

Earable IMU-Based Indoor Positioning

Yinqi Zhang, Xu Feng, Mai Nguyen, Zhiyuan Luo, and Khuong An Nguyen

Abstract Wearable inertial measurement unit (IMU) positioning has become an important approach for indoor location-based services, as it enables user motion to be estimated without dedicated environmental infrastructure. While smartphone-based positioning, head-mounted, shoe-mounted pedestrian dead reckoning (PDR), and other wearable positioning approaches have been widely studied, earable positioning has not yet been sufficiently understood, particularly with respect to walking-related factors. To address this gap, this paper presents a systematic investigation of earable IMU-based indoor positioning using a real-world dataset collected with two low-cost IM948 earable IMUs, two commercial-grade Xsens DOT earable IMUs, a pocket-carried smartphone IMU, and an iPhone-based ground-truth recording device. We evaluated the effects of path geometry, walking speed, stop-and-go motion, head motion, and walking direction on positioning performance. The positioning results showed preliminary observations that walking-related factors were associated with different trajectory-error patterns in the current controlled trials, with path geometry related to drift patterns, walking speed related to local motion consistency, and head motion associated with additional heading errors. Notably, in the tested trials, the earable IMUs showed lower average absolute trajectory error (ATE) than the Pocket IMU, achieving 2.54 m compared with 6.55 m. These preliminary findings suggest that the earable placement may provide a more stable sensing condition than pocket smartphone placement under the tested conditions.

Key words: Earable inertial measurement units (IMUs), pedestrian dead reckoning (PDR), indoor navigation, wearable sensing

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1 Introduction

Wearable sensing has become an important basis for indoor pedestrian navigation and location based services (LBS). In this context, wearable inertial measurement unit (IMU) positioning has attracted increasing attention because inertial sensors are low-cost, lightweight, and independent of external infrastructure [1]. In contrast to infrastructure based approaches such as WiFi [2, 3, 4], Bluetooth [5, 6, 7], RGB [8, 9, 10, 11], or RGB-D sensing [12, 13, 14, 15], IMU-based methods estimate user motion directly from body worn or mobile inertial sensors without dedicated environmental deployment [16, 17]. Recent studies have investigated both model-based and data-driven pedestrian inertial navigation, including step based pedestrian dead reckoning, shoe mounted inertial navigation, smartphone inertial odometry, and learning based inertial navigation [1, 18, 19, 20]. Smartphones are also commonly used as mobile and wearable sensing platforms because they contain embedded inertial sensors and are frequently carried on the body [21].

However, the performance of wearable IMU positioning is strongly affected by sensor bias, noise, sensor placement, mounting stability, and user motion [22]. A smartphone carried in a trouser pocket can be affected by loose clothing and changing device orientation. Head-mounted IMUs provide a promising alternative for wearable indoor navigation, because they can be integrated into hearing aids, earbuds, or other head worn devices for long term daily use [23]. Compared with glasses or larger head-mounted devices, earable sensors are lightweight, unobtrusive, and can support low power wireless data transmission while already containing IMU sensors. At the same time, head-mounted sensing introduces its own challenge: independent head motion may interfere with walking related motion and heading estimation, thereby reducing the reliability of inertial navigation [24].

Existing studies have investigated smartphone inertial navigation, hearing aid based gait sensing, and visual inertial datasets [18, 19, 23]. Earable sensing studies have mainly focused on gait recognition, temporal gait parameter estimation [23], health monitoring, or early in-ear inertial navigation prototypes [25]. These works provide important foundations for IMU-based pedestrian navigation and wearable sensing. Nevertheless, earable indoor navigation remains under explored as a positioning approach in its own right. In particular, there is still a lack of systematic property analysis for earable IMU navigation, a lack of widely used large scale public datasets, limited comparison of indoor walking factors, and few controlled studies that directly compare earable IMUs with Pocket IMUs under the same indoor walking conditions.

To address these gaps, this paper investigates earable IMU-based indoor navigation using four head-mounted IMUs and one pocket-carried smartphone IMU. The experiments are designed around straight, circular, and rectangular walking paths, with additional variations in stopping behaviour, head motion, walking speed, and clockwise or counter-clockwise walking direction. These controlled experimental settings support the analysis of earable IMU navigation properties and the construction of a real-world dataset. In addition, by applying the same PDR processing pipeline across all sensors, this work establishes a baseline indoor positioning sys-

tem for earable IMUs and enables a direct comparison between earable and pocket smartphone-based PDR.

The contributions of this paper are as follows:

- We provide a preliminary property analysis of earable IMU-based indoor navigation by investigating the effects of *path shape*, *head motion*, *stopping behaviour*, *walking speed variation*, and *walking direction* on inertial trajectory estimation under controlled trials.
- We publicly release a real-world multi-IMU indoor walking dataset covering multiple path geometries and motion conditions, including dedicated head-motion trials with corresponding ground-truth trajectories. The dataset was collected using four head-mounted earable IMUs and one pocket-carried smartphone IMU (Pocket IMU), and provides RTAB-Map ground-truth trajectory coordinates for the evaluated trials.
- We provide benchmark performance for earable IMU-based indoor navigation system using both low-cost and commercial sensors under multiple challenging indoor walking conditions.
- We compare earable IMU-based indoor navigation with Pocket IMU PDR under matched paths and walking behaviours, and discuss how sensor placement and mounting stability may contribute to the observed differences.

The remainder of this paper is organised as follows. Section 2 reviews related work on wearable IMU indoor positioning. Section 3 describes the experimental testbed, sensor setup, experimental design, data collection protocol, and ground-truth acquisition. Section 4 introduces the evaluation metrics, presents and discusses the experimental results. Section 5 concludes the paper.

2 Related Work

IMU-based positioning has been widely studied for indoor navigation because it is low-cost, infrastructure-free, and available on many mobile and wearable devices [1]. Smartphone IMU systems have reported promising results. RIDI achieved a mean positional error below 3% of the travelled distance by correcting low-frequency acceleration bias before double integration [18]. IONet formulated inertial odometry as a window-based learning problem and kept the maximum error around 2 m for 90% of the testing time [26]. RoNIN further evaluated neural inertial navigation under natural phone carrying conditions and reported meter-level absolute trajectory error (ATE) and relative trajectory error (RTE) [19]. Other wearable IMU systems have also been developed for head-mounted, glasses-mounted, headset, and foot-mounted settings. For example, a head-mounted pedestrian dead reckoning (PDR) method achieved 2.10% distance error using sensors placed on glasses and in a mouthguard [17], while HINNet reported 0.46% distance error using head-mounted Xsens DOT sensors [27]. However, the performance of earable IMU systems remains insufficiently investigated.

Unlike mainstream wearable IMU devices, earable sensing has primarily been employed for gait analysis, activity recognition, and health monitoring, with comparatively limited attention to indoor navigation [23, 28]. To the best of our knowledge, PilotEar is the only representative earable IMU navigation system. However, its indoor experiment was limited to a 10 m path and reported drift rates of 0.15 m/s using one earable and 0.11 m/s using two earables [25]. Table 1 summarises representative wearable IMU indoor navigation systems and compares their devices, path lengths, and reported distance errors in percentage.

Despite recent advances in wearable inertial sensing, earable IMU navigation remains insufficiently explored. To address this gap, this paper presents a new public dataset for earable IMU indoor navigation and systematically investigates its properties under controlled indoor walking conditions. Specifically, we compare earable IMUs with the Pocket IMU, evaluate low-cost IM948 earable IMUs against commercial-grade Xsens DOT earable IMUs, and analyse the effects of different indoor walking factors on navigation performance.

Table 1 Performance of representative wearable IMU indoor navigation systems.

Study / system	Devices	Path length	Distance error [†]
Head-mounted PDR [17]	Glasses, mouthguard	~68 m	2.10%
RIDI [18]	Smartphone	79–153 m	<3%
RoNIN [19]	Smartphone	~320–390 m	~0.9–1.6%*
PilotEar [25]	Custom earable	10 m	~8–13%*
IONet [26]	Smartphone	~120–140 m	~1.4–1.7%*
HINNet [27]	Xsens DOT	~89–173 m	0.46%

[†] Distance error is reported as the percentage error relative to the travelled distance.

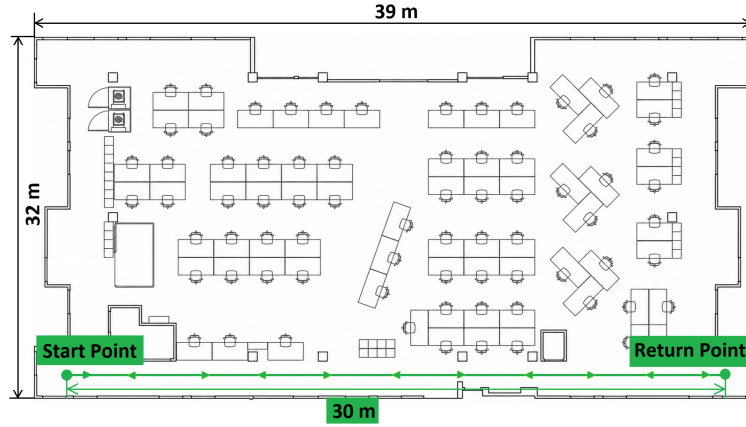
* Estimated or converted from the reported meter-level error or drift rate.

3 Experiments and Dataset

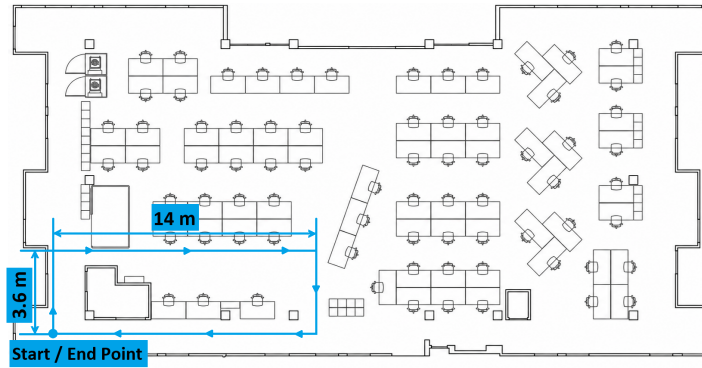
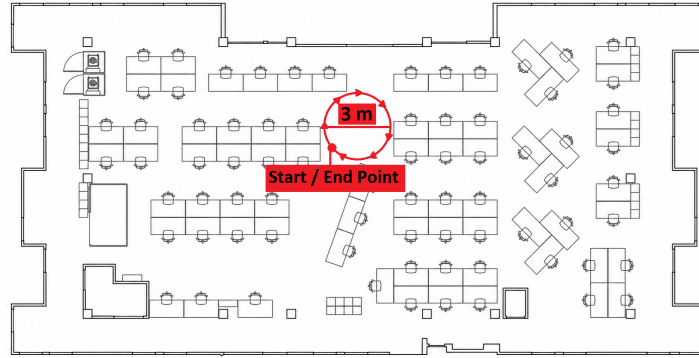
This section presents the experimental design, testbed, devices, data collection setup, ground-truth acquisition, and IMU-based trajectory estimation methods used to evaluate earable indoor positioning.

3.1 Testbed and Path Shape

The experiments were conducted in the first-floor office in the Bedford Building at University of London. The testbed is a complex real-world office environment with an



(a) Straight path (30 m one-way).

(b) Rectangular path (14 m $\times$ 3.6 m).

(c) Circular path (3 m diameter).

Fig. 1 Overview of the testbed floor plan and predefined walking routes. The testbed is a complex real-world office environment with an area of 39 m $\times$ 32 m.

area of 39 m × 32 m, as shown in Figure 1. The office environment contained desks, chairs, walls, partitions, computers, and everyday wireless devices. As a result, the testbed naturally included background signals from WiFi, Bluetooth, and other office electronics. This setting closely reflects typical indoor positioning scenarios and is therefore suitable for evaluating earable IMU trajectory estimation under realistic conditions.

There are three predefined path shapes: straight, rectangular and circular. The 30-metre long straight path in Figure 1(a) was used for one-way and return straight walking tests. This path mainly examines step-length accumulation error and heading drift during forward walking. The rectangular path in Figure 1(b) measured 14 m × 3.6 m and included multiple right-angle turns. It was therefore used to evaluate turn detection and the stability of heading updates. The circular path in Figure 1(c) had a route length of 10 m and introduced continuous heading changes through repeated loops, which was therefore used to test trajectory stability under sustained turning.

Together, these three paths represent basic walking trajectory types, including straight one-way and return walking, discrete right-angle turning, and continuous turning. This design provides a representative basis for evaluating earable IMU indoor positioning performance under different movement patterns and walking conditions.

3.2 Experiment Design

Before describing the data collection procedure and experiment design, we first state the research questions (RQs) that guided the experimental setup. In particular, the experiments were designed to answer the following research questions:

- RQ1: How do walking-related factors, including path shape, walking speed, head motion, stop-and-go behaviour, and walking direction, affect earable IMU-based PDR? (Section 4.2).
- RQ2: How do the low-cost IM948 earable IMUs compare with the commercial-grade Xsens DOT earable IMUs under the same walking routes and ground-truth conditions? (Section 4.3).
- RQ3: How does earable or head-mounted IMU positioning compare with Pocket IMU positioning under identical indoor walking conditions? (Section 4.3).

To answer these research questions, the experimental design was organised into two stages. The first stage focused on analysing the properties of earable IMU navigation under different walking-related factors. The second stage compared different sensing configurations under identical walking conditions, including low-cost IM948 earable IMUs, commercial-grade Xsens DOT earable IMUs, and the Pocket IMU.

3.2.1 Stage 1: Factor-wise earable IMU experiments

In the first stage, the experiments were not limited to a single walking trajectory as shown in Table 2. Instead, they were designed around the factors that can affect PDR performance, including path shape, path length, loop number, walking speed, head motion, stop-and-go walking behaviour, and walking direction. Path shape was used to test the stability of the algorithm under different trajectory geometries: the straight path mainly reflects accumulated distance error during forward walking, the rectangular path introduces multiple right-angle turns, and the circular path introduces continuous heading changes. Walking speed, head motion, and stop-and-go walking behaviour were included to test stride-length estimation, heading estimation, and motion-state recognition under more complex walking behaviours. Head motion was included because, in real-world earbud-based navigation, the direction of the head may differ from the actual walking direction, which can directly affect heading estimation. Walking direction was considered to assess whether opposite traversal directions produced different errors due to sensor mounting orientation or turning patterns.

Among these conditions, a simple reference case is needed as the starting point for comparison. Therefore, the benchmark condition is defined as straight walking at a normal speed, without head motion, stop-and-go behaviour, or directional changes. The remaining conditions are treated as variations of this benchmark, focusing on evaluating the impact of different factors. The current experimental dataset was collected from one adult participant with normal walking ability, and each controlled experimental condition was repeated twice. All the experiments conducted in this study are listed in Table 2. Note that: ‘Head motion’ indicates whether the participant deliberately moved their head up and down, left and right while walking. ‘Stop-and-go’ indicates whether the participant stopped midway through the walk and then resumed walking several times. ‘Speed’ denotes the instructed walking speed. ‘Direction’ denotes the route traversal direction. One-way refers to walking along the straight path in one direction, while return refers to walking back to the starting point.

3.2.2 Stage 2: Matched multi-device comparison experiments

The second stage was conducted to compare sensing configurations under matched walking conditions. Unlike the first stage, this experiment did not vary walking behaviour. The participant walked at a normal speed, without head motion or stop-and-go behaviour. The route settings were straight return, rectangular clockwise, and circular clockwise. In this comparison, the iPhone 13 Pro carried in the trouser pocket is referred to as the Pocket IMU. As shown in Table 3, under each route setting, two low-cost IM948 earable IMUs, two commercial-grade Xsens DOT earable IMUs, and one Pocket IMU were recorded simultaneously and compared against the same ground-truth trajectory.

Table 2 Summary of property analysis experiments for evaluating walking-related factors.

ID	Path shape	Length	Loop	Head motion	Stop-and-go	Speed	Direction
1	Straight	30 m	1	No	No	Normal	One-way
2	Straight	30 m	1	No	No	Fast	One-way
3	Straight	30 m	1	Yes	No	Normal	One-way
4	Straight	30 m	1	No	Yes	Normal	One-way
5	Straight	60 m	2	No	No	Normal	Return
6	Straight	60 m	2	No	No	Fast	Return
7	Straight	60 m	2	Yes	No	Normal	Return
8	Straight	60 m	2	No	Yes	Normal	Return
9	Rectangular	35.2 m	2	No	No	Normal	Clockwise
10	Rectangular	35.2 m	2	Yes	No	Normal	Clockwise
11	Rectangular	35.2 m	2	No	No	Fast	Clockwise
12	Rectangular	35.2 m	2	No	No	Normal	Counter-clockwise
13	Rectangular	35.2 m	2	No	Yes	Normal	Clockwise
14	Circular	9.42 m	3	No	No	Normal	Clockwise
15	Circular	9.42 m	3	Yes	No	Normal	Clockwise
16	Circular	9.42 m	3	No	No	Fast	Clockwise
17	Circular	9.42 m	3	No	No	Normal	Counter-clockwise
18	Circular	9.42 m	3	No	Yes	Normal	Clockwise

The dataset was collected from one adult participant with normal walking ability, and each experimental condition in this table was repeated twice. ‘**Length**’ denotes the distance or geometric size of one loop or one path traversal, rather than the total walking distance of the trial. ‘**Loop**’ denotes the number of times the route was repeated within one trial. The total walking distance is therefore $\text{Length} \times \text{Loop}$. ‘**Head motion**’ indicates whether the participant deliberately moved their head up and down, left and right while walking. ‘**Stop-and-go**’ indicates whether the participant stopped midway through the walk and then resumed walking several times. ‘**Speed**’ denotes the instructed walking speed. ‘**Direction**’ denotes the route traversal direction. One-way refers to walking along the straight path in one direction, while return refers to walking back to the starting point.

Table 3 Summary of the experiments comparing different sensing configurations, including low-cost IM948 earable IMUs, commercial-grade Xsens DOT earable IMUs, and the Pocket IMU.

ID	Path shape	Length	Loop	Head motion	Stop-and-go	Speed	Direction
1	Straight	60 m	2	No	No	Normal	Return
2	Rectangular	35.2 m	2	No	No	Normal	Clockwise
3	Circular	9.42 m	3	No	No	Normal	Clockwise

The dataset was collected from one adult participant with normal walking ability, and each matched multi-device comparison condition in this table was repeated twice. The columns are defined consistently with those in Table 2.

3.3 Devices

In the experiments, three IMU configurations were employed: two low-cost IM948 earable IMUs, two commercial-grade Xsens DOT earable IMUs, and one Pocket IMU. Table 4 summarises the devices used in the experiments, including their roles and names used in the paper.

Table 4 Summary of the sensing devices used in the dataset.

Device	Manufacturer	Role	Sensor type	Sampling rate
IM948	Chenyi Technologies Ltd., Guangzhou, China	Low-cost IM948 earable IMU	Accelerometer*, Gyroscope*, Magnetometer*, Thermometer, Barometer	60 Hz
Xsens DOT	Xsens Technologies BV, Enschede, Netherlands	Commercial-grade Xsens DOT earable IMU	Accelerometer*, Gyroscope*, Magnetometer*	60 Hz
iPhone 13 Pro (IMU) [†]	Apple, CA, United States	Pocket IMU	Accelerometer*, Gyroscope*, Magnetometer*, Barometer, Pedometer	60 Hz
iPhone 16 Pro Max	Apple, CA, United States	Ground-truth recording device	Accelerometer*, Gyroscope*, RGB camera*, LiDAR*, Magnetometer, Barometer, Pedometer, Microphone, GPS	5 Hz

* The sensors used in this study.

[†] Built-in IMU unit of an iPhone 13 Pro, used as the Pocket IMU; no other phone sensors were used.

For earable sensors, IM948 (see Figure 2(c)) is used as the low-cost IM948 earable IMU, while Xsens DOT (see Figure 2(d)) is used as the commercial-grade Xsens DOT earable IMU. They both were used for earable IMU sensing. For the Pocket IMU condition, an iPhone 13 Pro was used (see ‘Pocket IMU’ in Figure 2(a)), with IMU data recorded using Sensor Logger. Finally, an iPhone 16 Pro Max (see ‘iPhone ground-truth’ in Figure 2(a)) was used to record ground-truth trajectory using the RTAB-Map [29, 30]. The placement of the sensors on the participant’s body is illustrated in Figure 2.

A 3D-printed head mount (see Figure 2(b)) was used to securely fix the earable sensors to the head. One low-cost IM948 earable IMU and one commercial-grade Xsens DOT earable IMU were mounted near each ear. The side-specific labels used in the figures, tables, and result discussion are IM948 Left, IM948 Right, Xsens Left, and Xsens Right, where Left and Right denote the participant’s left and right sides. In the regular walking trials, the iPhone 16 Pro Max used to collect the ground-truth trajectory was positioned at chest level. However, in the head motion trials, the iPhone 16 Pro Max was instead fixed to the 3D-printed head mount to record

the ground-truth trajectory under the head motion condition. The Pocket IMU was placed in the trouser pocket.

For IM948 IMU data acquisition, the IM948 readings were recorded at 60 Hz and included timestamps, quaternions, Euler angles, angular velocity, gravity-compensated acceleration, raw acceleration, gyroscope, and magnetometer measurements. The Xsens IMU streams were also recorded at 60 Hz and contained recording time, quaternion, acceleration, and gyroscope data. These earable IMU measurements were collected via SDKs running on a Microsoft Surface. The 60 Hz sampling rate was chosen because the maximum sampling rate of the Xsens DOT in real-time streaming mode is 60 Hz. To ensure unified data acquisition and fair comparison across devices, the IM948 IMU, Xsens IMU, and Pocket IMU streams were all recorded at 60 Hz. This setting also reduced the transmission load and helped reduce data instability caused by packet loss during real-time recording.

To collect data from the Pocket IMU, Sensor Logger is leveraged. Sensor Logger is a mobile sensor-recording application that can record inertial and motion sensor data from devices such as iPhones. The Pocket IMU data were recorded at 60 Hz and included quaternion, Euler angular velocity, acceleration, gyroscope, and magnetometer data.

Finally, the iPhone 16 Pro Max equipped with RTAB-Map application was used to record ground-truth trajectories. RTAB-Map is a simultaneous localisation and mapping (SLAM) application that uses visual and LiDAR data from smartphone and reduces trajectory drift through loop closure and graph optimisation, with reported decimetre-level accuracy [29, 30]. In this study, RTAB-Map effectively leveraged the LiDAR sensor of the iPhone 16 Pro Max to generate ground-truth coordinates of current position, with the sampling rate set to the maximum of 5 Hz. The full RTAB-Map recording was saved during the experiments, including point cloud data and other mapping outputs, including three-dimensional coordinates and quaternion. The three-dimensional coordinates were used to generate the two-dimensional ground-truth trajectory, while the quaternion preserved the device orientation.

3.4 Dataset

To the best of our knowledge, there is currently no publicly available earable IMU dataset specifically designed for indoor navigation. Existing wearable IMU datasets and studies mainly focus on smartphones, foot-mounted sensors, head-mounted devices, gait analysis, or activity recognition, while earable IMU-based indoor positioning remains insufficiently represented. The uniqueness of the proposed dataset lies in its inclusion of multi-source IMU data collected during real walking, together with corresponding ground-truth locations. The four earable sensors were fixed in consistent positions during data collection, reducing variations caused by sensor placement. The dataset includes two low-cost IM948 earable IMUs, two commercial-grade Xsens DOT earable IMUs, one Pocket IMU, and RTAB-Map

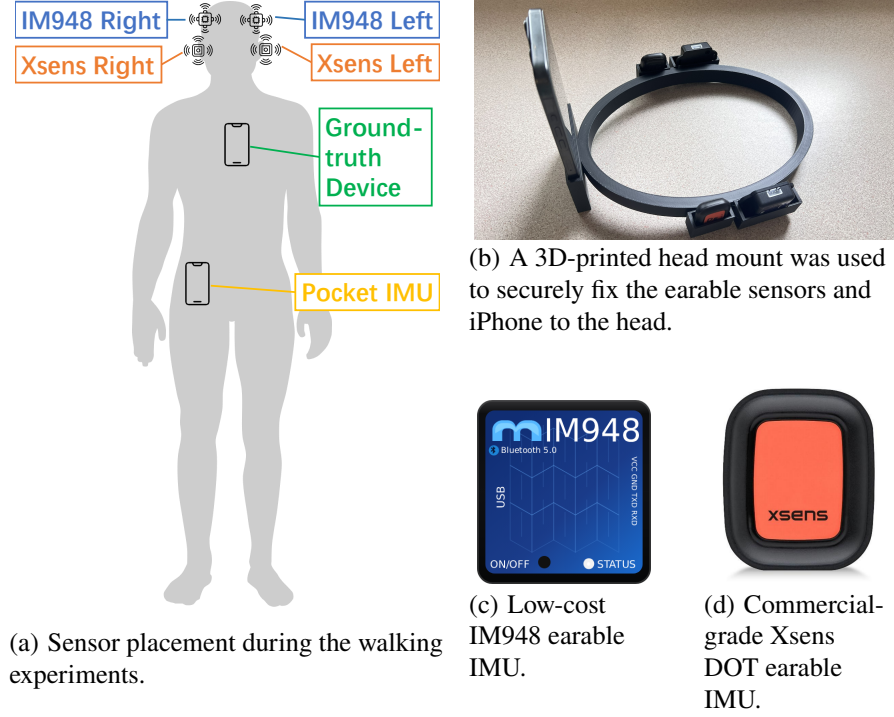


Fig. 2 Overview of the sensor placement used in the walking experiments, including the low-cost IM948 earable IMUs, the commercial-grade Xsens DOT earable IMUs, the iPhone ground-truth device, and the Pocket IMU. The labels IM948 Left, IM948 Right, Xsens Left, and Xsens Right denote the corresponding left- and right-side earable IMUs. Under normal walking conditions, the iPhone ground-truth device was mounted on the participant’s chest. For the head motion experiments, the iPhone was fixed to the head using the 3D-printed head mount shown in Fig. 2(b) to record head motion information.

ground-truth trajectories, supporting reproducible research and future benchmarking for earable indoor positioning.

The dataset contains synchronised multi-sensor IMU recordings collected in a complex indoor office environment. It includes four head-mounted earable IMU streams, consisting of two low-cost IM948 earable IMUs and two commercial-grade Xsens DOT earable IMUs, together with one Pocket IMU. Ground-truth trajectories were recorded using an iPhone 16 Pro Max with RTAB-Map SLAM system. The recorded sensor measurements include timestamps, quaternion, acceleration, gyroscope, and other device-dependent motion outputs. The controlled walking trials are listed in Tables 2 and 3, including straight, rectangular, and circular paths, as well as variations in walking speed, head motion, stop-and-go behaviour, and walking direction. The overall dataset statistics are summarised in Table 5.

In addition to the controlled trials, the released dataset also includes two long-walk sequences, each lasting more than 15 minutes. One long-walk sequence was

collected under random walking without head motion ground-truth, while the other includes intentional head motion ground-truth positions during walking. These long sequences are intended to support the evaluation of long-duration drift behaviour, continuous trajectory estimation, and the robustness of earable IMU positioning under natural head motion interference.

Overall, the dataset provides both controlled short-path trials for factor-wise analysis and longer walking sequences for more realistic continuous navigation evaluation. The dataset has been made publicly available on Zenodo: <https://zenodo.org/records/20594003>.

Table 5 Details of the proposed earable IMU indoor positioning dataset.

Dataset features	Technical Details
Experimental trials	42
Participant number	1
Condition repetition	2
Path types	Straight, rectangular, circular
Evaluated factors	Path shape, head motion, stopping behaviour, walking speed, walking direction
Total walking length	3688.17 m
Total experimental time	1 hour 48 minutes
IMU type and number	Low-cost IM948 earable IMU $\times$ 2, Commercial-grade Xsens DOT earable IMU $\times$ 2, Pocket IMU $\times$ 1
Measurements	Recording time, quaternion, Euler angles, angular velocity, free acceleration, acceleration, gyroscope, and magnetometer
Earable IMU sampling rate	60 Hz
Total IMU samples	1,164,439
Ground-truth sampling rate	5 Hz
Total ground-truth readings	25,628

3.5 Baseline PDR Pipeline

The same PDR pipeline (as shown in Figure 3) was applied to all IMU streams to ensure a fair comparison across devices. The algorithm consists of three steps. First, gait events are detected from the IMU signals and converted into per-step distances. Second, heading is estimated from the quaternion output. Third, the per-step distance and heading are integrated into a two-dimensional trajectory. This pipeline follows the step-frequency and step-length estimation principle used in head-mounted PDR [17, 27], while adding motion-state filtering to handle walking, stop, turn in place, and uncertain states.

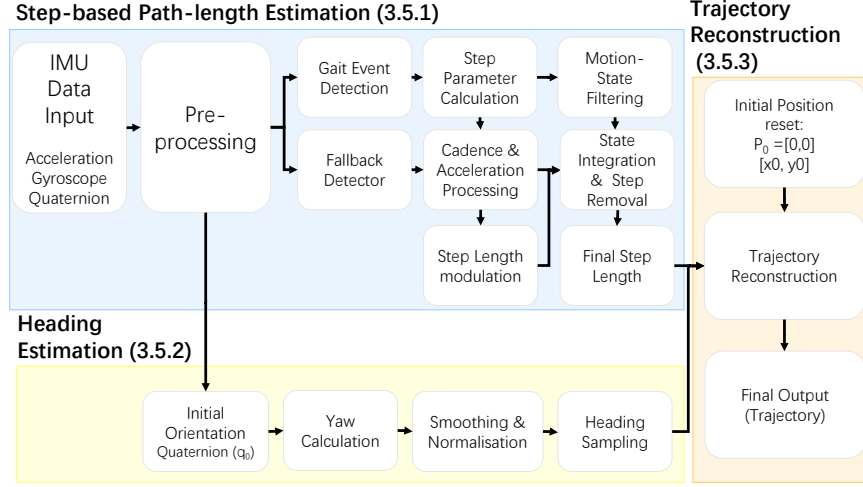


Fig. 3 Overview of the IMU-based trajectory estimation pipeline, including data preprocessing, step-based path length estimation, heading estimation, and final trajectory reconstruction.

3.5.1 Step-Based Path-Length Estimation

The first step estimates path length from gait events. The IMU data are cleaned, interpolated, and resampled before initial-contact detection [27]. The reproduced temporal gait model is first used to detect step events from acceleration and gyroscope signals. If the model output is unstable, an adaptive peak detector based on the acceleration norm is used as a fallback. For each detected step, the algorithm calculates the step interval, step frequency, and local acceleration amplitude.

Let t_i be the timestamp of the i th retained step. The step interval and step frequency are defined as

$$\Delta t_i = t_i - t_{i-1}, \quad f_i = \frac{1}{\Delta t_i}. \quad (1)$$

The acceleration amplitude $\hat{a}_i$ is computed from the local dynamic acceleration window around the detected step. A base step length l_0 is then modulated by cadence and acceleration amplitude:

$$l_i = l_0 \cdot m_i, \quad (2)$$

where m_i is the step-length multiplier for the i th retained step.

$$m_i = \text{clip} \left(1 + k_f \cdot \text{clip} \left(\frac{f_i - f_0}{f_0}, -0.8, 0.8 \right) + k_a \cdot \text{clip} (\hat{a}_i, -1.5, 1.5), 1 - L, 1 + L \right). \quad (3)$$

Here, $\text{clip}(v, a, b)$ limits the input value v to the interval $[a, b]$. If v is smaller than a , the output is a ; if v is larger than b , the output is b . f_0 denotes the reference step frequency used for cadence normalisation. In Eq. (3), the inner clip functions limit the influence of the step-frequency term and the local acceleration-amplitude

term, while the outer clip function constrains the final step-length multiplier to the range $[1 - L, 1 + L]$.

The reproduced temporal gait model was used first for initial-contact detection. When the model output was unavailable or unstable, an acceleration-norm adaptive peak detector was used as a fallback. To reduce false step accumulation, motion-state filtering was applied before trajectory integration. Samples were classified as walking, stop, turn in place, or uncertain using dynamic acceleration, acceleration-rate RMS, gyroscope-norm RMS, and candidate step density. Steps detected during stop states were removed, and turn-in-place states contributed zero path distance. The main parameters used in this process are summarised in Table 6.

Table 6 Main parameters used in the PDR baseline.

Parameter	Value	Description
l_0	0.70 m	Base step length.
k_f	0.12	Cadence modulation gain.
k_a	0.06	Acceleration-amplitude modulation gain.
L	0.10	Maximum step-length modulation range.
Accepted step interval	0.30–1.40 s	Valid interval between adjacent steps.
Stop window	0.80 s	Sliding window for motion-state classification.
Stop thresholds	0.20, 3.00, 8.00 deg/s	Dynamic acceleration RMS, acceleration-rate RMS, and gyroscope-norm RMS thresholds.
Turn threshold	10.00 deg/s	Gyroscope-norm RMS threshold for turn in place.
Structured turn threshold	7.00 deg/s	Gyroscope-norm RMS threshold for structured paths.

3.5.2 Heading Estimation

The second step estimates heading from the IMU quaternion. The quaternion at sample k is denoted as

$$\mathbf{q}_k = [w_k, x_k, y_k, z_k]. \quad (4)$$

Here, w_k , x_k , y_k , and z_k denote the four components of the quaternion at sample k . The term w_k is the scalar component, while x_k , y_k , and z_k are the vector components. The normalised quaternion is used to calculate the yaw angle, which is then converted into the heading used for PDR trajectory reconstruction. After normalisation, the yaw angle is calculated as

$$\psi_k = \text{atan2} \left(2(w_k z_k + x_k y_k), 1 - 2(y_k^2 + z_k^2) \right). \quad (5)$$

The yaw sequence is unwrapped and smoothed to reduce short-term noise. The heading used for PDR is then normalised by the initial yaw:

$$\theta_k = \hat{\psi}_k - \hat{\psi}_0, \quad (6)$$

where $\hat{\psi}_k$ is the smoothed yaw angle. The heading value at each retained step is sampled from θ_k and used for trajectory reconstruction.

3.5.3 Trajectory Reconstruction

The final step reconstructs the two-dimensional trajectory from the retained step distances and headings. Since the experiments were conducted in a 2D environment, this paper only calculates trajectories in the 2D plane. The trajectory starts from the origin:

$$\mathbf{p}_0 = [x_0, y_0]^\top = [0, 0]^\top. \quad (7)$$

For the i th step, the position is updated as

$$x_i = x_{i-1} + l_i \cos(\theta_i), \quad (8)$$

$$y_i = y_{i-1} + l_i \sin(\theta_i), \quad (9)$$

where l_i is the estimated step distance and θ_i is the heading at the same step. Each generated trajectory contains the step index, timestamp, two-dimensional position, cumulative distance, heading, and step distance. The IMU-estimated trajectory is later aligned with the RTAB-Map ground-truth and evaluated using absolute trajectory error (ATE), relative trajectory error (RTE), and trajectory similarity (TS).

4 Analysis and Results

This section provides the results of two experiments. The subsection 4.1 defines the three trajectory-level metrics used in this study: absolute trajectory error (ATE), relative trajectory error (RTE), and trajectory similarity (TS). The subsection 4.2 reports the first experiment, where the effects of path type, walking speed, walking direction, stop-and-go behaviour, and head motion are evaluated. The subsection 4.3 reports the second experiment, where the Pocket IMU is compared with four earable IMUs over three representative paths.

4.1 Evaluation Metrics

Three trajectory-level metrics are used to evaluate positioning accuracy: absolute trajectory error (ATE), relative trajectory error (RTE), and trajectory similarity (TS).

ATE measures the global deviation between the estimated trajectory and ground-truth:

$$ATE = \sqrt{\frac{1}{N} \sum_{i=1}^N \|\hat{\mathbf{p}}_i - \mathbf{p}_i\|^2}. \quad (10)$$

Here, N is the total number of synchronised trajectory samples, i is the sample index, $\hat{\mathbf{p}}_i$ is the estimated two-dimensional position at sample i , $\mathbf{p}_i$ is the corresponding ground-truth position, and $\|\cdot\|$ denotes the Euclidean norm. A lower ATE indicates that the estimated trajectory is globally closer to ground-truth.

RTE measures the local motion consistency between the estimated trajectory and ground-truth:

$$RTE = \sqrt{\frac{1}{N - \Delta t} \sum_{i=1}^{N - \Delta t} \|(\hat{\mathbf{p}}_{i+\Delta t} - \hat{\mathbf{p}}_i) - (\mathbf{p}_{i+\Delta t} - \mathbf{p}_i)\|^2}. \quad (11)$$

In this equation, Δt is the temporal interval used to calculate local trajectory displacement, $\hat{\mathbf{p}}_{i+\Delta t} - \hat{\mathbf{p}}_i$ represents the estimated local motion vector, and $\mathbf{p}_{i+\Delta t} - \mathbf{p}_i$ represents the corresponding ground-truth local motion vector.

TS measures the overall shape similarity between the estimated trajectory and ground-truth using normalised dynamic time warping (DTW) distance:

$$TS = \frac{1}{1 + \frac{\frac{1}{L} \sum_{(i,j) \in \mathcal{W}} \|\hat{\mathbf{p}}_j - \mathbf{p}_i\|}{s}}. \quad (12)$$

Here, $\mathcal{W}$ is the warping path obtained by DTW, L is the length of the warping path, $\hat{\mathbf{p}}_j$ is the estimated position matched by DTW, $\mathbf{p}_i$ is the corresponding ground-truth position, and s is the trajectory scale used for normalisation, defined by the diagonal length of the ground-truth trajectory bounding box. A higher TS value indicates greater trajectory similarity.

Therefore, ATE reflects global positioning accuracy, RTE reflects local trajectory consistency, and TS reflects the global shape similarity between the estimated trajectory and the ground-truth trajectory.

4.2 Impact of Walking Behaviour on Positioning Accuracy

Table 2 describes the experimental conditions used in the first experiment. The results in this part should be interpreted as preliminary observations from the current controlled trials, because the dataset was collected from one participant and no population-level statistical test or variance analysis was applied. For consistency, the straight one-way condition is treated as the benchmark in the following comparisons. The results are grouped by path type, walking speed, walking direction, stop-and-go behaviour, and head motion. For each factor, ATE, RTE, and TS are reported for IM948 Left and IM948 Right, together with representative trajectory figures where appropriate.

4.2.1 Effect of Path Type

Table 7 and Figure 4 provide the path-type comparison under normal walking without stop or head motion. This comparison was designed to examine whether changing the basic route geometry changes the drift pattern of the two IM948 sensors.

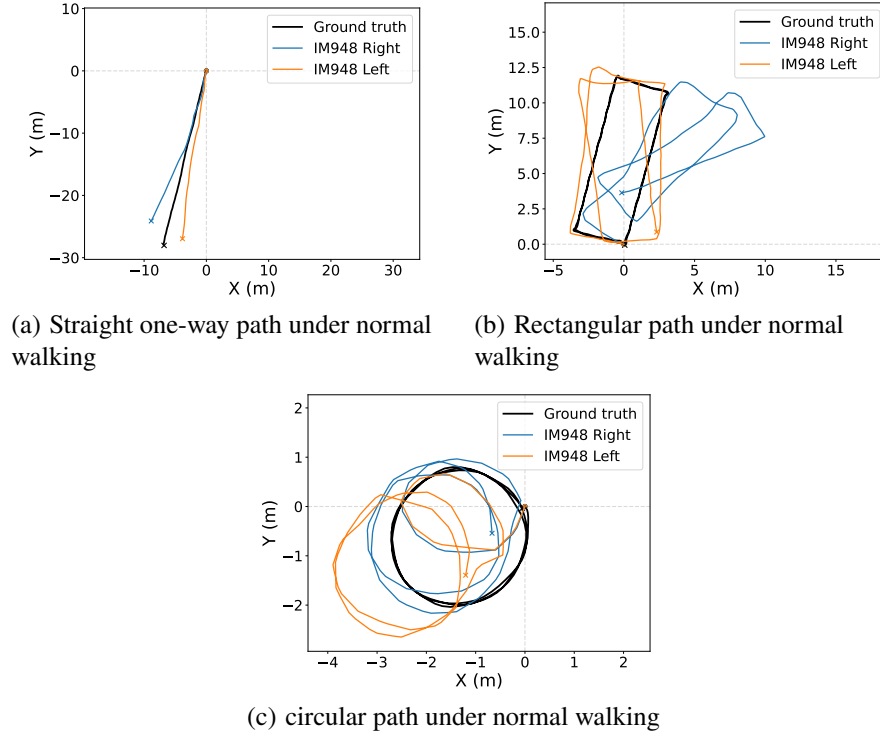


Fig. 4 Trajectory estimation performance is compared for straight one-way, rectangular, and circular paths under normal walking conditions, without stops or head motion. These examples show that route geometry changes both trajectory shape and side-specific drift, with the rectangular path revealing the strongest right side sensitivity around discrete turns. All trajectories start from the origin (0, 0), and the cross marker indicates the end position of each trajectory.

For the straight one-way path, both IM948 sensors preserved high trajectory similarity, with TS values of 0.96 on both sides. However, IM948 Right showed larger global and local errors than IM948 Left, as ATE/RTE increased from 2.03 m / 0.98 m on the left side to 2.61 m / 1.49 m on the right side. The TS value indicates that the estimated trajectory in the one-way trial preserved a shape similar to the ground-truth, but the ATE of the right sensor shows that the trajectory still had some drift relative to the ground-truth.

Table 7 Performance comparison across path types under normal walking conditions. Bold values highlight the best-performing results emphasized in the comparison, where lower ATE/RTE and higher TS indicate better performance.

Path	Left			Right		
	ATE (m)	RTE (m)	TS	ATE (m)	RTE (m)	TS
Straight one-way	2.03	0.98	0.96	2.61	1.49	0.96
Rectangular	1.67	1.44	0.94	4.58	2.52	0.81
Circle	1.83	2.30	0.84	1.29	1.79	0.92

The rectangular path showed a stronger side-specific difference. IM948 Left gave 1.67 m ATE, and 0.94 TS, whereas IM948 Right gave 4.58 m ATE, and 0.81 TS. The larger right side error and lower TS indicate that rectangular walking was associated with stronger right side drift in this trial. This may be related to the discrete turning corners, where heading transition and turn estimation may become more sensitive to sensor-side differences.

For the circular path, the left-right pattern was different. IM948 Right gave lower ATE/RTE and higher TS than IM948 Left, with 1.29 m ATE, 1.79 m RTE, and 0.92 TS on the right side compared with 1.83 m ATE, 2.30 m RTE, and 0.84 TS on the left side. Thus, the current path-type results showed that path geometry can change not only the magnitude of drift but also which side.

4.2.2 Effect of Speed

Table 8 and Figure 5 provide the speed comparison between normal and fast walking. The results are reported as current-trial observations, and the purpose was to examine whether walking speed is associated with different drift patterns across path geometries.

Table 8 Performance comparison between normal and fast walking. Bold values highlight the best-performing results emphasized in the comparison, where lower ATE/RTE and higher TS indicate better performance.

Path	Speed	Left			Right		
		ATE (m)	RTE (m)	TS	ATE (m)	RTE (m)	TS
Straight one-way	Normal	2.03	0.98	0.96	2.61	1.49	0.96
Straight one-way	Fast	3.80	2.27	0.91	3.54	2.04	0.91
Rectangular	Normal	1.67	1.44	0.94	4.58	2.52	0.81
Rectangular	Fast	2.10	2.10	0.93	3.63	3.27	0.82
Circle	Normal	1.83	2.30	0.84	1.29	1.79	0.92
Circle	Fast	2.06	1.57	0.75	1.59	1.35	0.82

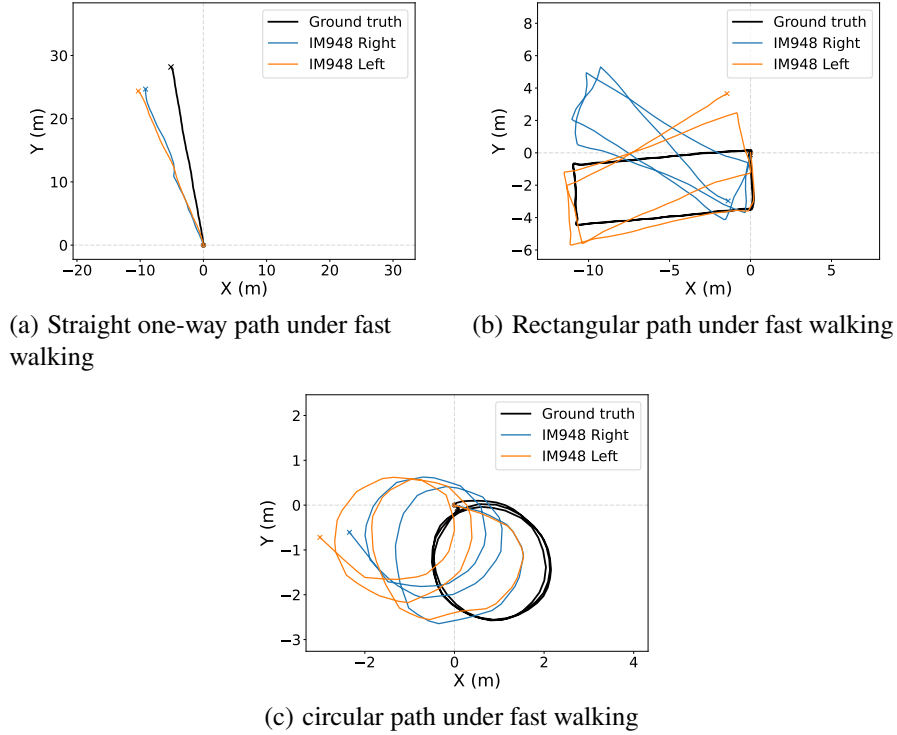


Fig. 5 Trajectory estimation performance is compared across straight one-way, rectangular, and circular paths under fast walking conditions. The result shows that faster walking does not uniformly worsen all metrics; instead, its effect depends on path geometry and is reflected mainly in local consistency and trajectory-shape similarity. All trajectories begin at the origin (0, 0), and the cross marker denotes the final position of each trajectory.

For the straight one-way path, the normal-walking trial showed relatively high trajectory similarity on both sides, with TS values of 0.96 for IM948 Left and 0.96 for IM948 Right. In the fast-walking trial, the main change appeared in local consistency: IM948 Left reported 2.27 m RTE and IM948 Right reported 2.04 m RTE. The TS values in the fast trial were 0.91 on both sides, suggesting that the straight-path shape was still partly preserved but less similar to ground-truth than in the normal-walking trial.

The rectangular path showed a mixed pattern rather than a uniform degradation. Under normal walking, IM948 Right had a large ATE of 4.58 m and a relatively low TS of 0.81, indicating strong right side drift in this trial. Under fast walking, IM948 Right reported a lower ATE of 3.63 m but a higher RTE of 3.27 m. This contrast suggests that fast walking is not simply associated with larger global error; instead, it may affect local turning consistency while the overall spatial offset changes differently.

For the circular path, the fast-walking trial also did not support a simple degradation claim. Under normal walking, IM948 Left reported 2.30 m RTE and IM948 Right reported 1.79 m RTE. In the fast-walking trial, the RTE values were lower, with 1.57 m for IM948 Left and 1.35 m for IM948 Right. However, the TS values in the fast trial were 0.75 and 0.82, lower than the normal-walking TS values of 0.84 and 0.92. This indicates that local displacement consistency and global shape similarity can behave differently in the current circular trials.

Overall, the speed results should not be described as showing that fast walking uniformly worsens trajectory estimation. In the current trials, speed is more appropriately described as a factor associated with path-dependent changes in local consistency and trajectory shape similarity.

4.2.3 Effect of Direction

Table 9 and Figure 6 provide the direction comparison. For the straight path, one-way walking was compared with return walking. For the rectangular and circular paths, clockwise walking was compared with counter-clockwise walking. Since no statistical test was applied, the direction-related differences are interpreted as current-trial observations.

Table 9 Performance comparison between walking directions. Bold values highlight the best-performing results emphasized in the comparison, where lower ATE/RTE and higher TS indicate better performance.

Path	Direction	Left			Right		
		ATE (m)	RTE (m)	TS	ATE (m)	RTE (m)	TS
Straight	One-way	2.03	0.98	0.96	2.61	1.49	0.96
Straight	Return	1.06	0.38	0.97	5.09	1.41	0.87
Rectangular	Clockwise	1.67	1.44	0.94	4.58	2.52	0.81
Rectangular	Counter-clockwise	1.38	0.86	0.93	1.29	1.08	0.95
Circle	Clockwise	1.83	2.30	0.84	1.29	1.79	0.92
Circle	Counter-clockwise	0.72	0.98	0.94	0.50	0.69	0.96

For the straight path, the one-way trial gave a more balanced global error between the two sides, with 2.03 m ATE for IM948 Left and 2.61 m ATE for IM948 Right. The return trial showed a different side pattern: IM948 Left had a low RTE of 0.38 m and a high TS of 0.97, while IM948 Right had a much larger ATE of 5.09 m and a lower TS of 0.87. This suggests that the return trial is associated with stronger right side global drift in the current straight-path results.

For the rectangular path, the clockwise trial showed clear right side drift, with IM948 Right reporting 4.58 m ATE and 0.81 TS. In the counter-clockwise trial, IM948 Right reported 1.29 m ATE and 0.95 TS, while IM948 Left reported 1.38 m ATE and 0.86 m RTE. These values indicate that the counter-clockwise rectangular

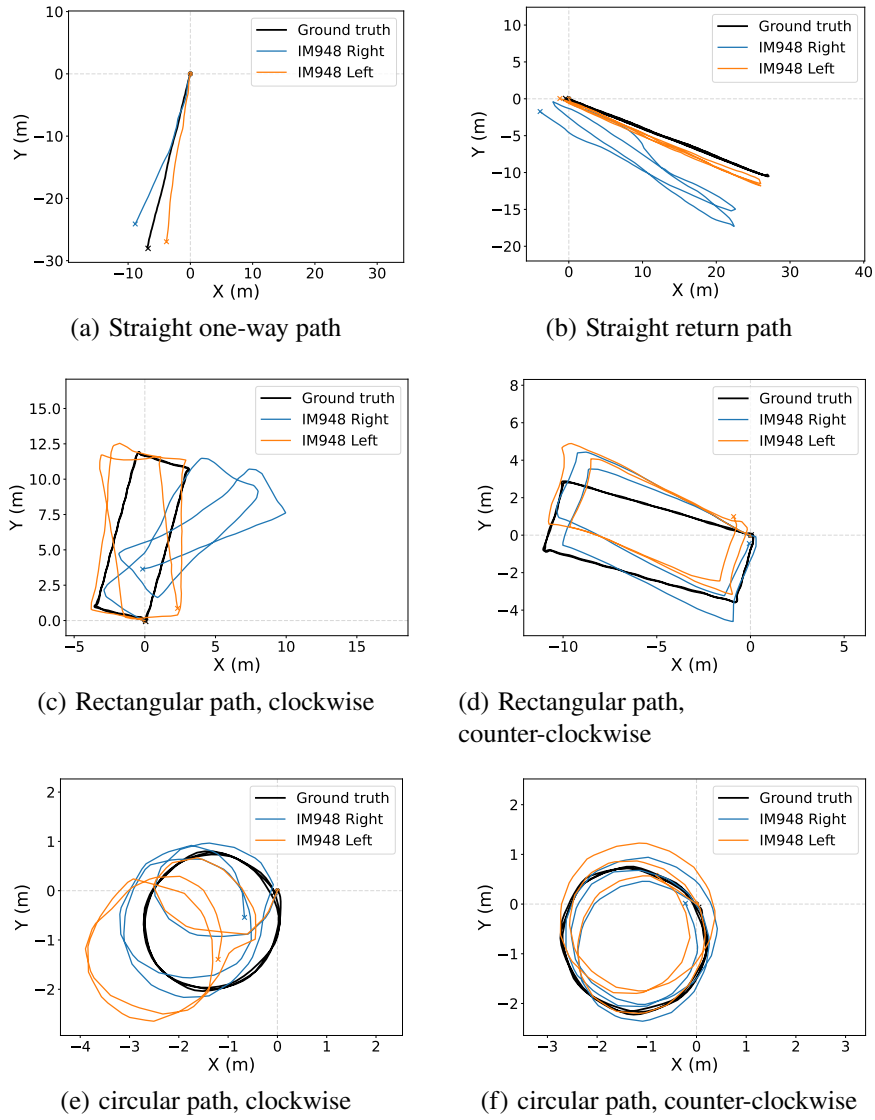


Fig. 6 Walking directions are compared for straight, rectangular, and circular paths. The straight path compares one-way and return walking, while the rectangular and circular paths compare clockwise and counter-clockwise walking. The result highlights that reversing walking direction changes side-specific drift, with counter-clockwise rectangular and circular trials showing lower errors and higher trajectory similarity in the current dataset. Each trajectory starts from the origin (0, 0), with the cross marker indicating its endpoint.

trial had lower error and better shape similarity for the right side IMU in the current data.

For the circular path, the counter-clockwise trial gave the lowest errors among the direction comparisons. IM948 Right reported 0.50 m ATE, and 0.96 TS, while IM948 Left reported 0.72 m ATE and 0.94 TS. The clockwise circular trial had higher RTE values, especially 2.30 m for IM948 Left and 1.79 m for IM948 Right. Therefore, the current circular results showed an observed tendency for counter-clockwise walking to produce lower errors and higher trajectory similarity.

In the current trials, walking direction was associated with different side-specific drift patterns. The counter-clockwise rectangular and circular trials showed better numerical results, but this tendency should be interpreted as an observation from the available trials rather than a general rule.

4.2.4 Effect of Stop-and-go Behaviour

Table 10 and Figure 7 provide the comparison between continuous walking and stop-and-go walking. These results report how the estimated trajectories differ under stop-and-go walking in the current trials, rather than establishing a general stop-related failure mechanism.

Table 10 Performance comparison under stop-and-go walking conditions. Bold values highlight the best-performing results emphasized in the comparison, where lower ATE/RTE and higher TS indicate better performance.

Path	Stop	Left			Right		
		ATE (m)	RTE (m)	TS	ATE (m)	RTE (m)	TS
Straight one-way	No	2.03	0.98	0.96	2.61	1.49	0.96
Straight one-way	Yes	5.56	2.06	0.86	3.54	1.29	0.90
Rectangular	No	1.67	1.44	0.94	4.58	2.52	0.81
Rectangular	Yes	2.41	1.58	0.89	4.60	3.81	0.83
Circle	No	1.83	2.30	0.84	1.29	1.79	0.92
Circle	Yes	1.38	1.25	0.84	1.29	1.22	0.84

For the straight one-way path, the no-stop trial showed high trajectory similarity on both sides, with TS values of 0.96 for IM948 Left and 0.96 for IM948 Right. In the stop trial, IM948 Left reported a large ATE of 5.56 m and a lower TS of 0.86, while IM948 Right reported 3.54 m ATE and 0.90 TS. This suggests that the stop trial is associated with stronger left side global drift and reduced shape similarity in the current straight-path result.

For the rectangular path, the no-stop trial already showed a large right side ATE of 4.58 m and a low right side TS of 0.81. In the stop trial, IM948 Right reported 3.81 m RTE, while IM948 Left reported 1.58 m RTE. This indicates that the stop condition may be associated with larger local inconsistency on the right side around turning segments in this trial. However, the ATE values for the rectangular right side

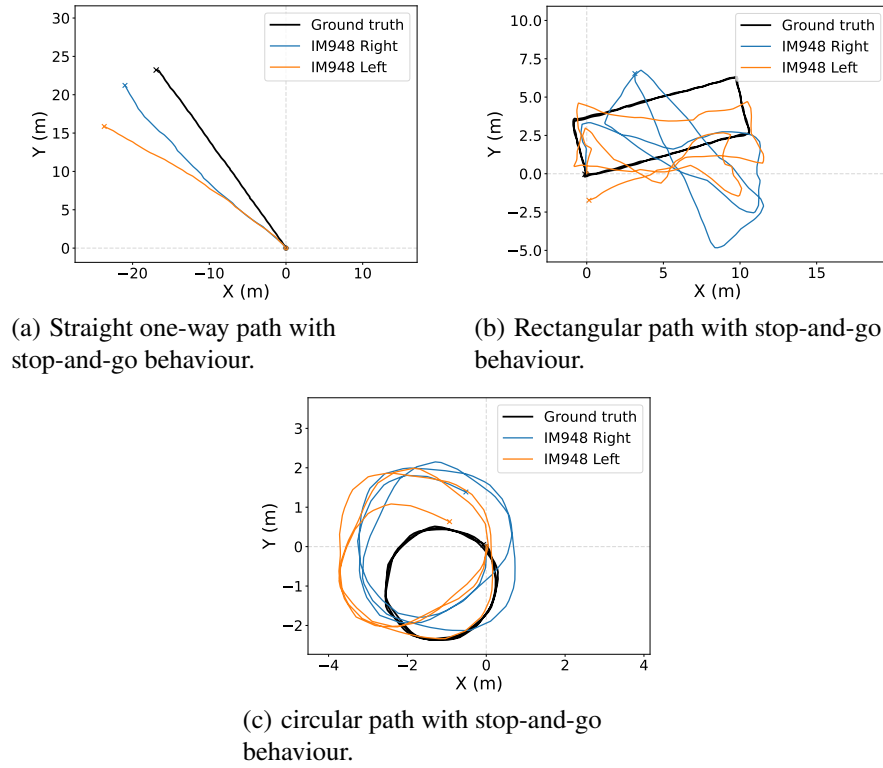


Fig. 7 Trajectory estimation performance is compared across straight one-way, rectangular, and circular paths under stop-and-go walking conditions. The result shows that stopping affects global offset and local consistency differently across path types, with the straight path showing stronger left side global drift and the rectangular path showing clearer right side local inconsistency. All plotted trajectories are initialised at the origin (0, 0), and the cross marker represents the trajectory endpoint.

results remained similar, so the effect should not be described as uniform degradation across all metrics.

For the circular path, the stop trial did not show the same ATE/RTE degradation. In the no-stop trial, IM948 Left reported 2.30 m RTE and IM948 Right reported 1.79 m RTE. In the stop trial, the RTE values were 1.25 m for IM948 Left and 1.22 m for IM948 Right. However, the right side TS in the stop trial was 0.84, lower than the no-stop right side TS of 0.92. This suggests that stop-and-go walking may alter trajectory shape similarity even when ATE/RTE did not become worse.

One plausible explanation for the observed stop-related changes is heading estimation during short pauses. When the subject stops briefly, the angular velocity may not immediately become zero, and the algorithm may not reliably estimate the duration of the stationary segment. This could allow heading error to be carried into the following walking segment. However, this study did not directly analyse

stop-detection failure, yaw-drift curves, or stationary-segment estimation. Therefore, this explanation should be interpreted as a plausible hypothesis for the current observations rather than a confirmed mechanism.

4.2.5 Effect of Head Motion

Table 11 reports the effect of head motion, and Figure 8 provides a representative trajectory from the straight one-way head motion trial. The figure is included because the large deviation is itself an important observed result, rather than a reason to exclude the trajectory from visual inspection.

Table 11 Performance comparison under head motion conditions. Bold values highlight the best-performing results emphasized in the comparison, where lower ATE/RTE and higher TS indicate better performance.

Path	Head motion	Left			Right		
		ATE (m)	RTE (m)	TS	ATE (m)	RTE (m)	TS
Straight one-way	No	2.03	0.98	0.96	2.61	1.49	0.96
Straight one-way	Yes	3.09	1.27	0.95	7.35	2.61	0.83
Rectangular	No	1.67	1.44	0.94	4.58	2.52	0.81
Rectangular	Yes	5.36	3.39	0.78	5.08	4.14	0.81
Circle	No	1.83	2.30	0.84	1.29	1.79	0.92
Circle	Yes	2.49	3.11	0.80	2.59	2.90	0.77

For the straight one-way path, the no head motion condition gave 2.03 m ATE, 0.98 m RTE, and 0.96 TS for IM948 Left, and 2.61 m ATE, 1.49 m RTE, and 0.96 TS for IM948 Right. With head motion, IM948 Left gave 3.09 m ATE, 1.27 m RTE, and 0.95 TS, while IM948 Right gave 7.35 m ATE, 2.61 m RTE, and 0.83 TS. The right side sensor showed a much larger degradation, indicating that head motion can produce asymmetric drift between the two sides.

For the rectangular path, the no head motion condition gave 1.67 m ATE, 1.44 m RTE, and 0.94 TS for IM948 Left, and 4.58 m ATE, 2.52 m RTE, and 0.81 TS for IM948 Right. With head motion, IM948 Left gave 5.36 m ATE, 3.39 m RTE, and 0.78 TS, while IM948 Right gave 5.08 m ATE, 4.14 m RTE, and 0.81 TS. Both sides showed large error values, indicating that head motion affects both global alignment and local turning consistency in the rectangular path.

For the circular path, the no head motion condition gave 1.83 m ATE, 2.30 m RTE, and 0.84 TS for IM948 Left, and 1.29 m ATE, 1.79 m RTE, and 0.92 TS for IM948 Right. With head motion, IM948 Left gave 2.49 m ATE, 3.11 m RTE, and 0.80 TS, while IM948 Right gave 2.59 m ATE, 2.90 m RTE, and 0.77 TS. The TS values decreased on both sides, showing that head motion reduces shape similarity during continuous curved walking.

In the current trials, head motion mainly affects heading estimation. The direction of the head does not always represent the direction of walking. Therefore, when

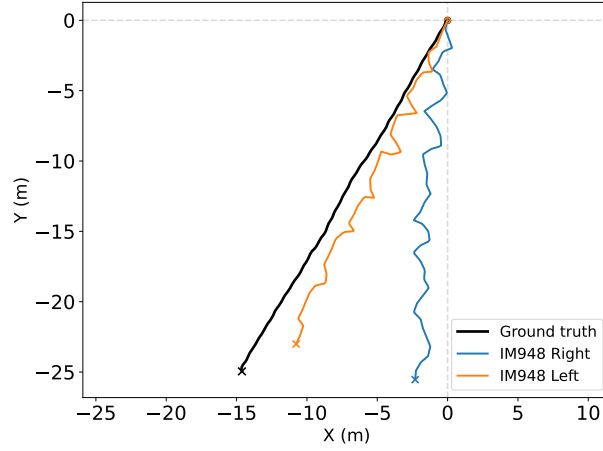


Fig. 8 Representative trajectory for the straight one-way path under head motion conditions. This trajectory is important because it visualizes the asymmetric drift caused by head motion; the full quantitative comparison in Table 11 shows that the right side sensor exhibits the largest degradation. All trajectories start from the origin (0, 0), and the cross marker indicates the end position of each trajectory.

independent head rotation is introduced, the heading used by the trajectory estimation pipeline can deviate from the walking direction, causing global drift and local inconsistency. This effect was especially visible in the straight one-way trial, where IM948 Right increased to 7.35 m ATE and 2.61 m RTE with a TS of 0.83.

4.2.6 Summary of Impact Factors

The results from Experiment 1 provide a compact summary of the preliminary drift observations. In the current trials, path type changed the drift pattern because straight one-way walking, rectangular turning, and circular walking imposed different heading constraints. Speed mainly affected local motion consistency, especially in the straight one-way and rectangular paths. Walking direction changed both error magnitude and side-specific behaviour; counter-clockwise walking gave lower errors for rectangular and circular paths in the current trials. Stop-and-go walking may have introduced heading drift during short pauses, because angular velocity did not immediately become zero and the algorithm could not reliably estimate short stop duration. Head motion introduced heading mismatch because head orientation did not always represent walking direction. These observations describe how each factor affected drift in the current experiment.

4.3 Performance Comparison across IMU Configurations

The experimental conditions used in the second experiment were described in Table 3. This experiment compares three IMU categories under identical walking routes and ground-truth conditions. In this section, IM948 Left and IM948 Right denote the two low-cost IM948 earable IMUs, Xsens Left and Xsens Right denote the two commercial-grade Xsens DOT earable IMUs, and the iPhone 13 Pro carried in the trouser pocket is referred to as the Pocket IMU. The iPhone 13 Pro was placed in the trouser pocket, while the four earable IMUs were mounted near the ears, as shown in Figure 2(a) and Figure 2(b). The three selected paths cover straight, rectangular, and circular walking trajectories, allowing device performance to be examined across different route geometries.

This comparison should be interpreted from two perspectives. The comparison between IM948 and Xsens DOT mainly reflects the difference between low-cost and commercial-grade earable IMUs under a similar head-mounted placement. In contrast, the comparison between the earable IMUs and the Pocket IMU reflects both sensor type and sensor placement, because the Pocket IMU was placed in the trouser pocket while the earable IMUs were fixed near the ears. Therefore, the difference between earable and pocket configurations should be interpreted partly as a placement- and mounting-stability effect, rather than as an intrinsic advantage of earable sensing alone.

Table 12 and Figure 9 provide the quantitative and trajectory-level comparison. The table reports ATE, RTE, and trajectory similarity (TS), where ATE reflects global trajectory deviation, RTE reflects relative local consistency, and TS reflects the preservation of the overall path shape. The results show clear differences across device type and sensor placement.

Among the earable devices, the low-cost IM948 earable IMUs show competitive performance compared with the commercial-grade Xsens DOT earable IMUs. On the circular path, IM948 Left has the lowest ATE, 1.78 m, whereas the two Xsens DOT devices show higher ATE values above 2.30 m. This indicates that IM948 Left gives a smaller global deviation on this path. In contrast, Xsens Right gives the lowest RTE, 1.17 m, suggesting better local relative consistency. The circular path therefore shows a metric-dependent difference rather than a simple hardware-grade advantage.

On the rectangular path, IM948 Left again shows strong error control, with an ATE of 2.15 m, which is close to Xsens Right and lower than Xsens Left. For relative error, IM948 Left also performs better than both Xsens devices, with an RTE of 1.94 m. However, Xsens Right achieves the highest TS, 0.91, indicating that it preserves the rectangular path shape slightly better. This result suggests that IM948 and Xsens DOT have different strengths under the same walking route: IM948 is stronger in error magnitude, while Xsens Right is slightly stronger in shape similarity on this path.

On the straight return path, the difference between IM948 and Xsens DOT becomes clearer. IM948 Left and IM948 Right keep the ATE below 2 m, whereas Xsens Right reaches 3.13 m and Xsens Left reaches 5.13 m. This indicates that the

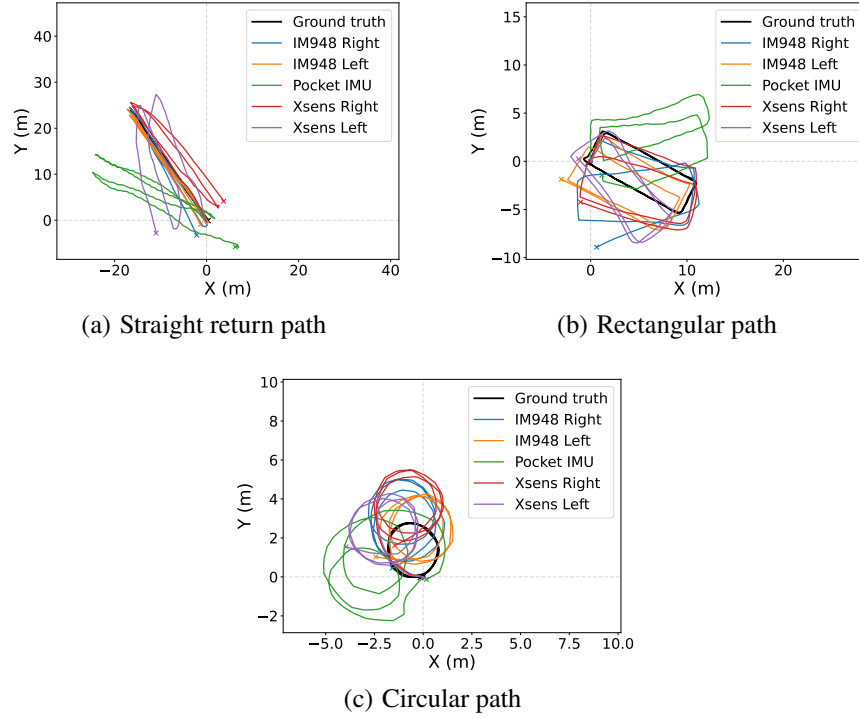


Fig. 9 Performance comparison between the four earable IMUs, the Pocket IMU, and the ground-truth trajectory over the three evaluated paths. The starting point of each trajectory is fixed at the origin (0, 0), and the cross marker shows the final trajectory position.

low-cost IM948 earable IMUs are less affected by accumulated global drift in this trial. Xsens Right still maintains a relatively low RTE, but its larger ATE suggests that local consistency does not fully prevent global trajectory displacement. Overall, these results suggest that the IM948 IMUs are comparable to the commercial-grade Xsens DOT earable IMUs and can be more stable in some path-metric conditions.

The comparison with the Pocket IMU shows a stronger placement effect. On the circular path, the Pocket IMU has an ATE of 3.14 m, larger than all four earable IMUs. However, the TS values show some device-level variation, since Xsens Right is slightly lower than the Pocket IMU in shape similarity. This indicates that the circular path mainly supports a placement-related advantage in global error rather than in every metric.

On the rectangular path, the Pocket IMU produces the largest RTE, 6.70 m, while all earable IMUs remain substantially lower. This difference is also visible in Figure 9(b), where the pocket trajectory deviates more strongly from the ground-truth path. The high TS of Xsens Right further shows that an earable IMU can preserve

Table 12 ATE, RTE, and trajectory similarity comparison between earable IMUs and the Pocket IMU over three walking paths. Bold values highlight the best-performing results emphasized in the comparison, where lower ATE/RTE and higher TS indicate better performance.

Path	Device	ATE (m)	RTE (m)	TS
Circular	IM948 Right	1.88	1.47	0.78
Circular	IM948 Left	1.78	2.11	0.84
Circular	Pocket IMU	3.14	3.60	0.71
Circular	Xsens Right	2.35	1.17	0.70
Circular	Xsens Left	2.32	2.39	0.77
Rectangular	IM948 Right	3.47	3.42	0.87
Rectangular	IM948 Left	2.15	1.94	0.90
Rectangular	Pocket IMU	5.34	6.70	0.82
Rectangular	Xsens Right	2.18	2.37	0.91
Rectangular	Xsens Left	3.14	2.74	0.86
Straight return	IM948 Right	1.73	0.67	0.97
Straight return	IM948 Left	1.27	0.57	0.98
Straight return	Pocket IMU	11.18	5.05	0.81
Straight return	Xsens Right	3.13	0.83	0.92
Straight return	Xsens Left	5.13	2.59	0.88

the overall rectangular shape more effectively than the pocket-carried smartphone under this route.

The straight return path gives the most visible separation between the pocket and earable placements. The Pocket IMU reaches 11.18 m ATE, while IM948 Left and IM948 Right remain below 2 m. Even the larger Xsens Left ATE is still lower than the Pocket IMU. Figure 9(a) shows the same trend visually: the pocket trajectory moves away from the reference direction, while the earable trajectories, especially the IM948 trajectories, remain closer to the ground-truth trajectory.

These differences are likely related to both sensor placement and mounting stability. A pocket-carried smartphone can be affected by pocket fabric movement, leg swing, local impacts, and small attitude changes during walking. In contrast, the earable IMUs are fixed near the ears, where the sensing position is closer to the upper body and less affected by leg motion. At the same time, the IM948–Xsens comparison suggests that hardware grade alone does not determine trajectory accuracy. Sensor-to-head alignment, attachment stability, and compatibility with the trajectory reconstruction pipeline may also affect the final trajectory.

Overall, the results show two main preliminary trends under the tested conditions. First, the low-cost IM948 earable IMUs provided competitive performance compared with the commercial-grade Xsens DOT earable IMUs across the tested routes. Second, the earable IMUs showed lower trajectory drift than the Pocket IMU in the current trials, especially on the straight return path. This difference should be interpreted partly as a placement- and mounting-stability effect rather than an intrinsic advantage of earable sensing alone.

5 Conclusion

In this paper, we investigated earable IMU-based indoor pedestrian positioning in a real-world indoor environment. We provided a real-world dataset covering straight, rectangular, and circular paths with different walking behaviours, including speed variation, stop-and-go walking, head motion, and walking direction. Based on this dataset, we established a baseline indoor positioning system for earable IMUs using a common PDR processing pipeline. The estimated trajectories were evaluated using ATE, RTE, and TS, which describe global positioning error, local motion consistency, and trajectory shape similarity, respectively.

The results provide four main preliminary observations from the current controlled trials. First, walking-related factors, including path shape, speed, direction, stop-and-go behaviour, and head motion, affected earable IMU trajectory estimation in different ways in the current controlled trials. Second, the low-cost IM948 earable IMUs performed competitively with the commercial-grade Xsens DOT earable IMUs, indicating that hardware grade alone did not determine trajectory accuracy under the tested conditions. Third, stop-and-go walking and head motion highlighted the importance of heading estimation, because the estimated heading can deviate from the actual walking direction during short stops and independent head rotations. Fourth, the comparison with the Pocket IMU suggested that the earable placement provided a more stable mounting condition than the trouser-pocket placement under the tested conditions. Overall, these patterns point to the roles of path geometry, sensor placement, heading drift, hardware grade, and head orientation mismatch, but they should be interpreted as preliminary findings from the current controlled trials rather than general conclusions for all users or environments.

For future work, we will increase the number of participants and repeated recordings to examine whether these observations remain consistent across different users and walking styles. We will also improve the heading estimation method, especially for separating head orientation from walking direction during head motion and stop-and-go walking. These extensions are necessary before the observed advantages of earable IMU placement can be generalised to broader indoor LBS scenarios.

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