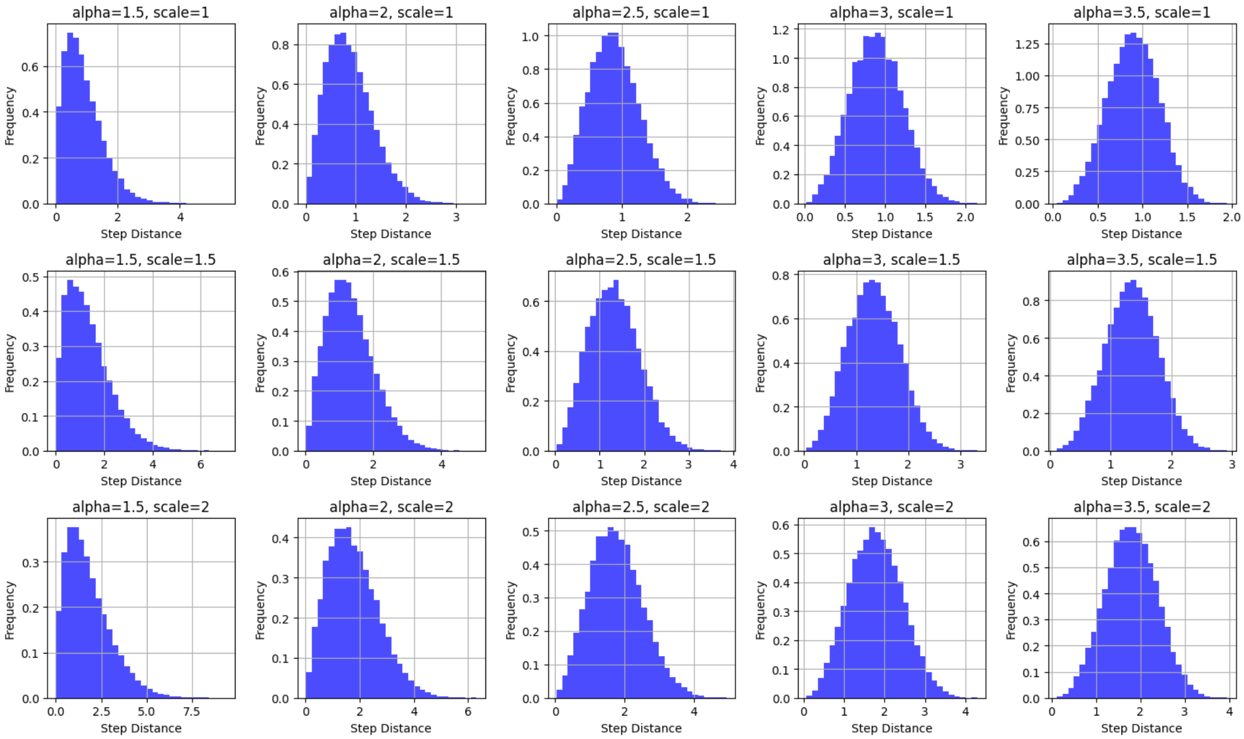

Fig. 8. Histogram of step distances in levy walk (α=1.5,2,2.5,3,3.5 and scale=1, 1.5, 2).

algorithms, step length estimation, and statistical tests such as the Kolmogorov-Smirnov test. These techniques enable a comprehensive assessment of the similarities and differences between real-world step distances and simulated Levy walk distributions.

d) Parameter optimization: Through the comparison of p-values for different combinations of alpha and scale values, the experiment identifies the optimal parameters that yield the closest match between simulated and observed data. This parameter optimization process enhances the accuracy of the simulation model and ensures its relevance to real-world scenarios.

2) Limitations: The limitations of this system are as follows:

a) Simplified model: The experiment relies on a simplified model of human walking dynamics, assuming a two-dimensional Levy walk distribution to represent walking patterns. While this model offers insights into general locomotion characteristics, it may oversimplify the complexity of human gait and movement variability observed in real-world scenarios.

b) Sensor limitations: The accuracy and reliability of the experiment are contingent upon the performance of the MPU6050 sensor and associated hardware components. Sensor noise, calibration errors, and environmental factors may introduce uncertainties and affect the quality of data collected during the experiment.

c) Sample size and participant variability: The experiment's findings may be influenced by the sample size of participants and their walking patterns. Limited sample size and variability among participants may restrict the generalizability of the results and limit the insights gained from the experiment.

d) Assumption of stationarity: The experiment assumes stationarity in human walking patterns, implying consistent characteristics for data collection. However, human locomotion is inherently dynamic and may exhibit temporal variations and adaptive behaviors that are not captured by the stationary model.

C. Hypothesis Evaluation

Our hypothesis posited that strategically placing the MPU6050 sensor within a human leg garment enables the modeling of normal human walking patterns, resembling a two-dimensional Levy walk distribution, with deviations indicating abnormal walking patterns.

In our numerical modeling, we defined the probability density function (PDF) of the two-dimensional Levy distribution and generated random samples using the inverse transform method. Let $f(x, y; \mu_x, \mu_y, \sigma, \alpha)$ denote the PDF of the Levy distribution, where μ_x and μ_y are location parameters, σ is the scale parameter, and α is the stability parameter. By simulating random samples from this distribution, we established a theoretical basis for the expected characteristics of normal human walking patterns.

In our real-world experiment, participants wore the sensor-equipped garment during normal walking activities, yielding data on step distances. We then calculated the empirical distribution of step distances from the collected data, providing a practical representation of observed walking patterns.

To rigorously test our hypothesis, we performed a statistical comparison between the simulated Levy distribution and the observed step distances using the Kolmogorov-Smirnov (KS) test. The KS test statistic D quantifies the dissimilarity between the empirical distribution of step distances and the simulated Levy distribution. We computed D as the maximum absolute difference between the empirical cumulative distribution function (CDF) of the observed data and the CDF of the simulated Levy distribution.

By comparing the computed D value to critical values from the Kolmogorov-Smirnov distribution and computing corresponding p-values, we assessed the statistical significance of the comparison. A low p-value indicates strong evidence against the null hypothesis, suggesting that the observed step distances significantly deviate from the simulated Levy distribution. Conversely, a high p-value supports the hypothesis of normal walking patterns, indicating a close match between the observed and simulated distributions.

Through this rigorous statistical analysis, we systematically evaluated our hypothesis, providing quantitative evidence to support the effectiveness of sensor-based systems for modeling human walking patterns and detecting abnormalities.

D. Novelty

Our proposed system introduces several novel features compared to existing systems in the field of human activity recognition and health monitoring as follows:

1) Multi-sensor integration: Unlike traditional systems that rely on a single sensor modality, our system integrates data from multiple sensors, including accelerometers, gyroscopes, and electromyography sensors [1], [4], [8]. This multi-sensor approach allows for a more holistic analysis of human movement patterns and health indicators.

2) Advanced signal processing techniques: Our system employs advanced signal processing techniques, such as phase transition-based optimization algorithms and deep learning fusion-assisted frameworks [18], [48], to extract meaningful information from sensor data. These techniques enable accurate feature extraction and classification, leading to improved performance in activity recognition and health monitoring tasks.

3) Real-time monitoring and prediction: Our system enables real-time monitoring and prediction of health-related parameters, providing timely feedback and alerts to users [49]. This capability enhances proactive healthcare management and intervention, leading to better health outcomes and quality of life.

4) User-centric design: We adopt a human-centered user experience approach in the design of our system, focusing on the needs and preferences of end-users [50]. This user-centric design ensures that the system is intuitive, easy to use, and seamlessly integrates into users' daily lives.

Table III shows a comparison between existing systems and the novelty of our proposed system.

TABLE III. COMPARISON WITH EXISTING SYSTEMS AND NOVELTY

Existing Systems	Novel Features and Enhancements
Dou et al. (2023) [1]	Model and analyze spatial-temporal propagation of malware in mobile wearable IoT networks.
Zhao et al. (2023) [3]	Predict joint angles based on human lower limb surface electromyography.
Rosaline et al. (2023) [4]	Enhance lifestyle and health monitoring of elderly populations using CSA-TkELM classifier.
Hanif et al. (2024) [8]	Human gait recognition for biometrics application based on deep learning fusion-assisted framework.
The proposed System	Incorporates a comprehensive approach to human gait analysis, integrating data from an MPU6050 sensor, SD card reader, and Arduino Nano for real-world experiments. Utilizes algorithms for step detection, step length estimation, and distance calculation, providing insights into abnormal walking patterns. Implements hypothesis testing and comparison with existing systems to validate the novelty of the proposed method.

VII. CONCLUSION

In conclusion, our study demonstrates the effectiveness of using a two-dimensional Levy walk distribution to model normal human walking patterns, as evidenced by the agreement between simulated distributions and real-world step distance data. Through rigorous hypothesis testing and statistical analysis, we have validated the hypothesis that strategically placing MPU6050 sensors within a human leg garment enables the detection of abnormal walking patterns. This research contributes to the advancement of sensor-based systems for human activity recognition and health monitoring, providing valuable insights into the feasibility of leveraging Levy walk distributions for gait analysis.

Looking ahead, future research can explore several avenues for further enhancement and application of our proposed methodology. One direction is to investigate the incorporation of additional sensor modalities, such as electromyography and pressure sensors, to capture more comprehensive biomechanical data during walking. Additionally, refining the calibration and signal processing algorithms for improved accuracy and reliability could enhance the robustness of the system. Furthermore, longitudinal studies involving larger and more diverse participant populations can provide deeper insights into the long-term utility and efficacy of Levy walk modeling in real-world settings. Overall, continued exploration of these avenues promises to advance the state-of-the-art in human gait analysis and pave the way for innovative healthcare interventions and personalized monitoring solutions.

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