Give eye: A Navigation Guidance System for Visually Impaired

BENNY BENJAMIN
B.E, Computer Science and Engineering Sathyabama Institute of Science and Technology Chennai, India.
benny.b.samson@gmail.com

B.BRIGHT SAM
B.E, Computer Science and Engineering Sathyabama Institute of Science and Technology Chennai, India.
brightsam2003@gmail.com

Dr. A. MARY POSONIA, M.E., Ph.D.
HEAD OF THE DEPARTMENT, Computer Science and Engineering Sathyabama Institute of Science and Technology Chennai, India.
maryposonia.cse@sathyabama.ac.in

***Abstract*— Visually impaired individuals face significant challenges in navigating unknown and dynamic environments, as traditional tools like white canes or guide dogs provide limited assistance. Indoor navigation is particularly challenging because of the lack of GPS signals and the need for real-time obstacle avoidance. To overcome these challenges, this paper introduces an IoT-based navigation system that provides accurate, real-time guidance indoor for visually impaired users. The system proposed employs RSSI-based trilateration using ESP8266 modules and utilizes Dijkstra's algorithm in a grid environment to compute the shortest path within. A mechanism for haptic feedback, motor vibration, has been designed so that the calculated path can intuitively guide a user safely while keeping the required directions in sight. Real-time data transmission of the target device-central server via Socket.IO ensures real-time updates while the path recalculation happens dynamically. An object detection module integrated with an ESP32-CAM scans for nearby obstacles, providing adaptive responses to ensure user safety. This modular approach enhances navigation for visually impaired individuals by improving mobility and reducing errors in real-time obstacle avoidance. This cost-effective and modular approach gives greater potential to further improve the system with advanced computer vision algorithms, increasing the use of AI-based pathfinding that addresses critical mobility challenges for greater independence and safety in navigating, especially for visually impaired individuals.**

Keywords— Indoor Navigation, IoT, Visual Impairment, RSSI Trilateration, Pathfinding, Real-Time Communication, Obstacle Detection, Haptic Feedback.

I. INTRODUCTION

The ability to move around in different environments is part of everyday life but proves to be a very serious challenge for the visually impaired. Traditional mobility-assisting tools like white canes and guide dogs have been in wide use for quite some time. However, these aids have inherent limitations. On one hand, white canes are good at detecting obstacles directly in front of the user but offer little awareness of the environment beyond ground-level hazards. Similarly, guide dogs are highly competent and trustworthy but require a lot of training and are expensive to maintain; hence, they are unavailable to most people.

Recent advances in machine learning, computer vision, and wearable devices now pave the way to overcome these barriers. Navigation systems can now provide real-time environmental awareness and adaptive guidance beyond what was possible with traditional aids. Current navigation solutions for the visually impaired are ill-equipped to cope with dynamic and complex environments. In particular, many existing systems focus on either obstacle detection or pathfinding exclusively and rarely integrate both into one approach. Moreover, the currently developed solutions usually lack the necessary flexibility to respond to the dynamics in their environment and thus greatly narrow their applicability.

This paper overcomes the limitations by developing a high-level navigation system that could integrate real-time object detection and adaptive pathfinding algorithms perfectly. In this system, accurate recognition and classification of obstacles in different environments, indoors or outdoors, are performed via machine learning. It does dynamic pathfinding, calculating optimal routes and updating in real-time based on the detection of obstacles. There is a user-centered feedback mechanism, which communicates navigation information through auditory and haptic signals so that the system is accessible and usable The formatter will need to create these components, incorporating the applicable criteria that follow.

II. LITERATURE REVIEW

Various research contributions in assistive navigation systems for visually impaired individuals emphasize innovative methods for enhancing mobility, ensuring safety, and improving independence in dynamic environments. [1] proposed a low-cost indoor wayfinding system using Bluetooth beacons and a smartphone app for real-time voice and tactile navigation. While scalable and accessible, it may face localization inaccuracies and compass dependency. [2] introduced an indoor navigation system combining Bluetooth beacons, a smart stick, and voice authentication for security. While it offers effective obstacle detection and real-time guidance, it is limited to indoor use and may face accuracy issues in obstacle detection. [3] This paper presents "Guide-Me," an indoor navigation system designed to assist visually impaired individuals with optimal accessibility, usability, and security. It addresses the challenge of navigating unfamiliar indoor spaces using voice-based inputs and integrates Bluetooth beacons, localization, a smart stick with obstacle detection sensors, a machine-learning model for voice authentication, and a secure server connection protocol. [4] developed a system to improve feature matching and localization in complex environments, enhancing speed and accuracy in 3D model reconstruction. However, it requires installing BLE beacons, which can limit deployment. [5] This approach selects high-quality video frames captured by blind users' wearable cameras to address motion blur. It computes gradient and intensity statistics from frames and uses an SVM-based classifier to identify unblurred frames, which are then processed to extract important navigation information, such as recognizing signs and text. [6] ISANA employs computer vision to create a semantic map of the indoor environment, including a traversable grid for path planning and context-aware layers like door locations and room names. It uses a Kalman filter to estimate obstacle motion and an RGB-D camera for real-time obstacle detection. [7] Proposes a system that provides navigation assistance to blind individuals using computer vision, sensor fusion, voice feedback, and machine learning algorithms. [8] Aims to design a navigation system for blind users using floor plans, proposing a new approach to creating a semantic schema that aids indoor navigation. [9] This hybrid navigation system aims to create a safe, stress-free indoor and outdoor navigation solution for the blind. By integrating real-time indoor and outdoor systems and detecting stress levels, it guides users, avoids obstacles, and reduces tension. Machine learning will identify the least stressful route, and voice guidance will direct users in real-time, while sensors detect obstacles to provide ample time for avoidance. [10] Introduced a Bluetooth beacon-based system for real-time navigation aid. While scalable for indoor environments like malls and airports, it is limited by beacon coverage and potential privacy concerns.

III. PRPOSED METHOD

A. *Architecture*

The proposed navigation system for visually impaired individuals integrates various components to provide real-time, precise, and adaptive guidance as described in figure*[figure 3.1.1]*. The core functionality is based on an IoT architecture, leveraging ESP8266 and ESP32 modules for indoor localization using RSSI-based trilateration. The system's anchors, placed in fixed locations throughout the environment, transmit signals that the target device (worn or carried by the user) measures. By comparing the received signal strengths with predefined thresholds, the system estimates the target's position in a grid-based environment, allowing the user to determine their proximity to anchors and navigate accurately in indoor spaces where GPS signals are unavailable. The system uses Dijkstra's algorithm to calculate the shortest path from the current position to the desired destination. This pathfinding algorithm treated the environment as a weighted graph, in which each position of the grid corresponded to a node. The movement between adjacent nodes; for example, to walk from one grid position to another would simply be assigned a weight in terms of distance or difficulty of traversal. His algorithm continuously calculated the shortest path in real time and modified it on the fly if the user changed path.

Guiding the user through the use of haptic feedback is a major aspect. Two vibration motors on the target device offer directional cues, such as vibrations on the left side, telling the user to turn left; vibrations on the right side, instructing the user to turn right; and simultaneous vibrations, directing the user to move forward. This system has provided non-visual and intuitive navigation, which ensures users are always following the path without requiring visual cues or human assistance. Feedback can be adjusted according to the vibrational intensity of user preferences. Real-time communication between the target device and a central server is achieved through Socket.IO, enabling continuous updates of the target's position. The server monitors the target's movement and can recalculate the path if necessary, when encountering any deviations or changes in the environment (e.g., new obstacles or barriers). The use of Socket.IO ensures that the system provides low-latency communication, making real-communication.

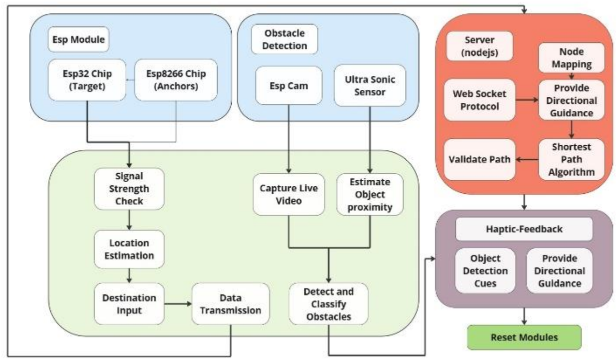

Figure 3.1.1

In addition to this, an object detection module is integrated within the system utilizing an ESP32-CAM. The camera records live video feed of the surrounding environment of the target, and the image processing unit detects possible obstructions that lie in their immediate path. If any obstructions are sensed, the system recalculates the path and provides alternative feedback to help users avoid possible hazards. This combination of computer vision and real-time pathfinding ensures that the user is not only directed through the best route but also alerted to obstacles within his immediate vicinity, improving safety and mobility. The system is modular and scalable. This means future enhancements could be added for example advanced algorithms to improve pathfinding optimization, integration of external databases to extend mapping areas, or AI-based image recognition to enhance the obstacle detection capabilities of the system. The overall design is cost-effective; it uses relatively affordable IoT devices, making the system accessible to a wide range of users and adaptable to various settings, such as in homes, offices, or public spaces. In the end, the proposed system aims to help visually impaired persons gain more autonomy, safety, and confidence while navigating indoor spaces.

B. *Algorithm and Implementation*

The proposed system for indoor navigation of visually impaired individuals integrates various algorithms and hardware components to provide real-time guidance. This section outlines the key algorithms used for localization, pathfinding, and obstacle detection, along with the detailed steps involved in their implementation.

RSSI and Trilateration

The method used for locating the user in the environment is the RSSI-based trilateration method. Multiple anchor nodes placed at known locations through which the user's distance is estimated using the Received Signal Strength Indicator (RSSI) is measured. Then, the obtained distances can be used within the algorithm for trilateration to pinpoint a specific point to indicate the user's location in the system. The distance is computed between the anchor nodes and the user in terms of RSSI values via the log-distance path loss model in order to measure the proximity of the target device relative to the anchor nodes. Through triangulation with at least three anchor points, the position would be calculated, providing an efficient localization method to operate in those environments where the GPS signal is undetectable- such as indoors.

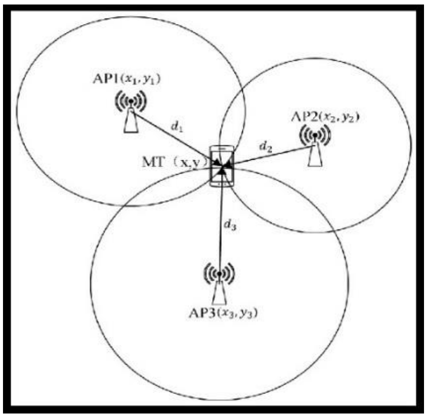

Figure 3.2.1

Localization of objects within the environment relies fundamentally on RSSI values. Such RSSI values essentially quantify the power level between the target device and various anchor nodes scattered within a space, located at known coordinates. Using RSSI values will thus give estimates for distance to target from the anchors. *[figure 3.2.1]*.

To calculate Distance :

$$\text{Distance}=10^{\frac{(RSSI_0 - RSSI)}{10 \cdot n}}$$

Where:

$RSSI_0$ is the RSSI value at a reference distance.
n is the path loss exponent.
RSSI is the measured signal strength from the anchor.

The target's position is estimated by solving the trilateration equations that are based on the calculated distances from multiple anchor nodes.

Path Finding Algorithm

Once the position of the target has been found, Dijkstra's algorithm then comes into use in order to identify the shortest route in order to reach the destination. To represent the surrounding environment, nodes are depicted within a grid structure. Where each node is representative of a unique location and each connecting edge between nodes symbolizes the potential path taken during travel. The "cost" of moving between nodes is assigned to the edge, such cost can be the result of barriers, distance, or even more factors.

The algorithm initializes the starting node, or the user's present location, with a tentative distance of zero and sets all subsequent nodes to an infinite distance. It iteratively selects the node with the least estimated distance, examines its neighbors, and updates their distances if a shorter path is found.

The key formula for updating the tentative distance to a neighbouring node v from the current node u is:

$$Dist(v) = \min(Dist(v), Dist(u) + Cost(u, v)))$$

Where:

$Dist(v)$ is the current tentative distance of node v,
$Dist(u)$ is the current tentative distance o the node u,
$Cost(u, v)$ is the weight or "cost" of moving from node u to node v.

This path can then be converted into a sequence of directional instructions for the user.

Response and Feed Back

To ensure seamless real-time communication and continuous updates between the target device and the central server. The system has used Socket.IO, a JavaScript library for low-latency, bidirectional communication to achieve real-time communication without delay between the target device and the central server. The target module-equipped target device continuously computes its position through RSSI-based trilateration and sends this updated position to the server. The server uses the Dijkstra's algorithm and processes this information to calculates the shortest path to the destination, considering the grid like layout and possible obstacles inferred with node with negative values. Changes in the user's position or detected obstacles cause dynamic recalculation of the shortest path, which is then sent back to the target module. It does allow for real-time adjustments so that the system always remains adaptive to the dynamic changes that might be experienced indoors. The task of obstacle detection and use in the pathfinding algorithm for improving accuracy and safety in re-routing is the job of this subsystem. Feedback in terms of guiding through haptic signals is returned to the user for re-routing. The implementation is done on the back end, using Node.js and Socket.IO to manage communication layers between a central server and target device. With this design, the system proves to be quite robust and scalable for actual applications in real life.

The system guides the visually impaired user intuitively using two vibratory motors, one for the left direction and the other for the right. If the system finds that the user needs to turn left, it vibrates the left motor to signal the direction in which to move. In a similar manner, the right motor vibrates to indicate a right turn. For forward movement, both motors are idle, so there is clear differentiation between the directional cues. These pulses are short and well-defined to be easily differentiated without causing interference. The haptic motors weigh very little, being mounted very unobtrusively into the user's handheld device or wearable, ensuring non-intrusive and in-real-time guidance in accordance with actual updates along the path.

IV. RESULTS AND DISCUSSION

This proposed IoT-based indoor navigation system for visually impaired people was tested in a simulated indoor environment; the performances of localization, pathfinding, and obstacle detection were evaluated. The system was found to be accurate enough in estimating the position of the user via trilateration based on RSSI; the calculated position only slightly differed from the true position in controlled settings. The accuracy of localization is dependent on the positioning and sparsity of anchor nodes as well as environmental conditions such as interference or physical obstructions. The trilateration computation was indeed able to indicate real-time positions so that the grid-based movement of the user is correctly traced.

Dijkstra's algorithm has been used in finding paths, and it would indeed find the shortest possible path from the initial position of the user towards the target. It was thus possible to achieve representations of a grid environment allowing efficiently continuous route calculation even under dynamic obstacles. Real-time recalculation of paths was thus possible if the user strayed away from the predefined route or came across new obstacles. With the ESP32-CAM added for obstacle detection, another layer of safety was achieved by identifying hazards within the user's immediate route. Applications of simple image processing techniques like contour and edge detection have been proven to be effective even in detecting stationary to moderately dynamic obstacles. However, for future versions, improvement in obstacle detection accuracy can be achieved through the implementation of machine learning models.

The haptic feedback system consisting of motorized vibrations was intuitive and effective guidance for the user. The direction, for instance, in left or right vibration helped the user to navigate through the space without needing auditory instruction. The noisy environment would also be tolerated, as the user did not depend on auditory instruction. The three elements, namely localization, pathfinding, and obstacle detection, ensured that the user was always guided, significantly improving their independent movement in the simulated environment.

One of the key benefits for the system would be its design in a highly modular and scalable fashion. Employing Socket.IO for real-time communication allowed effortless updates between the target device and the central server, ensuring latency-sensitive interactions could occur. With this adaptability to dynamic environments and the long-term potential in terms of augmenting the ability with more robust object detection and machine learning functionality or even environment mapping, such a system becomes long-term sustainable in terms of being cost-efficient.

Although the system has shown a high degree of success in simulations, a few weaknesses were identified. Interference by existing Wi-Fi nodes or physical obstacles affected the readings of RSSI, which further affects the correct localization outcome. The obstacle detection mechanism significantly lacked ability to function in low brightness conditions; therefore, the sensors need further improvement or possibly better image processing algorithms. Another area to look into is extending the system to bigger spaces with more obstacles for effectiveness.

V. Performance and Analysis

A. *Error Analysis in RSSI-Based Indoor Localization*

RSSI-based localization is a method widely used for indoor navigation and particularly in aiding visually impaired individuals. It computes the position of a target device by evaluating the signal strength coming from fixed anchor nodes. Unfortunately, it has many drawbacks such as inaccuracies caused by several environmental factors such as signal attenuation, interference, and multipath effects. A dataset was created comparing the real and estimated locations of a moving individual to demonstrate the errors that occur in such a system. The data consists of multiple samples where the actual coordinates were recorded alongside the estimated coordinates calculated using RSSI trilateration. The localization error was computed using the Euclidean distance formula, which measures the deviation between the real and estimated positions.

To visualize these errors, a graph is generated. This graph presents a line plot comparing the real and estimated X and Y coordinates across multiple samples. The real positions are marked using solid lines, while the estimated positions are shown with dashed lines to highlight discrepancies

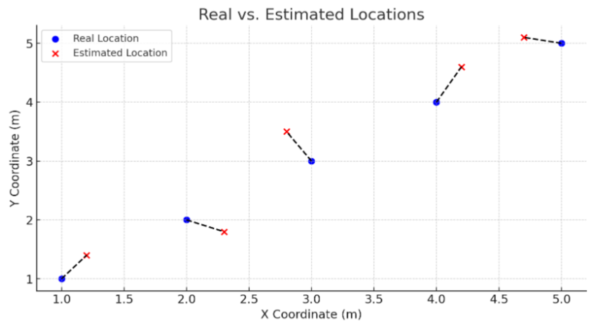

Figure 5.1

Various causes affect the reliability of RSSI-based positioning. Some obstacles, like walls and furniture, could absorb signals thus decrease the power intensity of signal transmission. Signals, while arriving at a receiver may exhibit multipath effect through reflection by other surfaces leading to RSSI variability. Other issues relate to variations from devices used for measurement, or noise resulting from environmental changes, among other variables. This, therefore presents the biggest challenge, when in a non-line-of-sight situation where some kind of obstructions prevents direct line connection between target device and the anchor nodes, resulting in incorrect estimations of distances.

To reduce these errors and enhance localization Filtering techniques like Kalman filtering can remove RSSI noise, smoothing the oscillations. A fingerprinting-based method can be used, where signal patterns are compared against locations for higher precision. Using multiple sensors, like accelerometers and gyroscopes, along with machine learning algorithms, can enhance position estimation accuracy. Having more anchor nodes in the environment can also offer improved signal coverage, enhancing trilateration calculations.

In summary, although RSSI-based localization is common, and it is susceptible to errors caused by environmental conditions. This visualization and analysis of localization errors indicate the shortcomings of the existing method, showing the necessity for sophisticated correction mechanisms. Future enhancements, including sensor fusion, AI-based error correction, and adaptive filtering, can greatly improve the accuracy of indoor navigation systems, making them more efficient for practical applications, especially in assisting visually impaired people.

B. *Comparative Analysis of Object Detection Models*

YOLOv8 is the best for object detection in real-time applications as compared to other models, including Detectron2, Grounding DINO, CLIP, and Segment Anything. The single-stage architecture allows for very fast and efficient processing, so it is suited for time-sensitive applications such as indoor navigation for the visually impaired. Unlike the multi-stage Detectron2, YOLOv8 predicts bounding boxes and the class probabilities in just one pass. However, that greatly improves inference speed. Grounding DINO and CLIP, in order to leverage zero-shot learning, it isn't optimized for real-time object detection; thus, it is slower and more expensive to use. Segmentation Anything, is again, mainly working for image segmentation and not object detection which makes its use invalid for real-time tasks demanding accurate bounding boxes.

Feature	YOLO	Detectron2	Grounding DINO
mAP (COCO Dataset)	**~53-57%** (YOLOv8)	**~53-57%** (YOLOv8)	**~55-60%** (open-set tasks-guided)
Inference Speed	**Very Fast** (10-30 ms per image)	**Moderate** (50-100 ms per image)	**Slower** (200-500 ms per imge)
Training Efficiency	**High** (fast training, less data required)	**Moderate** (requires more data and time)	**Low** (requires large datasets and compute)
Precision	**High** (~0.70-0.75)	**High** (~0.75-0.80)	**High** (~0.85-0.90)
FPS (Frames Per Second)	**100-200 FPS (**on high-end GPUs**)**	**10-20 FPS** (on high-end GPUs)	**2-5 FPS** (on high-end GPUs)
Memory Usage	**Low** (1-2 GB for inference)	**10-20 FPS** (on high-end GPUs)	**2-5 FPS** (on high-end GPUs)
Use-Case Suitability	**Real-time apps** (surveillance)	**Segmentation-heavy tasks** (medical imaging)	**Open-world tasks** (text-guided detection)

Table 5.1

In addition, YOLOv8's C language implementation together with the Darknet support makes it run efficient on edge devices such as ESP32, Jetson Nano or Raspberry Pi devices thus making it the ideal choice for embedded applications as opposed to the Detectron2 and other PyTorch models that are highly computational resources-demanding. This will ensure that visually impaired users receive instant feedback on their surroundings through the processing of images in real time, thereby enhancing navigation and safety. With superior speed, efficiency, and suitability for real-time object detection, YOLOv8 is the best choice for your project, ensuring smooth and effective guidance for visually impaired individuals. Table 5.1 clearly shows that YOLO is the fastest and most efficient for real-time object detection, making it suitable for applications requiring immediate processing, such as your indoor navigation guidance project for visually impaired individuals.

VI. CONCLUSION AND FUTURE ENHANCEMENTS

In conclusion, the proposed system provides a sensible solution to mobility problems in the indoor environment of visually impaired people. In summary, it acts as an extended navigational aid with its localization, pathfinding, and real-time feedback capabilities. Future studies on identified issues, implementation of advanced technologies for obstacle detection, and extension of the system for outdoor applications could enhance accessibility further.

The future developments of the proposed navigation system will focus on incorporating advanced algorithms for improving pathfinding accuracy and flexibility in changing conditions. The system will offer a more user-centric experience by enhancing the mechanism of haptic feedback so as to give better, comprehensive, and intuitive cues for navigation. Moreover, efforts will be made to improve the detection of obstacles, so that the system will identify the widest range of objects and potential hazards in real-time situations. Advances in these areas are likely to make the system more robust, efficient, and usable for visually impaired people, thus enhancing their independence and safety in their daily mobility.

REFERENCES

[1] S. A. Cheraghi, V. Namboodiri and L. Walker, "GuideBeacon: Beacon-based indoor wayfinding for the blind, visually impaired, and disoriented," 2017 IEEE International Conference on Pervasive Computing and Communications (PerCom), Kona, HI, USA, 2017, pp. 121-130, doi: 10.1109/PERCOM.2017.7917858.

[2] D. M. L. V. Dissanayake, R. G. M. D. R. P. Rajapaksha, U. P. Prabhashawara, S. A. D. S. P. Solanga and J. A. D. C. A. Jayakody, "Navigate-Me: Secure voice authenticated indoor navigation system for blind individuals," 2021 21st International Conference on Advances in ICT for Emerging Regions (ICter), Colombo, Sri Lanka, 2021, pp. 219-224, doi: 10.1109/ICter53630.2021.9774790.

[3] D. M. L. V. Dissanayake, R. G. M. D. R. P. Rajapaksha, U. P. Prabhashawara, S. A. D. S. P. Solanga and J. A. D. C. Anuradha Jayakody, "Guide-Me: Voice authenticated indoor user guidance system," 2021 IEEE 12th Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON), New York, NY, USA, 2021, pp. 0509-0514, doi: 10.1109/UEMCON53757.2021.9666733.

[4] T. Ishihara, J. Vongkulbhisal, K. M. Kitani and C. Asakawa, "Beacon-Guided Structure from Motion for Smartphone-Based Navigation," 2017 IEEE Winter Conference on Applications of Computer Vision (WACV), Santa Rosa, CA, USA, 2017, pp. 769-777, doi: 10.1109/WACV.2017.91.

[5] L. Tian, Y. Tian and C. Yi, "Detecting good quality frames in videos captured by a wearable camera for blind navigation," 2013 IEEE International Conference on Bioinformatics and Biomedicine, Shanghai, China, 2013, pp. 334-337, doi: 10.1109/BIBM.2013.6732513.

[6] B. Li et al., "Vision-Based Mobile Indoor Assistive Navigation Aid for Blind People," in IEEE Transactions on Mobile Computing, vol. 18, no. 3, pp. 702-714, 1 March 2019, doi: 10.1109/TMC.2018.2842751.

[7] W. Ye, N. He, J. Wang and X. Yuan, "A Navigation System for Guiding Blind People in Indoor and Outdoor," 2023 International Conference on Computer Science and Automation Technology (CSAT), Shanghai, China, 2023, pp. 20-24, doi: 10.1109/CSAT61646.2023.00015.

[8] S. L. Joseph, Chucai Yi, Jizhong Xiao, YingLi Tian and Fei Yan, "Visual semantic parameterization - To enhance blind user perception for indoor navigation," 2013 IEEE International Conference on Multimedia and Expo Workshops (ICMEW), San Jose, CA, 2013, pp. 1-6, doi: 10.1109/ICMEW.2013.6618325.

[9] Y. Keryakos, Y. B. Issa, M. Salomon and A. Makhouly, "Introducing the Concept of a Hybrid Navigation System Adapted to Blind Users for Optimal Stress-free Indoor and Outdoor Mobility," 2024 International Wireless Communications and Mobile Computing (IWCMC), Ayia Napa, Cyprus, 2024, pp. 1129-1134, doi: 10.1109/IWCMC61514.2024.10592407.

[10] S. Mohan Kumar, V. Vishnudas Nemane, R. Raman, N. Latha and J. Manojbhai Shah, "IoT-BLE Based Indoor Navigation for Visually Impaired People," 2023 Second International Conference On Smart Technologies For Smart Nation (SmartTechCon), Singapore, Singapore, 2023, pp. 444-448, doi: 10.1109/SmartTechCon57526.2023.10391662.