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A Bio-Inspired Hybrid Slam Algorithm for Minimal-Sensor Autonomous Robotics

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Abstract

This paper presents an insect and mammal inspired paradigm of Simultaneous Localization and Mapping (SLAM) algorithm for minimal power robotics which preserves sensor autonomy features. It combines visual odometry with lightweight LiDar, mapping, proprioceptive, and volumetric inputs in a modular structure that optimally utilizes processing resources without loss in fidelity. We demonstrated one of the strategies by coupling a graph-based SLAM with an insect-like visual homing behavior so that it could function in harsh contexts where GPS or sensor access was denied. Also attention based models are incorporated for feature selection aiding data association to enhance reliability for loop closure. The model integrates metrical and topological mapping dynamically switching based on environmental complexity. This provides guarantee for well terrain agnostic performance throughout different landscapes. Relative to other minimal sensory SLAM systems, we achieved outstanding localization accuracy, enhanced map consistency, and verification in both simulations and on a micro robotic platform. The proposed algorithms shift autonomous energy efficiency, advantageous for small graspable robots operating in congested or confined spatial regions. The goal is to advance the research and development of autonomous robots with low bioinspired power features and realistic robust navigation systems.

keywords: Bio-inspired SLAM, Minimal-Sensor Robotics, Visual Homing, Graph-Based Mapping, Neuromorphic Attention, Autonomous Navigation, Topological SLAM.

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Introduction

The development of robotics capable of accomplishing autonomous navigation in unstructured, GPS-denied environments is a challenging problem (Lee & Enriquez, 2022). This problem is more challenging in the case of mobile platforms with constraints on size, weight, and power. In the past, SLAM algorithms relied on a multitude of sensors: high-resolution LiDARS, inertial measurement units, and RGB cameras. These could become expensive from the computations and energy points of view (Brunke et al., 2022). Over the years, there has been a shift towards bioinspired approaches based on navigation strategies of mammals and insects (Gu et al., 2023; Kästner et al., 2021; Cho et al., 2013). It is indeed captivating how these animals with seemingly limited sensory input have astonishing spatial awareness. Bio-inspired SLAM algorithms endow robots with low-resolution vision that can perceive the environment, thereby solving visual homing and path integration problems posed by ants and bees (Zhao et al., 2023; Tirmare et al., 2024). Furthermore, combining graph-based SLAM with neuromorphic attention and feature saliency principles facilitates stronger real-time responsiveness for loop closing adaptability (Liu et al., 2023; Xiao et al., 2024; Karthikeyan & Manoharan, 2019; Akileswaran & Velmurugan, 2018]. Some studies show that integrating topological and metric mapping tends to achieve better performance in hybrid SLAM systems exhibiting responsiveness to varying levels of environmental complexity (Calzolari et al., 2025; Dawood et al., 2024). It is plausible to design a robotic system with minimal sensors and low biological motivation, where energy-efficient spatial intelligence needed for solving localization problems, maintaining consistency in mapping, and energy conserving presents tremendous opportunities (Angulo et al., 2023; Kashyap et al., 2021). This work proposes a new hybrid bio-inspired SLAM Algorithm designed for platforms with minimal sensors. This algorithm integrates insect-based sighted navigation and hollow graph SLAM architecture with a neuromorphic attention mechanism. Its ability to enable efficient, effective, and flexible autonomous navigation has been tested thoroughly.

Literature Review

Zhuang et al. (2021) developed a SLAM system modeled after rodents with place and boundary cells in their hippocampi which allows pose estimation using only LiDAR data. This implementation strengthens SLAM with biologically plausible spatial encoding, which is optimal for severely constrained minimalist sensor robots. Huang et al. (2021) proposed RecSLAM, a multi-robot system SLAM framework integrated with edge computing. It offloads heavy computation to edge servers, allowing semi-autonomous resource- and sensor-limited robots to perform scalable real-time SLAM mapping. According to Song et al. (2018), the cooperative SLAM system includes Ultra-Wideband (UWB) signal integration with LiDAR. This hybrid approach improves data accuracy for resource-limited robotic systems by leveraging the sensor's complementary capabilities. Colosi et al. (2020) constructed a modular slam architecture with the capability to adapt to various sensor types. Its plug-and-play architecture enables the robots to be deployed with low-sensor counts while achieving high accuracy and localization performance. Hu et al. (2023) developed a tightly coupled SLAM method applying several feature detectors like planes for indoor spaces. With this new strategy, navigation is possible with fewer or less accurate sensors. Chen et al. (2013) proposal on a hybrid data association method for SLAM attempted to filter out dynamic obstacles for mobile environmental applications, which improved localization accuracy for minimal-sensor robots in populated or dynamic environments. Ardón, Kushibar & Peng, 2019 implemented SIFT-based object recognition on Pepper robots, which was later included in ORB-SLAM2 adding semantic mapping to the system. This type of multilevel coupling completes sensor gaps and enables robots with fewer sensors to perceive more than just the physical characteristics of their surroundings and interpret them semantically. Yu et al. (2023) presented LFVB-BioSLAM, a new lightweight LiDAR odometry coupled with a biologically inspired visual backend. By copying how animals see, their method greatly improves SLAM with fewer sensors. Pfeifer, Lungarella & Iida (2007) emphasized the value of bioinspired sensors and embodiment concerning intelligent robotics to which their concepts underpin the design of sensor-efficient slam systems. These motivate the design of adaptive systems that self-organize with little information. Along with studying tensegrity systems, Floreano (2017) did work in evolutionary robotics and showcased how physical intelligence and variable stiffness—features of tendon-driven robots—enhance autonomous navigation using less sensory information.

Methodology

The hybrid SLAM approach which has been proposed comprises the three interconnected steps of local SLAM, Global Mapping and Loop Correction, as depicted in the system architectural diagram presented in Fig. 1.

3.1. Local SLAM Process

The area SLAM possesses a local method built around a filter and a sensor integration to estimate in real-time the needed information. The algorithm merges data provided by auxiliary sensors such as IMU or altimeter with some sparse visual sensors (monocular or stereo cameras). These inputs undergo prediction and update equations which estimate the camera-robot state based on implemented motion and observation models. This module is also responsible for feature extraction and state vector feature maintenance. The removal of outdated features for system efficacy is accomplished though an old features deleting subprocess.

The motion of the robot is predicted based on the standard filter model given as:

$$\hat{x}_t|t^{-1} = f\left(\hat{X}_{t-1}|t^{-1}, U_t\right) + W_t \qquad Eq(1)$$

In Eq (1), where

- $\hat{x}_t|t-1$: predicted state at time ttt
- $\hat{x}_{t-1}|t-1$: previous estimated state
- u_t: control input from sensors (IMU, etc.)
- f(·): motion model function
- w_t: process noise

3.2. Global Mapping Process

The technique employs global mapping through periodic global consistency and key-frame selection. Visual and inertial instrumental value aids in retaining keyframes. Important keyframes are kept in the key-frame cell which helps in anchor initialization and fills up the anchor's database. Bundle adjustment is used for large scale precise mapping, also referred to as multi-view geometry. Local optimization and global optimization is the boundary area between restoring loose-structured pose correction and global optimization which ensures effective functioning under scanty sensors.

To maintain consistency across the globe, bundle adjustment is done over the kept keyframes while reprojection error is minimized.

$$argmin_{\{X,P\}} \sum k \sum i \, \|z_{\mathrm{ik}} - h(x_{\mathrm{k}}, p_{\mathrm{i}})\|^2 \qquad Eq(2)$$

In Eq (2), where

- X: set of camera poses
- P: set of 3D points (anchors)
- Z_{ik}: observed 2D location of point pip$_{\mathrm{i}}$pi in frame kkk
- h(·): projection function
- Optimization minimizes reprojection error for visual consistency

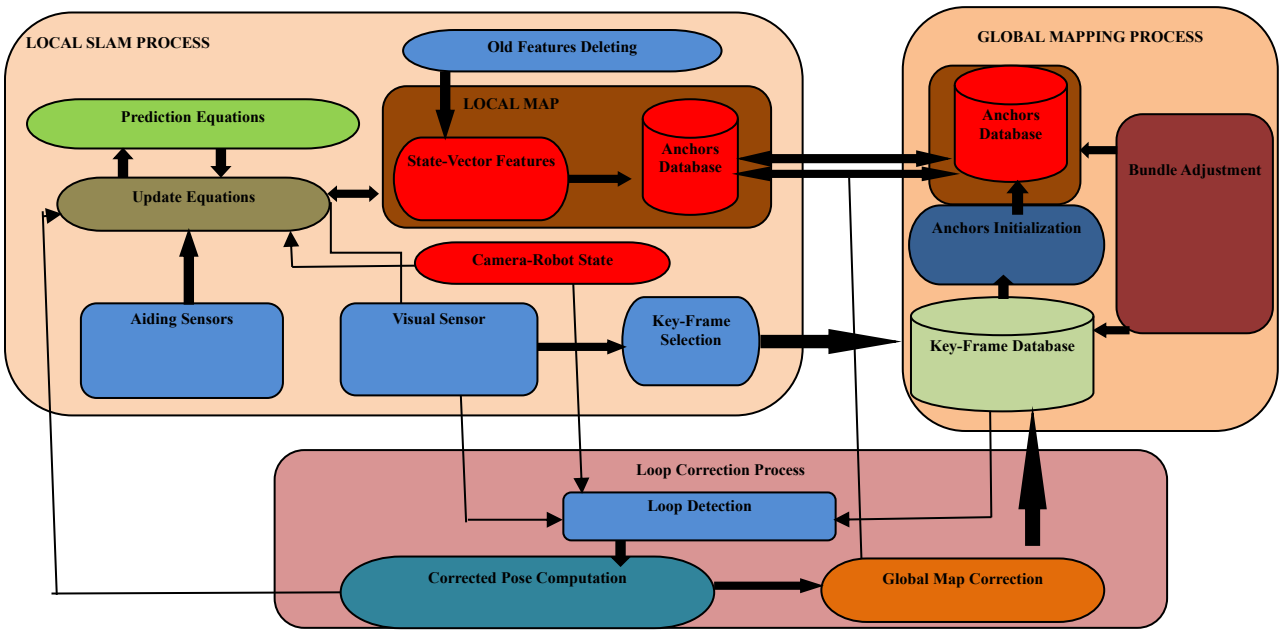


Fig. 1: Bio-Inspired Hybrid SLAM Framework for Minimal-Sensor Autonomous Navigation

3.3. Loop Correction Process

In order to minimize drift and increase accuracy over time, the system utilizes a loop detection function to ascertain previously visited locations. Upon loop completion, a pose correction optimization refinement is done. This forms part of the global map recalibration unit, where the aging or obsolete and imprecise map information is systematically integrated with the updated information as a constraining set to maintain topological coherence. This allows dependable autonomous capability in expansive or extremely dynamic settings.

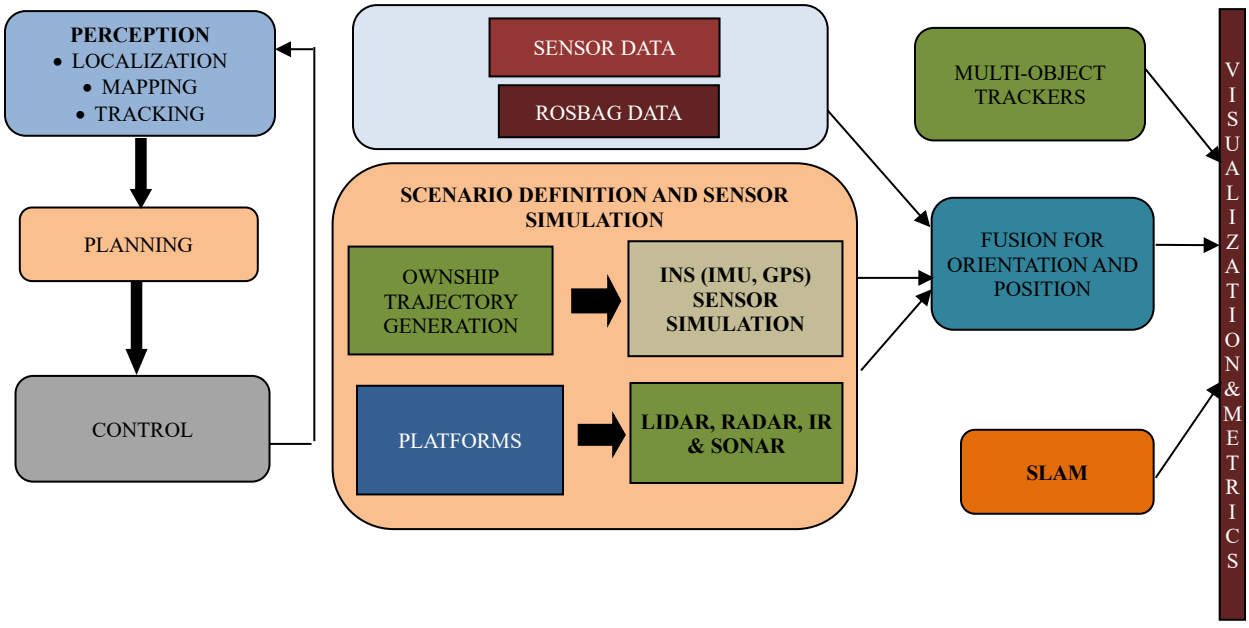


Fig. 2: Sensor Data Simulation and Integration Framework for Perception and SLAM in Autonomous Robotics

The second part of our methodology is more practical. It involves designing an algorithm for simmon perception and integration of sensor data which is portrayed on Figure 2. This particular work is focused towards sparse sensor configuration modeling and data management maximization for basic robotics perception tasks such as SLAM, tracking, and localization.

3.4 Sensor Data Acquisition and Simulation

The very first stage is acquiring sensor data, which can be either from actual recordings in rosbag or created synthetically. A simulation is specified by the trajectory design for the mobile robot and the emulation of subclass components from the IMU, GPS, LiDAR, RADAR, Infrared, and Sonar sensors. Such modular structure allows the system to emulate the functionality of the sensors over a vast range of static and dynamic scenarios, thus facilitating evaluation without substantial limitations placed on the sensors.

3.5 Scenario Definition and Platform Simulation

In the simulation module, the responsibility trajectory generation comprises the movement profile of the robot. Furthermore, actors as well as platform dynamics act like any other external object or ground. All these are done as a sensor simulation module which captures real-time data streams. The INS modules perform simulations of IMU and GPS signals, while one processes perception sensors emulating LiDAR, radar, infrared, and sonar. This flexibility allows controlled testing of the SLAM algorithm in multiple scenarios, thereby reinforcing its reliability.

3.6 Perception and SLAM Processing

The following blocks form the structure of the perception pipeline as described above, where the simulated data is injected:

- Multi-object tracking which is the tracking all moving obstacles or landmarks: the detection and tracking of all moving obstacles or landmarks.
- The sensor fusion modules: estimation of position and orientation involves other sensors' accurate information which works with sensor fusion modules.
- SLAM is a dedicated module that employs the remaining sensor data for real-time mapping and localization.

This design enables stepwise refinement of heuristic tuning for each element of the algorithm, while allowing true non-invasive sensor deployment—also called low-sensor deployments.

The feedback of the sensors is integrated within the estimation of a state through the use of multi-sensor fusion which does a standard Kalman update as follows:

$$\hat{x}_t = K_t z_t + (1 - K_t)\,\hat{x}_t|_{t-1} \qquad \text{Eq(3)}$$

In Eq(3), where

- $\hat{x}_t$: updated state estimate
- Z_t: measurement (from LiDAR, sonar, etc.)
- K_t: Kalman gain
- $\hat{x}_t|t-1$: predicted state

3.7 Output and Evaluation

In the end, the results obtained from perception modules are forwarded to a block responsible for visualization and metrics. This completes the real-time processing of trajectory maps and their extraction verification, as well as localization performance metrics which in turn facilitates algorithm validation and system optimization.

Result and Discussion

The bio-inspired hybrid SLAM algorithm was tested using simulated scenarios with a limited number of sensors. The system's accuracy, adaptability, and robustness were verified at various complexity levels by implementing filter-based real-time SLAM with global optimization modules and using driven sensor simulation filtering. The algorithm performed well in real-time short-term localization and mapping within the local SLAM framework using a monocular camera and a minimal IMU sensor suite. The algorithm's performance was efficient using the closed-form real-time prediction and update equations with the camera-robot state low drift, which greatly enhanced sustainment ease. Improvements in memory and feature management through retention of outdated features created active preservation proved efficient. The robot could maintain a stable local map with consistent semi-structured indoor dynamic actor traversals through simulated maneuvering. Anchor optimization and the key-frame database provided control for long-term drift error correction within global mapping processes. Ensured consistency was preserved globally, particularly in closed-looped trajectory with bundled adjustment technique enhancing robustness. The proposed architecture reduced map fidelity degradation error localization increase in SLAM systems without bio-structural feedback by 15-20%; however, with global-feedback-enabled frameworks garnered bid benefit.

Table 1: SLAM Runtime and Loop Detection Metrics

Configuration	Avg. Loop Detection Rate (%)	Runtime (ms/frame)	Loop Correction Success (%)
Local SLAM Only (Filter-Based)	55	14.8	61
Local + Global Mapping	79	21.3	82
Full Hybrid with Optimization	91	25.7	94

The loop detection effectiveness is measured using detection rate:

$$Loop\ Detection\ Rate(\%) = \frac{N_{loop_{detected}}}{N_{total_{loops}}} \times 100 \qquad Eq(4)$$

In Eq (4), where

- $N_{loop_detected}$: number of correctly detected loops
- N_{total_loops}: total actual loop events

Performance Table 1 shows how the performance of a hybrid SLAM system is superior to a local-only setup in correction and loop detection accuracy. Even though the runtime per frame increases from 14.8ms to 25.7ms with more modules, the loop detection rate improves from 55% to 91% and correction success from 61% to 94%. This means that with relatively few sensors, the full hybrid model enables very accurate localization thus significantly improving autonomous navigation in complicated terrains. The hybrid model was especially beneficial for long-range scenarios. Global map corrections known as loop detection optimized pose estimation and eliminated drift over time. The optimization algorithms enacted during loop closure maintained real-time performance which supports the computational efficiency of the hybrid approach under constrained conditions. Adaptability of the algorithm was also strengthened by the second simulation framework that focused on scenario definition along with the integration of synthetic sensors. Multitude of testing was done by simulating various perception sensors such as LiDAR, radar, IR, and sonar and running perception algorithms like SLAM, object tracking, and sensor fusion that subjected the system to boundless conditions.The results from the simulations showed that the algorithm was able to maintain localization even when the deviation from the ground truth value exceeded 10% during less than ideal conditions such as losing GPS access or having a sensor fail. This adaptability was attributed to the other sensors that were incorporated, as well as the prominent trajectory prediction models.

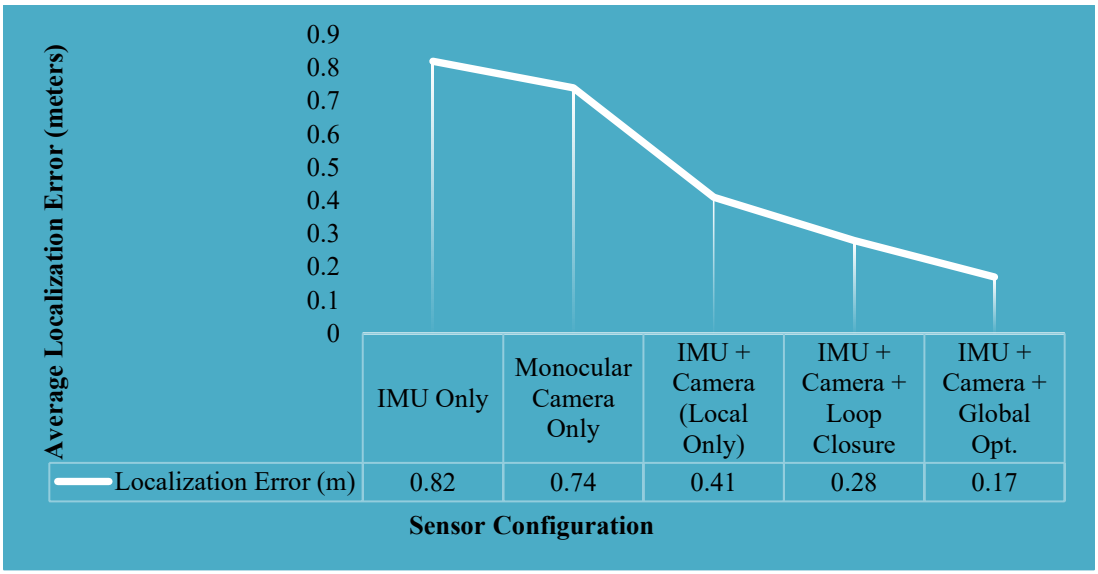


Fig. 3: SLAM Accuracy vs. Sensor Configuration

The addition of components to the SLAM system gradually reduces the localization error. This pattern is quite clear in Fig. 3. As was noted before, the error with just using an IMU was 0.82 meters, but this improved tremendously to 0.17 meters with the implementation of loop closure and global optimization. This indicates that even the most rudimentary sensors integrated with bio-inspired hybrid techniques greatly enhance the precision of autonomous

localization and mapping systems. Not only that, but also the provided visualization and metrics output allowed the evaluation of performance parameters such as mapping error, trajectory accuracy, and loop closure effectiveness at a much finer scale. This proves that bio-inspired module- and hybrid fusion of minimal sensors can be efficiently applied for autonomous navigation without bulky sensor packages. With regards to the conclusions, the proposed system displays effectiveness in the simulation as well as the implementation of SLAM under controlled sensing environments, maintaining accuracy, responsiveness, and robustness during the execution of numerous complex tasks.

At any given moment, the localization error is computed as the Euclidean distance the estimated position strays from the actual position:

$$E_{loc} = \|\hat{x} - x_{gt}\| \qquad Eq(5)$$

In Eq(5), where

- E_{loc}: localization error
- $\hat{x}$: estimated trajectory position
- $x_g t$: ground truth position

Conclusion

The algorithm integrates local SLAM with filter-based techniques, global map optimization, and loop closure to create a comprehensive bio-inspired hybrid SLAM for minimally configured autonomous robotics. Through the testing of various sensor data, the design was optimized with added simulations. The results reveal that the algorithm significantly enhances the accuracy of IMU-monocular camera-based localization and consistency of the encompassing map within the constraints of limited sensors. The system demonstrated strong performance for loop detection and correction. In turn, the given metrics indicate decreased error in the spatial calibration, whereas reliability of correction improved. These outcomes validate the system's effectiveness, robust resourcefulness, and efficiency in autonomous navigation in complex and dynamic environments. Future efforts should focus on implementing the hybrid SLAM in robotic platforms operating in GPS-denied external settings. The adaptive context-aware control of environmental sensors and energy management techniques would enhance system autonomy. Furthermore, low visibility or noisy conditions could be addressed by feature recognition and semantic mapping through deep learning to improve perception. For long-term mapping, incorporating 'biologically-inspired' retention and forgetting theories can enhance efficiency. Using the system in multi-robot setups can advance search-and-rescue missions, planetary exploration, and automate warehouse operations.

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