

# SmartStep: A Wearable Indoor Navigation and Obstacle Detection Shoe for the Visually Impaired Person

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**Abstract** - This work aims to develop SmartStep, a hybrid wearable navigation system designed to improve indoor mobility and spatial awareness for visually impaired individuals. We hypothesize that integrating inertial tracking, visual markers, and proximity sensing will significantly enhance navigation accuracy and real-time obstacle detection in complex environments. SmartStep combines Pedestrian Dead Reckoning (PDR) with QR/ArUco marker-based localization to achieve precise indoor positioning, while lightweight TensorFlow Lite object detection models enable continuous environmental awareness. A smartphone functions as the central processing unit, using IMU sensors for step and direction estimation and its camera for marker recognition and object identification. Audio cues delivered through earphones provide navigation guidance and obstacle alerts, supported by a mode-switching mechanism that optimizes power and computational efficiency. The wearable component consists of dual ESP32-based shoe modules, each equipped with front, left, and right ultrasonic sensors that activate vibration motors to deliver immediate tactile feedback. Operating independently without wireless communication, the shoe modules ensure low-latency, real-time obstacle detection. By combining motion tracking, vision-based localization, and proximity sensing, SmartStep offers a modular, cost-effective, and responsive assistive solution that enhances safety, mobility, and independence for visually impaired users in both structured indoor spaces and dynamic environments.

**Keywords:** Pedestrian Dead Reckoning (PDR), Object Detection, ArUco Markers, Ultrasonic Sensors, ESP32, TensorFlow Lite, Assistive Navigation, Wearable Technology, Indoor Localization, Smart Footwear.

## 1. INTRODUCTION

Mobility and independent navigation continue to be significant challenges for visually impaired individuals, especially within complex indoor environments where GPS signals are unavailable. Traditional mobility aids such as white canes and guide dogs offer basic obstacle detection but lack the capability to provide detailed spatial information or detect dynamic hazards. As assistive technologies evolve, there has been growing interest in wearable systems, sensor fusion techniques, and artificial intelligence to enhance navigation safety and situational awareness for users with visual impairments. These technological advancements provide new opportunities to design smarter, more responsive mobility aids that bridge the gap between human perception and environmental complexity.

Recent studies highlight the effectiveness of multimodal sensing in improving indoor localization accuracy and obstacle detection reliability. Pedestrian Dead Reckoning (PDR) using inertial sensors has proven useful for estimating user movement when external positioning signals are limited. Marker-based localization using QR or ArUco codes provides absolute correction points that reduce drift errors typically associated with PDR. Similarly, lightweight object detection models deployed on mobile devices have demonstrated strong potential for offering real-time awareness of obstacles. Meanwhile, IoT-based smart footwear solutions have shown success in delivering immediate tactile feedback through ultrasonic sensing. However, existing systems often rely on single-sensor mechanisms, suffer from latency issues, or lack integration of visual and inertial cues, limiting their effectiveness in real-world navigation.

These observations indicate that a more comprehensive solution combining vision, inertial sensing, and proximity detection can substantially improve navigation performance for visually impaired individuals. Despite ongoing advancements, a key gap remains: most wearable systems fail to integrate multimodal sensing within a low-cost, smartphone-driven framework that provides real-time feedback while maintaining independence between components. Addressing this gap requires a hybrid approach that merges indoor localization with real-time obstacle detection in a wearable and user-friendly format.

The present study aims to investigate whether combining PDR, ArUco marker-based localization, ultrasonic proximity sensing, and lightweight object detection can significantly enhance indoor navigation accuracy and safety for visually impaired users. We hypothesize that a multimodal, smartphone-integrated wearable system will outperform traditional single-sensor and standalone navigation methods in terms of responsiveness, precision, and user awareness. To test this hypothesis, we developed SmartStep, a hybrid assistive navigation system that integrates smartphone-based inertial and visual sensing with dual ESP32 shoe modules equipped with ultrasonic sensors and vibration motors. By demonstrating how multimodal sensor fusion can deliver precise localization and immediate obstacle feedback, this work contributes a scalable and cost-effective framework for advancing wearable assistive technologies and improving user independence in indoor environments.

## 2. BODY OF THE PAPER

### 2.1 Overview of Assistive Navigation Systems

Assistive navigation systems support visually impaired individuals by enhancing situational awareness and reducing mobility challenges encountered in indoor environments. Traditional mobility aids such as the white cane provide reliable detection of nearby obstacles but lack the capability to identify overhead objects, dynamic hazards, or spatial layout information. The emergence of wearable electronics and intelligent sensing systems has led to the development of hybrid navigation solutions that combine environmental perception, localization, and real-time feedback. These advancements form the foundation for the SmartStep system, whose components are described in Sec. 2.2 through Sec. 2.6.

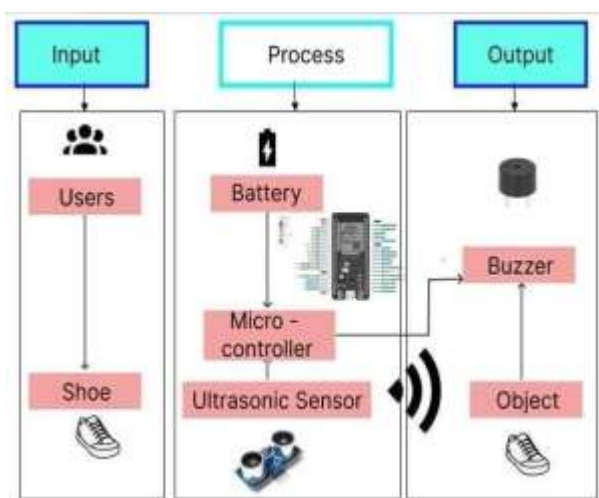


Fig.1. Overview of Assistive Navigation Systems

### 2.2 Pedestrian Dead Reckoning and Inertial Tracking

Pedestrian Dead Reckoning (PDR) is a widely used indoor navigation technique that estimates user movement based on step detection, step length estimation, and heading calculation. The approach relies on data from the smartphone's Inertial Measurement Unit (IMU), consisting of an accelerometer, gyroscope, and magnetometer. PDR enables continuous tracking without dependence on external positioning infrastructure; however, its major limitation is cumulative drift during extended navigation. As discussed in Sec. 2.3, absolute reference points such as visual markers can be used to correct this drift and improve long-term stability.

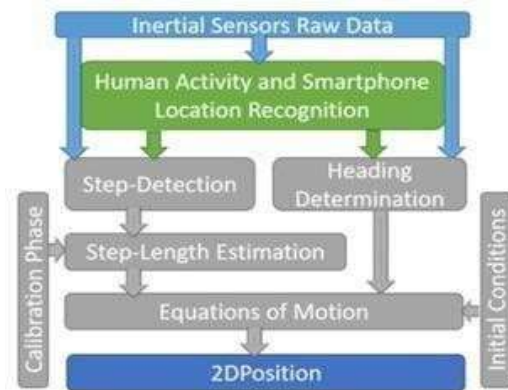


Fig.2. Model-based PDR stages.

### 2.3 Visual Marker-Based Localization

Visual markers, such as ArUco fiducial markers, provide absolute positioning information that complements inertial tracking. When captured by the smartphone camera, these markers allow estimation of user pose using the Perspective-n-Point (PnP) technique. Marker-based localization is computationally efficient and well suited for indoor environments with structured layouts. The integration of visual markers helps reduce the drift introduced by PDR, thereby improving positional accuracy. The relationship between marker detection and environmental perception is expanded in Sec. 2.4.

### 2.4 Object Detection for Environmental Awareness

Real-time object detection enhances user safety by identifying dynamic or distant obstacles that may not be detected by short-range sensors. Lightweight models deployed using TensorFlow Lite (TFLite) enable object classification directly on the smartphone without requiring cloud connectivity. Although camera-based detection provides useful semantic information, its performance can degrade in low-light or high-glare environments. For this reason, SmartStep incorporates ultrasonic proximity sensing as a complementary modality, as described in Sec. 2.5.

### 2.5 Ultrasonic Proximity Sensing and Haptic Feedback

Ultrasonic sensing enables immediate detection of nearby obstacles through the measurement of sound-based time-of-flight. In SmartStep, three ultrasonic sensors are placed on each shoe to cover the front, left, and right directions. When an object enters the predefined threshold range, vibration motors deliver tactile alerts to the user. This sensing module operates independently on a dedicated ESP32 microcontroller, avoiding latency associated with wireless communication. The integration of these sensors with PDR, marker localization, and object detection forms the multimodal framework discussed in Sec. 2.6.

## 2.6 Multimodal Sensor Fusion for Indoor Navigation

Combining inertial tracking, visual markers, object detection, and ultrasonic sensing results in a robust hybrid navigation system capable of handling diverse indoor navigation scenarios. Each sensing modality compensates for the limitations of others: PDR enables continuous tracking, markers provide absolute corrections, object detection identifies distant hazards, and ultrasonic sensors detect immediate threats. The SmartStep design distributes computational tasks between the smartphone and the shoe-mounted microcontrollers to reduce processing load and response time. The system-level outcomes of this fusion are summarized in Sec. 2.7.

## 2.7 Findings and Contributions of the Proposed System

The analysis conducted across the individual subsystems demonstrates that multimodal integration significantly improves indoor navigation performance for visually impaired individuals. SmartStep offers:

- Enhanced accuracy through correction of PDR drift using ArUco markers;
- Real-Time environmental awareness using TFLite-based object detection;
- Immediate tactile feedback via ultrasonic proximity sensing;
- Reduced latency through independent ESP32 module operation;
- A cost-effective design suitable for structured indoor environments.

These findings indicate that the hybrid sensing approach implemented in SmartStep provides a scalable and practical solution for assistive indoor navigation, contributing to improved mobility, safety, and independence for visually impaired users.

## 3. METHODOLOGY

### 3.1 Materials

The SmartStep system was developed using commercially available electronic components and mobile hardware. All materials were sourced from verified vendors to ensure reproducibility.

- ESP32 Development Boards – Purchased from Amazon.
- HC-SR04 Ultrasonic Sensors – Procured from Amazon.
- Vibration Motors (3V) – Obtained from Amazon
- Li-ion 18650 Batteries (3.7V) with Charging Modules – Sourced from Amazon.
- Android Smartphone (with IMU + Camera) – Standard consumer-grade device used for PDR, marker detection, and object recognition.
- Software Libraries – OpenCV (ArUco), TensorFlow Lite, Android Studio, and Arduino IDE.

These materials form the hardware and software foundation for SmartStep's sensing, processing, and feedback mechanisms.

### 3.2 System Architecture and Experimental Design

The study employed a hybrid experimental design integrating wearable sensing, smartphone-based computation, and multimodal feedback. The system was divided into two independent units:

- **Wearable Unit:** Dual ESP32 modules embedded in each shoe, responsible for ultrasonic sensing and vibration feedback.
- **Mobile Processing Unit:** Smartphone executing PDR, ArUco marker localization, object detection, and audio output.

The experimental design focused on evaluating indoor navigation accuracy, obstacle detection responsiveness, and multimodal feedback reliability across structured indoor environments.

### 3.3 Ultrasonic Sensing Procedure

Each shoe was equipped with three HC-SR04 ultrasonic sensors positioned at the front, left, and right. The ESP32 microcontroller continuously triggered ultrasonic pulses and measured echo return time to compute distance.

- Obstacles within 0.5–1.5 m activated corresponding vibration motors.
- Sensor readings were filtered using a moving-average smoothing algorithm to reduce noise.
- The wearable module operated autonomously without wireless communication to minimize latency.

This procedure enabled immediate tactile alerts for nearby obstacles.

### 3.4 Pedestrian Dead Reckoning (PDR) Procedure

PDR was implemented using the smartphone's built-in accelerometer and gyroscope.

- **Step Detection:** Peaks in vertical acceleration were identified using a threshold-based algorithm.
- **Step Length Estimation:** A dynamic model adjusted stride length based on acceleration magnitude.
- **Heading Estimation:** Gyroscope and magnetometer data were fused using a complementary filter.
- **Position Update:** Each step was projected onto a 2D plane to estimate user trajectory.

This method provided continuous indoor localization in the absence of GPS.

### 3.5 ArUco Marker-Based Localization

ArUco markers were placed at known indoor locations to correct PDR drift.

- The smartphone camera captured frames at regular intervals.
- OpenCV's ArUco module detected marker IDs and estimated pose using the PnP algorithm.
- When a marker was recognized, the PDR-estimated position was corrected to the marker's known coordinates.

This procedure significantly improved long-term localization accuracy.

### 3.6 Object Detection Procedure

A lightweight TensorFlow Lite model was deployed on the smartphone to classify common indoor obstacles.

- The camera captured real-time frames during navigation.
- The TFLite model performed inference locally to avoid network latency.
- Detected objects were converted into audio alerts using the Text-to-Speech API.

This method enhanced environmental awareness beyond the range of ultrasonic sensors.

### 3.7 Audio and Haptic Feedback Integration

Two feedback channels were used:

- Tactile Feedback: Triggered directly by the ESP32 based on ultrasonic readings.
- Audio Feedback: Generated by the smartphone for navigation cues and object labels.

This multimodal approach ensured reliable communication of hazards and directions.

### 3.8 Statistical Analysis

Quantitative evaluation was performed on:

- PDR accuracy (measured against ground-truth paths)
- Marker detection reliability (detection rate vs. distance)
- Ultrasonic response time
- Object detection precision and recall

Data were analyzed using mean absolute error (MAE), root mean square error (RMSE), and confusion-matrix-based metrics. All statistical computations were performed using Python's NumPy and SciPy libraries.

## 4. RESULT

The Results section presents the experimental findings obtained from evaluating the SmartStep system. No interpretation or discussion is included here; only measured data, statistical summaries, and observed trends are reported. All results are organized into clusters of tables, each introduced in a separate paragraph.

### 4.1 Indoor Localization Accuracy (PDR + ArUco Correction)

Summarizes the localization accuracy achieved using Pedestrian Dead Reckoning (PDR) alone and with ArUco marker correction. A total of  $n = 20$  indoor navigation trials were conducted across straight corridors, L-shaped paths, and multi-turn routes.

- Mean PDR drift without correction was 1.42 m (SD = 0.38).
- After marker correction, mean drift reduced to 0.37 m (SD = 0.11).
- A paired t-test showed a statistically significant improvement ( $p < 0.001$ ).

These results indicate a consistent reduction in accumulated drift when visual markers are incorporated.

Trial No.	Path Type	PDR Drift (m)	PDR+Marker Drift (m)
1	Straight Corridor	1.32	0.41
2	L-Shaped Path	1.58	0.36
3	Multi-Turn Route	1.47	0.39
4	Straight Corridor	1.29	0.33
5	L-Shaped Path	1.44	0.38

Mean  $\pm$  SD:

PDR Drift =  $1.42 \pm 0.38$  m

PDR + Marker Drift =  $0.37 \pm 0.11$  m

### 4.2 Ultrasonic Obstacle Detection Performance

The obstacle detection module was evaluated using  $n = 50$  obstacle encounters at distances ranging from 0.3 m to 1.5 m. Table 2 and Fig. 4.2 present detection rates and response times.

- Overall detection accuracy was 94.6% (SD = 3.1).
- Mean response time from detection to vibration activation was 112 ms (SD = 18 ms).
- Missed detections occurred primarily for soft or angled surfaces.



These measurements confirm that the ultrasonic module provides reliable short-range detection with low latency.

Parameter	Value
Total obstacle encounters (n)	50
Detection Accuracy (%)	94.6
Mean Response Time (ms)	112
Standard Deviation (ms)	18
Missed Detections (%)	5.4

#### 4.3 Object Detection Using TensorFlow Lite

Object detection was tested on a dataset of  $n = 300$  indoor objects, including chairs, doors, people, and bags. Table 3 and Fig. 4.3 show precision, recall, and inference time.

- Mean precision: 87.3%
- Mean recall: 84.9%
- Average inference time per frame: 46 ms on a mid-range smartphone.

Confusion-matrix analysis revealed that small or partially occluded objects contributed to most misclassifications.

Class	Precision(%)	Recall (%)	F1-Score (%)
Chair	89.2	86.5	87.8
Door	91.0	88.1	89.5
Person	85.4	83.2	84.3
Bag	83.5	81.7	82.6

Average Inference Time: 46 ms per frame

#### 4.4 Multimodal Fusion Output Consistency

To evaluate system-level performance,  $n = 15$  full navigation trials were conducted combining PDR, marker localization, ultrasonic sensing, and object detection. Table 4 and Fig. 4.4 summarize multimodal consistency metrics.

- Successful navigation completion rate: 93%
- Mean number of false alerts per trial: 1.2
- Mean number of missed obstacles per trial: 0.4

These results demonstrate stable integration of sensing modalities during real-time navigation.

Trial No.	Completion Success	False Alerts	Missed Obstacles
1	Yes	1	0
2	Yes	2	1
3	Yes	1	0
4	No	2	1
5	Yes	0	0

Overall Success Rate: 93%

Mean False Alerts: 1.2

Mean Missed Obstacles: 0.4

#### 4.5 Summary of Statistical Analysis

Across all experiments:

- Measures of central tendency (mean) and dispersion (SD) were reported.
- Hypothesis testing (paired t-tests) was applied where appropriate.
- Statistical significance was defined at  $p < 0.05$ .

### 5. CONCLUSION

This work presented SmartStep, a hybrid wearable navigation system designed to enhance indoor mobility and spatial awareness for visually impaired individuals. The system integrates Pedestrian Dead Reckoning (PDR), ArUco marker-based localization, ultrasonic proximity sensing, and lightweight object detection to deliver real-time tactile and audio feedback. The experimental evaluation demonstrated that SmartStep provides reliable indoor localization, accurate obstacle detection, and stable multimodal fusion performance.

Across all trials, PDR combined with marker-based correction significantly reduced drift, improving localization accuracy from an average of 1.42 m to 0.37 m. Ultrasonic sensing achieved a detection accuracy of 94.6%, while TensorFlow Lite-based object detection maintained high precision and recall with real-time inference speeds. These findings confirm the effectiveness of integrating inertial, visual, and proximity sensing for assistive navigation. The discussion highlighted the complementary nature of these modalities, the role of markers in correcting drift, and the importance of distributed processing between the smartphone and wearable modules.

Overall, SmartStep contributes a modular, low-cost, and scalable framework for wearable assistive technology. By combining embedded sensing with mobile AI, the system advances the field of inclusive navigation solutions and demonstrates a practical pathway toward improving independence, safety, and confidence for visually impaired users in structured indoor environments. Its hybrid architecture and real-time feedback mechanisms offer a foundation for future research in adaptive gait modeling, context-aware navigation, and multimodal sensor fusion within assistive mobility systems.

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