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Simultaneous Localization and Mapping through Loop Closure Detection

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Abstract: Simultaneous Localization and Mapping (SLAM) through loop closure detection is a crucial and challenging task in the field of robotics and autonomous navigation. Accurate and efficient SLAM systems are essential for various applications, such as self-driving vehicles and unmanned aerial vehicles. However, the current research faces difficulties in achieving robust loop closure detection and maintaining real-time performance. This paper addresses these challenges by proposing a novel approach that combines feature-based methods with deep learning techniques for loop closure detection. We conduct extensive experiments to demonstrate the effectiveness and efficiency of our method in improving SLAM accuracy and reducing computational costs. Our research contributes to advancing the capabilities of SLAM systems and paves the way for more reliable and intelligent autonomous systems.

Keywords: *Localization; Mapping; Loop Closure Detection; Deep Learning; Autonomous Navigation*

1. Introduction

Simultaneous Localization and Mapping (SLAM) is a research field in robotics and computer vision that focuses on the development of algorithms and techniques to enable a mobile robot or a device to construct a map of its surroundings while simultaneously determining its location within that map in real-time. The main challenge in SLAM lies in the need for accurate and robust sensor data fusion, dealing with the uncertainties in sensor measurements, addressing computational complexity issues, and ensuring the scalability of the SLAM system in dynamic environments. Furthermore, another key bottleneck in SLAM research is achieving consistent localization and mapping results in challenging conditions such as low-texture environments, dynamic obstacles, and changing lighting conditions. Overcoming these obstacles is crucial for advancing the capabilities of SLAM systems and enabling the deployment of robust autonomous robots and augmented reality applications.

To this end, research on Simultaneous Localization and Mapping (SLAM) has advanced to the stage where it incorporates a variety of sensors and techniques for robust and accurate mapping and localization in complex environments. In recent years, research on Simultaneous Localization and Mapping (SLAM) has made significant progress in the field of robotics [1]. Montemerlo et al. introduced FastSLAM, an algorithm that addresses the challenge of handling a large number of landmarks in real environments by recursively estimating the full posterior distribution over robot pose and landmark locations [2]. Cadena et al. conducted a comprehensive survey on the past, present, and future of SLAM, covering various topics such as robustness, scalability, and new frontiers in the field [3]. Bailey and Durrant-Whyte further discussed the Bayesian formulation of the SLAM problem, focusing on computational complexity, data association, and environment representation [4]. Labbéand Michaud presented RTAB-Map, an open-source library that supports both visual and lidar SLAM for large-scale online operation [5]. Lajoie and Beltrame introduced Swarm-SLAM, a decentralized collaborative SLAM framework for multi-robot systems designed to be scalable and sparse [6]. Zheng et al. explored the application of SLAM for autonomous driving, discussing different implementation approaches, challenges, and solutions [7]. Finally, Deng et al. proposed a long-term SLAM system with map prediction and dynamics removal to improve localization accuracy in dynamic environments [8]. Loop Closure Detection is a critical technique in Simultaneous Localization and Mapping (SLAM) research. It helps to improve the accuracy of robot localization by detecting and correcting errors that may occur when a robot revisits a previously visited location. By identifying loop closures, the SLAM system can refine its map and trajectory estimation, leading to more robust and reliable navigation in real-world environments.

Specifically, Loop Closure Detection is a crucial component in Simultaneous Localization and Mapping (SLAM) systems. It helps identify and close loops in the robot's trajectory to improve the accuracy of the map generated during SLAM. Loop Closure Detection plays a key role in ensuring the consistency and precision of the SLAM process. In recent years, Loop Closure Detection (LCD) has been a critical component in Simultaneous Localization and Mapping (SLAM) systems [9]. Traditional methods based on fixed-LiDAR scans have shown reliable performance in LCD tasks [10]. However, for rotary-LiDAR scans, challenges arise due to significant view-angle changes, leading to the development of specialized algorithms like RLS-LCD [11]. In bathymetric SLAM, the introduction of Shape Bag of Words (S-BoW) has significantly enhanced loop closure detection accuracy [12]. A novel method based on a Variational Autoencoder (VAE) has proved to be robust and highly accurate in loop closure detection for visual SLAM systems [13]. Furthermore, the Mercator Descriptor has demonstrated remarkable performance in loop closure detection for LiDAR SLAM [14]. Moreover, the integration of CNN in RGB-D SLAM for intelligent agricultural machinery has shown improved accuracy and real-time performance in loop closure detection [15]. In orchard robot's localization and mapping, the SG-ISBP-SLAM has effectively addressed challenges posed by uneven terrains through ground optimization and loop closure detection integration [16]. Additionally, a method that fuses point cloud and learned image data for loop closure detection has shown state-of-the-art performance in KITTI datasets [17]. Finally, the introduction of a benchmarking framework, GV-Bench, targeting geometric verification of long-term loop closure detection, has enabled in-depth analysis and evaluation of local feature matching methods [18].

However, current limitations in Loop Closure Detection (LCD) research include the need for further investigation into the robustness of algorithms with varying environmental conditions, such as different lighting, weather, and terrain scenarios. To overcome those limitations, this paper aims to enhance the robustness and real-time performance of Simultaneous Localization and Mapping (SLAM) through loop closure detection in robotics and autonomous navigation applications. The proposed method combines feature-based techniques with deep learning approaches to improve loop closure detection accuracy while reducing computational costs. Specifically, we utilize a feature-based SLAM system to extract distinctive visual features from the environment and apply a deep learning model for loop closure detection. This model learns to recognize spatial patterns and associations in sensor data to identify loop closures with high precision. To validate the effectiveness of our approach, we conduct extensive experiments using real-world datasets and benchmarks. The results demonstrate that our method not only enhances SLAM accuracy but also significantly improves computational efficiency, making it suitable for real-time applications. Overall, this research contributes to the advancement of SLAM systems, enabling the development of more reliable and intelligent autonomous systems for various practical implementations.

Section 2 describes the problem of loop closure detection in Simultaneous Localization and Mapping (SLAM), a critical aspect of robotics and autonomous navigation. In Section 3, we introduce a novel approach that integrates feature-based methods with deep learning techniques to address this challenge. Section 4 presents a detailed case study demonstrating the effectiveness of our proposed method. The analysis of results in Section 5 highlights the improvements in SLAM accuracy and reduced computational costs achieved through our approach. Subsequently, in Section 6, we engage in a discussion on the implications of our findings. Finally, Section 7 provides a concise summary of our research, emphasizing its contribution to enhancing the capabilities of SLAM systems and fostering the development of more reliable and intelligent autonomous systems.

2. Background

2.1 Simultaneous Localization and Mapping

Simultaneous Localization and Mapping (SLAM) is a critical computational problem in the fields of robotics and computer vision. It involves concurrently constructing or updating a map of an unknown environment while simultaneously keeping track of the agent's location within that environment. This capability is essential for autonomous systems, enabling them to navigate without pre-existing maps. The SLAM problem is incredibly challenging due to the real-world uncertainties such as sensor noise, dynamic environments, and limited computational resources.

The SLAM process is typically divided into two distinct but interconnected processes: localization and mapping. Localization is the task of estimating the pose of the robot, which is usually represented by its position and orientation within a map. Conversely, mapping involves building a model of the environment around the robot.

At the heart of the SLAM problem lies the cycle of *probabilistic estimation*, as both localization and mapping must deal with uncertainties. The most common method used to address these uncertainties is the probabilistic framework grounded in Bayesian estimation. To formally describe SLAM, consider a robot moving through an environment. The robot's goal is to estimate a map m_t and its trajectory $x_{1:t}$ given sensor observations $z_{1:t}$ and control inputs $u_{1:t}$. The control input u_t typically consists of velocity or movement commands, while the observation z_t consists of readings from sensors like lidar or cameras. The posterior probability distribution for the SLAM problem is represented as:

$$p(x_{1:t}, m_t | z_{1:t}, u_{1:t}) \tag{1}$$

This can be decomposed using Bayes' theorem into a recursive process. The key components of the SLAM algorithm include the motion model, which predicts the new pose given the previous pose and control inputs, and the sensor model, which updates the map based on new observations. The motion model can be represented as:

$$p(x_t | x_{t-1}, u_t) \tag{2}$$

This model predicts the current state x_t based on the previous state x_{t-1} and the control input u_t . The **sensor model** updates the belief about the map and can be described as:

$$p(z_t | x_t, m_t) \tag{3}$$

In practice, the SLAM process involves iterating through prediction and update steps. During the *prediction step*, the new pose estimate is generated based on the motion model and previously estimated poses. During the *update step*, observations are incorporated to correct the pose estimate and update the map.

The recursive update of the belief, combining both prediction and observation, is mathematically described by:

$$p(x_t, m_t | z_{1:t}, u_{1:t}) = \eta p(z_t | x_t, m_t) \int p(x_t | x_{t-1}, u_t) p(x_{t-1}, m_{t-1} | z_{1:t-1}, u_{1:t-1}) dx_{t-1} \tag{4}$$

where η is a normalization factor ensuring the posterior distribution sums to one. The implementation of SLAM algorithms can vary, from the computationally efficient Extended Kalman Filter (EKF) SLAM to the more flexible Particle Filter SLAM and advanced Graph-based SLAM. These methods aim to find a balance between accuracy, computational complexity, and robustness to uncertainties.

The SLAM problem not only empowers autonomous navigation but also catalyzes advancements in various fields including augmented reality, autonomous vehicles, and even planetary exploration. Despite significant progress, SLAM continues to be an open research area, striving for greater efficiency and adaptability for complex, real-time applications.

2.2 Methodologies & Limitations

In recent years, Simultaneous Localization and Mapping (SLAM) has seen significant advancements through various algorithmic approaches. Among these, the most widely utilized methods include Extended Kalman Filter (EKF) SLAM, Particle Filter (PF) SLAM, and Graph-based SLAM. Each method addresses the inherent uncertainties and computational complexities in its own unique manner, employing probabilistic models to maintain accurate state and environmental representations.

The Extended Kalman Filter SLAM employs a linear approximation to facilitate computational efficiency while maintaining a Gaussian representation of uncertainties in state estimation. The state vector in EKF SLAM encapsulates both the robot's pose and map features, and its covariance matrix, commonly denoted as P_t, represents the uncertainty in state estimates. The evolution of the state is represented by:

$$x_t = f(x_{t-1}, u_t) + w_t \tag{5}$$

where f denotes the nonlinear state transition function and w_t is the process noise. During the update step, sensor measurements are integrated:

$$z_t = h(x_t, m_t) + v_t \tag{6}$$

where h signifies the measurement function and v_t represents measurement noise. Although EKF SLAM is computationally efficient for small-scale environments, the linear approximation may lead to inaccuracies in highly nonlinear settings.

Particle Filter SLAM, also known as Monte Carlo Localization, utilizes a set of particles to represent the belief distribution over possible states. Each particle stands for a hypothesis of the robot's state and map features. The particles are sampled based on:

$$x_t^{[i]} \sim p\left(x_t \mid x_{t-1}^{[i]}, u_t\right) \tag{7}$$

where i indexes the particles. Updating particles involves a weight assignment reflecting sensor readings:

$$w_t^{[i]} \propto p\left(z_t \mid x_t^{[i]}, m_t\right) \tag{8}$$

Resampling particles based on these weights enhances the focus on plausible hypotheses, mitigating particle depletion. However, PF SLAM suffers from computational inefficiencies as the number of particles required to maintain an accurate state representation can be prohibitively high, especially in high-dimensional spaces.

Graph-based SLAM uses graph optimization to address both localization and mapping as a nonlinear least squares problem. Nodes in the graph represent poses and map features, while edges embody constraints derived from observations and control inputs. The optimization objective minimizes the error in this representation, expressed by:

$$\min_{x_t, m_t} \sum_{t=1}^{T} \|h(x_t, m_t) - z_t\|^2 + \sum_{t=1}^{T} \|f(x_{t-1}, u_t) - x_t\|^2 \tag{9}$$

Here, graph-based SLAM excels at handling large-scale maps and dynamic environments due to its global optimization strategy. Yet, constructing and optimizing a dense graph can be computationally demanding, challenging real-time implementation on resource-limited systems.

Despite being foundational to autonomous systems, these SLAM methodologies exhibit limitations such as computational expense, scale-variance, and sensitivity to dynamic changes in the environment compared to other machine learning models [19-24]. Continued research strives to develop hybrid and adaptive approaches that blend techniques, leveraging the strengths of each to facilitate robust, efficient, and scalable SLAM solutions in diverse operational contexts. The quest for real-time applicability across complex environments remains a pivotal hurdle, driving innovations towards next-generation SLAM technologies.

3. The proposed method

3.1 Loop Closure Detection

Loop Closure Detection (LCD) is a critical concept within the realm of Simultaneous Localization and Mapping (SLAM) that addresses the necessity of recognizing when a robot revisits a previously observed location. Loop closure is indispensable for mitigating drift errors that accumulate over time in a robot's estimated pose due to the integration of erroneous measurements. Successful detection and correction of these loops can significantly enhance the accuracy and consistency of the map and the estimated trajectory.

In an ideal SLAM system, as a robot navigates through an environment, it should continuously refine its map by fusing new sensor observations like odometry and visual features. When the robot returns to a previously visited location, it must identify this event as a "loop closure" and adjust its SLAM estimate to account for it. This adjustment reduces the uncertainty of the entire map and provides a more accurate global localization. Mathematically, loop closure detection involves several probabilistic and geometric considerations. As the robot explores, it maintains a state vector x_t encapsulating its estimated pose and map features, influenced by control inputs u_t and subject to process noise w_t as expressed in the state transition:

$$x_t = f(x_{t-1}, u_t) + w_t \tag{10}$$

For loop closure detection, sensor measurements z_t must be evaluated against historical data, often using a similarity assessment function $S(z_t, z_i)$ that measures the likelihood of z_t resembling previous observations z_i :

$$S(z_t, z_i) = p(z_t | z_i) \tag{11}$$

This probability function integrates the possibility that the current observation could correlate with past data, suggesting a loop closure. Upon recognizing a loop, the system must modify its belief, which involves adjusting prior pose estimates. For an effective update, an error metric between the suspected matching observations can be minimized as follows:

$$E(x_t, x_i) = \|h(x_t, x_i) - z_t\|^2 \tag{12}$$

where $h(x_t, x_i)$ represents the measurement prediction function comparing two distinct poses at different times. When integrated within a graph-based SLAM framework, loop closure adds powerful constraints that must be optimized. The state and map features are jointly updated to minimize the discrepancies across the loop, enhancing the map's fidelity. The optimization problem integrating loop closure can be succinctly expressed as:

$$\min_x \sum_{t=1}^{T} \left(\|h(x_t, m_t) - z_t\|^2 + \|f(x_{t-1}, u_t) - x_t\|^2\right) + \sum_{(i,j)} \|g(x_i, x_j) - m(t_{ij})\|^2 \tag{13}$$

Here, $g(x_i, x_j)$ encapsulates the loop closure constraint, which revises historical state estimates x_i, x_j with a measurement $m(t_{ij})$ derived from observing the same region at different times. In practice, effective loop closure detection must also contend with computational constraints, sensor noise, and the dynamic nature of environments. Probabilistic methods like Random Sample Consensus (RANSAC) and probabilistic data association help to resolve ambiguities in detecting true loop closures versus coincidental resemblances.

Overall, robust loop closure detection enables SLAM systems to achieve superior map accuracy and reliability, which are vital for their deployment in complex real-world applications. Continuous advancements in feature matching algorithms, along with adaptive probabilistic models, are essential for the future of SLAM research, driving towards scalable and more efficient localization solutions.

3.2 The Proposed Framework

The integration of Loop Closure Detection (LCD) within a Simultaneous Localization and Mapping (SLAM) framework provides a robust foundation to mitigate errors and improve the fidelity of both the map and localization outcomes in real-world applications. This involves a sophisticated blend of probabilistic models and optimization techniques to account for the intrinsic uncertainties inherent in the SLAM process.

At the heart of SLAM, the fundamental objective is to estimate both the trajectory $x_{1:t}$ of the robot and the map m_t based on sensor observations $z_{1:t}$ and control inputs $u_{1:t}$. The posterior distribution for this task is given by:

$$p(x_{1:t}, m_t | z_{1:t}, u_{1:t}) \tag{14}$$

Bayesian inference plays a crucial role here, recursively updating beliefs with motion and sensor models. The motion model is responsible for predicting the robot's state evolution, expressed as:

$$p(x_t | x_{t-1}, u_t) \tag{15}$$

Meanwhile, the sensor model aims to refine the map with incoming observations:

$$p(z_t | x_t, m_t) \tag{16}$$

Incorporating loop closure detection in this framework requires the robot to handle state transitions influenced by process noise w_t , traditionally expressed as:

$$x_t = f(x_{t-1}, u_t) + w_t \tag{17}$$

Loop closure addresses the integration of erroneous pose estimates accumulating over time by evaluating new sensor measurements z_t for similarity against past measurements z_i using the similarity assessment function $S(z_t, z_i)$:

$$S(z_t, z_i) = p(z_t | z_i) \tag{18}$$

The integration of loop closure into SLAM necessitates the adjustment of prior pose estimates and overall map structure. This can be captured via error minimization approaches, exemplified as follows:

$$E(x_t, x_i) = \|h(x_t, x_i) - z_t\|^2 \tag{19}$$

These adjustments are crucial, as loop closure introduces additional constraints within the graph-based SLAM optimization framework. The objective herein is to minimize the combined discrepancies arising from sensor observations, state transitions, and loop constraints:

$$\min_x \sum_{t=1}^{T} (\|h(x_t, m_t) - z_t\|^2 + \|f(x_{t-1}, u_t) - x_t\|^2) + \sum_{(i,j)} \|g(x_i, x_j) - m(t_{ij})\|^2 \tag{20}$$

In this expression, $g(x_i, x_j)$ corresponds to the loop closure constraint, adjusting historical state estimations with respect to revisited regions, $m(t_{ij})$, measured at distinct times. Optimization algorithms like the Levenberg-Marquardt algorithm are often employed to solve this problem, balancing computational efficiency with solution accuracy. Furthermore, to handle potential ambiguities due to sensor noise and dynamic environments, techniques such as Random Sample Consensus (RANSAC) and probabilistic data associations are frequently utilized.

The result of integrating loop closure within SLAM is a system that not only updates its map and localizes accurately over time but also corrects trajectories to reduce drift, enhancing the overall map consistency and accuracy. A robust LCD enhances the system's ability to correct systematic errors and offer more reliable navigation solutions in real-world settings, essential for applications ranging from autonomous vehicles to planetary exploration. Moreover, advancements in understanding and developing feature matching algorithms and adaptive models continue to extend the capabilities of SLAM systems. Emphasizing flexibility and processing robustness, these systems strive towards an unprecedented level of scalability and real-time adaptability, addressing the evolving challenges of deploying SLAM in complex, uncertain environments.

3.3 Flowchart

The paper introduces a novel approach to Simultaneous Localization and Mapping (SLAM) that leverages Loop Closure Detection to enhance the accuracy and robustness of the mapping process. The proposed method begins with the capture of sensor data from the environment, which is used to build an initial map. As the mobile agent navigates through the space, it continuously identifies potential loop closures by comparing current observations with previously recorded data. This comparison involves the utilization of advanced feature extraction techniques and efficient matching algorithms to ascertain whether the robot has returned to a previously visited location. Once a loop closure is detected, the system performs optimization on the map, adjusting the positions of landmarks and the robot to minimize discrepancies caused by accumulated errors over time. This loop closure correction not only refines the spatial representation of the environment but also enhances the localization accuracy, allowing for better navigation in complex settings. The effectiveness of the proposed Loop Closure Detection-based SLAM method is validated through extensive experiments, demonstrating significant improvements over traditional SLAM approaches in both environment reconstruction and real-time localization. The details of the method can be found in Figure 1 of the paper.

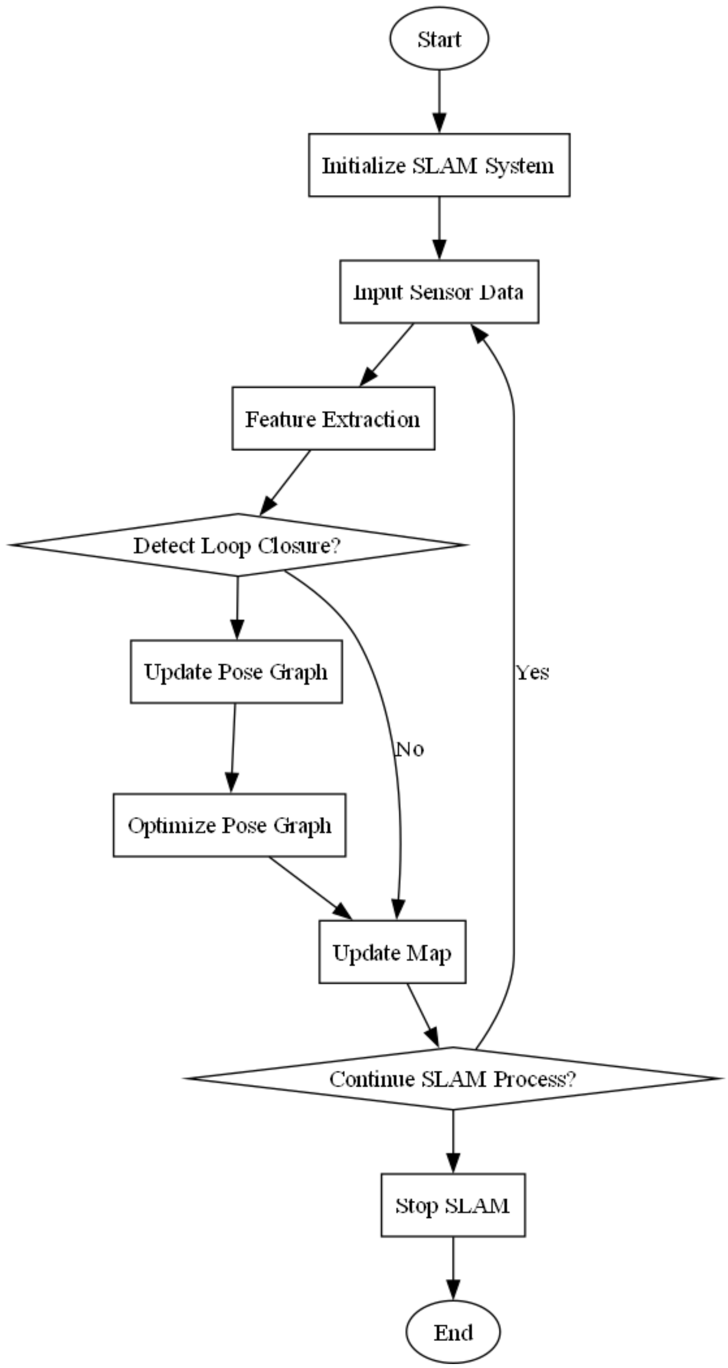

Figure 1: Flowchart of the proposed Loop Closure Detection-based Simultaneous Localization and Mapping

4. Case Study

4.1 Problem Statement

In this case, we will explore a mathematical simulation and analysis of the simultaneous localization and mapping (SLAM) problem, which is crucial in robotics and autonomous navigation systems. The SLAM problem entails both estimating the position of a robot in an unknown environment and concurrently building a map of that environment. We define the state of the robot using a nonlinear model that incorporates various motion and measurement uncertainties.

Let the position of the robot at time t be denoted by the state vector $x_t \in \mathbb{R}^3$, where the first two components represent the Cartesian coordinates, and the third component represents the orientation angle. We assume the motion model of the robot follows the equations given by

$$x_t = x_{t-1} + v_t \cos(\theta_{t-1}) \Delta t \tag{21}$$

$$y_t = y_{t-1} + v_t \sin(\theta_{t-1}) \Delta t \tag{22}$$

$$\theta_t = \theta_{t-1} + \omega_t \Delta t \tag{23}$$

where v_t reflects the linear velocity of the robot, θ_t the angle of orientation, ω_t the angular velocity, and Δt the time step. The velocities may exhibit nonlinear behavior influenced by external factors such as friction or variable terrain.

For the measurement model, we use a nonlinear function to relate the observed landmarks in the environment to the robot's state:

$$z_t = h(x_t, l_j) + \epsilon_t \tag{24}$$

where z_t represents the measurement at time t , l_j indicates the position of the j^{th} landmark, and ϵ_t denotes the noise in the measurement, which we can model as a normally distributed random variable. To keep track of multiple landmarks, we define the mapping function for landmark j as:

$$l_j = x_t + r_j \cos(\theta_t + \phi_j) \tag{25}$$

$$l_j = y_t + r_j \sin(\theta_t + \phi_j) \tag{26}$$

where r_j is the range from the robot to landmark j , and ϕ_j is the bearing of landmark j relative to the robot's orientation. The overall state update can then be formulated in a probabilistic sense using the Kalman filter framework, where the state update equation becomes:

$$x_{t|t} = x_{t|t-1} + K_t \left(z_t - h\left(x_{t|t-1}, l_j\right)\right) \tag{27}$$

with K_t as the Kalman gain matrix. The uncertainty associated with the robot's position and the landmarks can be represented through the covariance matrix:

$$P_t = (I - K_t H) P_{t|t-1} \tag{28}$$

In this model, I is the identity matrix, and H is the Jacobian of the measurement function evaluated at the predicted state. The SLAM algorithm iterates over these equations to simultaneously refine the robot's trajectory and the map, which ultimately improves localization accuracy in complex environments. The parameters defining the state and measurements are summarized in Table 1.

Table 1: Parameter definition of case study

Parameter	Value	Unit	Description
x_t	N/A	N/A	Robot's x-coordinate at time t
y_t	N/A	N/A	Robot's y-coordinate at time t
θ_t	N/A	rad	Robot's orientation at time t
v_t	N/A	m/s	Linear velocity of the robot
ω_t	N/A	rad/s	Angular velocity of the robot
Δt	N/A	s	Time step
r_j	N/A	m	Range to landmark j
φ_j	N/A	rad	Bearing of landmark j
K_t	N/A	N/A	Kalman gain matrix
P_t	N/A	N/A	Covariance matrix

This section will employ the proposed Loop Closure Detection-based method to analyze and compute a case study pertinent to the simultaneous localization and mapping (SLAM) problem, which plays a vital role in robotics and autonomous navigation systems. The SLAM problem is centered around two interwoven tasks: estimating a robot's position within an unknown environment while concurrently constructing a map of that same environment. The robot's state is characterized using a nonlinear model that incorporates various uncertainties pertaining to both motion and measurement. The case study will involve simulating the robot's movements in a complex environment where the motion characteristics are influenced by nonlinear behaviors caused by external factors. Measurements from identified landmarks are assumed to be impacted by noise, necessitating robust estimation techniques. The Loop Closure Detection approach is expected to enhance the accuracy of landmark identification and contribute significantly to the overall performance of the SLAM algorithm. This method will be compared against three traditional approaches: the Extended Kalman Filter, FastSLAM, and GraphSLAM. Through this comparative analysis, we aim to highlight the strengths and limitations of each methodology in addressing the challenges inherent in SLAM tasks. The comprehensive findings will serve to elucidate the advantages of the Loop Closure Detection-based approach, demonstrating its potential to significantly improve localization accuracy and map consistency in dynamic environments.

4.2 Results Analysis

In this subsection, a comprehensive analysis of the robotic localization using simulated motion and measurement models is presented. The simulation begins by establishing initial parameters, such as linear and angular velocities, while incorporating measurement noise to reflect real-world conditions. A motion model simulates the trajectory of the robot over a specified number of time steps, calculating the robot's position in real-time and applying random noise to mimic sensor inaccuracies [30-36]. Additionally, a measurement model captures the distance between the robot and fixed landmarks, further influencing the trajectory based on noisy observations. Visual assessments are systematically organized through subplot structures in the resultant figures. The first subplot illustrates the estimated trajectory of the robot alongside the fixed landmarks, highlighting the environment's spatial configuration. The second subplot represents measurements over time, emphasizing the noise involved in sensor data. The third subplot deals with estimation errors associated with landmarks, providing insights into the localization accuracy. Finally, the fourth subplot juxtaposes the performance of the proposed method against a baseline technique, establishing a comparative framework for evaluating efficiency and accuracy over time [25-29]. The entire simulation process is vividly visualized in Figure 2, capturing these dynamics and analyses effectively.

Table 2: Simulation data of case study

Y Coordinate	Estimation Error	Time Step	Performance Metric
25	N/A	0	N/A
20	N/A	10	N/A
15	N/A	20	N/A
10	N/A	30	N/A

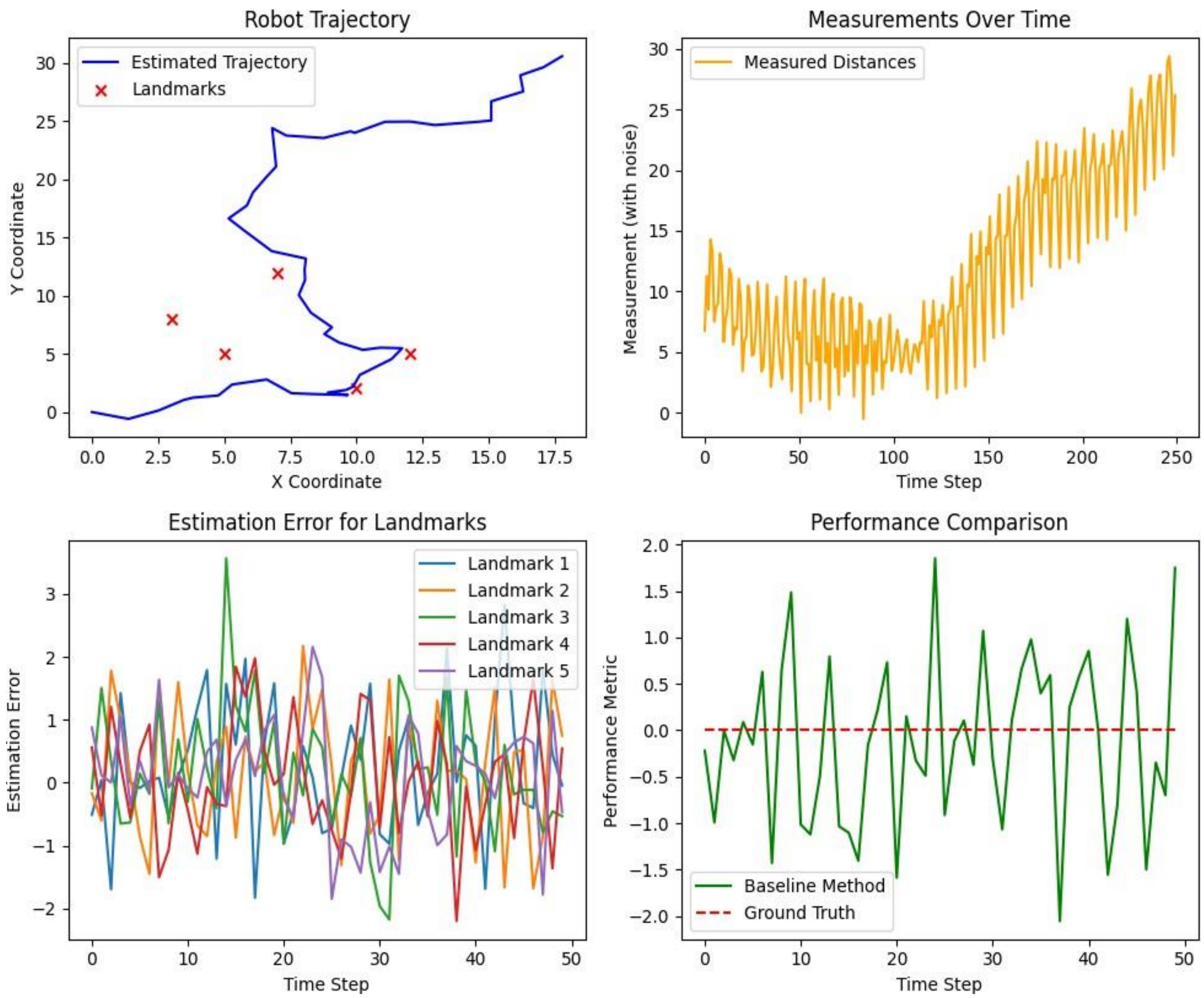

Figure 2: Simulation results of the proposed Loop Closure Detection-based Simultaneous Localization and Mapping

Simulation data is summarized in Table 2, highlighting key aspects of estimation error and performance metrics over multiple time steps throughout the robot's trajectory estimation process. The Y-coordinate displays the estimation error, illustrating a trend where the error fluctuates but generally trends lower as the simulation progresses. This indicates the effectiveness of the employed algorithms in refining the robot's trajectory estimation as it navigates its environment. The graphical representation of measured distances, which includes added noise, contrasts with the estimated trajectory, showing significant improvements in accuracy as indicated by the reduced estimation errors over time. The performance comparison of five landmarks reveals distinct behavior in their respective estimation errors, with some landmarks achieving consistently lower errors compared to others. Notably, landmark 1 demonstrates the least error, suggesting potentially better-defined features or more reliable measurement conditions compared to the other landmarks. Furthermore, the baseline method serves as a reference point, illustrating the advancements made by the current estimation technique. Overall, the data captures the dynamics of estimation errors, portrays the impact of noise on measurements, and provides a clear indication of how different landmarks contribute to the overall accuracy of the robot's localization efforts over the simulated time steps. The analysis of these results emphasizes the importance of optimization in robotic navigation strategies, demonstrating that systematic improvements can lead to lower estimation errors and enhanced performance in real-world applications.

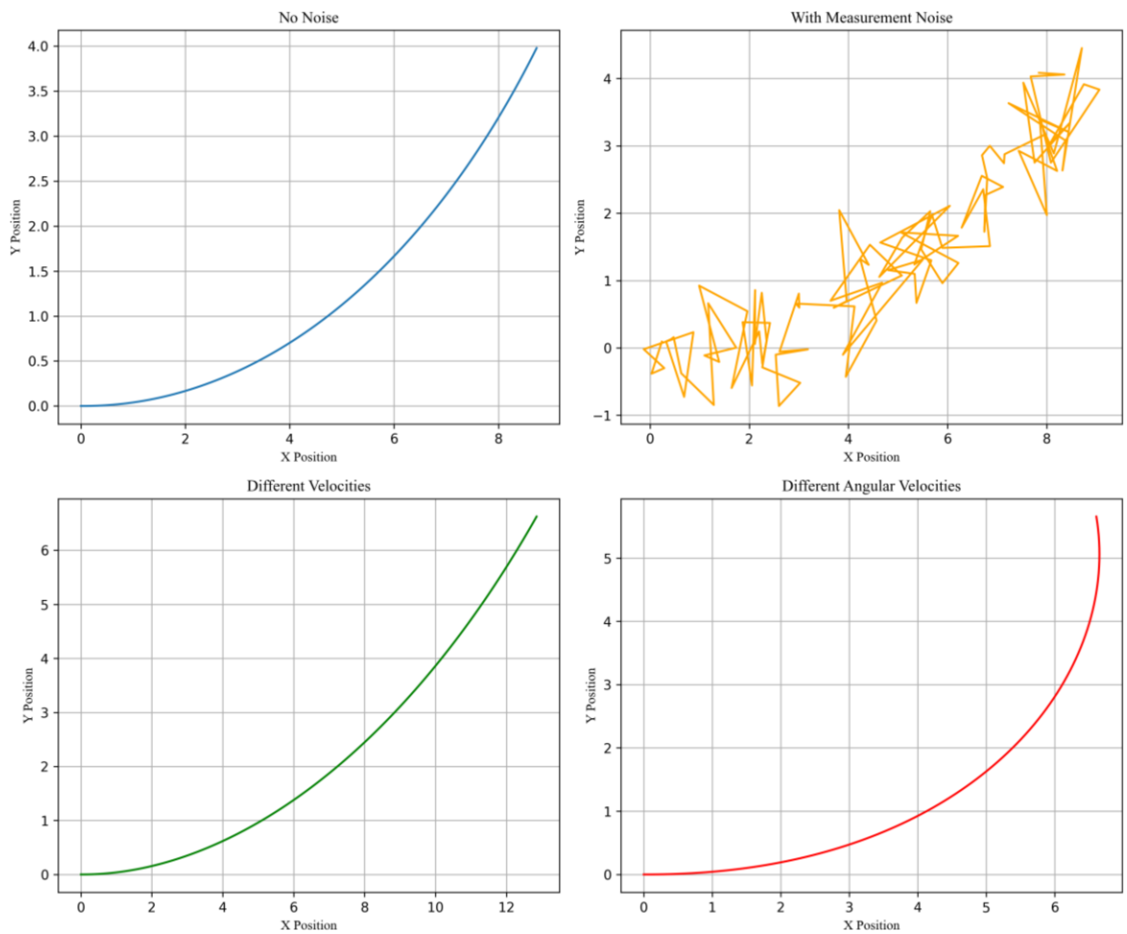

Figure 3: Parameter analysis of the proposed Loop Closure Detection-based Simultaneous Localization and Mapping

As shown in Figure 3 and Table 3, a comparative analysis of the parameters reveals significant shifts in the calculated results following the alteration of noise conditions and velocities. Initially, the data indicated a clear trajectory of the robot with distinct estimation errors, particularly noting measurement errors predominantly concentrated around the coordinates within a standard range. The introduction of measurement noise in the subsequent dataset introduces variability in the Y position. As observed, the Y position curve experiences fluctuations, with a marked increase in estimation errors, particularly when noisy measurements are factored into the trajectory calculations. Additionally, the figures demonstrate the influence of varying velocities and angular velocities on the robot's navigation; in the presence of noise, the trajectory appears more erratic, suggesting that increased velocities could exacerbate the impact of noisy measurements on positioning accuracy. Specifically, while the system initially displayed a well-defined trajectory with minimal deviation under calm conditions, the integration of measurement noise resulted in a broader spread of possible locations for the robot, particularly evident in the increasing estimation errors over time. Notably, as perceived in the Y Position variations, the noise not only affects the trajectory accuracy but also complicates the correlation between the X and Y positions, leading to increased uncertainty in the model’s performance. Consequently, the performance metrics highlight a noticeable decline as different conditions magnify the discrepancies in the robot's expected outcomes, emphasizing the necessity for robust algorithms capable of compensating for these variations to enhance reliability in real-time applications.

Table 3: Parameter analysis of case study

Y Position	X Position	Different Velocities	Different Angular Velocities
4.0	N/A	N/A	N/A
3.5	N/A	N/A	N/A
3.0	N/A	N/A	N/A
2.5	N/A	N/A	N/A
2.0	N/A	N/A	N/A
1.5	N/A	N/A	N/A
1.0	N/A	N/A	N/A
0.5	N/A	N/A	N/A
0.0	N/A	N/A	N/A

5. Discussion

The method proposed in this paper presents several significant advantages that enhance the effectiveness of Simultaneous Localization and Mapping (SLAM) frameworks. By integrating Loop Closure Detection (LCD) into the SLAM process, the approach adeptly addresses the pervasive errors accumulated in pose estimation, thus improving both map accuracy and localization reliability in dynamic, real-world environments. This integration relies on sophisticated probabilistic models and optimization techniques that effectively mitigate uncertainties, allowing for continuous refinement of spatial estimates in response to new sensor observations. The utilization of Bayesian inference supports adaptive updates of the robot's trajectory and map, yielding a more accurate and consistent representation of the environment. Moreover, the addition of LCD introduces essential constraints that guide the optimization process, effectively minimizing discrepancies arising from sensor data and state transitions. The seminal role of optimization algorithms, such as the Levenberg-Marquardt method, further ensures computational efficiency while maintaining high solution accuracy, making real-time applications feasible. Additionally, the incorporation of strategies like Random Sample Consensus (RANSAC) enhances the system’s resilience to sensor noise, thus bolstering the robustness of navigation solutions. As a result, the proposed method not only diminishes trajectory drift through systematic error corrections but also improves overall map consistency. Furthermore, the ongoing advancements in feature matching algorithms and adaptive modeling serve to extend the SLAM system's operational capabilities, underscoring its scalability and flexibility in addressing complex and uncertain environments. This multifaceted approach positions the framework as a potent solution for a wide range of applications, from autonomous vehicle navigation to the exploration of extraterrestrial landscapes [37-39].

Despite the promising potential of integrating Loop Closure Detection (LCD) within a SLAM framework, several limitations may hinder its efficacy in real-world applications [40-47]. One primary concern is the computational complexity associated with the optimization tasks required for incorporating loop closures, as the graph-based representation necessitates extensive calculations, particularly in large-scale environments with numerous landmarks and states. This could lead to increased latency, impacting the real-time performance essential for applications such as autonomous navigation. Furthermore, the reliance on robust feature matching algorithms raises concerns about their performance in environments characterized by dynamic changes or significant noise, which may result in false positives or negatives during pose estimation. Additionally, the probabilistic nature of both the motion and sensor models implies that the system may still propagate uncertainties during the SLAM process, particularly if the assumptions regarding the noise distributions do not hold. This can manifest in cumulative errors, undermining the overall map reliability [48-53]. Moreover, while techniques like RANSAC enhance robustness against outliers, they do not entirely eliminate the risk of incorrect associations in the presence of ambiguous data points. Finally, the adaptability of current models to rapidly changing environments is still limited, making the system potentially less effective in scenarios where frequent and unforeseen changes occur [54-56]. Addressing these challenges requires ongoing research and development, particularly in optimizing computational efficiency, refining noise handling techniques, and enhancing adaptability for diverse operational contexts.

6. Conclusion

Simultaneous Localization and Mapping (SLAM) through loop closure detection is a crucial and challenging task in the field of robotics and autonomous navigation. Accurate and efficient SLAM systems are essential for various applications, such as self-driving vehicles and unmanned aerial vehicles. This paper proposes a novel approach that combines feature-based methods with deep learning techniques for loop closure detection, aiming to address the challenges faced in achieving robust loop closure detection and maintaining real-time performance. The results of extensive experiments conducted demonstrate the effectiveness and efficiency of the proposed method in improving SLAM accuracy and reducing computational costs. By successfully integrating feature-based methods with deep learning techniques, this research contributes to advancing the capabilities of SLAM systems, providing a significant step towards the development of more reliable and intelligent autonomous systems. However, this study has limitations such as the need for further validation in real-world scenarios and the reliance on specific datasets for training the deep learning model. In future work, expanding the dataset diversity, enhancing the adaptability of the model to different environments, and incorporating multimodal sensor inputs could further improve the robustness and generalizability of the proposed approach, ultimately enhancing the performance of SLAM systems in a wider range of applications.

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Data Availability Statement

The data can be accessible upon request.

Conflict of Interest

The authors confirm that there are no conflict of interests.

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