Step Counting by Optimum Fusion of IMU Sensor Measurements*

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Abstract

Localizing, detecting, navigating and tracking devices, especially smartphones in dynamic environments, has received significant attention from the research community in recent years, as knowledge of the current position is helpful in numerous applications, ranging from emergency situations to the analysis of human activities. Smartphones, as well as other smart devices operate at low cost and without additional infrastructure. This can be realized by utilizing the smartphones' inertial sensors, such as magnetometers, accelerometers, and gyroscopes. In this paper, we propose a novel approach for detecting pedestrian steps, which can be used for estimating the distance covered by the pedestrian, from raw Inertial Measurement Unit (IMU) data by separating each measurement to its 3 degrees of freedom. This approach utilizes the optimum combination of the motion sensors' degrees of freedom, through an intelligent break down of the off-the-shelf smartphone raw data from the built-in sensors. Data are gathered from five different body positions and three corresponding speeds, resulting in a rich dataset which accounts for many different input patterns and possible scenarios. From the experimental evaluation results, it becomes evident that the proposed step counting approach outperforms the commonly used approaches, that rely on single (combined) measurements from the sensors, under a variety of input conditions. The optimum combination, with the lowest average percentage error (0.613%) of all tested combinations, is achieved by deploying smartphone on the pedestrian's arm at slow speed.

Keywords

Pedestrian Dead Reckoning, step counting, Inertial Measurement Unit, accelerometer, linear accelerometer, gyroscope, magnetometer

1. Introduction

Localization and tracking people has attracted considerable attention from both the academia and industry in recent years, since the awareness of the current position is beneficial in numerous areas, such as search and rescue, localizing people with disabilities, mining locations, wilderness areas, emergency services and military. Nevertheless, smart devices and smartphones attract attention in academia and industries due to their rapid integration with everyday life. Almost everyone, despite of age and gender, carries at least a smartphone on a daily basis. The smartphones usage is expected to climb to almost eight billion by 2028 [1]. Smartphones, as well as other smart devices, are hardware with advanced computing capabilities used to gather data from the physical world, thus providing the opportunity of developing services and applications to perform various actions.

Pedestrian Dead Reckoning (PDR) utilizes the motion sensors for estimating the distance and direction of pedestrians. The method of determining one's present location using their previously known position and moving that position forward over time using predetermined or estimated trajectories and speeds (or, alternatively, stride lengths and directions) is known as pedestrian dead reckoning, or PDR [2]. The total distance covered is the product of the stride length and number of steps taken. Typically, the steps can be estimated by utilizing the data of an IMU, while for accurate stride length estimation, a study of human and animal locomotion may be required. The work presented, concentrates on the step detection algorithm, as part of the PDR system. The fact that PDR does not depend on external measurements, makes it a good alternative, especially in the absence of Global Navigation Satellite

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System (GNSS). However, developing a PDR system is a challenging task since it depends on the smart devices's IMU low-cost sensors, which are easily affected by a variety of factors and they are highly sensitive to movements. In the present study, an accurate and robust step counting system was achieved without a predefined smartphone placement and based entirely on raw data received from the IMU sensors.

The remainder of this paper is organized as follows. Section II includes the related work. In section III, the proposed step counting system algorithm is detailed. Section IV examines the experimental data to confirm the algorithm's performance and evaluates the findings of the experiments. Section V provides a discussion of the results and future directions.

2. Related Works

The step detection and counting, also called pedometer, is commonly used by numerous applications for estimating the total distance walked by pedestrians. The accelerometer is the most commonly used sensor for step detection, since its magnitude remains nearly constant as the pedestrian is standing still and specific patterns (magnitudes) can be observed while walking. The gravity acceleration measurements can be adjusted by passing the acceleration magnitudes through a low-pass filter [3]. Other methods for processing the acceleration magnitudes include the Principal Component Analysis (PCA) and principal component regression [4]. Also, algorithms based on Kalman Filters are used for handling real-time step frequency updates [5]. Techniques, such as setting a threshold [5], [6], double threshold detection, which are based on filtering the magnitude of acceleration followed by applying a threshold on the filtered data [7], peak detection, measuring the peaks of the vertical acceleration [8, 9, 10, 11, 12, 13, 14, 15, 16] and windowed peak detection techniques [17] can also be utilized. The acceleration signal patterns on inertial force trigger step events [18], which in turn can be used for step counting through the peak and time domain set for dual-feature step detection [9]. Alternatively, the step detection can be achieved by utilizing the correlation coefficients for identifying whether the collected measurements exhibit similar tendencies [19]. False steps can be identified by setting a threshold between maximum and minimum peaks [20].

The PDR step detection techniques commonly depend on the smartphone placement, noise and bias reduction algorithms as well as prior sensors' calibration. IMU sensors are sensitive to movements, for example the accelerometer is sensitive even to little noise, gyroscope is extremely sensitive and suffers from drifts, and magnetometer suffers from nearby magnetic fields interference. Previous step detection algorithms assumed that sensors are mounted in a fixed position relative to the pedestrian's body mainly for the stability of measurement. The number of steps is counted by detecting the peaks of acceleration and the smartphone is required to be mounted for accurate measurements and disturbances avoidance [21]. However, there is an identified need in various applications to promote alternative smartphone placement, such as free walking [5, 3]; texting/calling, swinging [12, 13]; keeping in bags and pockets [22, 16, 17, 23]; holding in front of the body in a vertical direction [14, 18, 20]; holding in hand with the screen facing upwards [15].

Measurements fluctuations can occur even under steady state conditions, such as accelerometer magnitude fluctuations due to the presence of gravity. Commonly, the smartphone sensors are inexpensive with poor accuracy and sensitivity. They are noisy and their bias and scale-factor performance are low. The noise is more evident under low Signal-to-Noise Ratio (SNR) conditions. Therefore, different techniques are used to eliminate them, while the aim of the work presented is to use off-the-shelf smartphones with no data pre-processing methods. Furthermore, the axis whose data has the maximum magnitude is commonly selected [24]. Alternatively, the Discrete Kalman Filter provides noise reduction and flattening of insignificant acceleration changes [5]. The gravity from the accelerometer signal can be eliminated, by shifting up the y-axis about $9.8m/s^2$ through a high-pass filter [8]. The high-pass filter can also be followed by a low-pass filter, such as a moving average filter, for smoothing the signal and reducing the random noise [8].

Bias reduction is also considered an important task for developing a PDR step detection system.

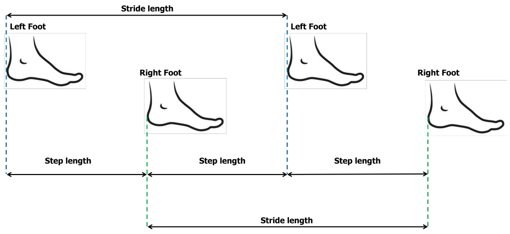

Figure 1: Stride vs Step Length

Bias is the error in the measurements, even after they are calibrated, and it needs to be estimated and removed. One way to achieve this is by placing the smartphone motionless on a plain surface and note the measurements, in an attempt to identify and adjust differences in the acceleration measurements, i.e., due to the presence of gravity [25]. Other noise reduction techniques include the Finite Impulse Response (FIR) low-pass filter [17] and a 3-degree Savitzky-Goby Filter [13]. Furthermore, the magnetometer measurement disturbances can be eliminated through a quaternion-based Extended Kalman Filter (EKF) [3]. The authors in [3] eliminated the small jitters produced during pedestrians' walking and holding the smartphone, by setting a threshold for the gauge errors of steps. Similarly, the authors in [16] calibrated the magnetometer bias by following the ellipsoid filling method. Nevertheless, each component should be calibrated using predetermined offset parameters, as the raw data are offset due to the surrounding magnetic environment and sensor's conditions [26].

3. Methodology

PDR step detection is an infrastructure-less technique, mainly used in navigation. The accuracy of the steps taken by pedestrians over time, without a predefined smartphone placement is of vital importance. Furthermore, the aim of the work presented is to evaluate the proposed PDR step counting system on different off-the-shelf smartphones, placed at the most typical pedestrian body positions using the peak detection method.

3.1. Smartphone Placement and Speeds

Pedestrians typically place their smartphones on their upper arm, hand pelvic and thigh [4]. For the work presented, ankle is also added, after considering the recently introduced ankle bands for measuring pedestrians' walking by monitoring the way heels strike the ground while walking [27].

3.2. Stride Lengths

A gait analysis, which is a study of the way people walk and/or run and consists of the step and stride length, was carried out for each participant. The step length is the distance measured from the toe of the right foot to the toe of the left foot, or from the heel of the right foot to the heel of the left foot. Similarly, the stride length is the distance measured from heel to heel of the same foot or toe to toe of the same foot. As a result, a stride consists of two steps, as shown in Figure 1. Both are estimated by dividing the distance travelled by the number of steps or strides respectively.

3.3. Data Analysis

The data analysis was carried out using MATLAB R2023. Specifically, an Android application was used for collecting data from the smartphone motion sensors, i.e., accelerometer (m/s^2), linear accelerometer (m/s^2), gyroscope (*degrees/s*), gravity (m/s^2) and magnetometer (μT). In particular, the accelerometer is an electromechanical device which measures the force of acceleration caused by movement or gravity or vibration, and acceleration is a measurement of the change in velocity or speed divided by time.

Linear accelerometer is a software-based motion sensor that reports the linear acceleration of the sensor frame, not including gravity. While, theoretically the difference between accelerometer and linear accelerometer is the gravity component (gravity at rest is $9.8m/s^2$) on the z-axis, the data collected for x- and y-axes were also different. Furthermore, gyroscope estimates the speed of rotation, thus it determines the orientation of the smartphone from the initial state of rest. Magnetometer estimates the magnetic field to which the smartphone is subjected, whereas in the absence of any magnetic or ferromagnetic object, the magnetometer provides the coordinates of the earth's magnetic field (magnetic North). Gravity sensor is another software-based motion sensor that calculates its values using more than one hardware sensor.

For the work presented, smartphones were deployed in 5 different body positions i.e., Hand, Arm, Waist, Leg and Ankle, for three different speeds, i.e, slow, normal and fast, and iterated three times by carrying out experiments with different participants, thus a total of 45 datasets were extracted and analysed. Initially, the total number of steps was estimated using all motion sensors raw measurements, i.e., Accelerometer, Linear Accelerometer, Gyroscope, Gravity and Magnetometer, compared with the actual number of steps taken and the more accurate sensor measurements were selected. It was observed that only four sensor measurements, i.e., Accelerometer, Linear Accelerometer, Gyroscope and Magnetometer, appeared relevant to the step counting task. These four sensors measurements were fused by using all possible 3-sensor combinations as follows:

- Acc. - L. Acc. - Gyro. (ALG)
- Acc. - L. Acc. - Mag. (ALM)
- L. Acc. - Gyro. - Mag. (LGM)
- Mag. - Acc. - Gyro. (MAG)

While in the existing literature, the PDR step detection systems are built by considering the sensors' axes as a single measurement, in the work presented the sensors' measurements were split and analysed based on their 3 axes (x, y, z). Therefore, for each sensor fusion combination, i.e., ALG, ALM, LGM and MAG, each sensor was analysed based on its three axes; thus providing a total of nine different measurements (entries) and 84 total possible combinations. The method was compared with the single measurement method, where each sensor measurement is utilized as a single combined measurement of all 3 axes.

3.4. Step Counting Algorithm

Although data pre-processing is commonly used in the existing literature during the development of a step counting system, it eliminates the opportunity of utilizing off-the-shelf smart devices, as well as requires high computational cost. In the work presented, the proposed step counting system entirely depends on the raw motion sensor measurements. Specifically, the step counting algorithm, shown in Algorithm 1, begins with the collection of the raw sensor data measurements. Then, each sensor datastream is split into three measurements (i.e, x-, y- and z-axes), thus providing a total of nine different datastreams and 84 total possible combinations (i.e., 9 choose 3).

Then, the collected raw sensor data measurements magnitude is estimated using Equation (1), and any constant effects are removed by subtracting the mean from the magnitude,

$$Magnitude = \sqrt{(data_x)^2 + (data_y)^2 + (data_z)^2} \tag{1}$$

where $data_x$, $data_y$ and $data_z$ represent the input sensor data for x-, y- and z-axes respectively.

The standard deviation estimation follows, using Equation (2), which is used as the threshold value,

$$STD(X) = \sqrt{\frac{\sum_{i=1}^{N}(X_i - \hat{X})^2}{N-1}} \tag{2}$$

where N is the number of measurements in the dataset, X_i represents each of the values and $\hat{X}$ is the mean of $X_i, i = 1, ..., N$.

Algorithm 1 Step Counting Algorithm

Input three sensor datastreams at a time (i.e., ALG, ALM, LGM, MAG)
Split each sensor datastream into three components (x-, y-, z-axes), thus providing a total of nine different sensor component datastreams and 84 total possible combinations (i.e., 9 choose 3)
for *iteration* $= 1, 2, \dots, 84$ **do**
    Estimate the magnitude
    Deduct the magnitude mean
    Set the threshold to 1 standard deviation
    Estimate the total number of steps (peaks above the threshold)
end for

All output results, above the threshold value, are considered as pedestrian steps. The error is the absolute difference between the counted and estimated numbers of steps. The overall percentage error is computed for the total number of steps, as well as various error statistics including the average, median, minimum and maximum errors for each body position and corresponding speeds.

4. Experiments and Results

For the present work, three volunteers participated in the experiments. The participants were chosen as non-athletes and they were in prior asked to describe their exercise workouts, experience level and state any injuries or illnesses they may have. All three of them stated that they usually exercise, mostly walking in the morning, and they had no injuries or illnesses. Therefore, all three experiments were carried out in the morning, i.e., 6:00-7:00 am, using the same professional gym treadmill (Technogym Excite Run 500i), in the same gymnasium, within the same week, i.e., Monday, Thursday and Friday, for avoiding any external biases. In particular, two women and one man participated in the experiments, aged between 18-50 years, each one equipped with five different off-the-shelf smartphones deployed at different body positions, using commercial running water resistant smartphone cases, as illustrated in Figure 2, numbered 1 to 5, representing Hand, Arm, Waist, Leg and Ankle respectively. Furthermore, the smartphone models are listed in Table 2. Each body position was experimented at three different speeds, 3.3km/h (slow), 4.6km/h (normal) and 5.9km/h (fast) [4]. The five different body positions at three different speeds resulted in 3 * 5 * 84 = 1260 different sensor fusion combinations examined for each experiment. Moreover, the Android application update interval was set to 0.01 seconds, thus a frequency of 100Hz, generating a data stream of 90,000 entries for each body position including all three speeds. An assistant guided the participants throughout the experiments by providing a briefing prior to each experiment. The participants were instructed to walk at three different speeds with a duration of 15 minutes each. The assistant clearly stated that the experiments were timed and they had the option to terminate at any time they felt tired or sick. Additionally, the participants were encouraged to have a short warm-up before the experiment, such as body stretching exercises and walking on their own pace on the gym's indoor mini running track. During their free walking, the assistant measured and recorded their step length, which was later compared with their step length while walking on the treadmill. All experiments were video recorded using an iPad Pro and watched afterwards for verifying the total number of steps taken, as well as the step length. The pedestrians' step lengths were measured using artificial landmarks placed on the treadmill. The distances covered during the experiment were 0.82km, 1.05km and 1.47km for slow, normal and fast speeds respectively, as recorded by the gym treadmill. It is noted that the total speed for each experiment was between 3.65km and 3.75km due to the extra time at the beginning, middle and end of each experiment. Specifically, the experiment duration was 49 minutes, thus walking for 1 minute until the assistant progressively set the speed to 3.3km/h (slow) followed by 15 minutes walking at a steady speed. After completing the first lap, the participants were instructed to walk for 1 additional minute, while the assistance progressively set the speed to 4.6km/h (normal) followed by 15 minutes walking at a steady speed. Similarly, after completing the second lap, the participants were instructed to walk for an additional minute while the assistant progressively set

Table 1
Optimum combinations of sensor axes for step counting using proposed algorithm

	Slow							Normal							Fast						
				Avg.%	Mdn.%	Min%	Max%				Avg.%	Mdn.%	Min%	Max%				Avg.%	Mdn.%	Min%	Max%
Hand	Acc_y	Acc_z	L. Acc_z	2.118	2.411	1.206	2.737	L. Acc_x	Gyro.$_z$	Mag.$_z$	0.887	1.151	0.314	1.195	Acc_x	L. Acc_y	Mag.$_x$	7.423	6.836	0.914	14.520
Arm	Acc_y	Acc_z	L. Acc_z	0.613	0.561	0	1.277	Acc_x	Acc_y	Acc_z	1.159	1.212	0.692	1.572	Acc_x	L. Acc_x	Mag.$_y$	2.258	1.977	1.356	3.441
Waist	Acc_y	L. Acc_x	Mag.$_x$	3.722	3.649	1.702	5.816	Acc_z	Mag.$_x$	Mag.$_y$	3.171	1.212	0.629	7.673	L. Acc_y	Gyro.$_y$	Mag.$_x$	1.861	0.565	0.215	4.802
Leg	Acc_z	Gyro.$_z$	Mag.$_z$	6.758	6.383	6.241	7.649	Gyro.$_z$	Mag.$_x$	Mag.$_z$	4.532	3.030	1.635	8.931	L. Acc_x	Mag.$_y$	Mag.$_z$	4.803	4.409	1.921	8.079
Ankle	Acc_z	L. Acc_y	Mag.$_y$	11.720	12.411	1.474	21.277	Acc_x	L. Acc_x	Mag.$_y$	5.912	5.030	2.956	9.748	Acc_x	L. Acc_x	Mag.$_y$	6.055	6.075	2.486	9.604

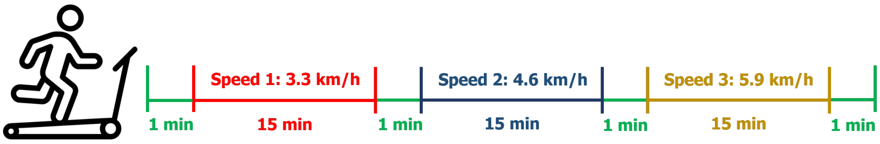

Figure 2: Experiment Timeline

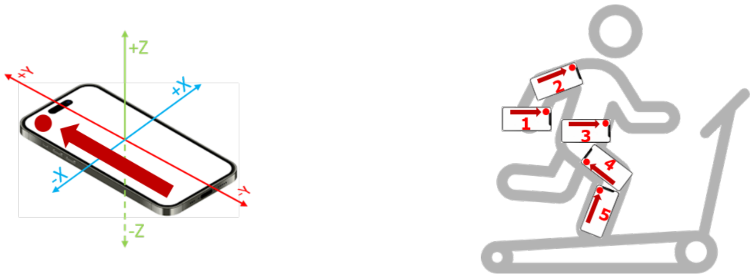

Figure 3: Smartphone Placement

Table 2
Body position vs Smartphone model

Smartphone Number	Body Position	Smartphone Model
1	Hand	Xiaomi Mi 11 Lite 5G
2	Arm	Xiaomi Mi 11i
3	Waist	Xiaomi Poco X3 NFC
4	Leg	Huawei P10 lite
5	Ankle	Honor 6X

Table 3
Steps Counted and Step Length

Participant	Slow	Normal	Fast	Height	Free walking	Treadmill
1	1425	1650	1860	165cm	66-67cm	56-58cm
2	1410	1590	1770	170cm	68-71cm	57-59cm
3	1410	1590	1770	170cm	68-71cm	57-59cm

the speed to 5.9km/h (fast) and walked for 15 minutes at a steady speed. Finally, the participants walked for an additional minute for cooling down. The experiment timeline is shown in Figure 2. In addition, the smartphone orientation axes and their employment orientation is demostrated in Figure 3. During the experiment, the duration of each speed interval was recorded by the assistant, as well as the number of steps was counted by using an electronic hand clicker counter. The total counted number of steps walked by each participant is listed in Table 3. Besides, it was concluded that the step length is directly related to the pedestrian's height, as well as their step length was smaller compared to free walking on the gym's indoor mini running track. The participants' height and step length are shown in Table 3.

The optimum combination for each experiment, i.e., the one that achieves the minimum average error, is reported in Table 1, together with other error statistics such as median, minimum and maximum

Table 4
Optimum combination of sensor data for step counting using single measurement method

	Slow					Normal					Fast				
	Method	**Avg.%**	**Mdn.%**	**Min%**	**Max%**	**Method**	**Avg.%**	**Mdn.%**	**Min%**	**Max%**	**Method**	**Avg.%**	**Mdn.%**	**Min%**	**Max%**
Hand	ALG	11.690	10.246	9.22	15.603	LGM	9.166	8.931	3.962	14.606	MAG	15.727	22.655	1.299	23.226
Arm	ALG	10.447	10	7.298	14.042	MAG	15.226	14.465	4.545	26.667	ALM	13.542	25.254	1.017	24.355
Waist	ALG	17.168	18.456	3.191	29.858	ALM	7.520	6.729	3.818	12.012	ALG	10.184	7.627	3.602	19.322
Leg	ALM	30.294	24.610	10.386	55.886	ALM	24.685	14.182	13.585	46.289	ALM	35.784	38.361	6.505	62.486
Ankle	ALM	14.656	11.206	0.421	32.340	ALM	10.001	11.576	0.629	17.799	ALM	16.388	15.650	10.395	23.118

error. For comparison purposes, we also implement the Single Measurement method, which considers each sensor datastream as a combined measurement of all 3 axes components.

5. Discussion

Throughout all experiments, body positions and their corresponding speeds, there were combinations with zero error. That is, the number of steps estimated was exactly the same with the number of steps counted. From Table 1, it can be observed that the optimum combination, with the lowest average percentage error (0.613%), of all tested combinations, is achieved by deploying a smartphone on the pedestrian's arm at slow speed with the combination of Accelerometer-y, Accelerometer-z and Linear Accelerometer-z. The biggest average error was 11.72% and it was produced by using the combination of Accelerometer-z, Linear Accelerometer-y and Magnetometer-y on the ankle at slow speed. Furthermore, the optimum body position for holding a smartphone while walking is the arm with an overall average error of 4.0295% and median 3.7509%, whereas the ankle produced the highest overall average error 23.6873% and median 23.5169%. However, the optimum results are most frequently obtained from the combination of Accelerometer-x, Linear Accelerometer-x and Magnetometer-y, followed by Accelerometer-y Accelerometer-z and Linear Accelerometer-z. Moreover, regarding the normal speed, the optimum combination includes the Linear Accelerometer-x, Gyroscope-z and Magnetometer-z with an average error of 0.887% and median 1.1515%, which provides new opportunities for future research, since most pedestrians utilize a smartphone armband during walking. The results revealed that the proposed method outperformed the Single Measurement method; i.e., where each sensor datastream is considered as a single combined measurement. The estimated number of steps using the Single Measurement method are shown in Table 4. In addition, the optimum combinations of the proposed method and Single Measurement are compared in Figure 4. Specifically, for Single Measurement, the lowest average error (7.520%) and lowest median error (6.729%) was achieved using the combination of Accelerometer, Linear Accelerometer and Magnetometer (ALM), deployed on the waist at normal speed. Similarly, the minimum error (0.421%) was achieved using the same combination, deployed on the ankle at slow speed, whereas the maximum error was observed on the leg at fast speed.

The aim of this research is to achieve the lowest overall error for the optimum combination. Firstly, despite the fact that in reality the walking speed is complicated, in the work presented we considered three different speeds. Secondly, the pedestrians were equipped with five different off-the-shelf smartphones aiming to find the optimum body position, which is concluded to be the arm, a realistic body position placement for most pedestrians, which in turn provides opportunities for future work.

6. Conclusions

This paper presents an accurate and robust step counting algorithm based on the optimum combination of the axes components from the four following IMU sensor data streams: accelerometer, linear accelerometer, gyroscope and magnetometer. The intended method focuses on the usage of off-the-shelf smartphones deployed at a variety of different body positions. The performance of the proposed method is evaluated by using experiments with different volunteers. The experimental results showed that

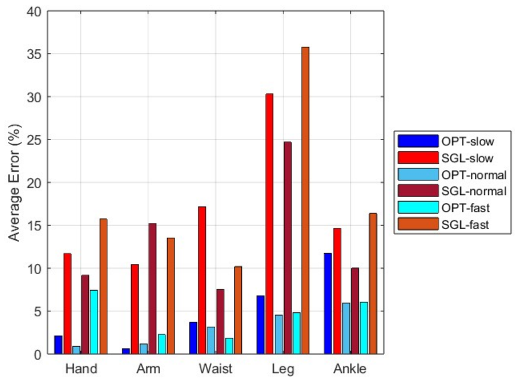

Figure 4: Comparison of optimal results between Proposed Method (OPT) and Single Measurement (SGL)

the proposed method outperforms the commonly-used methods which consider the motion sensors' measurements as a single combined measurement. In the future, we plan to extend the algorithm to include the pedestrian's heading and even track the location.

7. Online Resources

All the sensor data captured and used in the presented study, is available at https://github.com/conisaia/Step-Counting-by-Optimum-Fusion-of-IMU-Sensor-Measurements

Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

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