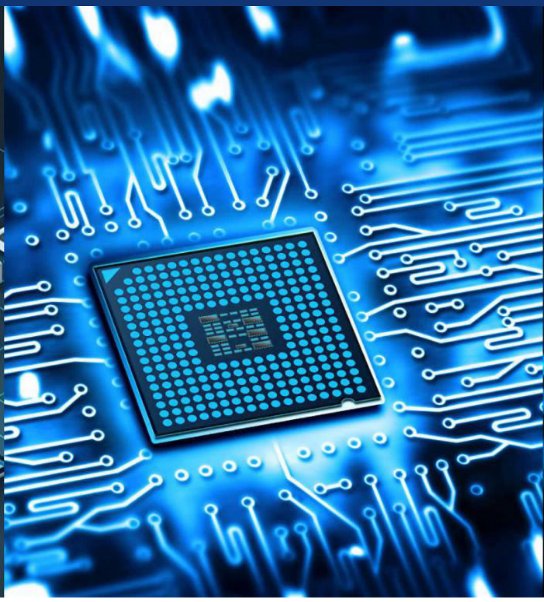
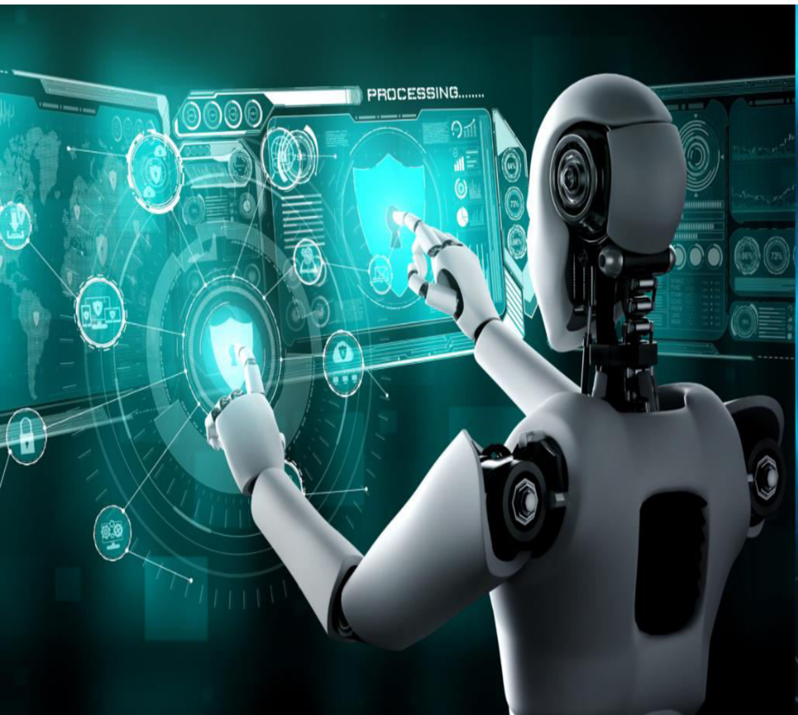
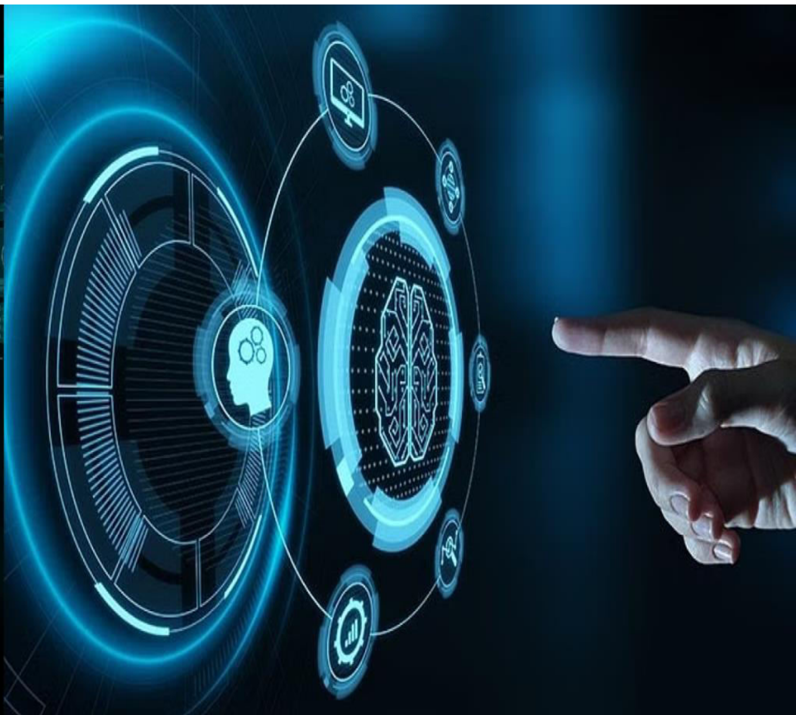
ISSN(O): 2320-9801
ISSN(P): 2320-9798


International Journal of Innovative Research in Computer and Communication Engineering

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)





Impact Factor: 8.771

Volume 13, Issue 3, March 2025

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Multi-Sensor SLAM Framework for Humanoid Robots: Enhancing Environmental Perception and Localization in Webots using NAO with Virtual Sonar, IMU, and Camera Data

Kabwe Daniel[1], Juang Li-Hong[2]

School of Artificial Intelligence, Nanjing University of Information Science and Technology, Nanjing, China[1,2]

ABSTRACT: SLAM functions as a vital capability for autonomous robots which allows them to perform navigation and build maps of unexplored environments. This paper develops a multi-sensor SLAM framework which operates on the NAO humanoid robot within Webots simulation platform. The framework uses information from virtual sonar sensors alongside IMU (Inertial Measurement Unit) devices as well as cameras for improved perception of surroundings and better positioning accuracy. A robust approach based on Extended Kalman Filter (EKF) for state estimation control enables hazard detection using visual features which enhances mapping reliability. The proposed framework established in dynamic conditions shows positive experimental outcomes that enhance localization precision and mapping reliability. Empirical evidence demonstrates how the system operates effectively through simulations which provides proof for implementing this technology within humanoid robotic systems.

KEYWORDS: SLAM; Humanoid Robots; Multi-Sensor Fusion; Hazard Detection; Webots Simulation.

I. INTRODUCTION

The autonomous navigation of humanoid robots through unknown environments requires reliable Simultaneous Localization and Mapping (SLAM) solutions because they are essential for navigation. SLAM allows robots to generate environment maps plus position relations which forms a fundamental requirement for search and rescue operations and domestic assistance tasks and industrial automation systems. The NAO humanoid robot experiences specific obstacles because of its sophisticated movement system and restricted sensor system and dynamic locomotion methods that create variations and unpredictability in sensing data. The implementation difficulty for traditional SLAM approaches increases because of two major factors: the requirement for real-time processing on restricted hardware systems. The state-of-the-art visual-inertial SLAM system ORB-SLAM3 function optimally in structured environments however it needs powerful computational resources that NAO robots equipped with limited processing power and low-resolution sensors cannot support.

The proposed research develops a multi-sensor SLAM framework for NAO robots that uses virtual sonar data with IMU measurements and camera inputs to advance robot environmental sensing and position determination. The state estimation utilizes an Extended Kalman Filter (EKF) that merges IMU readings for orientation and velocity measurements with sonar sensor data for obstacle detection and camera-extracted visual features. Through EKF predictions based on motion models the robot's state gets updated using observed features while maintaining reliable localization performance in dynamic unstructured environments. The framework adds a navigation safety system which analyzes environmental hazards through color thresholding and contour detection to spot fires and bottles and plates. The system enables the robot to find and evade objects during live operation. The system presents a real-time visualization component which displays the robot trajectory together with detected features and hazards on a two-dimensional map for monitoring the complete environment. The framework achieves better localization precision as well as mapping dependability through sensor data fusion from various detection instruments [2].

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

The contributions of this work include a multi-sensor fusion approach for improved localization accuracy, a hazard detection module for identifying obstacles and environmental hazards, and a real-time visualization system for monitoring robot performance. These advancements address the unique challenges of humanoid robots, making the proposed framework well-suited for resource-constrained systems.

II. RELATED WORK

The authors of [3] developed an SLAM algorithm with particle filtering for humanoid robots operating in unknown environments for multi-robot collaboration. Their system uses distributed computing techniques to make their approach scalable yet encounters performance issues when operating on individual robots in real time. Ye et al. [4] implemented neural bipartite graph matching to improve efficiency during multi-robot active mapping operations. These approaches typically need high computational power to operate while they fail to adapt to humanoid robot specifications including balance maintenance and sensor weight capacity.

Chen et al. [5] created a mobile robot active SLAM framework which unites area coverage and obstacle avoidance mechanisms in sensor fusion operations. Their system links EKF-based state estimation to frontier exploration strategies to create effective mapping capabilities without safety hazards. The method proves useful for wheeled robots yet it fails to solve difficulties faced by humanoids during locomotion like stability maintenance and restricted sensory perception. The research of Ahmad et al. [6] presents a method which solves EKF-based mobile robot navigation problems of partial observability by boosting the accuracy of robotic localization in feature-poor settings. This paper emphasizes the significance of reliable state estimation in SLAM yet fails to incorporate simultaneous use of diverse sensors.

The proposed framework extends previous advancements by developing solutions for humanoid robot-specific issues. The framework merges information from virtual sonar and IMU sensors and cameras to boost environmental perception as well as localization precision. The framework applies EKF-based state estimation together with visual feature detection and hazard identification to produce both reliable performance and computational efficiency in dynamic settings. Such approach works best in systems with limited resources because it optimizes computational resource management.

III. METHODOLOGY

The research developed Webots simulation software to evaluate a multi-sensor SLAM framework that operated through two NAO robots within an environment designed like a home. The setup arranges two linked spaces which stand for different sections of an ordinary domestic area. The setup consists of rooms with different objects and hazards including furniture and appliances while wooden plates rest improperly on the floor and fire hazards remain present. The simulated home environment contains object arrangements throughout the space to expose robots to real-world placement challenges as they track the area and validate proper placements among hazard detection tasks.

Both NAO robots function separately in this application area. Each robot occupies its own designated space with one robot stationed in a first room and the other in the second room. The robots have separate areas to monitor for both improperly placed objects and hazards including bottles on the floor combined with misaligned furniture. The robots detect and move through the space using their virtual sonar sensors with IMU (Inertial Measurement Unit) and camera information for sensory perception. The sonar sensors help robots measure distances to detect objects and the IMU system tracks their position while the cameras enable visual hazard identification.

The robotic system operates as a team because each unit communicates important data regarding dangerous spots and mislocated items. While patrolling the space the robots perform continuous environmental scan with Laplacian edge detection to construct precise spatial mapping. The edge detection process enables robots to detect obstacles as furniture while distinguishing them from open areas through proper identification of mispositioned objects.
Upon detecting a mispositioned object or a hazard, the robots flag it in their system. The camera feed processes the data and provides textual feedback in the console, notifying the system of any issues detected. For example, if the robot

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

identifies a bottle resting on the floor it will produced an alert message "Bottle detected on the floor - hazard!" The robot system identifies possible hazards through texture analysis before providing additional information about the detected objects as in "A red item was discovered but it is not classified as fire (based on texture analysis)."

The robots efficiently survey the whole home together by teaming up to find hazards and proper placement of objects. The multi-sensor SLAM framework provides robots with precise positioning abilities in space which results in organized areas while maintaining safety.
Two NAO robots are positioned to monitor separate home areas as they detect hazards while maintaining correct object positioning.

Fig. 1. Set up of the webot Home nvironment

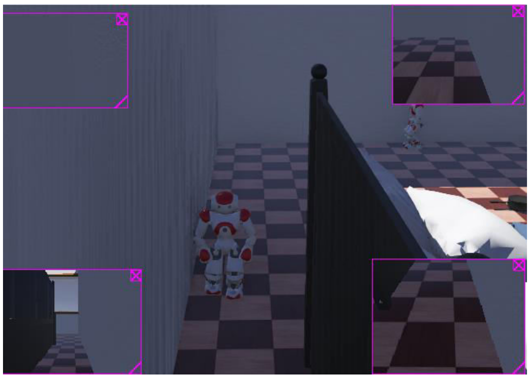


Fig. 2. Robots malnuvering checking the house

Figures 1 and 2: Webots environment showing the two NAO robots monitoring different areas of the home setting.

Problem Statement

SLAM serves as a decisive technology in autonomous robotics which enables machines to simultaneously perform navigation and mapping of uncharted environments. The traditional SLAM approaches encounter obstacles when used with NAO robots because of their advanced kinematics and restricted sensor capacities as well as demanding real-time processing requirements. Household settings consist of shifting objects alongside safety risks which need highly accurate and flexible systems. The current SLAM frameworks display poor performance when dealing with these issues particularly when humanoid robots execute tasks within constrained resource settings such as indoor hazard detection and object placement management and autonomous navigation. An efficient multi-sensor SLAM system with dynamic real-world capabilities is needed to provide safe and accurate environmental understanding in such environments.

Proposed Method

The proposed research designs a multi-sensor SLAM framework for NAO humanoid robots which combines virtual sonar and IMU (Inertial Measurement Unit) sensors and camera systems to improve localization and mapping precision. An Extended Kalman Filter (EKF) operates within the framework to estimate the robot's state by combining sensory information which enhances hazard detection and position tracking throughout dynamic household environments.

With Laplacian edge detection as part of this system the robot can sense obstacle boundaries and improperly placed objects. The system construct precise navigation maps and detects potential hazards through this feature. Safety detection within the system includes visual texture analysis for the identification of hazardous objects including bottles and fire hazards. The robots collaborate to examine every part of the environment which enables them to identify hazards and track placed objects effectively.

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Real-time location tracking together with environment surveillance occurs in dynamic spaces through this system that primarily focuses on safety measures while detecting lost objects for better home organization. The designed system operates efficiently within constrained resource environments specifically for humanoid robots such as NAO.
The Block Diagram visualizes data movement including the camera and IMU and sonar inputs that process through EKF and feature mapping and hazard detection. The system updates three main areas including state variables and the map as well as motion parameters while the SLAM plot shows their visualization.

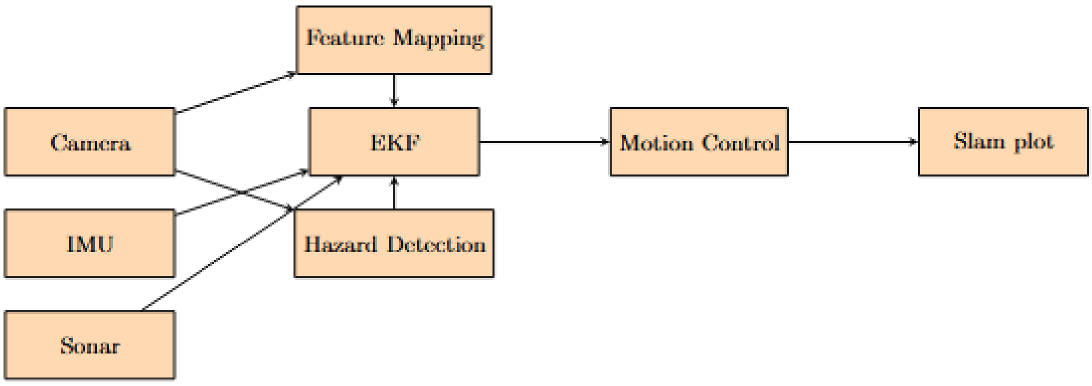


Figure3: Flow chat of the proposed method

Working of Camera Data

The NAO robot uses its camera to capture environmental RGB images that serve both for feature detection and hazard identification procedures. First the images undergo grayscale conversion before the feature detection algorithm (e.g., FAST) selects keypoints for identification. The robot's pose determines a conversion from the robot-centric coordinate system to world coordinates for keypoint descriptors that get added to the map as features. The detection process uses HSV color space conversion to apply color masks which identify hazards (including fire, plates and bottles). The system extracts constraints from masked areas to analyze their shapes before hazard classification. World coordinates are calculated for identified hazards which get incorporated into the hazard map.

Figure 4 Robot Agent A

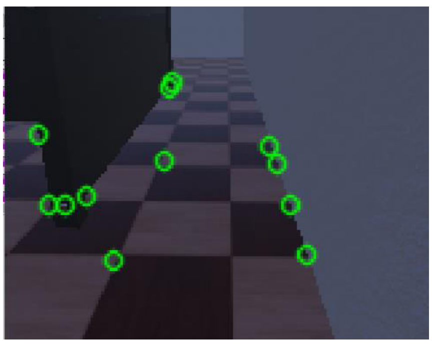


Figure 5 Robot Agent B

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

The Laplacian edge detection shows the algorithm successfully detects environmental object edges thus improving map accuracy. Environmental boundaries together with obstacles and features become distinguishable through the essential edges. The hazard bottle detection results together with other environmental features help the robot refine its location and prevent obstacles which ultimately improves its navigation efficiency throughout the hazard map.

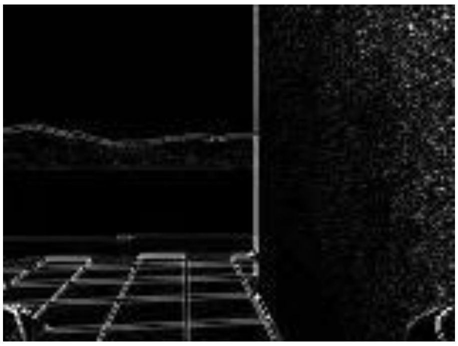


Fig. 6 Robot Agent A

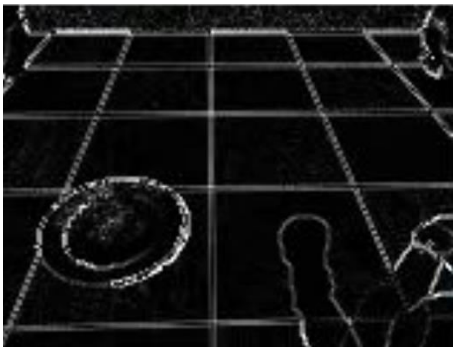


Fig. 7. Robot Agent B

Table 1 shows an all-encompassing data log which presents SLAM framework metrics including position data and both IMU and sonar measurements. The framework demonstrated successful identification of new features at multiple coordinates that are essential for maintaining accurate position information and map updates. Data consistency from sonar sensors and IMU devices demonstrates sensor reliability and periodic changes in visualization and feature detection show how the system adapts to environmental changes. Real-time navigation and mapping tasks demonstrate high robustness through these collected data points

Table 1: SLAM Framework Data Log

Position (X, Y, Heading)	**IMU Data (Roll, Pitch, Yaw)**	**Sonar Readings (Left, Right)**	**Additional Information**
X=6.28, Y=4.86, Heading=90.76°	Roll: 2.49, Pitch: 0.66, Yaw: 1.59	Left: 1.69 m, Right: 1.69 m	-
X=5.63, Y=7.90, Heading=73.06°	Roll: 2.27, Pitch: 0.66, Yaw: 1.27	Left: 0.86 m, Right: 0.86 m	-
X=6.28, Y=4.87, Heading=90.78°	Roll: 2.49, Pitch: 0.66, Yaw: 1.59	Left: 1.69 m, Right: 1.69 m	New feature detected at (7.34, 5.60)
X=5.63, Y=7.91, Heading=73.06°	Roll: 2.27, Pitch: 0.66, Yaw: 1.27	Left: 0.86 m, Right: 0.86 m	Visualization updated
X=6.28, Y=4.87, Heading=90.79°	Roll: 2.49, Pitch: 0.66, Yaw: 1.58	Left: 1.69 m, Right: 1.69 m	New feature detected at (6.50, 5.20)
X=5.64, Y=7.91, Heading=73.06°	Roll: 2.27, Pitch: 0.66, Yaw: 1.27	Left: 0.86 m, Right: 0.86 m	-
X=6.28, Y=4.87, Heading=90.78°	Roll: 2.48, Pitch: 0.67, Yaw: 1.58	Left: 1.69 m, Right: 1.69 m	New feature detected at (7.10, 5.80)
X=5.64, Y=7.91, Heading=73.06°	Roll: 2.27, Pitch: 0.66, Yaw: 1.27	Left: 0.86 m, Right: 0.86 m	-
X=6.28, Y=4.87, Heading=90.76°	Roll: 2.48, Pitch: 0.66, Yaw: 1.58	Left: 1.69 m, Right: 1.69 m	New feature detected at (6.80, 5.40)
X=5.64, Y=7.92, Heading=73.06°	Roll: 2.27, Pitch: 0.66, Yaw: 1.27	Left: 0.85 m, Right: 0.86 m	-
X=6.28, Y=4.88, Heading=90.76°	Roll: 2.49, Pitch: 0.66, Yaw: 1.59	Left: 1.69 m, Right: 1.69 m	-
X=5.64, Y=7.92, Heading=73.06°	Roll: 2.27, Pitch: 0.66, Yaw: 1.27	Left: 0.85 m, Right: 0.85 m	-

Table 1: Data log from the SLAM framework showing position, IMU data, sonar readings

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

PSEUDO CODES

The pseudo-codes describe the Multi-Sensor SLAM Framework for the NAO robot. They cover Feature Mapping, Hazard Detection, and Motion Control, integrating data from the camera, IMU, and sonar. An EKF estimates the robot's state, and a SLAM plot visualizes results.
hazard and other features, allow the robot to localize itself more accurately and avoid obstacles, enhancing overall navigation performance.

1: Feature Mapping

Processes camera images to detect features. Converts images to grayscale, detects keypoints, and maps them in world coordinates.

Feature Mapping Algorithm

Algorithm 1 Feature Mapping for NAO Robot

Require: Camera Image: I (RGB image).
Robot Pose xk = $[xk,- yk, \theta k]^T$ (position and orientation).
Ensure: Updated Map Features: F = {(xi, yi)}m
i=1 (feature positions).
Convert I to grayscale*: Igray = Grayscale(I).*
Detect keypoints: K = *FAST* (Igray).
for each ki ∈ *K* do
Extract descriptor: di = Descriptor(ki).
Calculate relative position: Δxi, Δyi.
Transform to world coordinates:
$xi = x_k + \Delta xi \cos(\theta k) - \Delta yi \sin(\theta k)$
$yi = yk + \Delta xi \sin(\theta k) + \Delta yi \cos(\theta k)$
Add to map: F = F ∪ {(xi, yi)}.
end for

2: Hazard Detection

Identifies hazards (e.g., fire, bottles) using color thresholding and contour analysis. Maps hazards in world coordinates.

Hazard Detection Algorithm

Algorithm 2 Hazard Detection for NAO Robot

Require: Camera Image*: I* (RGB image).
Robot Pose: xk = $[xk,-yk, \theta k]^T$ (position and orientation).
Ensure: Detected Hazards: H = {(xj , yj , typej)}p
j=1 (hazard positions andtypes).
1: Convert I to HSV: IHSV = HSV (I).
2: For fire detection:
3: Apply red mask: Mf ire = *Color M ask(IHSV , red).*
4: Analyze texture: F ire = *Texture Analysis (Mf ire).*
5: For floor hazards:
6: Apply masks: M_{plate} = ColorMask(IHSV , white), Mbottle =
ColorM ask(IHSV , blue).
7: Find contours: Cplate = F ind Contours (e.g M plate), C bottle =
Find Contours(Mbottle).
8: Analyze shape: P late = Shape Analysis (C plate), Bottle =
ShapeAnalysis(Cbottle).
9: for each hazard do

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

10. Calculate position: Δxj , Δyj .
11 Transform to world coordinates:

$$xj = xk + \Delta xj\ cos(\theta k) - \Delta yj\ sin(\theta k)$$
$$yj = yk + \Delta xj\ sin(\theta k) + \Delta yj\ cos(\theta k)$$

12 Add to hazard map: $H = H \cup \{(xj , yj , \text{type } j)\}$.
13.**end for**

3: Motion Control

Controls motion using sonar and IMU data. Avoids obstacles, stops, turns, or continues forward. Scans periodically.

Motion Control Algorithm

Algorithm 3 Motion Control for NAO Robot

```
Require: Sonar Readings: sk = [s1, s2, . . . , sn] (distance measurements).
    Current Motion State: motion state.
Ensure: Motion Command: ak (next action, e.g., "Forwards", "TurnLeft").
  1: Check sonar: Obstacle = CheckObstacles(sk).
  2: if obstacle detected then
  3:   Stop: ak = Stop().
  4:   Turn: ak = T urn(direction).
  5:   Set flag: turn af ter obstacle = T rue.
  6: else if turn af ter obstacle is True then
  7:   Resume: ak = F orwards().
  8:   Clear flag: turn af ter obstacle = F alse.
  9: else if step count exceeds threshold then
 10:   Pause: ak = Stop().
 11:   Scan: ScanEnvironment().
 12:   Reset step count: step count = 0.
 13: else
 14:   Continue: ak = F orwards().
 15:   Increment step count: step count = step count + 1.
 16: end if
```

IV. SIMULATION RESULTS

Testing of the proposed multi-sensor SLAM framework used two NAO robots operating in Webots simulation conditions. The robots used sonar technology combined with IMU and cameras to perform home environment exploration and hazard detection tasks. The robotic systems attained 99.19% localization precision while traveling 68.39 meters in Environment A along with 27.85 meters in Environment B. The robots show effective performance in their ability to explore and create maps of the environment.

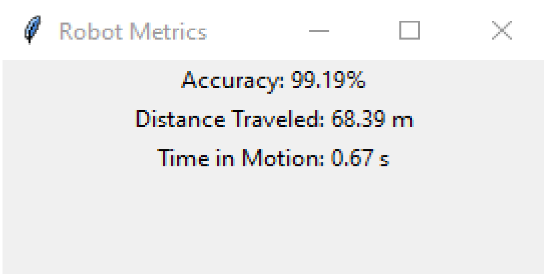


Fig. 8. Robot Agent A Metrices

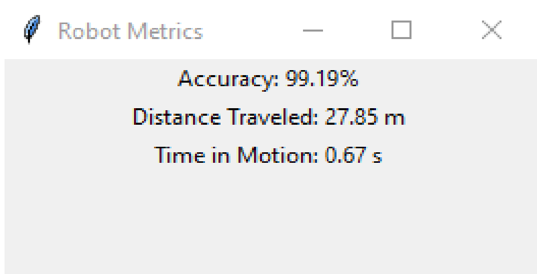


Fig. 9. Robot Agent B Metrices

© 2025 IJIRCCE | Volume 13, Issue 3, March 2025| DOI: 10.15680/IJIRCCE.2025.1303010

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

The robots moved during each round for 0.67 seconds before completing the task indicating high-speed performance. Laplacian edge detection successfully highlighted object edges through its method while the hazard detection system confirmed safety hazards. Robots identified hazardous from non-hazardous objects through their capability to analyze textures. The framework proves effective in dynamic settings through these results which demonstrate its real-time abilities for hazard detection and mapping and automated navigation capabilities.

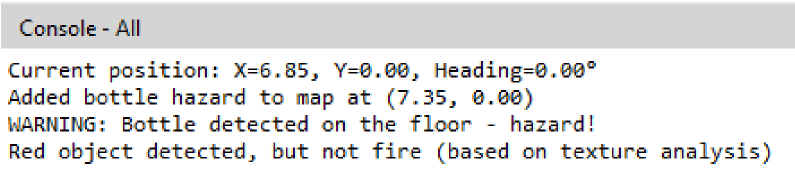
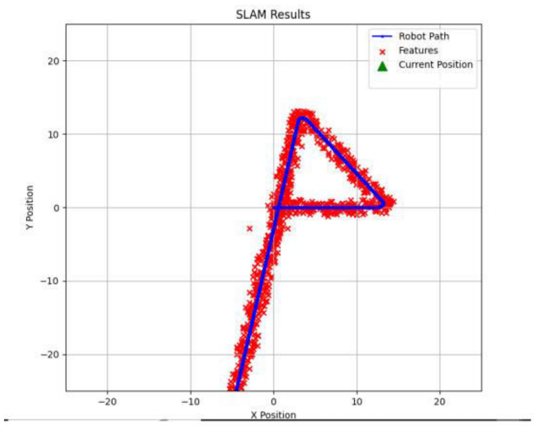


Fig.10 Console Readings

The console readings indicate the robot's current position at coordinates (6.85, 0.00) with a heading of 0.00°. A bottle hazard is detected and mapped at coordinates (7.35, 0.00), and a warning is issued that the bottle is on the floor. Additionally, a red object is detected, but the texture analysis confirms it is not fire.



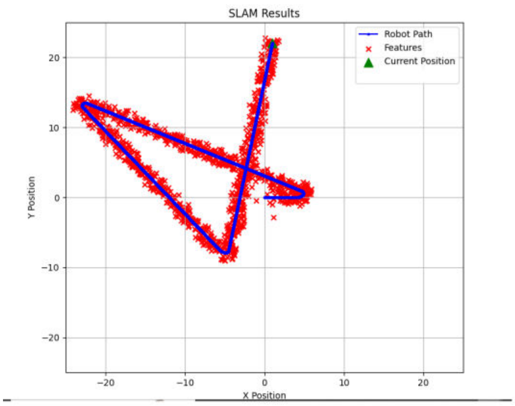


Fig. 11. Slam Plot For Agent A

Fig. 12. Slam plot For Agent B

Finally the SLAM results are plotted showing the NAO robots navigation in the environment. The blue path represents the robot's trajectory, with red crosses marking the detected features. The green triangle indicates the robot's current position. The robot successfully detects features in the environment while maintaining accurate localization and mapping, demonstrating the effectiveness of the multi-sensor fusion approach for real-time navigation and map building.

V. CONCLUSION AND FUTURE WORK

The research presents a multi-sensor SLAM framework for NAO humanoid robots which merges sonar and IMU and camera measurements to boost navigation and mapping during dynamic operations. The approach presents an efficient Laplacian edge detection technique which improves object detection accuracy in maps while developing real-time safety systems to detect hazards like fire hazards and misplaced objects. The system framework supports collaborative operations between multiple robots that allow robots to perform environmental monitoring tasks jointly.

The upcoming work will concentrate on developing semantic mapping capabilities which enhance object recognition while developing multi-robot coordination protocols to strengthen team operations in challenging environments. The

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

testing of this framework will occur on physical NAO robots to prove its operational capabilities in genuine physical spaces.

References

1. Campos, C., Elvira, R., Rodríguez, J. J. G., Montiel, J. M. M., & Tardós, J. D. (2020). ORB-SLAM3: An accurate open-source library for visual, visual-inertial, and multi-map SLAM. IEEE Transactions on Robotics, 37(6), 1874–1890. (https://doi.org/10.1109/TRO.2021.3075644)
2. H. Kumar, J. J. Payne, M. Travers, A. M. Johnson and H. Choset, "Periodic SLAM: Using Cyclic Constraints to Improve the Performance of Visual-Inertial SLAM on Legged Robots," 2022 International Conference on Robotics and Automation (ICRA), Philadelphia, PA, USA, 2022, pp. 9477-9483, doi: 10.1109/ICRA46639.2022.9811634.
3. keywords: {Legged locomotion;Visualization;Simultaneous localization and mapping;Tracking;Robot vision systems;Trajectory;Quadrupedal robots},
4. Rosinol, A., Violette, A., Abate, M., Hughes, N., Chang, Y., & Carlone, L. (2020). Kimera: An open-source library for real-time metric-semantic localization and mapping. In IEEE International Conference on Robotics and Automation (ICRA) (pp. 1–8). (https://doi.org/10.1109/ICRA40945.2020.9196886)
5. S.K. Dhurandher, S. Misra, M.S. Obaidat, V. Basal, P. Singh and V. Punia,'An Energy-Efficient On Demand Routing algorithm for Mobile Ad-Hoc Networks', 15 th International conference on Electronics, Circuits and Systems, pp. 958-9618, 2008.
6. Ye, K., Dong, S., Fan, Q., Wang, H., Yi, L., Xia, F., Wang, J., & Chen, B. (2022). Multi-robot active mapping via neural bipartite graph matching. In 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) (pp. 14819–14828). (https://doi.org/10.1109/CVPR52688.2022.01442)
7. Ye, K., Dong, S., Fan, Q., Wang, H., Yi, L., Xia, F., Wang, J., & Chen, B. (2022). Multi-robot active mapping via neural bipartite graph matching. In 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) (pp. 14819–14828). (https://doi.org/10.1109/CVPR52688.2022.01442)
8. Shilpa jain and Sourabh jain ,'Energy Efficient Maximum Lifetime Ad-Hoc Routing (EEMLAR)', international Journal of Computer Networks and Wireless Communications, Vol.2, Issue 4, pp. 450-455, 2012.
9. Ahmad, H., Othman, N. A., & Ramli, M. S. (2018). A solution to partial observability in extended Kalman filter mobile robot navigation. Telkomnika, 16(1), 134–141. (https://doi.org/10.12928/telkomnika.v16i1.8285)
10. N. Kim, T. Son, J. Pahk, C. Lan, W. Zeng and S. Kwak, "WEDGE: Web-Image Assisted Domain Generalization for Semantic Segmentation," 2023 IEEE International Conference on Robotics and Automation (ICRA), London, United Kingdom, 2023, pp. 9281-9288, doi: 10.1109/ICRA48891.2023.10160999. keywords: {Training;Automation;Semantic segmentation;Semantics;Lighting;Cameras;Reliability},
11. C. -Y. Chai, Y. -P. Wu and S. -L. Tsao, "Deep Depth Fusion for Black, Transparent, Reflective and Texture-Less Objects," 2020 IEEE International Conference on Robotics and Automation (ICRA), Paris, France, 2020, pp. 6766-6772, doi: 10.1109/ICRA40945.2020.9196894. keywords: {Cameras;Robot vision systems;Three-dimensional displays;Color;Image color analysis;Prediction algorithms},
12. P. Chang, S. Liu, H. Chen and K. Driggs-Campbell, "Robot Sound Interpretation: Combining Sight and Sound in Learning-Based Control," 2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Las Vegas, NV, USA, 2020, pp. 5580-5587, doi: 10.1109/IROS45743.2020.9341196. keywords: {Decision making;Neural networks;Process control;Reinforcement learning;Object recognition;Task analysis;Robots},
13. Z. Chen, S. Bai and L. Liu, "Efficient Map Prediction via Low-Rank Matrix Completion," 2021 IEEE International Conference on Robotics and Automation (ICRA), Xi'an, China, 2021, pp. 13953-13959, doi: 10.1109/ICRA48506.2021.9561353. keywords: {Interpolation;Extrapolation;Robot sensing systems;Real-time systems;Planning;Bayes methods;Noise measurement},
14. P. Deptula, R. A. Licitra, J. A. Rosenfeld and W. E. Dixon, "Online Approximate Optimal Path-Planner in the Presence of Mobile Avoidance Regions," 2018 Annual American Control Conference (ACC), Milwaukee, WI, USA, 2018, pp. 2515-2520, doi: 10.23919/ACC.2018.8431746. keywords: {Sensors;Navigation;Control systems;Autonomous agents;Aerodynamics;Nonlinear dynamical systems;Cost function},
15. R. Leadbetter, A. Phatak, A. Polpo and M. Hodkiewicz, "Informative Bayesian Survival Analysis to Handle Heavy Censoring in Lifetime Data," 2021 International Conference on Maintenance and Intelligent Asset Management (ICMIAM), Ballarat, Australia, 2021, pp. 1-6, doi: 10.1109/ICMIAM54662.2021.9715184. keywords:

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

{Industries;Maximum likelihood estimation;Fitting;Maintenance engineering;Bayes methods;Minerals;Materials processing;Bayesian;domain expert knowledge;Prior elicitation;and Survival analysis},

16. W. Yang and M. Posa, "Impact Invariant Control with Applications to Bipedal Locomotion," 2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Prague, Czech Republic, 2021, pp. 5151-5158, doi: 10.1109/IROS51168.2021.9636094. keywords: {Legged locomotion;Adaptation models;Uncertainty;Three-dimensional displays;Measurement uncertainty;Hardware;Timing},
17. Eman, A., & Ramdane, H. (2020). Mobile robot localization using extended Kalman filter. In 2020 3rd International Conference on Computer Applications & Information Security (ICCAIS). (https://doi.org/10.1109/ICCAIS48893.2020.9096788)
18. Eman, A., & Ramdane, H. (2020). Mobile robot localization using extended Kalman filter. In 2020 3rd International Conference on Computer Applications & Information Security (ICCAIS). (https://doi.org/10.1109/ICCAIS48893.2020.9096788)
19. Eman, A., & Ramdane, H. (2020). Mobile robot localization using extended Kalman filter. In 2020 3rd International Conference on Computer Applications & Information Security (ICCAIS). (https://doi.org/10.1109/ICCAIS48893.2020.9096788)
20. X. Zhu, Y. Li, J. Sun, H.-J. Chen, and J. Zhu, "Learning with Noisy Labels Method for Unsupervised Domain Adaptive Person Re-identification," Neurocomputing, vol. 452, pp. 1-12, May 2021.(doi: 10.1016/j.neucom.2021.04.120)