

# A Walking Support System with Pedestrian Dead Reckoning and Foot Pose Tracking for Visually Impaired Individuals

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## ABSTRACT

This paper presents a wearable system that combines pedestrian dead reckoning (PDR) and foot pose tracking to achieve adaptive walking support for visually impaired individuals in neighborhood-scale navigation. Unlike vision-dependent approaches, our method leverages a foot-mounted IMU and four infrared distance sensors to simultaneously estimate foot kinematics and user trajectory. The system hierarchically applies invariant extended Kalman filtering (InEKF) to fuse inertial data itself and infrared ground-distance measurements, simultaneously optimizing foot gesture estimation, step-length calibration, and drift-resistant PDR. We design a vibrotactile interface with vibration motor array to provide intuitive feedback for obstacle avoidance and path guidance, offering a practical solution for assistive mobility with natural foot proprioception.

## CCS CONCEPTS

• **Hardware** → **Sensor applications and deployments**; • **Human-centered computing** → *Haptic devices*; *Accessibility design and evaluation methods*.

## KEYWORDS

foot pose tracking, pedestrian dead reckoning, invariant EKF, wearable assistive technology, sensor fusion

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## 1 INTRODUCTION

Precise localization forms the cornerstone of autonomous navigation in robotic systems, the same challenge manifests acutely for visually impaired individuals, whose mobility depends on continuous awareness of foot-ground interactions. They face three fundamental walking difficulties: (1) inability to maintain straight-line walking trajectories due to lack of heading references, (2) failure to detect ground-level obstacles (e.g., curbs, potholes) before physical contact, and (3) difficulty perceiving stair transition points (both initial and final steps) leading to tripping hazards.

Existing vision-based solutions suffer from three critical limitations for walking assistance: (1) high power consumption requiring impractical battery configurations, (2) large form factors and high hardware costs that hinder wearability, and (3) inability to reliably detect ground-level obstacles due to perspective constraints.

To overcome these limitations, we propose a foot-mounted sensor system that combines inertial measurement units (IMUs) and infrared distance sensors to achieve simultaneous foot pose tracking and pedestrian dead reckoning. This system provides real-time tactile feedback through vibration patterns to enable visually impaired users to navigate urban environments with improved safety and confidence.

## 2 RELATED WORKS

### 2.1 PDR Related work

Pedestrian Dead Reckoning (PDR) is a method for estimating a user's current position by propagating a previously known location using estimated velocity and heading over time [4]. It plays a vital role in environments where GPS is unavailable, enabling location tracking of people and objects. The zero velocity update technique, which utilizes the stationary state of the foot during the stance phase of walking for state correction, was first introduced by Foxlin in the NavShoe project and demonstrated effective performance in gait estimation [3].

Kang et al. [6] proposed SmartPDR, a smartphone-based indoor pedestrian tracking system that requires no additional infrastructure or pretrained data, offering strong practicality and deployability. Asraf et al. [2] further developed a deep learning-based PDR framework, which incorporates a smartphone-based location classification network followed by heading change and distance regression modules for user localization.

## 2.2 Multi-sensor Fusion

Footprint tracking and foot attitude measurement are vital in health care field, such as geriatric rehabilitation and mobility aid for the visually impaired individuals. Models of potential ankle injury dynamics and risk factors can be derived through foot attitude characterization and gait measurement. [1] Multi-IMU fusion techniques enable accurate reconstruction of lower-body kinematics and skeletal movement patterns during walking. [9] IMU and IR are often implemented simultaneously, providing an integrated kinematics status. [7] Based on multiple sensor data, typical characteristics can be drawn from certain application scenarios. [5]

## 3 SYSTEM CONFIGURATION

In the system, we use infrared radiation sensor (IR), inertial measurement unit (IMU), GPS unit, ultrasonic rangefinder and vibration motor. IR sensor provides the distance between shoes and the ground. IMU provides the attitude angle of shoes. GPS unit is used to align dead reckoning. Ultrasonic rangefinder can achieve forward obstacle avoidance. Vibration motor can send user warnings before obstacles and provide direction guidance.

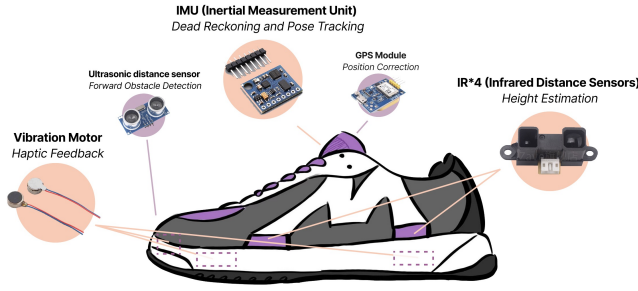


Figure 1: The sensor system employed in the project

## 4 PEDESTRIAN DEAD RECKONING

This section incorporates the InEKF-based pedestrian dead reckoning framework proposed in [10]. The method unifies system states (attitude, velocity, position) through their representation as matrices on the special Euclidean group  $SE_2(3)$ , achieving structural invariance through group-affine dynamics. Unlike conventional EKF that linearizes in Euclidean space, we adopt right-invariant multiplicative error modeling [8] via exponential mapping to transform group-space errors into linear error state vectors in Lie algebra space. This error model maintains consistent linearization of system dynamics around estimated trajectories, effectively addressing the linearization error accumulation caused by operating point deviations in traditional EKF while preserving the geometric structure properties of the system.

Inertial navigation with low-cost IMUs often suffers from drift due to sensor noise and bias. To mitigate this, the proposed method introduces stationary pseudo-measurements during the stance phase of walking, when the foot is in contact with the ground and its velocity can be approximated as zero. This constraint enables zero-velocity updates within the Kalman filter to correct the estimated state.

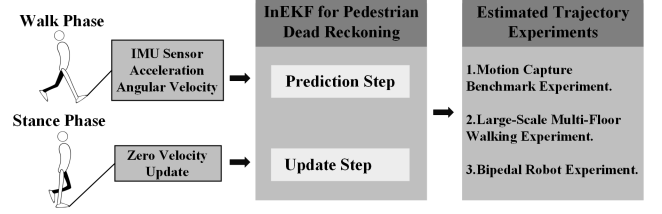


Figure 2: The pedestrian walking consists of walk phase and stance phase, which correspond to the prediction step and innovation update step in InEKF.

To improve long-term performance, gyroscope and accelerometer biases are added to the state vector and estimated jointly. These biases are modeled as first-order Gaussian processes driven by Brownian motion and are incorporated into both the state propagation and covariance update stages [8].

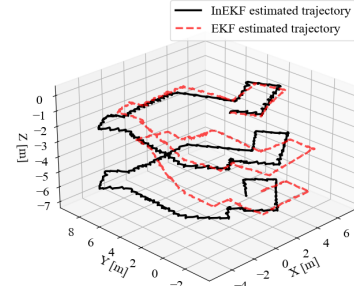


Figure 3: 3D rendering of a multi-floor indoor walking trajectory (from third-floor to first-floor) by stairs.

## 5 MULTI-SENSOR FUSION KALMAN FILTER

### 5.1 Algorithm Implementation

For multi-sensor data alignment, we employ a Kalman filter fusion algorithm alongside elementary filters (e.g., lowpass and complementary filters).

The sensor showing the smallest height measurement establishes the coordinate system's origin, while others are placed at predefined XY positions with their heights as Z-values. We first fit a plane to these 3D points, then use both the estimated plane and attitude angle as Kalman filter inputs to refine the final height estimation while suppressing noise and inconsistencies.

The detailed filtering procedure is shown below:

- 1) Adjust the measurement according to the attitude angle:  

$$adMeasure = Measure \times \cos(roll \times DTR) \times \cos(pitch \times DTR)$$
 Where  $DTR = 0.01745$
- 2) Calculate the Kalman gain  

$$Kg = \frac{P}{P+R}$$
 Where P is the error covariance, variant predetermined to be 0.9. R is the measurement noise covariance, constant predetermined to be 2.

- 3) Update the estimated data  
 $ED = ED + Kg \times (adMeasure - ED)$
- 4) Update the error covariance  
 $P = (1 - Kg) \times P + Q$   
 Where  $Q$  is the procedural noise covariance, constant pre-determined to be 0.003.

## 5.2 Data Analysis

Over the course of our study, we systematically collected 100 discrete datasets, each comprising synchronized measurements from all sensors. Data acquisition occurred at precisely timed 50 ms intervals during the motion cycle.

To evaluate the effectiveness of multi-sensor fusion Kalman filter approach, we performed a comparative analysis between raw data and processed data outputs. The results are presented in Figures 5.

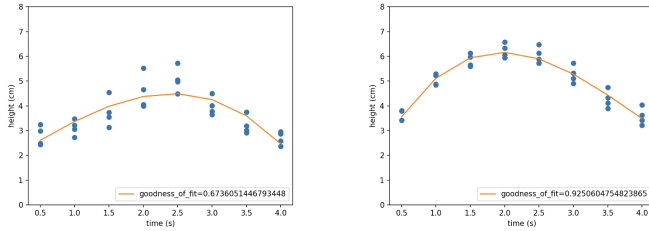


Figure 4: The feedback system employed in the project

Our analysis reveals significant improvements through signal processing:

- The processed data exhibits a 37% higher goodness-of-fit ( $R^2 = 0.925$ ) compared to raw measurements ( $R^2 = 0.673$ )
- Error margins were reduced by approximately 35% across test cases

## 6 FEEDBACK SYSTEM

### 6.1 System Output

Our Approach leverages invariant extended Kalman filtering (In-EKF) to fuse these modalities, addressing both local foot kinematics and global trajectory estimation. Furthermore, Our system incorporates GPS-aided position estimation to correct inertial drift in pedestrian dead reckoning, while ultrasonic sensors enhance obstacle detection in complex urban environments. By fusing foot-mounted IMU data, infrared terrain profiling, and absolute positioning signals, the solution provides reliable walking assistance through fused sensor data, enabling both neighborhood-scale navigation for continuous path following and real-time detection of micro-scale terrain features including curbs, stair transitions, and ground-level obstacles within residential environments.

### 6.2 Haptic Feedback Modalities

The vibrotactile interface implements four distinct feedback states through spatially distributed vibration motors:

- **Idle Rhythm:** Heel pulses synchronize with natural gait cadence to maintain baseline situational awareness without cognitive overload.

- **Directional Guidance:** Lateral edge vibration activates when users deviate from straight paths, with intensity scaling proportionally to yaw angle displacement. The asymmetric stimulation creates a perceptible "pulling" sensation toward the correct heading.
- **Obstacle Warning:** Forefoot vibration bursts trigger when detecting impediments within 0.5m, utilizing frequency modulation to indicate proximity. This suppresses forward stepping motions through pre-movement inhibition.
- **Step-off Prevention:** When a height difference is detected between front and rear sensors, sustained vibrations activate along the foot's inner edge to warn of potential steps or curbs.

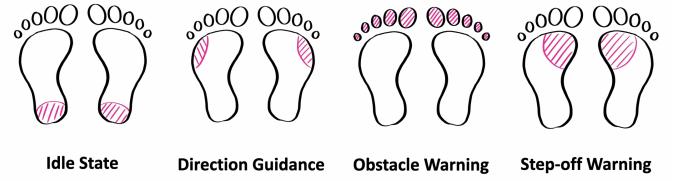


Figure 5: The feedback system employed in the project

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