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Conference Paper

Adaptive Filter Approach for Enhancing Localization Accuracy in Mobile Robots

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Abstract

This article focuses on improving the positional accuracy of mobile robots. Positional accuracy is crucial for robots to reach target points precisely and efficiently. The study combines data from wheel odometry and LiDAR sensors using an adaptive complementary filter. This method aims to merge the advantages of these two data sources while minimizing their disadvantages. LiDAR sensors can map the environment with high accuracy but suffer from issues such as delayed updates due to processing time and reduced reliability in the presence of moving objects. On the other hand, wheel odometry provides real-time data but is prone to errors caused by mechanical wear and slippage, especially on uneven or slippery surfaces. The adaptive complementary filter dynamically weights the reliability of sensor data to address these challenges.
In the study, the proposed method continuously optimizes the robot's position and orientation, enhancing motion accuracy. Experimental results demonstrate that during scenarios such as wheel slippage, the system relies more on LiDAR data to maintain positional accuracy, while during straight-line movements, wheel odometry is prioritized for its reliability. This research presents an effective solution for enabling mobile robots to operate more reliably under real-world conditions.

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Keywords: *Mobile Robot, Localization, Complementary Filter*

1. Introduction

In mobile robots, localization accuracy is critical for tasks ranging from precise navigation to ensuring smoother and more rigid movement. Factors such as wheel slippage or sensor errors can negatively impact localization accuracy. This study combines the position data obtained from lidar sensors with wheel encoder data adaptively to achieve more accurate and stable localization. While lidar sensors provide less precise position data, wheel encoder data offers higher precision. However, accumulated errors in wheel encoder data can hinder the robot's ability to reach its target effectively.

Ekim's study integrated UWB, LiDAR, and odometry data to develop localization and initialization algorithms for mobile robots. The research aimed to provide more accurate and reliable localization through sensor fusion within the ROS ecosystem [1]. In another study, Yıldız developed an autonomous robotic system using sensor fusion techniques to enhance system performance and create a more reliable robotic platform through the integration of diverse sensor data [2]. Liu et al. conducted a comprehensive review of sensing technologies used in indoor autonomous mobile robots, evaluating the advantages, limitations, and applications of various sensor technologies while summarizing advancements in the field [3]. Benziane et al. analyzed and experimentally evaluated attitude estimation and control methods using linear-like complementary filters, assessing their potential and performance in control systems [4]. Neto et al. proposed an adaptive complementary filter algorithm for mobile robot localization, aiming to enhance accuracy by dynamically fusing information from various data sources [5]. Mahony et al. developed nonlinear complementary filters operating on special orthogonal groups, demonstrating their effectiveness in providing high accuracy and stability, particularly in attitude estimation and orientation control, through theoretical analysis and applications [6]. Zhang and Singh introduced the LOAM (Lidar Odometry and Mapping) algorithm for real-time lidar odometry and mapping, offering a significant solution for mobile robot applications by simultaneously generating high-precision odometry and environmental maps from lidar data [7]. Wang et al. developed the F-LOAM algorithm for fast lidar odometry and mapping, aiming to improve the efficiency and accuracy of real-time applications, thereby enhancing environmental perception and localization capabilities of mobile robots [8]. Zhang and Singh further developed a real-time lidar odometry and mapping algorithm with low drift, targeting improved accuracy and processing speed by simultaneously performing odometry and mapping from lidar

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data [9]. They also combined visual and lidar data to develop a low-drift, robust, and fast odometry and mapping algorithm, showing that this integration enhances environmental perception and localization performance, yielding more reliable results for mobile robot applications [10]. Zheng and Zhu proposed an efficient lidar odometry algorithm for autonomous driving, offering a solution for real-time applications by achieving high accuracy with reduced computational costs [11]. Papadopoulos and Misailidis reviewed odometry methods for differential drive robots and evaluated their applicability to path planning, proposing odometry models aimed at improving accuracy and reliability in differential drive systems [12]. Tseng et al. developed a complementary filter method for motion and attitude estimation using inertial measurements, demonstrating its performance in terms of accuracy and stability and its suitability for various applications [13]. Martinelli analyzed odometry errors in mobile robots with synchronized drive systems, providing a detailed examination of error types and proposing methods to reduce these errors [14]. Lastly, Ozcan and Atali investigated lidar-based localization methods for warehouse logistics, aiming to improve efficiency by achieving high-accuracy position estimation using lidar data [15].

2. Materials and Methods

An adaptive complementary filter is a data processing technique used to optimally combine information from two or more data sources. Unlike traditional complementary filters, which separate high and low-frequency components using fixed weights or parameters, the adaptive complementary filter dynamically adjusts its parameters based on environmental conditions or the accuracy levels of the sensors.

This method is particularly effective when integrating sensor data with varying reliability levels. In an adaptive complementary filter, the reliability of each sensor is determined based on environmental conditions or the characteristics of the data sources, and the filter parameters are updated accordingly. For example, if one source is more reliable at high frequencies while another performs better at low frequencies, the adaptive filter combines their data weighted accordingly to produce the final output.

The most significant advantage of adaptive complementary filters is their ability to quickly adapt to changing conditions in dynamic systems, thus improving system stability and accuracy. In this study, position data calculated from the lidar sensor and wheel encoders is adaptively combined.

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The lidar data source is advantageous for generating detailed environmental maps and detecting objects with precision. Its immunity to external factors and ability to provide accurate position measurements make it reliable. However, it has limitations, such as errors caused by moving objects, delayed updates due to processing times, and sensitivity to environmental factors like sunlight or fog. Additionally, lidar performance may degrade in noisy and unstructured environments.

The wheel odometry data source, on the other hand, provides real-time position information without requiring additional sensors and performs accurately on smooth surfaces. However, challenges like wheel slippage on slippery or uneven surfaces, mechanical wear, and accumulated computational errors over time can negatively affect accuracy. By combining the advantages of these two data sources and balancing their limitations, this study achieves a more accurate and reliable localization system.

The data from both sensors is divided into instantaneous position changes and orientation:

$$\Delta P_{wheel} = (\Delta x_{wheel}, \Delta y_{wheel}, \Delta \theta_{wheel})$$
$$\Delta P_{lidar} = (\Delta x_{lidar}, \Delta y_{lidar}, \Delta \theta_{lidar})$$

The reliability of the sensors is dynamically calculated based on the magnitude of position and orientation differences. The difference between the two sensors is computed as the square root of the sum of the squares of the scaled position difference and the angular difference. This difference dynamically reduces the reliability coefficients using a logarithmic model.

The reliability coefficients of the sensors are determined based on the magnitude of the difference:

$$M_{wheel} = \sqrt{(\Delta x_{wheel})^2 + (\Delta y_{wheel})^2}$$
$$M_{lidar} = \sqrt{(\Delta x_{lidar})^2 + (\Delta y_{lidar})^2}$$
$$e_{diff} = \sqrt{(M_{wheel} - M_{lidar})^2 + (\Delta \theta_{wheel} - \Delta \theta_{lidar})^2}$$

The reliability coefficient is calculated as a function of e_{diff} :

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$$\alpha_{wheel} = \frac{1}{1 + kln(1 + e^{p}_{diff})}$$
$$\alpha_{lidar} = 1 - \alpha_{lidar}$$

The combined motion and angular changes of the sensors are computed based on their reliability coefficients:

$$M_{combined} = \alpha_{wheel} M_{wheel} + \alpha_{lidar} M_{lidar}$$
$$\Delta\theta_{combined} = \alpha_{wheel} \Delta\theta_{wheel} + \alpha_{lidar} \Delta\theta_{lidar}$$

The calculated position change is updated according to the robot's orientation:

$$\Delta x = M_{combined} \cdot cos(\theta_{robot})$$
$$\Delta y = M_{combined} \cdot sin(\theta_{robot})$$

The final combined position is updated iteratively:

$$Xcombined(t) = Xcombined(t-1) + \Delta x$$
$$Ycombined(t) = Ycombined(t-1) + \Delta y$$

3. Results

This study presents an adaptive filter approach based on sensor fusion to enhance the localization accuracy of mobile robots. Data from encoders and lidar sensors were dynamically weighted through reliability coefficients, and the robot's position was computed as a combination of these data sources. The proposed mathematical model demonstrated the ability to quickly respond to sensor reliability changes, especially under conditions such as wheel slippage, ensuring the robot maintains accurate orientation and position.

Experimental results show that the proposed method effectively increases reliance on lidar sensors during wheel slippage, preserving localization accuracy. Conversely, during straight movements, the method relies more on encoder data. Additionally, transforming the composite movement into the world coordinate system by considering orientation prevented misestimation of the movement direction and further improved system accuracy.

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Table 1

	Lidar Odometry	Wheel Odometry	Filter Result
XY Error	20 mm	2mm	2mm
Angular Error	1 Degree	0.2 Degree	0.23 Degree
XY Accumulated Error	2 cm	10cm	2cm
Angular Accumulated Error	1 Degree	3 Degree	1.8 Degree

The tests in Table 1 were conducted by moving the robot over a distance of 500 meters. As observed, while wheel odometry provides more precise results, it suffers from accumulated errors. On the other hand, lidar odometry fails to deliver precise data due to issues such as noisy measurements. The filtering process successfully combines the strengths of both methods, resulting in a more robust localization calculation.

In conclusion, this adaptive filtering method offers an effective solution for mobile robots to operate more reliably under real-world conditions. As a result, the robot achieves more accurate and dependable movement.

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