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RESEARCH ARTICLE

Design and Implementation of an Inertial Navigation System for Pedestrians Using Self-Correction Based on Zero Velocity Update Algorithms

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Abstract

In pedestrian navigation systems, pedestrian positioning is typically computed using an inertial navigation algorithm. To mitigate cumulative drift errors inherent in the integration process of such systems, the zero-velocity update (ZUPT) technique is commonly employed. However, the effectiveness of ZUPT heavily depends on the accurate detection of zero-velocity intervals. This work evaluates and compares two distinct zero-velocity detection algorithms: an iterative model based on human gait phases and a sensor-based approach relying on inertial data during stationary periods. The detected zero-velocity information is subsequently utilized as a measurement vector within a Kalman filter framework to correct navigation errors during stance phases. Both algorithms were experimentally validated using four real pedestrian trajectories with durations of 6, 11, 16, and 22 minutes. The sensor-based method consistently outperformed the gait-model-based approach across all tested trajectories. Notably, during the longest 22-minute trial, the gait-model algorithm yielded a final positioning error of 3.6778 m, whereas the sensor-based algorithm achieved a lower error of 2.3798 m, representing a 35.3% improvement and the highest observed error reduction. On average, the proposed sensor-based method reduced positioning errors by approximately 30.4% compared to the iterative gait model. These findings demonstrate both the superior accuracy and robustness of the sensor-based zero-velocity detection method across varying walking durations, confirming its viability for real-time pedestrian navigation applications.

1. Introduction

Pedestrian navigation systems provide real-time location information for individuals equipped with such systems, enabling critical applications in emergency response, military operations, and indoor localization. For instance, firefighters operating in hazardous environments can be accurately located using a pedestrian navigation system, thereby enhancing crew safety and facilitating rapid rescue interventions (Park & Suh, 2010).

Inertial navigation systems (INS) offer a significant advantage over alternative localization technologies, such as vision-based or wireless communication systems, in that they operate autonomously without requiring external infrastructure, such as landmarks, base stations, or pre-installed wireless networks. This self-contained characteristic makes INS particularly suitable for GPS-denied environments, including indoor spaces,

tunnels, and urban canyons, where satellite signals are unreliable or unavailable.

Despite their autonomy and independence, inertial navigation systems suffer from a fundamental limitation: the accumulation of drift errors over time. The position and velocity estimates are obtained by integrating accelerometer and gyroscope measurements, a process that inherently amplifies even small sensor biases and noise, leading to unbounded error growth. In pedestrian applications, this drift can result in positioning errors of several meters within minutes of operation, severely compromising the reliability of the system for practical use.

To mitigate this cumulative drift, the zero-velocity update (ZUPT) technique has been widely adopted in pedestrian inertial navigation systems. ZUPT exploits the periodic nature of human gait, wherein the foot remains in contact with the ground during the stance phase for

approximately 0.1 to 0.3 seconds. During these brief intervals, the velocity of the foot is theoretically zero, providing an opportunity to correct the accumulated velocity error. By detecting these zero-velocity intervals and resetting the velocity estimate to zero within a Kalman filter framework, the growth of positioning errors can be significantly constrained.

However, the effectiveness of ZUPT is critically dependent on the reliable detection of zero-velocity intervals. Several zero-velocity detection methods have been proposed in the literature, broadly falling into two categories: model-based approaches and sensor-based approaches. Model-based methods rely on predefined mathematical models of human gait to predict the timing of stance phases. While these methods are conceptually straightforward, they exhibit significant limitations in real-world applications. Human walking patterns are inherently variable, influenced by factors such as walking speed, step length, cadence, terrain type, and individual physiological differences.

On the other hand, sensor-based approaches detect zero-velocity intervals by comparing the outputs of inertial sensors (accelerometers and gyroscopes) to empirically determined thresholds. These methods offer greater adaptability to varying gait patterns, as they directly reflect real-time sensor measurements. Nevertheless, they are susceptible to sensor noise, bias drift, and threshold sensitivity. Improper threshold selection can result in either missed detections (if the threshold is too low) or false detections (if the threshold is too high), both of which compromise the overall system performance.

The primary objective of this study is to minimize the final positioning error in a foot-mounted inertial navigation system by evaluating and comparing two zero-velocity detection methods, and identifying which approach achieves the lowest cumulative drift across walking trajectories of different durations.

To evaluate the performance of these methods, the present work provides a rigorous experimental comparison of two representative zero-velocity detection algorithms: an iterative gait-model-based algorithm and a sensor-output-based algorithm. Both methods are implemented within a Kalman filter framework and evaluated under identical experimental conditions across four real pedestrian trajectories of varying durations (6, 11, 16, and 22 minutes). The objectives of this study are twofold: (1) to assess the positioning accuracy of each algorithm, and (2) to evaluate their robustness and practical viability for real-time pedestrian navigation

applications. The experimental results demonstrate that the sensor-based method consistently outperforms the model-based approach, achieving an average positioning error reduction of approximately 30.4% across all tested trajectories.

2. Objectives

This study aims to achieve the following research objectives:

1. To implement and evaluate two zero-velocity detection algorithms within a ZUPT-aided inertial navigation system: (i) an iterative gait-model-based approach, and (ii) a sensor-output-based approach.
2. To quantitatively compare the positioning accuracy of both detection algorithms under identical experimental conditions, using real pedestrian trajectories of varying durations (6, 11, 16, and 22 minutes).
3. To assess the robustness of each algorithm with respect to walking duration and accumulated inertial drift, thereby determining their reliability for practical navigation scenarios.
4. To quantify the error reduction achieved by the superior algorithm relative to the alternative method, expressed as a percentage improvement in final positioning error.
5. To validate the real-time feasibility of the proposed algorithms by testing them on real-world inertial measurement unit (IMU) data collected from foot-mounted sensors.

3. Related Work

The foundation of modern ZUPT-aided pedestrian navigation systems was established by Foxlin (2005), who first demonstrated the effectiveness of foot-mounted inertial sensors combined with zero-velocity updates for pedestrian tracking (Foxlin, 2005). Subsequently, the modeling errors inherent in standard Kalman filter implementations of ZUPT were examined, revealing systematic biases in position estimates that arise from the assumption of zero-mean velocity errors during stance phases (Nilsson et al., 2012). These foundational studies established the core framework that remains widely adopted in the field.

Modern pedestrian positioning systems rely on multiple technologies, each with its own advantages and disadvantages. For example, some systems use satellite signals. While these systems offer good accuracy, they can suffer from signal loss in enclosed spaces, as well as from interference and other issues.

In addition, some systems rely on pedestrian positioning by equipping inertial navigation systems with auxiliary sensors, such as altimeters and weight or pressure gauges; however, this can increase the cost of the positioning device. Therefore, to avoid the aforementioned drawbacks, purely inertial navigation

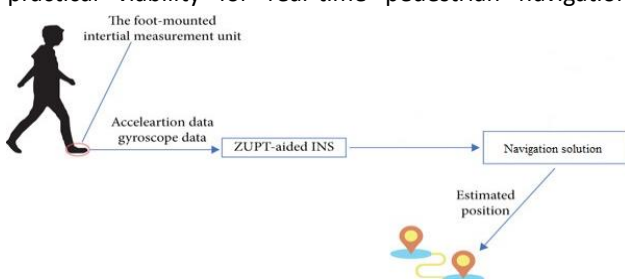


Figure 1. Overview of the pedestrian navigation system.

systems have been adopted. These systems are fully integrated within the device and thus do not require any external signals, unlike the Global Positioning System (GPS). Furthermore, the cost of additional sensors for correcting inertial navigation errors can be avoided by employing computational algorithms, such as the zero-velocity update (ZUPT) algorithm. This approach has attracted considerable attention from researchers in the field, as most studies on this topic rely on it, with minor variations such as the method used for slow walking, fast walking, or sometimes running. This depends on the inertial measurement unit used, the operating range of the sensors, the model employed for detecting zero-velocity intervals, and the Kalman filter model used.

In one study, accelerometer, gyroscope, and pressure sensor measurements were combined to detect zero-velocity periods. This research relied on placing the inertial measurement unit in the heel of the walking shoe. An adaptive threshold and stair recognition technology were developed to improve detection accuracy and reliability. The proposed inertial navigation system achieved a positioning error of 0.21% of the distance traveled, equivalent to 522 meters, or approximately 1.1 meters (Ma et al., 2018).

Another study presented a pedestrian navigation system using foot-mounted inertial sensors in wearable body area networks. An inertial navigation algorithm was employed with a zero-velocity update algorithm, in addition to a direction estimation algorithm. These were combined using a Kalman filter, where the state vector contained position, velocity, orientation angles, and quaternion transition elements. The system achieved a positioning error of 0.825% of the total distance traveled, equivalent to 204.32 meters, or approximately 1.7 meters (Zhou, et al., 2014).

Several advances have been made in pedestrian navigation systems. For instance, recent studies have explored machine learning-based zero-velocity detection (Kone et al., 2020), adaptive Kalman filtering techniques (Pulido-Herrera & Kaufmann, 2010), and hybrid systems integrating inertial navigation with external aids such as UWB and vision-based localization (Treuillet & Royer, 2010). While these approaches demonstrate promising results, they often require additional computational resources or external infrastructure.

More recent studies have explored deep learning-based zero-velocity detection using LSTM networks and Informer models (Zhang et al., 2025), as well as Cubature Kalman Filter (CKF) approaches to address nonlinearities in pedestrian motion (Xu et al., 2024). While these modern techniques demonstrate improved adaptability and accuracy, they often require substantial computational resources or extensive training data, which limits their practical deployment in real-time, low-cost applications.

The present work, although developed in 2020, remains relevant as it provides a systematic experimental comparison of two fundamental zero-velocity detection methods under realistic walking conditions, offering

insights that complement and inform these more recent developments.

To provide a clear overview of the current state-of-the-art in pedestrian inertial navigation systems and to position our work within this landscape, Table 1 summarizes the key characteristics of relevant studies. The table includes foundational works (Foxlin, 2005), established systems (Zhou et al., 2014; Ma et al., 2018), and recent approaches (Zhang et al., 2025). As shown, many advanced techniques achieve superior accuracy but often require high computational resources or extensive training data. In contrast, our work provides a systematic experimental comparison of two fundamental zero-velocity detection methods under realistic slow-walking conditions, offering a practical benchmark for researchers working in resource-constrained environments. While our method may not outperform every approach, it provides a robust and reproducible benchmark specifically for slow-walking scenarios.

4. Research Methodology

The design and implementation of the pedestrian inertial navigation system using zero-velocity update (ZUPT) techniques rely on the integration of three main computational algorithms: (1) an inertial navigation algorithm, (2) a zero-velocity detection algorithm, and (3) an Extended Kalman Filter (EKF) for fusing the outputs of the previous algorithms to estimate the pedestrian position.

The experimental data were collected using a foot-mounted EPSON M-G362 MEMS IMU. According to the manufacturer's datasheet, the accelerometer has a full-scale range of ± 3 g, and the gyroscope has a range of ± 150 deg/s. The IMU was attached to the right foot, and data were recorded at a sampling frequency of 125 Hz.

Prior to each walking trial, an initial alignment procedure was performed to estimate and compensate for sensor biases. The IMU was kept stationary for 60 seconds at the beginning of each recording. During this period, the average values of the accelerometer and gyroscope outputs were computed to estimate the accelerometer bias and gyroscope drift. These estimated biases were then subtracted from the raw sensor measurements during the subsequent walking trial to correct the inertial data in real time. This alignment step was repeated before every trial to ensure that the bias estimates were representative of the sensor conditions at the start of each experiment, thereby improving the accuracy of the inertial navigation solution.

It is important to note that this procedure constitutes a bias and drift compensation step, not a full sensor calibration. The factory-calibrated sensor parameters (such as scale factors and misalignment) were used as provided by the manufacturer, and no additional calibration was performed. No additional preprocessing or filtering was applied to the raw sensor data beyond this bias correction.

Figure 2 illustrates the system architecture and data flow diagram of the proposed pedestrian navigation

framework. The process begins with an initial alignment phase, during which the IMU is kept stationary for 60 seconds to estimate the accelerometer bias and gyroscope drift. Following this alignment period, raw inertial data are acquired from the foot-mounted IMU during walking. The

Table 1. Comparison of ZUPT-based pedestrian navigation systems.

previously estimated biases and drift are then subtracted from the raw measurements to obtain corrected inertial data. These corrected data are subsequently processed

Study	Method	ZUPT Detection Method	Sensors	Algorithm	Accuracy	Limitations
Foxlin (2005)	ZUPT-based INS (NavShoe)	Stance phase detection (~0.5s stationary)	InterSense InertiaCube3 (9-axis: gyro + accel + magnetometer), Gyro max: 1200°/s, Accel range: ±6 g, 300 Hz	EKF	0.34 m (0.3% of distance) over 118.5 m, 322 s	Heading drift not corrected
Zhou et al. (2014)	PDR + INS + ZUPT + orientation estimation	State machine (4 states): angular velocity threshold + timer + pitch angle	Shimmer IMU (MMA7361 ±6g, 500 series gyro ±500°/s, HMC5843 magnetometer), 50 Hz	EKF	1.7 m (0.825% of distance) over 206m, time not specified	2D only; requires external aids for 3D
Ma et al. (2018)	Multi-sensor fusion with adaptive threshold	Adaptive threshold (IMU + pressure sensor)	MPU9250 (9-axis: accel + gyro + magnetometer), configurable gyro ranges: ±250, ±500, ±1000, ±2000 °/s, accel ranges: ±2, ±4, ±8, ±16 g + FSR 406 pressure sensor (force range: 0.2–20 N), insole-mounted, 400 Hz	KF	0.21% (walking, Person A); 0.26% (walking, Person B) over 522 m, time not specified	Requires extra pressure sensor; individual variability
Zhang et al. (2025)	Deep Learning (Informer model)	Binary classification (7D training data: 6D IMU + 1D label)	IMU (6D: gyro + accel; model not specified), Foot-mounted, 1000 Hz	KF	19.77 m cumulative error over 2000 m, time not specified	Needs training data & high computational cost
Our Work	Comparative evaluation of two ZUPT detection methods	Method 1: Gait phase model Method 2: Threshold-based (sensor outputs)	EPSON M-G362 MEMS IMU (±3 g, ±150°/s), Foot-mounted, 125 Hz	EKF	Method 1 (Gait Model): from 1.2508 m (at 6 min) to 3.6778 m (at 22.2 min). Method 2 Sensor-based (threshold): from 0.8641 m (at 6 min) to 2.3798 m (at 22.2 min), Ground truth path not measured	Slow walking only; single participant

through two parallel and independent paths: the inertial navigation algorithm, which computes position, velocity, and attitude via dead-reckoning, and the zero-velocity

detection module, which evaluates two distinct detection methods, a gait-phase model and a threshold-based approach, to identify stance phases. The outputs of both

paths are then fused within an Extended Kalman Filter (EKF), where the detected zero-velocity intervals serve as measurement updates to correct the accumulated navigation errors. Finally, the corrected position estimates are assessed using the return-to-start error metric, enabling a comparative evaluation of the two detection methods.

Four walking trajectories were conducted, with durations of 6, 11, 16, and 22 minutes. All experiments were performed in an indoor environment on a flat surface. The walking speed was maintained at a slow pace, typically ranging between 0.3 and 1 m/s, due to the limited dynamic range of the IMU sensors (particularly the ± 3 g accelerometer range); faster movements could cause sensor saturation. Each trajectory was repeated multiple times in separate experimental sessions to verify the accuracy of the algorithms and the validity of the results.

The ground truth reference for each trajectory was defined as the starting point (origin), and the positioning error was calculated as the distance between the final estimated position and the known starting point.

The following subsections describe the algorithms and implementation steps in detail.

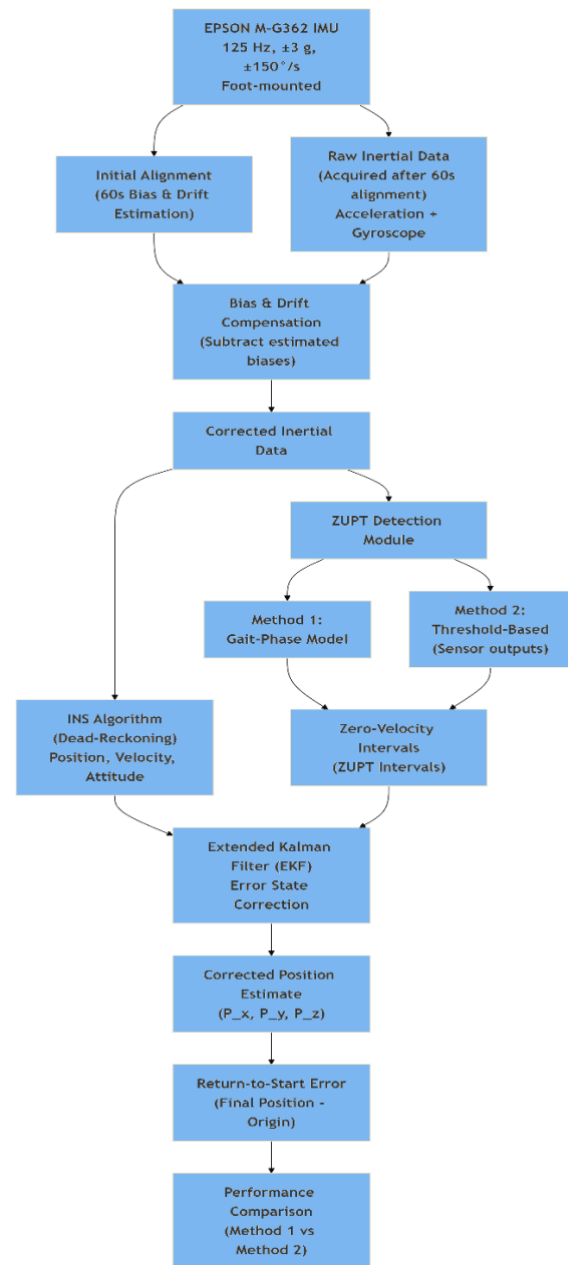


Figure 2. System architecture and data flow diagram of the proposed pedestrian navigation system.

4.1 Inertial Navigation

Inertial navigation is one of the most widely used navigation methods today. It relies on measurements provided by accelerometers and gyroscopes to track the position and orientation of an object relative to a known starting point, initial direction, and initial velocity.

An inertial measurement unit (IMU) contains three mutually perpendicular gyroscopes and three mutually perpendicular accelerometers, which measure angular velocity and linear acceleration, respectively. Based on the signals measured by these devices, it is possible to track the position and orientation of a moving object (Woodman, 2007).

Inertial navigation is used in a wide range of applications, including the medical field, where it can be used in the design of prosthetic limbs, as well as in aviation

navigation for aircraft, spacecraft, land vehicles, submarines, and ships.

Recent developments in IMU design have led to the manufacture of small and lightweight navigation systems, which significantly reduce cost and size in the design of such systems, and have expanded the range of possible applications. There are two types of inertial navigation systems: gimballed and strapdown systems. The difference between these two categories lies in the reference frame in which the gyroscopes and accelerometers operate.

4.1.1 Navigation Equations

According to Newton's second law of motion, a change in motion occurs when a force is applied to an object. Dividing both sides of the equation by the object's mass results in the specific acceleration, as follows:

$$\frac{f}{m} = a = S \quad (1)$$

In inertial navigation, accelerometers detect the accelerations caused by the forces applied to the body; these forces are called deterministic forces, denoted by S .

Using Coriolis' theorem, which states that the total velocity of a vehicle v_i , in a non-rotating frame of reference, equals the vehicle's velocity v_s plus the velocity resulting from the Earth's rotation, it became possible to derive the equations in the inertial frame of reference. An inertial frame of reference is a fixed frame of reference in space, whose z-axis coincides with the Earth's axis of rotation. Hence:

$$v_i = v_s + \Omega_{ie} \times r_i \quad (2)$$

where:

- Ω_{ie} : Earth's rotational velocity vector, defined as $\Omega_{ie} = [0, 0, \omega_{ie}]^T$,
- ω_{ie} : Earth's rotation speed,
- r_i : vehicle position vector.

By differentiating both sides of equation (2) with respect to time, we obtain:

$$\dot{v}_i = \dot{v}_s + \dot{\Omega}_{ie} \times r_i + \Omega_{ie} \times v_i \quad (3)$$

Since Ω_{ie} is a constant and known vector, $\dot{\Omega}_{ie}=0$. Thus, equation (3) simplifies to:

$$\dot{v}_i = \dot{v}_s + \Omega_{ie} \times v_s + \Omega_{ie} \times (\Omega_{ie} \times r_i) \quad (4)$$

The left-hand side of equation (4) equals the total acceleration applied to the system. Therefore:

$$S^i + g^i = \dot{v}_s + \Omega_{ie} \times v_s + \Omega_{ie} \times (\Omega_{ie} \times r_i) \quad (5)$$

where:

- S^i : forces acting on the body,
- g^i : gravitational force acting on the system.

By isolating the acceleration $\dot{v}_s$, we obtain the following navigation equation, the solution of which yields the velocity of the vehicle or moving object:

$$\dot{v}_s = S^i - \Omega_{ie} \times v_s + g^i - \Omega_{ie} \times (\Omega_{ie} \times r_i) \quad (6)$$

Finally, we transform equation (6) from the inertial frame to the Earth frame. In the Earth frame, we have:

$$\dot{v}_e = \dot{v}_s - \Omega_{ie} \times v_s \quad (7)$$

Substituting into equation (6), we obtain:

$$\dot{v}_e = S_e - 2\Omega_{ie} \times v_e + g_e - \Omega_{ie} \times (\Omega_{ie} \times r_e) \quad (8)$$

Integrating equation (8) gives the velocity v_e , and integrating the velocity v_e gives the position. Therefore,

any small change in acceleration results in a quadratic change in position (Weston & Titterton, 2004).

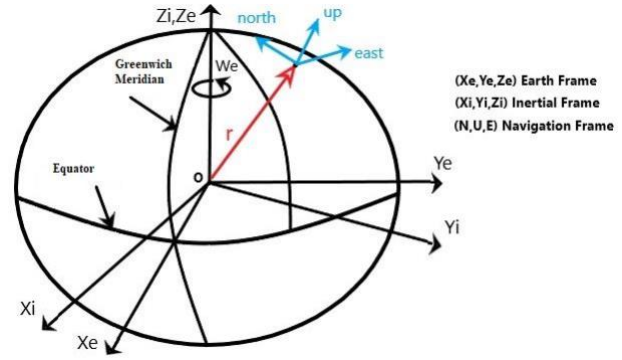


Figure 3. Inertial frame, Earth frame, and Local Level frame (NUE).

4.1.2 Initial Alignment

Initial alignment is a key operation in inertial navigation systems. The primary objective of this operation is to determine the initial rotation matrix between the body frame and the navigation frame, a process commonly referred to as initial alignment (Salychev, 2004).

The output of the accelerometer f can be expressed as:

$$f = a + g \quad (9)$$

where:

- a : acceleration of the moving object,
- g : total acceleration due to gravity.

When an object is at rest, $a=0$; therefore:

$$f = g \quad (10)$$

Writing equation (10) in matrix form with respect to the axes of the local level frame (NUE):

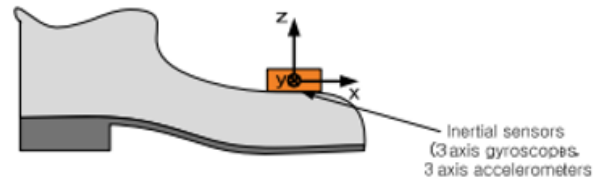
$$f_n = \begin{bmatrix} f_N \\ f_U \\ f_E \end{bmatrix} = \begin{bmatrix} 0 \\ g \\ 0 \end{bmatrix} \quad (11)$$

where f_n is the accelerometer output in the local level frame.

To transform from the local level frame to the body frame, we have:

$$f_b = C_l^b \cdot f_n \quad (12)$$

where C_l^b is the rotation matrix between the local level frame and the body frame, given by:



$$C_l^b = \begin{bmatrix} \cos\theta \cdot \cos\psi & \sin\theta & \cos\theta \cdot \sin\psi \\ -\sin\phi \cdot \sin\psi - \cos\phi \cdot \sin\theta \cdot \cos\psi & \cos\theta \cdot \cos\phi & \sin\phi \cdot \cos\psi - \sin\theta \cdot \cos\phi \cdot \sin\psi \\ -\cos\phi \cdot \sin\psi + \sin\theta \cdot \sin\phi \cdot \cos\psi & -\cos\theta \cdot \sin\phi & \cos\phi \cdot \cos\psi + \sin\theta \cdot \sin\phi \cdot \sin\psi \end{bmatrix} \quad (13)$$

where:

- Ψ : rotation angle about the Z-axis (yaw),

- Θ : rotation angle about the Y-axis (pitch),
- φ : rotation angle about the X-axis (roll).

Substituting into equation (12), we obtain:

$$f_b = \begin{bmatrix} f_x \\ f_y \\ f_z \end{bmatrix} = \begin{bmatrix} g \cdot \sin\theta \\ g \cdot \cos\theta \cdot \cos\varphi \\ -g \cdot \cos\theta \cdot \sin\varphi \end{bmatrix} \quad (14)$$

By comparing both sides of equation (14), the values of φ and θ can be deduced from the accelerometer outputs as follows:

$$\theta = \arcsin\left(\frac{f_x}{g}\right) \quad (15)$$

$$\varphi = \arctan\left(-\frac{f_z}{f_y}\right) \quad (16)$$

4.2 Zero-Velocity Detection Algorithms

Zero-velocity detection is an essential component of pedestrian navigation systems using inertial sensors. In inertial navigation, velocity errors tend to grow quadratically over time due to integration of acceleration errors and attitude inaccuracies, which in turn leads to significant growth in position estimation errors. Zero-velocity detection algorithms provide the necessary information to reset the velocity error and correct the position estimate periodically.

In general, this process presents a significant challenge for inertial navigation systems. However, during normal human walking, the foot undergoes a stationary stance phase when it supports the full body weight. This has made foot-mounted IMUs a popular choice for pedestrian tracking. Alternative methods, such as step counting and step length estimation, can also be used, but they are generally less accurate than algorithms that rely on zero-velocity detection every few seconds.

Several approaches exist for zero-velocity detection. Some methods rely solely on gyroscope measurements, others on accelerometer readings, and others combine both to detect stationary periods more reliably. In this project, two zero-velocity detection methods are studied, tested, and compared.

4.2.1 Method 1: Gait-Phase Model

Normal human gait consists of several repetitive foot phases: heel contact with the ground, stance, push-off, and swing. When sensors are attached to the foot, the primary axis of rotation during walking is the Y-axis. Therefore, the gyroscope measurements along this axis follow a characteristic pattern corresponding to the gait phases, and can be used to identify zero-velocity intervals (Skog et al., 2010).

Figure 5 shows the Y-axis gyroscope output during a typical walking step. The signal exhibits a consistent

pattern consisting of four phases: a zero phase
Figure 4. Illustration of a foot-mounted IMU.

corresponding to the stance period, a positive phase during push-off, a negative phase during swing, and a final positive phase associated with heel contact.

To detect the zero-velocity phase, the incoming signal is processed sequentially using a segmentation approach. A threshold is applied to the Y-axis gyroscope values, and a window of length W defines the number of samples compared against this threshold. In this segmentation process, it is important to consider the sequence of phases 1 through 4, as the gyroscope Y-axis signal produces two positive outputs (phases 2 and 4). The zero-velocity phase occurs immediately after phase 4, assuming the correct sequence of phases has been followed.

In this study, a window of 100 consecutive samples (corresponding to 800 ms at the 125 Hz sampling rate) from the gyroscope Y-axis was examined. A zero-velocity interval was declared if at least 90 out of the 100 samples fell within a predefined range defined by the threshold $\alpha = 0.2$ (i.e., $|gyro_y| \leq 0.2$). This condition ensures that the foot is sufficiently stationary to apply a zero-velocity update. The threshold was empirically determined through preliminary trials to maximize detection accuracy across all walking trajectories.

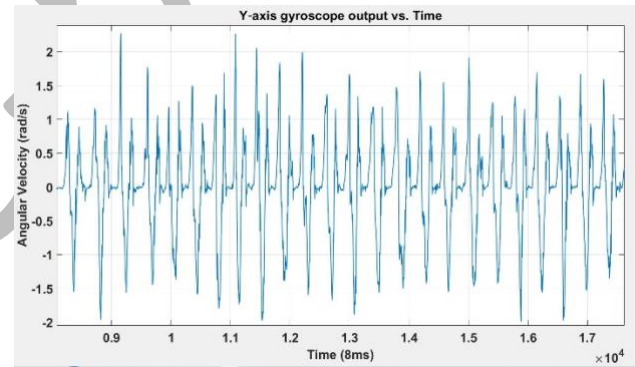


Figure 5. Y-axis gyroscope output during a typical walking step.

4.2.2 Method 2: Threshold-Based Detection

When the IMU is stationary, the accelerometer measures only the gravitational acceleration, and the gyroscope output is theoretically zero. This principle forms the basis of the second zero-velocity detection method. This method uses a generalized likelihood ratio test (GLRT)-based approach, where a sliding window of $W = 10$ samples (corresponding to 80 ms at the 125 Hz sampling rate) is used to compute a test statistic T . The statistic is defined as:

$$T = \frac{1}{10} \sum_{i=1}^W \left(\frac{\|w_i\|^2}{\sigma_w^2} + \frac{\left\| a_i - g \cdot \frac{\bar{a}}{\|\bar{a}\|} \right\|^2}{\sigma_a^2} \right) \quad (17)$$

where:

- w_i and a_i are the gyroscope and accelerometer readings at sample i ,
- $\bar{a}$ is the mean acceleration vector over the window,

- g is the gravitational constant (9.81 m/s^2),
- σ_w^2 and σ_a^2 are the noise variances of the gyroscope and accelerometer, respectively.

The noise variances were derived from the sensor datasheet. The Angular Random Walk (ARW) is specified as $0.1^\circ/\sqrt{h}$ which corresponds to $\sigma_w = 0.1 * \frac{\pi}{180} \text{ rad/s}$ in the discrete-time implementation. The Velocity Random Walk (VRW) is specified as $0.04 \text{ (m/s)}/\sqrt{h}$ and then empirically tuned to $\sigma_a = 0.01 \text{ m/s}^2$ through preliminary experiments to achieve optimal detection performance under slow walking conditions ($0.3\text{--}1 \text{ m/s}$). A zero-velocity interval was declared when the test statistic fell below an empirically determined threshold:

$$T < \gamma, \gamma = 1187$$

This threshold was selected experimentally to ensure reliable detection of zero-velocity intervals during slow walking, while avoiding false detections that could arise from sensor noise or slight foot movements during stance phases.

4.3 Extended Kalman Filter Implementation

This section describes the application of the Extended Kalman Filter (EKF) to integrate the inertial navigation algorithm with the zero-velocity detection algorithm in the proposed pedestrian navigation system.

The state vector contains the navigation solution variables, including position, velocity, and quaternion elements, and is defined as:

$$x = [P_x, P_y, P_z, v_x, v_y, v_z, q_1, q_2, q_3, q_4] \quad (18)$$

The corresponding state transition matrix F is given by:

$$F_{(10 \times 10)} = \begin{bmatrix} F_p(3 \times 6) & 0(3 \times 4) \\ 0(3 \times 3) & F_v(3 \times 6) \\ 0(4 \times 6) & F_q(4 \times 4) \end{bmatrix} \quad (19)$$

This matrix is derived from the position, velocity, and quaternion update relationships between successive time steps.

The measurement vector corresponds to the linear velocity at the instant a zero-velocity interval is detected. The measurement matrix H is therefore defined as:

$$H_{(3 \times 10)} = [0(3 \times 3) \quad I(3 \times 3) \quad 0(3 \times 4)] \quad (20)$$

The EKF was configured with the following noise covariance matrices, which were empirically tuned through preliminary experimental trials:

- **Measurement noise covariance matrix (R):** $R = \sigma_v^2 \cdot I_{3 \times 3}$, where $\sigma_v = 0.001 \text{ m/s}$ reflecting the expected accuracy of the zero-velocity detection during stance phases.
- **Process noise covariance matrix (Q):** The continuous-time process noise covariance matrix Q_c is defined as:

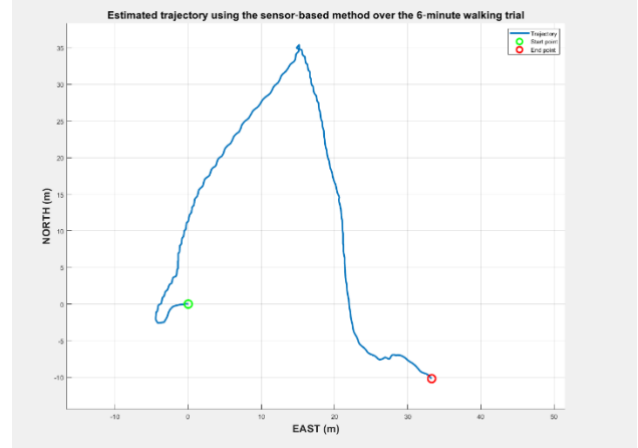
$$Q_c = \begin{bmatrix} 0_{3 \times 3} & 0 & 0 \\ 0 & \sigma_a^2 \cdot I_{3 \times 3} & 0 \\ 0 & 0 & \sigma_w^2 \cdot (G_q G_q^T) \end{bmatrix} \quad (21)$$

where $\sigma_a = 0.01 \text{ m/s}^2$ and $\sigma_w = 0.1 * \frac{\pi}{180} \text{ rad/s}$ ($\approx 0.001745 \text{ rad/s}$) are the standard deviations of the accelerometer and gyroscope noise, respectively.

The matrix G_q is derived from the quaternion kinematics and is given by:

$$G_q = \frac{1}{2} \begin{bmatrix} -q_2 & -q_3 & -q_4 \\ q_1 & -q_4 & q_3 \\ q_4 & q_1 & -q_2 \\ -q_3 & q_2 & q_1 \end{bmatrix} \quad (22)$$

This matrix relates the quaternion derivative to the angular velocity measurements and is essential for propagating the uncertainty in the orientation states.



The discrete-time process noise covariance matrix was then computed as $Q = Q_c \cdot \Delta t$, where $\Delta t = 1/125 \text{ s}$ is the sampling interval.

The filter was initialized with a diagonal state covariance matrix:

$$P_0 = \text{diag}([10^{-10}, \dots, 10^{-10}, 10^{-6}, \dots, 10^{-6}]) \quad (23)$$

reflecting the initial uncertainty in the state estimates. The first six diagonal elements correspond to the position and velocity states, while the remaining four correspond to the quaternion states, indicating higher initial uncertainty in the orientation estimates compared to the position and velocity estimates.

5. Experimental results

Both zero-velocity detection methods were tested on four walking trajectories with durations of 6, 11, 16, and 22 minutes. The results presented in this section include trajectory plots for the 6-minute trial as a representative example. A summary table is provided at the end of the section to report the final positioning errors for both methods after integration with the Extended Kalman Filter (EKF) across all tested trajectories.

It should be noted that each trajectory begins and ends at the same point, as the starting point was adopted as the primary reference for computing the positioning error.

5.1 Results of the Gait-Model-Based Method

In this section, the gait-model-based zero-velocity detection method was applied together with the inertial navigation algorithm to the real walking trajectory. Figure 6 shows the estimated trajectory for the 6-minute trial using this method. The resulting positioning error was:

$$d_{ZUPT1} = 39.3048 \text{ m}$$

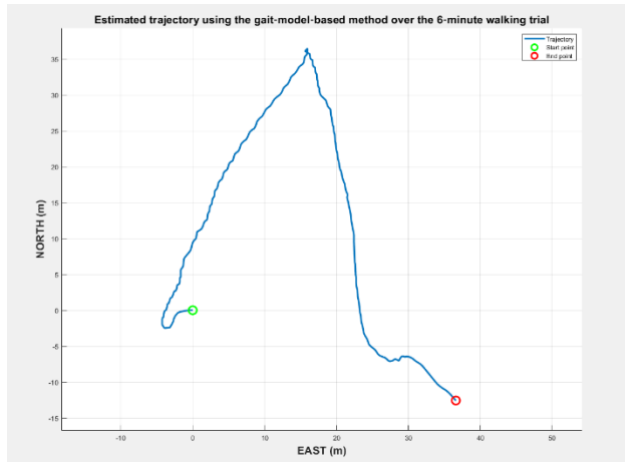


Figure 6. Estimated trajectory using the gait-model-based method over the 6-minute walking trial.

5.2 Results of the Sensor-Based Method

In this section, the sensor-based zero-velocity detection method was applied together with the inertial navigation algorithm to the same walking trajectory. Figure 7 shows the estimated trajectory for the 6-minute trial using this method. The resulting positioning error was:

$$d_{ZUPT2} = 36.2055 \text{ m}$$

5.3 Results of EKF Integration with Both Zero-Velocity Detection Methods

In this section, the Extended Kalman Filter (EKF) was applied to integrate the zero-velocity detection algorithms with the inertial navigation algorithm on the same walking trajectories. Figure 8 shows the estimated trajectory when applying the EKF with the gait-model-based method. The resulting positioning error was:

$$d_{EKF1} = 1.2508 \text{ m}$$

Similarly, the EKF was applied with the sensor-based method. Figure 9 shows the estimated trajectory for this configuration. The resulting positioning error was:

$$d_{EKF2} = 0.8641 \text{ m}$$

5.4 Summary of Positioning Errors

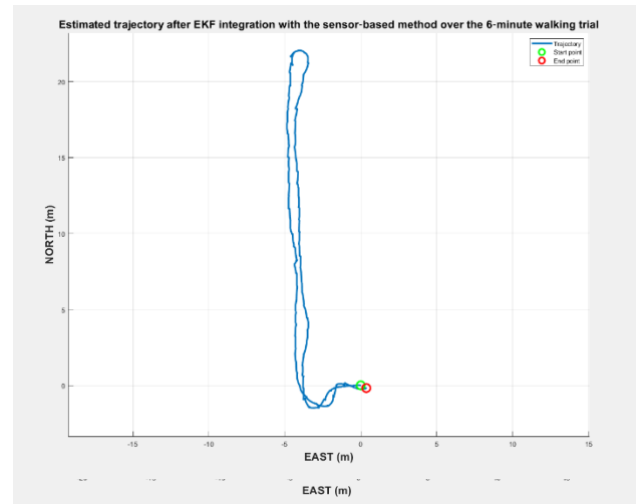


Table 2 summarizes the final positioning errors for both zero-velocity detection methods after integration with the Extended Kalman Filter (EKF) across all four walking trajectories. The sensor-based method consistently achieves lower positioning errors than the gait-model-based approach across all tested durations, with an average improvement of approximately 30.4%.

Table 2. Final positioning errors after EKF integration for both zero-velocity detection methods across all walking trajectories.

Duration (min)	Gait-Model-Based + EKF (m)	Sensor-Based + EKF (m)	Improvement (%)
6	1.2508	0.8641	30.9%
11	2.4238	1.8051	25.5%
16	3.2442	2.2777	29.8%
22	3.6778	2.3798	35.3%

6. Discussion

The experimental results are discussed here in relation to the main objectives of this study. First, regarding the objective of implementing and evaluating two zero-velocity detection methods, the results show that the sensor-based method consistently outperforms the gait-model-based approach across all tested durations. Second, with respect to the integration of the EKF for error correction, the results demonstrate that the EKF effectively reduces cumulative drift, as evidenced by the lower positioning errors compared to open-loop navigation. Third, concerning the testing on real pedestrian data, the experiments on four trajectories of Figure 7. Estimated trajectory using the sensor-based method over the 6-minute walking trial.

The algorithms were verified through five experiments conducted during walking trials, where the inertial data were acquired and the position estimates were generated in real time, confirming the viability of the system for real-world pedestrian navigation applications.

The starting point of each walking trajectory was used as the ground-truth reference for error computation. The positioning error for each trial was calculated as the distance between the final estimated position and the

Figure 8. Estimated trajectory after EKF integration with the gait-model-based method over the 6-minute walking trial.

known starting point. This approach provides a reliable measure of the cumulative drift error for each algorithm without requiring external reference systems such as GPS.

The results show that the cumulative errors in the inertial navigation algorithm are reduced when zero-velocity detection algorithms are applied. This improvement is attributed to the correction of velocity errors during rest periods.

Furthermore, the positioning errors are significantly reduced when using the EKF compared to the results obtained with either zero-velocity detection method alone. This is because the state vector in the EKF includes position, velocity, and quaternion elements, enabling correction of velocity, position, and orientation errors, which enhances the overall accuracy.

The difference between the two zero-velocity detection methods is relatively small, but the sensor-based method consistently achieves better results, particularly over longer durations.

The integration of the EKF with the sensor-based method resulted in a positioning error on the order of 2.4 meters after a 22-minute walking trial, demonstrating the effectiveness of the proposed approach for extended pedestrian navigation.

The sensor-based method consistently outperformed the gait-model-based approach across all tested durations. This improvement can be attributed to the fact that the sensor-based method directly relies on real-time inertial measurements during stance phases, making it more adaptive to the actual motion characteristics of the pedestrian. In contrast, the gait-model-based method assumes a fixed repetitive walking pattern. However, human walking is inherently variable; even when a person attempts to walk at a constant speed, natural fluctuations in step length, cadence, and foot placement occur. These variations are not captured by a fixed gait model, leading to accumulated errors in the zero-velocity detection and subsequent drift correction. As a result, the model-based method accumulates larger drift errors over time, as observed in the 22-minute trial where the error reached 3.6778 m compared to 2.3798 m for the sensor-based method.

While the sensor-based method generally outperforms the gait-model-based approach, the performance gap is more pronounced in longer trajectories (e.g., 22 minutes) than in shorter ones (e.g., 6 minutes). This suggests that the gait-model-based method may be sufficient for short-duration applications where computational simplicity is prioritized. However, for longer walking durations, the adaptive nature of the sensor-based method becomes increasingly advantageous, as it is less sensitive to the cumulative effects of gait variability.

As expected, positional errors increase over time due to the accumulation of inertial integration errors.

It is important to note that the experimental conditions in this study, specifically the slow walking speed imposed by sensor limitations, differ from those in many published works that report results under normal walking

speeds. Consequently, a direct quantitative comparison with these studies would not be scientifically meaningful. Nonetheless, when considering the error magnitudes, our method achieves positioning errors, for example 0.8641 m over 6 minutes, that are competitive with those reported in the literature under less restrictive conditions, such as 1.1 m in Ma et al. (2018) and 1.7 m in Zhou et al. (2014). This suggests that our approach offers robust performance even under challenging slow-walking scenarios.

A C# interface was developed, and all previous algorithms were integrated and tested in real time. The same accuracy obtained in the offline experiments was achieved in the real-time tests.

7. Conclusion

This paper has presented the design and implementation of a pedestrian inertial navigation system based on inertial navigation algorithms, zero-velocity update (ZUPT) techniques, and an extended Kalman filter (EKF) for error correction. The system was evaluated under realistic walking conditions and demonstrated the ability to maintain positioning accuracy without reliance on external sensors or reference signals.

The main contributions of this work are threefold. First, it provides a systematic experimental comparison of two zero-velocity detection methods, a gait-model-based approach and a sensor-based threshold method, under identical conditions across multiple walking durations. Second, it quantifies the performance advantage of the sensor-based method, which achieved an average error reduction of 30.4% compared to the gait-model-based approach. Third, it offers a focused evaluation of the slow-walking scenario, a condition that has received limited attention in the existing literature.

The experimental results confirm that the sensor-based method consistently outperforms the model-based approach across all tested trajectories. The positioning error for the sensor-based method ranged from 0.8641 m over a 6-minute walk to 2.3798 m over a 22-minute walk, compared to 1.2508 m and 3.6778 m for the model-based method. The observed performance gap was more pronounced in longer trajectories, suggesting that the sensor-based method is particularly beneficial for extended navigation sessions, whereas the model-based approach may still be suitable for short-duration applications where computational simplicity is a priority.

The EKF played an essential role in mitigating cumulative drift. The integration of zero-velocity measurements as updates within the filter effectively bounded the error growth that would otherwise render the inertial solution unusable over time. This confirms the value of ZUPT-aided EKF frameworks in practical pedestrian navigation systems.

Nevertheless, the findings should be interpreted in light of several limitations. The experiments were restricted to slow walking speeds (0.3–1 m/s) due to the limited dynamic range of the IMU ($\pm 150^\circ/\text{s}$ gyroscope, ± 3 g accelerometer). The evaluation was also limited to a single participant, and the ground truth was defined as the

starting point rather than an external reference system. Furthermore, the primary performance metric used was the return-to-start error, which, although widely adopted for assessing cumulative drift, does not capture instantaneous positioning errors along the trajectory.

Future work will address these limitations by extending the evaluation to a wider range of motion patterns, including normal walking and running, using an IMU with a broader dynamic range. The threshold-based detection method could be enhanced through adaptive parameter tuning techniques, such as machine learning-based selection or real-time adjustment based on gait characteristics. The integration of inertial data with opportunistic external aids, such as UWB, Wi-Fi ranging, or visual-inertial odometry, represents a promising direction for further improving long-term accuracy in GPS-denied environments. Additionally, deep learning models for zero-velocity detection may be explored as an alternative to the methods evaluated in this study. Finally, future experiments will involve multiple participants and include external reference systems to enable a more comprehensive validation of positioning accuracy and robustness.

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