

Sensory Architecture Applied to Robotic Systems in Forest Environments

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Abstract: The development of technologies to enable robots to operate autonomously in challenging forest environments is crucial for promoting effective natural resource management and preventing forest fires, standing out as a priority on environmental conservation and public safety agendas. This article presents a detailed discussion on the development of an innovative sensory architecture, specifically designed to integrate a wide range of advanced sensors. The main objective of this architecture is to provide highly accurate inputs to a system, thereby empowering a forest robot to make autonomous and adaptive decisions in real-time.

To achieve this ambitious goal, the proposed sensory architecture defines a comprehensive set of crucial variables, which are carefully selected and strategically integrated. This design results in a distributed system capable of processing multiple subsystems in parallel and efficiently. This innovative approach enables the conversion of a conventional forest mulcher machine into a fully autonomous and highly intelligent forest robot.

Furthermore, the article details the procedures and methodologies used to experimentally validate the robustness and effectiveness of the developed system. Through rigorous testing and comprehensive analyses, the system's ability to handle a variety of adverse environmental conditions and typical operational challenges in forest environments is demonstrated. These experimental validations are essential to ensure the reliability and accuracy of the system in real-world situations.

Keywords: Sensors, ROS, Sensor fusion, Distributed system, Autonomous decision-making, Forest environments.

1. Introduction

Forest fires have devastated vast forested areas in recent years, causing negative impacts on nature, such as air quality degradation, water pollution, and decreased flora [1]. The onset of a forest fire begins before the fire itself, and one of the causes is the accumulation of available plant biomass for combustion, making it crucial to implement measures

to mitigate its occurrence [2]. Thus, preventive methods are necessary to reduce the risk of fires, and one of these methods involves vegetation removal [3]. Vegetation removal can be done in multiple ways; however, forest mulching machines are capable of clearing vegetation and are an asset for this type of work, thus contributing to fire prevention.

However, working in environments such as forests and agriculture is arduous, and farmers are

increasingly aware of the need to automate their processes through robotic systems [4]. However, robot navigation must include location/positioning systems that allow estimating the position and orientation of a robot in a given environment. Thus, the two approaches used for acquiring a robot's position are: relative and absolute localization. Relative localization uses methods such as odometry and inertial navigation system (INS). Absolute localization uses methods such as the Global Navigation Satellite System (GNSS), which can be obtained by Global Positioning System (GPS) receivers [5]. However, in forest environments, it has been considered challenging due to the estimation of their position over time, making odometry unreliable due to the unstructured environment present in the forest and also the signals from GNSS receivers can be degraded due to tree density [6].

Therefore, for forest environments, the correct choice of sensors and their fusion contributes to addressing the challenges of perceiving an external environment in order to support various perceptual layers such as position, obstacle detection, using sensors such as RGBD cameras or Light Detection and Ranging (LiDAR), and segmentation and classification of objects in a scenario [7].

Thus, this paper aims to contribute to the development of a sensor architecture that allows providing variables to a navigation system with robustness, achieving maximum redundancy, in order to transform a forest mulching machine into an autonomous forest robot for vegetation clearing in forest environments. To achieve this, strategies were adopted considering a forest scenario to ensure safe and coherent locomotion of the forest robot. Therefore, a system composed of a wide variety of sensors in a robotic system was developed, so that when navigation algorithms are applied, it can navigate autonomously.

This paper is organized as follows: Section 2 introduces the state-of-the-art on mobile robotics applications in the forest, Section 3 describes the project within which this article is framed, Section 4 introduces the forest robot and its method of operation, Section 5 discusses the methodologies used in the sensor system, indicating the algorithms and strategies employed, Section 6 consolidates the experimental validations, aiming to verify the robustness of the proposed methodologies, Section 7 provides the conclusion on the work carried out as well as future work.

2. Related Work

Mobile robotics has found a wide range of applications, with one of the most prominent being the integration of robots in forestry and agriculture. In the forest, robotics can be applied to various tasks such as environmental preservation and monitoring.

For instance, in a study conducted by Hellström et al., the authors developed a robotic prototype capable

of precise localization through the integration of multimodal sensors, including GPS for odometry estimation, inertial measurements, and the use of laser and radar sensors for obstacle detection [8]. Olsen et al. are developing a robot that utilizes computer vision and image processing techniques to identify weeds with an accuracy rate of 90%, enabling targeted herbicide spraying [9]. In [10], the authors carried out significant tasks in the context of forest robotics, including the creation of a forest image dataset, training for tree trunk detection using 13 Deep Learning models, and conducting a tree trunk mapping experiment.

In summary, the advances made in forest robotics in recent years have been substantial. However, the field is still in its early stages due to challenges posed by the forest environment, such as uneven terrain [6]. Additionally, most research in this area focuses on developing solutions that either require human teleoperation or are limited to structured environments. Therefore, the F4F (Forest for Future) project aims to develop a multimodal sensor system that can be applied to existing forest mulching machines, making them autonomous in vegetation removal tasks.

3. The F4F Project

This paper is part of a pilot project PP8 – Demonstration of Forest Cleaning Techniques and Tools, within the F4F – Forest for the Future project (CENTRO-08-5864-FSE-000031). The main objective of the project is to develop and demonstrate autonomous forest machines for vegetation cutting. To achieve this goal, existing remotely controlled forest platforms available on the market are adapted with the necessary hardware and software for localization and operation, ensuring safe and efficient operation, and innovative solutions for forest machines for vegetation cutting.

4. The Forestry Robot

The robot consists of a forestry mulcher machine called the Green Climber LV 600 PRO from MDB, as shown in Fig. 1, equipped with an internal combustion engine. This machine is an ideal choice for performing vegetation clearing tasks on roads and highways, as well as in forests with high vegetation density.

Its control/teleoperation is via a remote control that sends radio frequency signals to a module, as schematically illustrated in Fig. 2, which is connected to the tractor's outputs, allowing control of the hydraulic movements of the equipment installed on the machine. The outputs of the machine correspond, for example, to the movement of the tracks, adjustment of the tool height, engine speed control, crusher control, among others.

To convert this forestry machine into an autonomous robot, a sensory system was equipped,

consisting of an aluminum box housing a set of sensors to enable various levels of autonomy for autonomous navigation.



Fig. 1. Forestry Robot.

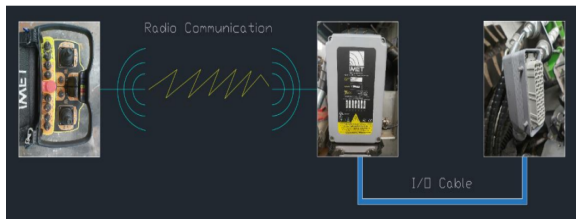


Fig. 2. Radio frequency control of the forestry machine.

4. Work Developed

This chapter will address the work carried out regarding the development of the sensory system. This system is called Sentry, and regarding its physical structure, it consists of an aluminum box integrating a set of sensors, located at the rear of the robot as depicted in Fig. 3. Subsequently, this system is connected to the forestry machine via a plug, thus gaining total control over it. Regarding the software structure, this system is divided into various subsystems to enable the robot to achieve different levels of autonomy.

4.1. Architecture of the Sensory System

The developed sensory system consists of a distributed system as depicted in Fig. 4. This system comprises a minicomputer, named NVidia Jetson Xavier Nx, which acts as the brain of the system and is responsible for managing all processes. Connected to this are sensors such as GPS, IMU, Magnetometer, LIDAR, RGBD cameras, and Thermal cameras, forming a distributed sensor architecture, as shown in Fig. 4. The purpose is to create other subsystems, thus achieving redundancy in information during robot operation and ensuring greater system efficiency for autonomous navigation.

In [11] and [12], a more detailed development of the architecture depicted in Fig. 4 and the vision

system architecture encompassing the use of cameras is demonstrated, respectively.



Fig. 3. Sentry System Integrated into the Forestry Machine.

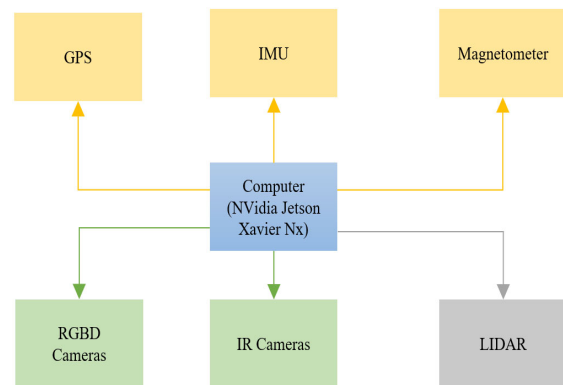


Fig. 4. Sensory Architecture.

Each subsystem will have an independent task to provide variables for the autonomous navigation of the robot. These variables include:

- Position;
- Orientation;
- Obstacle perception;
- Safety.

By merging these variables, the robot will be able to move autonomously when navigation algorithms are applied.

To determine each of the aforementioned variables, it was necessary to integrate a set of sensors, as shown in Table 1. For determining the position and orientation variables, the Duro Inertial sensor was used, composed of a GNSS receiver (Global Navigation Satellite Systems), a 6 DoF IMU sensor for measuring acceleration and rotation rate, and a three-dimensional Magnetometer sensor to measure magnetic fields. For acquiring the Obstacle Perception variable, a Velodyne VLP-16 was used, consisting of 16 laser channels with a 360° field of view, providing comprehensive environmental understanding and high spatial resolution for object detection. Finally, for determining the Safety variable, two Intel Realsense D435i RGBD cameras and two Flir ADK thermal cameras were used. Through the RGBD cameras,

objects can be identified and distance measurements can be made to them, while the infrared cameras are utilized to detect objects in adverse weather conditions such as the presence of dust particles.

Table 1. Sensors used in the Sentry System.

Variable	Sensor Used	Sensor Name	Estimated Price (per unit)
Position	GNSS Receiver + IMU	Duro Inertial	5000.00€
Orientation	Magnetometer + IMU		
Object Perception	LIDAR	Velodyne VLP-16	4500.00€
Safety	RGBD Cameras	Intel Realsense D435i	550.00€
	Thermal Cameras	Flir ADK	2500.00€

4.2. Position Variable

This variable is determined through the application of an Extended Kalman Filter. The Kalman filter is a technique that integrates sensory measurement data, including noise, with a dynamic model to enhance corrections of a system's estimates. This filter is commonly used in position estimation in autonomous driving systems [13].

In this case, the Kalman Filter will estimate the position by fusing two navigation systems: INS and GNSS. The INS system originates from IMU sensor data which, through the accelerometer and gyroscope, can provide the vehicle's position, velocity, and attitude [14]. In the Sentry system, the Kalman filter will use the INS system for a prediction step and the GNSS receiver for the update step of the filter. With this filter, it is possible to minimize the error given by the GNSS receiver and the IMU, achieving a more robust position estimate over time.

4.3. Orientation Variable

The robot's orientation is acquired through the Magnetometer and the IMU. This orientation is related to the rotation of the robot around its Z-axis and is referred to as Heading, representing a direction vector. To obtain the heading, a set of procedures must be followed, as illustrated in Fig. 5, where the magnetometer sensor undergoes a calibration process, followed by a filtering process using a Moving Average filter, responsible for removing noise present in this sensor. Finally, a model is applied to compensate for the inclination of the heading in the X and Y axes. Ultimately, a compensated heading is obtained, indicating the direction in which the robot is oriented, with the X-axis corresponding to East and the Y-axis corresponding to North.

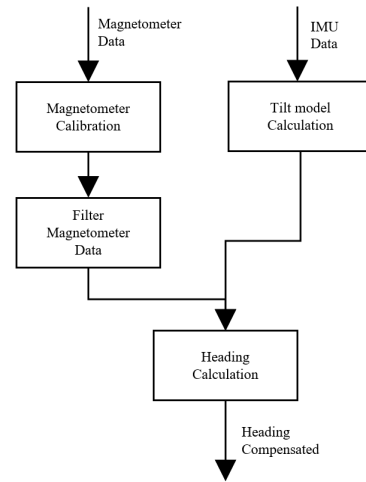


Fig. 5. Orientation Acquisition Method.

4.4. Object Perception Variable

For environmental perception, a LIDAR sensor is utilized. An adaptive clustering algorithm, termed "adaptive_clustering", is applied to the Point Cloud provided by the LIDAR. In order to enable the robot to successfully navigate around obstacles, it is essential for it to identify what is within its Field of View (FOV). To this end, this algorithm has been incorporated, capable of detecting the presence of objects, both static and dynamic. Furthermore, it is crucial to determine the dimensions of these obstacles. The clustering process of LIDAR scan data plays a fundamental role in object detection in specific environments. With the help of clustering, we can identify and distinguish different present objects [15].

However, within the scope of this project, the primary function of LIDAR clustering is to detect the presence of objects, without the need for further analysis. Clustering brings with it a significant advantage, as it considerably reduces the processing load of the point cloud data. This is achieved by defining regions of interest and specific distances, which, in turn, simplifies the processing of the data obtained by the LIDAR.

The interaction between this algorithm and the Sentry system was via the Robotic Operating System (ROS), where a ROS package called "adaptive_clustering" was utilized as depicted in Fig. 6.

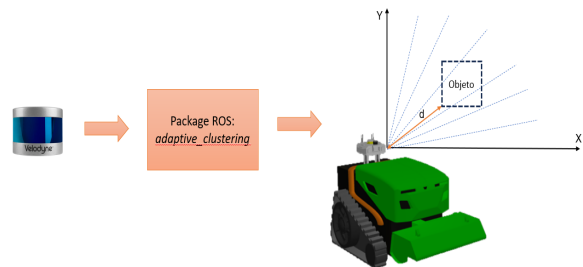


Fig. 6. Object Perception Robot System.

Visually, each cluster is represented by a polygon, which includes the maximum and minimum X and Y coordinates of the points that compose it. These coordinates are crucial for determining the distance relative to the LIDAR, in this specific case, the Velodyne, as they are perpendicular to it. Subsequently, this information becomes extremely important for avoiding obstacles during the robot's navigation.

4.5. Safety Variable

The navigation of a forest robot must consider safety issues such as the detection of people, animals, etc. For this purpose, a vision system composed of 2 RGBD cameras and 2 thermal cameras assists in these safety matters by using an object detection algorithm, in this case, YOLOv5. YOLOv5 is an object detection algorithm and is a vision model referred to as "You Only Look Once" (YOLO). This algorithm belongs to the YOLO family due to its efficiency and speed in real-time object detection. YOLOv5 represents the fifth generation of this series, which offers significant improvements over previous versions [16]. By combining YOLOv5 with distance measurement to objects, the robot's state can be changed while it operates, thus providing safe navigation of the robot in a given environment.

4.6. Interaction among Subsystems

For the interaction between subsystems, the ROS framework was used, which is an open-source framework that allows robots to perform tasks. ROS serves as a common software platform for people building or using a robot [17]. By using ROS, communication with all sensors is achieved, enabling the manipulation of all data coming from these sensors and implementing subsystems to run simultaneously. Fig. 7 illustrates the software architecture behind the Sentry system along with ROS.

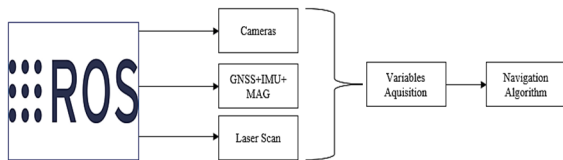


Fig. 7. Software architecture of the Sentry System.

5. Validation Experiment

This chapter aims to validate the implemented and suggested algorithms in the Sentry system in order to verify if the chosen sensors offer the intended functionalities to the system and also to verify if the proposed variables are correctly processed for application in navigation algorithms.

5.1. Position Variable Validation

To validate the Position variable, an experiment was conducted in a forest environment, where the robot performed a straight-line autonomous trajectory of 10 meters. In this test, a navigation algorithm was selected, and a destination coordinate was given to the Sentry system to autonomously guide the robot to the final coordinate. The robot initialized its trajectory at point 0.0,0.0 facing East, and a destination coordinate of 10.0,0.0 was set. To evaluate the position variable, the same trajectory was performed twice, once without a Kalman filter, i.e., with data provided directly by the GNSS sensor, and another trajectory with the Kalman filter.

Fig. 8 shows the path taken by the robot to reach the destination coordinate.



Fig. 8. Straight-line path taken by the robot for position evaluation.

Thus, the impact of the Kalman filter on the position variable is intended to be evaluated, and for this purpose, evaluation indicators were used, namely the maximum distance from the trajectory and the root mean square (RMS) for all points along the trajectory.

Fig. 9 displays the data obtained from the trajectory performed by the robot, where it is graphically visible that the Kalman filter achieves a better estimation of the position as the trajectory is closer to the reference. Additionally, without the filter, more oscillations in the position are observed, which stem from measurement errors and limitations imposed by the GNSS sensors. The results obtained from the evaluation indicators of the position is shown in Table 2.

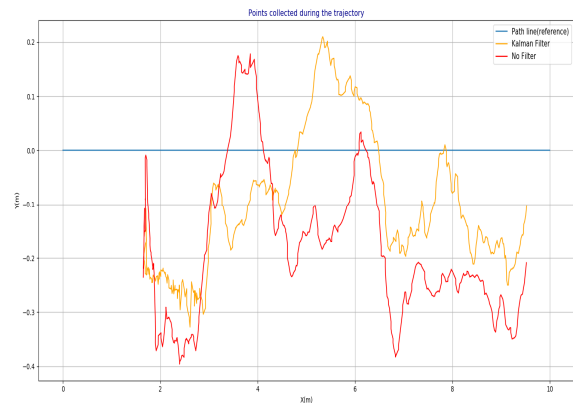


Fig. 9. Points collected during the trajectory without Filters and with Kalman Filter.

Table 2. Results obtained from the evaluation indicators of the position.

Max (m)		RMS (m)	
Kalman Filter	Without Filter	Kalman Filter	Without Filter
0.291	0.442	0.151	0.279

5.2. Validation of the Orientation Variable

To validate the Orientation variable, the experiment conducted in Section 5.1 was utilized to collect data regarding the robot's orientation angle, in this case, the Heading based on the trajectory depicted in Fig. 8. Based on this test, the aim is to analyze if the process implemented in Fig. 5 can provide proper orientation to the robot when it navigates autonomously. Thus, Fig. 10 graphically displays the angular variation concerning the reference angle (in this case, 0°).

**Fig. 10.** Heading during the linear trajectory.

Based on the results obtained in Table 3 and the data displayed graphically in Fig. 10, promising results are observed for the orientation variable. It is noticeable that there is a discrepancy in the data concerning the Reference Heading, which is attributed to the fact that this type of machine cannot move perfectly straight and also due to vibrations transmitted by the combustion engine.

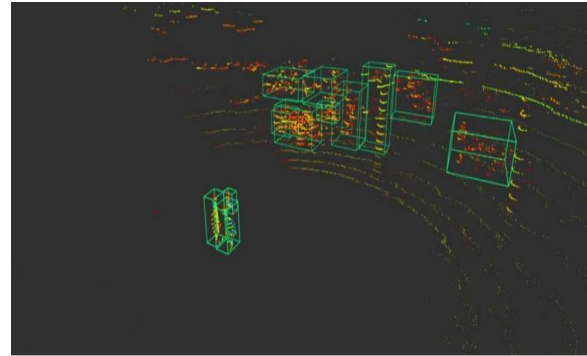
Table 3. Performance indicators for the Orientation variable.

Max (°)	Variance (°)
10.15	7.02

5.3. Validation of Object Perception Variable

The test conducted with the LIDAR sensor aimed to evaluate the ability of the adaptive clustering algorithm to detect obstacles in a forest environment. Fig. 11 illustrates the output of this algorithm when detecting obstacles, and creating polygons around the identified objects. In each polygon, the maximum and

minimum values of the X and Y coordinates, along with the distance to the detected object, are recorded. This test was conducted with the machine in teleoperation to assess the impact of vibrations on the system's performance.

**Fig. 11.** Adaptive clustering algorithm in the point cloud of Velodyne VLP-16.

5.4. Validation of the Safety Variable

To assess the performance of the safety variable, an experiment was conducted to evaluate the capability of the YOLOv5 algorithm to operate on the Jetson Xavier Nx. For this purpose, two thermal cameras and the RGB camera from Intel, along with the depth camera, were used. The result of this experiment can be observed in Fig. 12, where the functionality of the YOLOv5 algorithm was validated by detecting objects at a rate of 100ms. This information is crucial for the robot to navigate autonomously during a trajectory.

**Fig. 12.** Output of the YOLOv5 Algorithm with NVidia Jetson Xavier Nx.

6. Conclusions and Future Work

The work presented in this paper aims to develop a sensory system that enables the conversion of a forest mulcher machine into a forest robot. The architecture of this system is presented along with a cost analysis

of the sensors used. Within this system, a sensory network has been implemented that can be integrated with ROS, thus creating a multimodal architecture that can be implemented in any forest mulcher machine (subject to its locomotion configurations), providing important variables such as position, orientation, object perception, and security for the correct operation of the robot in autonomous mode.

The proposed methodology regarding sensors results from a study conducted on which algorithms and techniques to provide a set of variables to the system with robustness. For this purpose, the Sentry system was divided into different subsystems in order to scale different important tasks to enable the application of navigation algorithms.

The experimental validations allow evaluation of whether the proposed methodologies allow offering conditions for the robot to move autonomously in a forest environment. Regarding the position variable, the Kalman filter proved to be a valuable asset for position estimation over time by integrating two navigation systems (INS/GNSS). Regarding the orientation variable, the proposed methodology can provide a direction vector to the Sentry system, thus indicating the direction in which the robot is facing. In the object perception variable, by using the "adaptive_clustering" algorithm, it is possible to quickly detect the presence of dynamic and static objects. The security variable, using the YOLOv5 algorithm, helps to detect and identify objects, which is a great advantage for the robot to make real-time decisions.

In conclusion, it is believed that the Sentry system is an asset for application in other forest mulcher machines. Subsequently, in [18-20], developments in navigation are demonstrated to validate the operation of the Sentry system and its variables in autonomous navigation. However, there is still room for future work. To this end, other localization techniques should be explored, such as addressing the integration of Simultaneous Localization and Mapping (SLAM) systems, while also creating mapping. Another aspect to consider is the exploration of advanced Artificial Intelligence techniques for the interpretation and understanding of objects in a forest environment, in order to enhance navigation.

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Advances in Robotics and Automatic Control: Reviews

Sergey Y. Yurish, Editor

Industrial robots offer many benefits, including cost reduction, increased rate of operation and improving quality, along with improved manufacturing efficiency and flexibility. The demand for industrial robotics is majorly observed in industries such as automotive, electrical & electronics, chemical, rubber & plastics, machinery, metals, food & beverages, precision & optics, and others. In its turn, industrial automation control market will witness considerable growth during the same period with the growing demand of products such as sensors, drives and various robots.

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