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An indoor localization system for estimating human trajectories using a foot-mounted IMU sensor and step classification based on LSTM

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Abstract

This study presents the results of designing a system that determines the location of a person in an indoor environment based on a single IMU sensor attached to the tip of a person's shoe in an area where GPS signals are inaccessible. By adjusting for human footfall, it is possible to accurately determine human location and trajectory by correcting errors originating from the Inertial Measurement Unit (IMU) combined with advanced machine learning algorithms. Although there are various techniques to identify stepping, our study successfully recognized stepping with 98.7% accuracy using an artificial intelligence model known as Long Short-Term Memory (LSTM). Drawing upon the enhancements in our methodology, this article demonstrates a novel technique for generating a 200-meter trajectory, achieving a level of precision marked by a 2.1% error margin. Indoor pedestrian navigation systems, relying on inertial measurement units attached to the feet, have shown encouraging outcomes.

Keywords: *inertial measurement units, machine learning, recurrent neural network, AHRS.*

1. INTRODUCTION

In the last 20 years, the system for determining the location of people in places where GPS signals cannot be received has been actively developed and research works are being carried out [1]. Indoor positioning is often difficult because construction materials considerably decrease or weaken GPS-based navigation signals. There are many methods for tracking pedestrians in indoor environments, and one possible alternative is navigation based on body-mounted inertial sensors. The goal of this computational method is to infer the position, orientation, and speed of a person in motion [1]. A very detailed comparison of works similar to our

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research is presented in article [1], wherein leg movements are classified using machine learning methods such as CNN, RNN, SVM, LDA, and QDA. In the following research [1, 2, 3, 4, 5], we investigated the efficacy of a sensor-based classification system for locomotion. The experiment involved strategically placing sensors to capture movement data, varying the number of sensors deployed, and classifying different types of locomotion. The achieved classification accuracy ranged from 86% to 100%, indicating the robustness of the sensor configuration and the effectiveness of the classification algorithm. Several commercial wearable systems such as Fitbits, Garmin, and the Apple Watch have developed widely used systems for recording daily activity [2, 7]. Commercial pedometers continue to develop into sophisticated technology that uses accelerometer signals to count steps [2, 12]. This article explores the combination of the Attitude and Heading Reference System (AHRS) algorithm with a Long Short-Term Memory (LSTM) model for foot inertial navigation. In this study, inertial sensing was used to determine location rather than to identify different walking conditions. Four healthy participants walked under specific conditions. The IMU is attached to the outside of the left shoe. Inexpensive IMUs employing microelectromechanical systems face challenges when depending on continuous direct integration over extended intervals, leading to the accumulation of position errors over time [3, 10]. While IMUs can calculate direction through integration, prolonged use may introduce drift, resulting in significant directional errors [3-5]. Also, when considering the use of accelerometers and magnetometers to find direction, the data they provide is sensitive to noise, leading to notable errors in the calculated direction [7-10]. To address errors in inertial sensors, researchers have commonly used zero velocity detectors such as ZUPT in their studies [3-4, 11]. The limitation of filters based on ZUPTs resides in the aspect that the optimal zero-velocity detection parameters depend on the type of motion ZUPT has four issues [4, 6, 11]. It works best when the velocity is close to zero, can only correct roll and pitch angles, may assume zero velocity incorrectly in some cases, and struggles with different walking or running styles, potentially missing or incorrectly identifying zero-velocity situations. The performance of an INS assisted by zero-velocity is significantly affected by both motion and surface characteristics [8, 11, 13]. To enhance the reliability of zero-velocity detectors across different types of motion, various adaptive approaches have been introduced [5-6, 9].

Several machine learning methods have been utilized for motion classification in research studies [1, 2, 5] performed a comparison of distinct classification approaches, encompassing Naive Bayes, logistic regression, KNN, and SVM, to identify motion patterns through the utilization of diverse body-mounted sensors [1, 13, 17]. In our research, the application of machine learning for classifying stepping on and stepping off events contributes to increased accuracy in mitigating errors originating from the Inertial Measurement Unit (IMU) sensor. Furthermore, the enhancement of the human location detection algorithm is achieved through the calculation of zero velocity.

2. STRUCTURE OF THE PROPOSED SYSTEM

Many people tend to walk at approximately 0.94 – 1.36 Hz and climb stairs at 1.31-2.92 Hz [15, 16]. Therefore, we used the the MPU6050 IMU chip from InvenSense, which can measure acceleration with a minimum full-scale range ±2g, ±4g, ±8g and ±16g, tilt with ±250, ±500, ±1000 and ±2000°/sec sensitivities (MEMS triple-axis gyroscope, triple-axis accelerometer). This chip is known for its high accuracy and widespread usage in various products and research. IMU transmitted data to the PC through the ESP32's Wi-Fi link. The IMU's sampling frequency was set to 250 Hz, with an acceleration range of ±16g and a gyro range of ±2000°/sec. For the research work, a software solution was created by creating the system hardware with the general structure shown in Figure 1.

A system consists of three main components. It includes:

• A preprocessing unit: The wearable device also included an interface circuit capable of converting the analog signals from the sensor into a 16-bits digital format feeding responsible for converting and transmitting it to the computer via Wi-Fi technology.

• Unit for classifying walking and stepping using machine learning algorithm.

• Unit for digital signal processing, coordinate transformation, velocity and trajectory estimation using previously classified data.

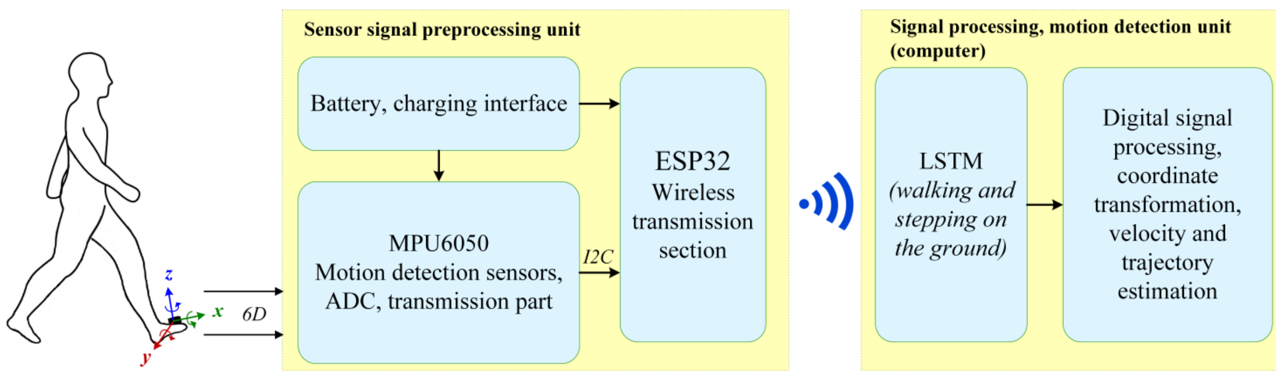

Figure 1. System structure

In this study, we made device module using Mini MPU6050 IMU sensor, ESP32C3SuperMini microcontroller and battery charger. In the Figure 2 shown 3D PCB design of the device module and actual photo of the sensor attached to the shoe.

Figure 2. 3D PCB design of model and actual photo of the sensor module

3. LSTM MODEL AND DATA PRE-PROCESSING

Through the utilization of IMU data, we develop a predictive model to identify step occurrences using deep learning algorithms. Four healthy participants (3 men, 1 woman, ages: 30-53, height: 1.69 ± 0.08 m; mass: 62.1 ± 20 kg) took part and gathered step data, in this study. Individuals with varying walking speeds, diverse shoe sole materials, different walking surfaces, and severe lower limb injuries were excluded. The IMU was placed around the midpoint of the foot, secured with the shoelaces. Each participant completed 10 laps with diverse walking trajectories.

First, we set up the inertial sensor on the microcontroller. Here, let the number of iterations be N=1000. Here we have inertial sensor offset a_{x_offset}, a_{y_offset},a_{z_offset}, g_{x_offset}, g_{y_offset}, g_{z_offset}, values are calculated.

$$a_{x_{\_offset}} = \frac{1}{N}\sum_{j=1}^{N} a_{xj} \tag{1}$$

But a_{z_offset} value is calculated as follows:

$$a_{z_{\_offset}} = \frac{1}{N}\sum_{j=1}^{N} a_{xj} - 2048 \tag{2}$$

From here we:

$$a_x = a_x - a_{\_x_{offset}} \tag{3}$$

Filtered as follows to ensure minimal noise, regardless of the configuration:

$$if(-50 < a_x < 50):\ \ a_x = 0 \tag{4}$$

Using this filtered data, a database is created that categorizes whether or not it has been stepped on. We have generated footprint data for four individuals. This database contains data for walking straight, walking around a corner, walking in a circle, and going up and down stairs.

An LSTM model is a type of recurrent neural network designed to handle sequences by overcoming the vanishing gradient problem. It is especially good at grasping long-term patterns in sequential data. Also, the soles of the walking shoes were different, and the walking was done at different speeds. The format of the collected data is shown in the table below. Human walking data were recorded at 4ms intervals. If the person placed their foot on the ground, a button located on the sole was pressed, which we labeled as 1. If the foot is off the ground, the label will be 0. The amount of data used for machine learning consists of approximately 18 minutes of recordings covering a walking distance of 1500 meters.

Table 1. Main parameters

Time(ms)	Label	a_x	a_y	a_z	g_z	g_y	g_z
4	1	372	160	2011	0	0	0
8	1	370	170	2020	0	0	0

The model below is used for training.

```
Model: "Sequential"
Layer (type)          Output Shape        Param #
=================================
LSTM                  (None, 256)         264192
Dense                 (None, 128)         32896
Dense                 (None, 1)           129
=================================
Total params: 297,217
Trainable params: 297,217
Non-trainable params: 0
```

We split the data into 90% for training and 10% for testing. Training is configured to have the following hyperparameters: optimizer='adam', loss='binary_crossentropy', epochs=25, batch_size=64. The graph below illustrates the learning process.

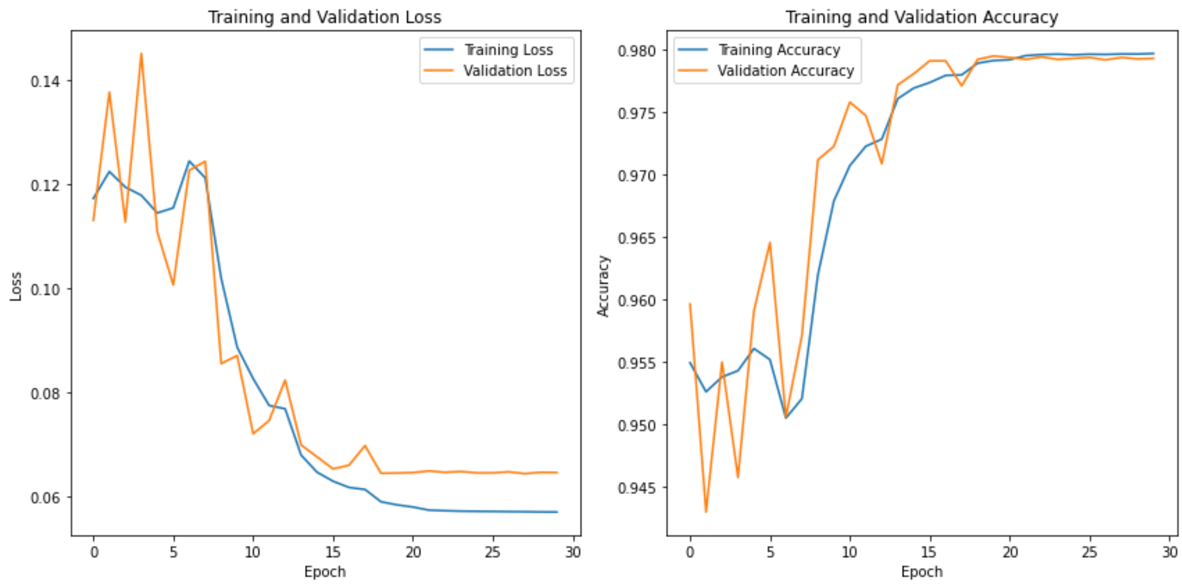

Figure 3. Training model results

Our model predicts stepping with 98.7% accuracy.

Table 2. Classification Report

	Precision	Recall	F1-score
0	0.98	0.99	0.99
1	0.99	0.98	0.99
Accuracy			0.99
Macro avg	0.99	0.99	0.99
Weighted avg	0.99	0.99	0.99

We predicted 180 seconds of walking data by inputting it into an LSTM model. The results are tabulated below using a confusion matrix.

Table 3. Confusion matrix

	Predicted class 0	Predicted class 1
True class 0	2003	21
True class 1	36	1940

As observed in the graph below, certain areas are mistakenly assumed to be stepped on when there is no footstep, while no step is inferred when one is actually taken. In Figure 4, the actual leg action is depicted in orange, while the predicted leg action is represented in blue.

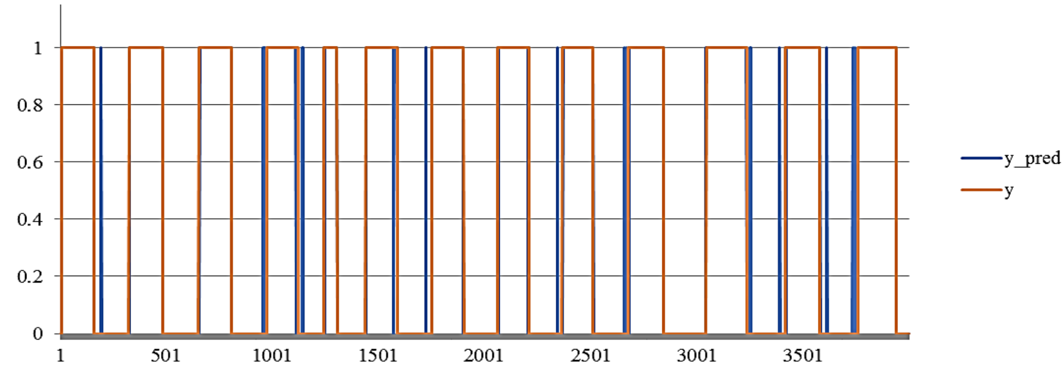

Figure 4. Predicted results vs true label

We filter out small noises, depicted in blue in Figure 4, which should not occur, using a low-pass filter. The results, after noise filtering, are depicted in the graph below.

$$y_{filter}[n] = (1-\alpha)y_{filter}[n-1] + \alpha y_{pred}[n] \tag{5}$$

$$\alpha = \frac{1}{1+\frac{2\pi f_c}{f_s}} \tag{6}$$

Here: fc =2Hz– cut-off frequency, and fs =250Hz– sampling frequency

After filtering, the actual values of the foot-stepping label generated by the button below the shoe sole and the LSTM-trained values appear to be completely coincident. Utilizing this machine learning model alongside a low-pass filter, we demonstrate its high discriminatory capability in determining whether a step has been taken or not, as illustrated in Figure 5.

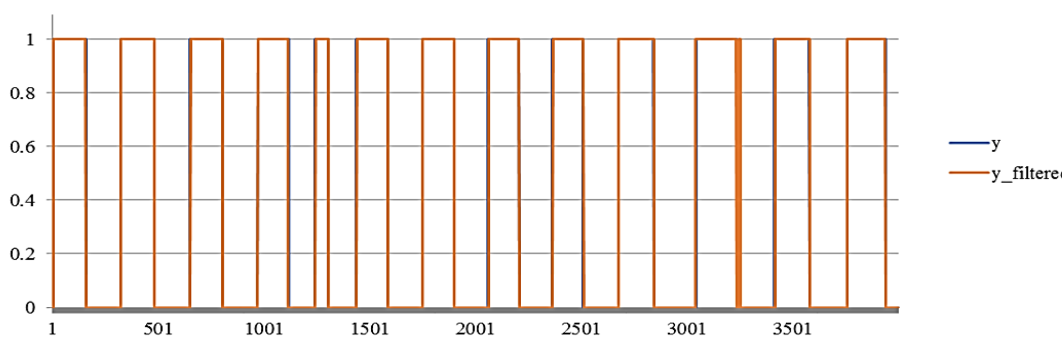

Figure 5. Filtered predicted results vs true label

We use the machine learning-generated stepping value to calculate the human walking trajectory in the next step. This involves correcting errors in the IMU sensor by assuming zero velocity when the foot is on the ground.

4. MODEL FOR DETERMINING LOCATION

The main difference between determining the motion of a walking human and determining the motion of other mobile robots or machinery is gait. The movement of the legs of a walking person can be divided into two categories: stepping on the ground and walking. This classification will greatly facilitate the calculation of human movement trajectories. The previous section was able to successfully distinguish between stepping on the ground and walking using machine learning. This result can be used to determine the three-dimensional trajectories of human movement. Figure 6 shows the acceleration values and angular velocity values obtained from the IMU sensor, taking into account the steps taken while walking on the stairs.

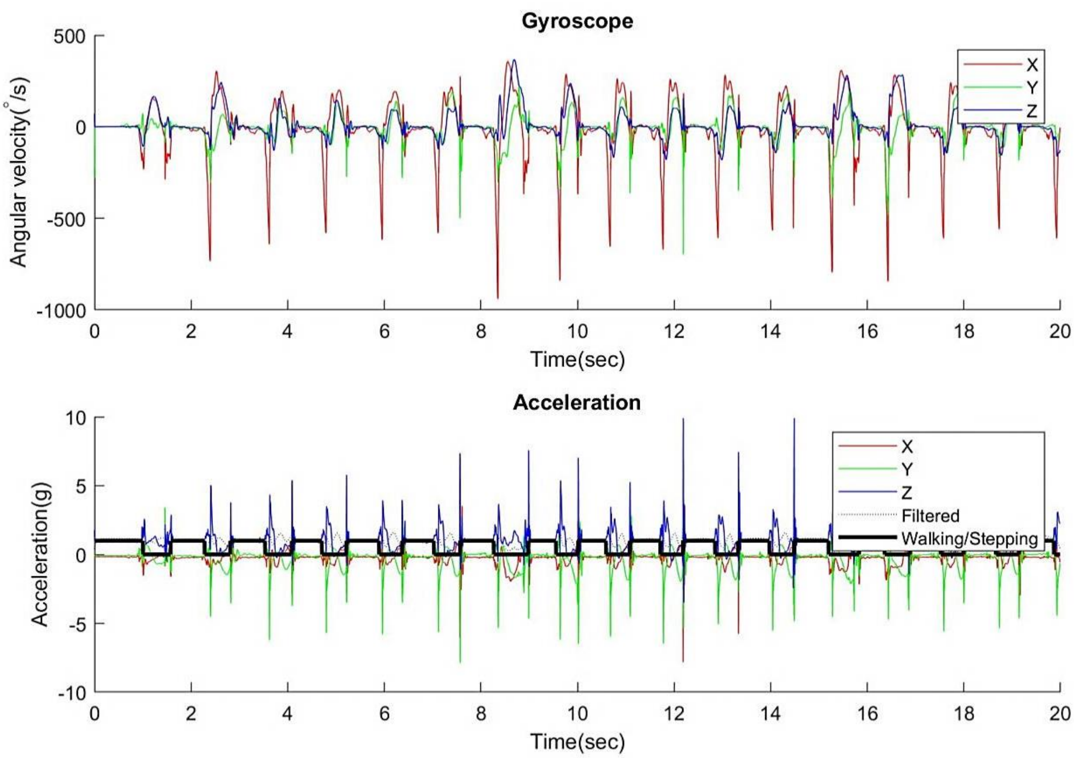

Figure 6. Acceleration and angular velocity while stair walking

The acceleration and angular velocity measurements derived from IMU sensors represent data within the body's coordinate system, necessitating their conversion to ground coordinate data. An attitude and heading reference system (AHRS) consists of sensors on three axes that provide attitude information including roll, pitch and yaw. These are sometimes referred to as MARG (Magnetic, Angular Rate, and Gravity) sensors and consist of (MEMS) gyroscopes, accelerometers and magnetometers. The reference of AHRS comes from the gravity field of the earth and the magnetic field of the earth, its static accuracy depends on the measurement accuracy of the magnetic field and the measurement accuracy of the gravity, and the gyro determines its dynamic performance. But in these paper we don't use magnetometers, because we don't need to determine true north. The AHRS is employed for the transformation of coordinates from the body frame to the ground coordinate system.

$$\theta = \tan^{-1}\left(\frac{-a_x}{\sqrt{a_z^2+a_y^2}}\right) \tag{7}$$

$$\phi = \tan^{-1}\left(\frac{-a_x}{a_z}\right) \tag{8}$$

$$\psi = \tan^{-1}\left[\frac{\omega_x \cos\phi+\omega_z \sin\phi}{\omega_y \cos\theta+\omega_x \sin\theta \sin\phi-\omega_z \cos\phi \sin\theta}\right] \tag{9}$$

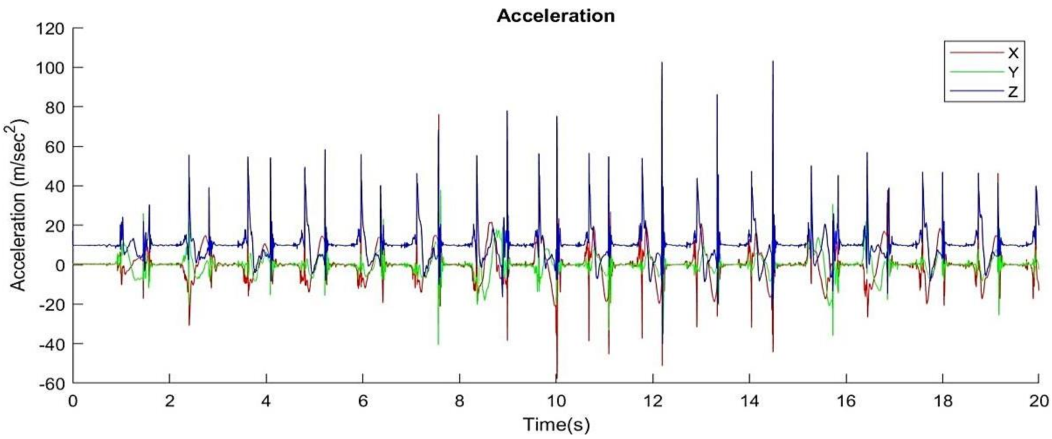

Figure 7. Acceleration value converted to world coordinate

The value of 9.81 m/s² is indicated along the Z-axis due to gravitational force, even when the object is stationary. This acceleration needs to be subtracted.

$$acc_z = acc_z - 9{,}81m/s^2 \tag{10}$$

When computing velocity based on acceleration values, utilize the outcomes from the stepping on the ground and walking classification. Given that the position of a person's foot remains constant during stepping on the ground, there is no need to calculate velocity in this segment, it suffices to calculate speed exclusively during walking.

$$\begin{gathered} v_{x(t+1)} = v_{x(t)} + acc_{x(t)} * dt \\ v_{y(t+1)} = v_{y(t)} + acc_{y(t)} * dt \\ v_{z(t+1)} = v_{z(t)} + acc_{z(t)} * dt \end{gathered} \tag{11}$$

Having successfully classified between walking and stepping, it is possible to calculate the velocity exclusively during walking using the provided formula. Conversely, velocity can be directly computed as zero when stepping on the ground. Therefore, there is no need to employ the acceleration value from the shock instead of the movement during stepping for speed calculation.

$$\text{If (stepping==true)} \quad \begin{gathered} v_{x(t+1)} = 0 \\ v_{y(t+1)} = 0 \\ v_{z(t+1)} = 0 \end{gathered} \tag{12}$$

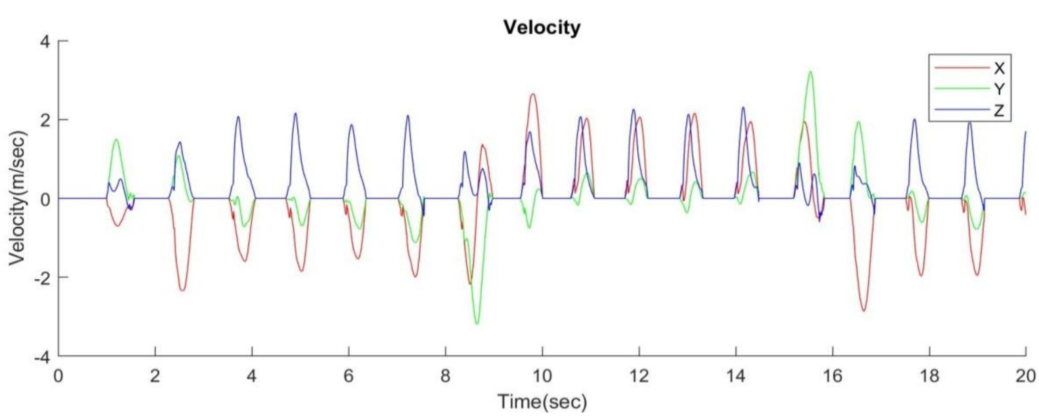

Figure 8. Velocity values along three axes

This method reduces the error that accumulates during velocity calculation by considering the interval from acceleration. Figure 9 shows that the walking experiment involved ascending stairs from the first floor to the second floor. From the Z-axis data, it becomes evident how many steps have been taken. Ascending and Descending stairs is more concussive than walking. Nevertheless, the test results indicate that this issue has been resolved through effective classification.

$$\begin{aligned} x_{t+1} &= x_t + v_{z(t+1)} * dt \\ y_{t+1} &= y_t + v_{y(t+1)} * dt \\ z_{t+1} &= z_t + v_{z(t+1)} * dt \end{aligned} \tag{13}$$

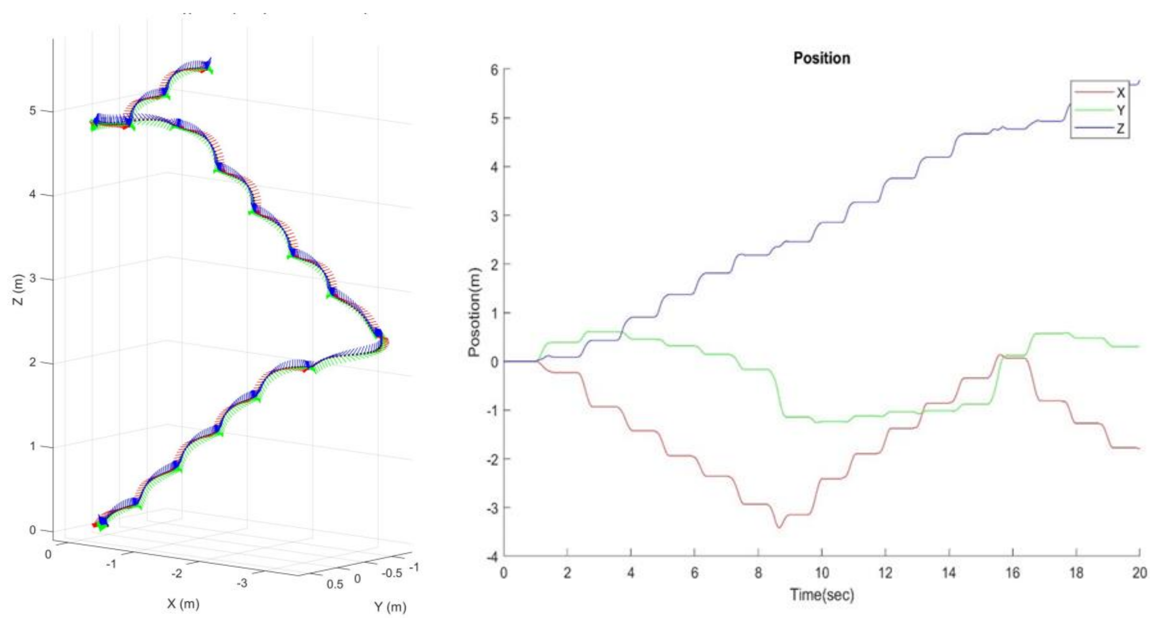

Figure 9. Trajectory of walking on the stairs

The trajectory graph along the three axes clearly indicates that a walk is being performed. The position coordinates (x,y,z) are not related to GPS coordinates, indicating that coordinates only represent values within an indoor coordinate system. This study presents an enhanced method for estimating foot trajectory and stride length using acceleration and angular velocity data measured by a foot-mounted IMU.

5. CONCLUSION

In summary, this paper introduces a novel indoor human localization system using a single inertial sensor on a person's shoe in GPS-denied environments. The approach combines an Attitude and Heading Reference System algorithm with a Long Short-Term Memory model, achieving an impressive 98.7% accuracy in recognizing steps.

In the unit for classifying walking and stepping using machine learning algorithm, specifically the LSTM model, is applied to identify step occurrences based on data from four participants. In the case of 200 m long straight-line pedestrian motion, the experimental result shows that the proposed algorithm has a maximum of 4.2 m errors when compared to the ground-truth values. The LSTM model's outcomes contribute to enhancing velocity estimation and minimizing errors associated with drift during trajectory estimation. About 14 cm of displacement error occurs along the vertical axis in a straight walk of about 20 meters.

Overall, the presented system holds promise for indoor human localization, offering insights into addressing challenges and opening avenues for future research.

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