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An Evaluation of the Fusion of Relative Positioning Sensors in the Accuracy of Land Mobile Robot´s Localization Systems

Henrique Santos[a], Artur Kronbauer[b], Jorge Campos[c*]

[a]Senai-CIMATEC, Av. Orlando Gomes, 1845, Piatã, Salvador - BA, 41650-010, Brazil
[b,c]Salvador University (Unifacs), Av. Tancredo Neves, 2131, Salvador-BA, 41820-021, Brazil
[b,c]Bahia State University (UNEB), Rua Silveira Martins, 2555, Salvador-BA, 41150-000, Brazil
[a]Email: henriqueavilassa@gmail.com, [b]Email: arturhk@gmail.com, [c]Email: jorge@unifacs.br

Abstract

The precise location of a robot is a fundamental challenge and one of the most important tasks for robot´s navigation systems. For autonomous navigation, the robot must be aware of its pose and the map of the environment so that it can set the path it must follow to perform a task. Most terrestrial robots use an odometry system based on the movement of the wheels to keep track of their location. Wheel odometry has high sensitivity to the kind of pavement, which leads to an inaccuracy that increases over time. One way to improve the robot's positioning accuracy is by merging all kinds of sensors capable of measuring the robot's displacement and speed. The most used sensors to improve knowledge of the robot's position on low-cost robotic platforms are cameras and inertial sensors. This work analyzes the accuracy of the positioning systems based on the odometry obtained from the wheels, inertial sensors, and visual odometry. To analyze the precision of the robot's movement, the real trajectories of a two-wheeled robot are compared with the expected trajectory (ground truth) using different combinations of the mentioned sensors. The results of the experiment provide a good indication of the cost-benefit of using these types of sensors to perform the odometry of robotic platforms.

Keywords: Robotic Navigation Systems; Relative Positioning Sensor; Sensor fusion; Odometry; Robot ego-motion.

1. Introduction

The human determination and desire to create a device with the ability to automatically perform complex and repetitive tasks is an ambition that has long inhabited the imagination of modern societies. Currently, artificial intelligence and robotics are in virtually every field and environment.

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* Corresponding author.

Mobile robots, for example, can be found far below in the abyssal depths of the oceans, far away exploring other planets in the solar system, and especially around us in everyday environments performing mundane tasks.

Mobile robots vary in size, complexity, and purpose. A considerable portion of these robots, however, aim to be autonomous in their decisions and movements. This characteristic makes the navigation system of these machines one of the main components to guarantee not only the execution of the intended task, but also the safety of people on the path of the robot, the environment nearby, and the robot itself. Thus, it is of fundamental importance that the robot continuously and accurately keeps track of its position and orientation in space, be able to identify obstacles and count on the support of sophisticated algorithms, allowing it to move efficiently, effectively, and safely.

Considering the types of sensors and the strategy used to figure out robots' position over time, there are three usual approaches employed by navigation systems: absolute, relative, and mixed positioning systems. For absolute positioning systems, the robotic platform has sensors that use triangulation of cell phone towers, electronic beacons, or satellite signals to determine the precise position of the robot in outdoor environments. For relative positioning systems, the set of information necessary to determine the location and orientation of robotic platforms comes from successive observations of sensors embedded in the robotic platform. These electronic devices collect analog samples of physical quantities (e.g., distance, speed, three-dimensional acceleration, rotation rate), use images of the environment, or any other source of information that allows the determination of the robot´s position, inferred by considering the initial position of the robot and how much and in which direction the robot moved. Mixed positioning systems combine relative and absolute positioning strategies to enhance accuracy and to guarantee that there is location information even in places where absolute positioning sensors do not work well or do not work at all (e.g., indoor environments).

This paper analyzes the impact that a combination of a set of different sensors has on the accuracy of a robot's relative localization system. The main objective of this work is to provide a quantitative analysis of the individual and combined impacts that some usual sensors have on the robotic localization system. The proposed analysis aims to identify how each sensor affects the robot's ego-motion during navigation. The sensors chosen for this evaluation are 1) encoders to measure the displacement and orientation of the platform through the rotation of the wheels, 2) the Inertial Measurement Unit (IMU) composed of gyroscopes and accelerometers, sensors capable of determining accelerations, speeds, and displacements (linear and angular), and 3) a Kinect camera, which based on the captured images performs visual odometry. These sensors are cheap, easy to configure, and widely available, thus they are usually the first options to be considered as part of the hardware of low-cost robotic platforms. It is expected that the evaluation, results, and discussions presented in this paper will serve as a reference for students, researchers, designers, and hobbyists in the field of robotics. It is also expected that the evaluation of the contribution of the various sensor configurations to the accuracy of the navigation system will support decision-making in the specification of low-cost robotic vehicles.

The remainder of this paper is structured as follows: Section 2 reviews similar initiatives to evaluate the impact of the use of different kinds of sensors on the accuracy of the navigation systems of robots and autonomous vehicles. Section 3 discusses major sensors used to keep track of the robot´s location over time. Section 4 presents an experiment evaluating the contribution of some relative positioning sensors on the accuracy of the robot navigation systems. Section 5 concludes and indicates future works.

2. Multisensory Approach to Localization Systems

Navigation systems of robotic platforms are comprised of a complex grouping of hardware and software dedicated to the difficult task of moving the robot towards its goal in an autonomously, safely, and efficient way. This complex system is well summarized by the “See-Think-Act” model [5]. The “See” component represents the robot´s perception of its position and orientation in the environment. In addition to the robot´s ego-motion, the “see” part of the model also takes care of identifying moving objects (e.g., people and other vehicles) and the location of obstacles (e.g., walls and furniture). The “Think” component represents the cognitive process of the robot's navigation system. This component is responsible for processing all information used for autonomous navigation, (i.e., construction of the map of the environment and the determination of the best path or alternative paths to achieve the goal). Finally, the “Act” component converts high-level navigation instructions into commands for the robotic platform actuators to execute the planned movement.

Although knowing the map of the environment where the robot is inserted is essential for planning routes and avoiding known obstacles, it is also imperative that robots can situate themself in this same environment, knowing as precisive as it can be their location and orientation. Thus, the “See” and “Think” parts of the model are usually treated together in a process called Simultaneous Localization and Mapping (SLAM). SLAM emphasizes the consonance of two different techniques: mapping and localization. Despite having different objectives, these techniques are intrinsically intertwined. On one hand, the map is an essential piece of information to subsidize spatial awareness of the robot in the environment. On the other hand, estimating the position of the robot is essential to ensure the accuracy of the map being constructed by the very robot. This work focuses on the “See” part of the model, more precisely on how to keep the robot´s self-location knowledge as close as possible to its real position in indoor environments and the impact that a combination of different sensors has on the accuracy of the robot´s positioning system.

Concerning the combination of sensors, several initiatives have sought to improve the localization accuracy of mobile robotic platforms using sensor fusion techniques and probabilistic localization methods. As an alternative to improve the measurement of linear and angular displacements experienced by robots, some researchers have incorporated as many sensors as the robotic platform can support and the robot owner can afford. The combination of multivariate types of sensors, however, requires a mathematical treatment to accommodate sensors of different technologies and precision. For this purpose, it is usual to use the Kalman filter. The Kalman Filter is an algorithm that performs data fusion, a process that involves the association, correlation, and combination of data from different sources. This algorithm provides resources to deal with nonlinear systems efficiently, estimating the states of a system, even if the system is fed by measurements containing uncertainties. The application of the Kalman filter results in more accurate data, provides smoothing of data with disturbance, linearization of system states, and estimation of parameters in positioning systems, among other advantages [1,2].

Concerning robot´s positioning systems, there are two typical methods used to keep track of a robot´s localization: absolute positioning and relative positioning. Absolute positioning systems estimate the position of the robot with respect to a reference system. This feature eliminates cumulative errors but does not exempt these systems from other errors, especially in indoor environments. In terms of coverage, the reference system of absolute positioning sensors varies from small regions (ports, airports, factory floors) to areas that cover the entire surface of the globe. Among the sensors used for absolute positioning, the most usual are electronic compass, directional beacons using radio frequency signals, and satellite positioning systems. Relative positioning or dead reckoning estimates the current position and orientation of the robot from an initial position taken as a reference and the displacements (linear and angular) experienced by the robot over time. The process for measuring the movements of the robot is generally called odometry. The use of absolute and relative positioning systems is not mutually exclusive, quite the opposite, whenever it is technically and financially possible, these systems are combined to increase accuracy and robustness.

The use of absolute or mixed positioning systems is the first choice for outdoor robots. For indoor robots, however, relative positioning systems is the only option, which make odometry a critical task for these systems. Odometry can be accomplished through a variety of sensors and technologies, being most commons odometry based on wheel encoders, inertial units, and images. Odometry based on wheel encoders relies on the fact that wheel's rotations can be converted into linear and angular displacements [6]. Wheels' odometry is one of the most used methods for determining the positioning of robotic vehicles because this kind of sensor is cheap and demands low computational cost to estimate positions [7]. Inertial odometry is made through Inertial Measurements Units (IMU) sensors. The IMU consists of an accelerometer, a gyroscope and in some cases a magnetometer [8]. IMU makes measurements considering inertial variations in the movement. The functioning of the IMU consists of transforming the physical phenomena associated with the inertia of the movement into analog electrical signals, which can be processed and used to estimate orientation, speed, displacement, and angular speed. Visual odometry is another usual technique to keep track of the robot´s position over time [9]. This technique estimates the movement of the robot by processing sequences of images captured by cameras rigidly fixed to the robotic platform. In favorable environments, that is, in environments where it is possible to identify well-defined control points in the image, visual odometry produces accurate displacement and rotation information. This technique, however, has a higher financial and computational cost, when compared to the techniques that use encoders and IMUs. Thus, a detailed cost-benefit analysis is essential to support the decision to incorporate or not the visual odometry technique in the robot's navigation system.

There are several initiatives studying combinations of sensors to improve the robot´s location. Nguyen and his colleagues [1] proposed an improved localization system for autonomous mobile robots using a sensor fusion technique. The approach described in the paper uses data from a relative positioning sensor (i.e., encoders on the robot's wheels) and two sensors for absolute positioning (i.e., Satellite Location Sensor (GPS) and compass). In this work, the real positioning data (ground truth) is compared with the positioning data obtained by different combinations of the sensors, namely: i) only the encoder; ii) encoder + GPS; iii) encoder + compass; and iv) encoder + GPS + compass. The contribution of this work is twofold. Firstly, the paper shows the impact that some combinations of sensors have on the accuracy of the positioning system. Secondly, the paper conducts an experiment fusing data with and without Extended Kalman Filter (EKF). The results presented demonstrate that the fusion of sensors using EKF leads to greater precision when compared to the combination of sensors without the use of this technique.

Reference [2] presented an initiative to enhance the orientation of a mobile robotic platform fusing IMU, video camera, and Light Detection and Ranging (LIDAR) sensors. The main goal of this work was to evaluate the enhancement in the robot orientation when adding a LIDAR in a platform with IMU and a video camera. It seems that the authors target a broad category of autonomous robots and not only terrestrial robots with wheels, since they do not include the encoder in their experiment. The sensor fusion technique also used EKF. As a method of validation, the evaluation of the average error of the following configurations of sensors was compared: i) IMU + camera; ii) IMU + camera + 2D LIDAR (laser scanning in the XY plane), and iii) IMU + camera + 3D LIDAR (laser scanning in multiple planes). The results show that LIDAR significantly reduces the orientation error. Using 3D LIDAR allows a complete 3D orientation estimation, while 2D LIDAR improves orientation information only in the displacement plane, which is the information needed by mostly robots.

The work of de [3] seeks to improve navigation´s performance and to enhance the estimation of the pose of mobile robots using the EKF technique, fusing visual odometry computed from a monocular camera and accelerations and orientations gathered from an IMU. In this work, the authors analyzed the complete 6D relative location in three e-puck robots using monocular vision tracking and IMU modules. The main contribution of this paper is the implementation of an algorithm for monocular odometry. The solution combines Speeded-Up Robust Feature (SURF) and Random Sample Consensus (RANSAC) algorithms to find interest points (features) under different viewing conditions using a Hessain matrix. This approach proved to be easy to implement, has a low computational cost, and to improve localization accuracy. The experiment developed evaluates the accuracy of the positioning measurements (linear and angular) in a multi-robot system. The performance of the experiments was verified by the ground truth data and Root Means Square Errors (RMSEs).

Reference [4] developed a localization system for autonomous mobile robots in indoor environments using multiple ultrasonic sensors. The algorithm proposed the usage of odometry measurements and distance estimation through observations captured by these kinds of sensors. To estimate the location of the robot, three Transceivers (Tx) were fixed on the ceiling of a room with known positions in a global coordinate system, and three Receivers (Rx) were installed on the top of the robot. The localization system uses the fusion of ultrasonic sensors with wheel odometry data to estimate the position and precise orientation of the robot in a laboratory. The type of sensors used in this experiment is not usual outside controlled environments such as research labs, but the results serve as a reference for localization systems projects aiming at incorporating ultrasonic sensors or alike.

An analysis of some of the related work shows that inertial sensors are prevalent for most localization systems, being used in virtually all types of environments. When robots have wheels, data from the encoders are also prevalent, despite its inaccuracy, caused by the sensitivity of this sensor to the type of pavement and the topography of the terrain. Another technique widely used to improve the robot's location is visual odometry, which is based on data generated by video cameras. Our work carries out an analysis of the contribution of the main sensors used to improve estimates of the location of the robots, that is, inertial sensors, encoders, and video cameras. The next section presents some details of the robotic platform and the design of an experiment designed to evaluate the contribution of different combinations of these sensors in estimating the robot´s position over time.

3. Robotic Platform and Experiment´s Design

The main goal of the designed experiment is to evaluate the contribution that the combination of some relative localization sensors have to the accuracy of the robot's navigation system. The sensors chosen for this experiment were wheel encoders, an IMU sensor, and a Kinect camera. These sensors were chosen because they are based on different technologies and are very popular. Technologically speaking, they are accountable for performing three kinds of relative positioning: traditional odometry (wheel encoders), inertial odometry (IMU), and visual odometry (Kinect). Their popularity comes from the relatively low cost to purchase these sensors and the ease of use when compared to other relative positioning techniques. Encoders, for example, are inexpensive sensors and are present in virtually all land vehicles with wheels or tracks. When encoders are combined with another sensor for odometry purposes, the IMU is always the first option. This sensor is one of the most used sensors in all types of robotic platforms (aerial, terrestrial, aquatic, and underwater). Visual odometry has been gaining ground with the possibility of using both monocular and stereo odometry. The former is used on platforms with reduced processing power, and the latter on platforms with a greater processing capacity that requires high accuracy in its positioning system.

The robotic platform chosen for the experiment is based on the open-source project called Linorobot (https://linorobot.org/). The Linorobot project offers two-wheel drive (2WD), four-wheel drive (4WD), or crawler robotic land platform designs. Linorobot is based on the Robot Operating System (ROS) and has support for several types of localization sensors. The robotic platform used in this experiment is a two-wheel drive version of Linorobot, driven by two direct current motors (24V, 350RPM). Each wheel is equipped with encoders (CHIHAI MOTOR) to perform odometry. Other localization sensors embedded in our platform are the inertial measurement unit (MPU-6050) and a video camera (Kinect V1). The MPU-6050 sensor contains an accelerometer and a MEMS-type gyroscope on a single chip. There are 3 axes for the accelerometer and 3 axes for the gyroscope, with a total of 6 degrees of freedom (6DOF). Kinect has an RGB camera with a resolution of 640x480 pixels and a depth camera of 320x240 pixels, both capable of operating at 30 frames per second. The microcontrollers used were the Teensy 3.5 for low-level control, connected with a Raspberry Pi 3 B+ board, used for high-level control. The Raspberry board features a 64bit, 1.4GHZ, quad-core processor and 1GB of SDRAM. A 64GB class 10 memory card was added to this board. The installed operating system is Ubuntu 16.04, working with the ROS Kinect version (Figure 1).

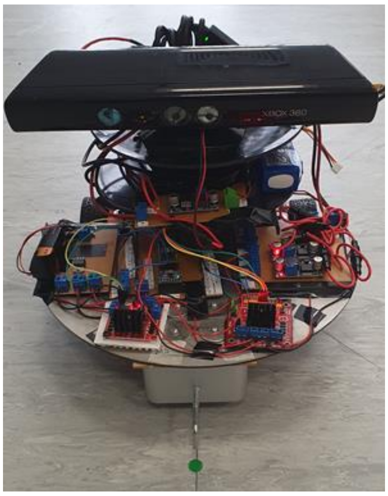

Figure 1: Two-wheel robotic platform used in the experiment.

The experiment was designed to compare the position of the robotic platform performing a known path (ground truth) with the position of the platform registered by the robot's navigation system. For the sake of simplicity, we assume that the linear and angular errors of the robot's position and orientation are caused by the inaccuracy of the embedded relative localization sensors or by the combination of them. Since we performed the experiment in a controlled environment, systematic errors or errors caused by external factors were considered negligible.

The designed path for the experiment is a square of 70.7 cm in size, which results in a diagonal of approximately 100 cm (Figure 2). The robot starts the route at one of the vertices of the square and travels along each side of it, making 90-degree turns when passing through checkpoints (vertices of the square). Linear and angular errors are measured at each checkpoint. The linear error is the Euclidean distance measured from the vertex drawn on the ground to the position of the robot in the field. Angular error is the difference between the rotation angle of the robot and the right angle of a square.

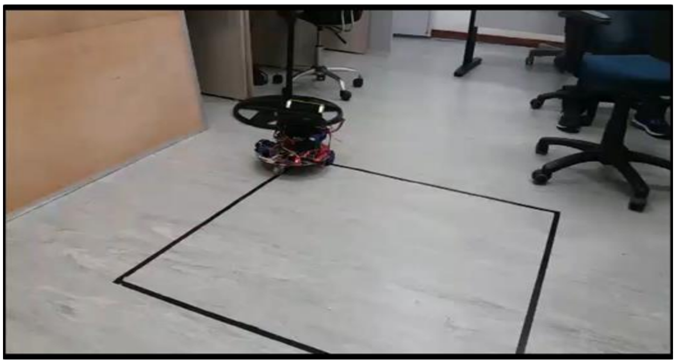

Figure 2: Path performed by the robot during the experiment. Linear and angular errors are measured at each vertex of the square

For each combination of sensors, the robot executes ten times the closed square path. Linear and angular errors are computed at every checkpoint. Measurements taken at each checkpoint are used to compute the Root Mean Square Error (RMSE), both for distances and rotations. The RMSE linear (Equation 1) is the Euclidian distance between the real position of the robot (x_i,y_i) and the coordinates of the checkpoint on the ground (X,Y). The RMSE angular (Equation 2) is the difference between the rotation angle that the robot executes at the checkpoints (Ω_i) and the right angle of a square (90 degrees).

$$RMSE_{linear} = \frac{1}{N}\sum_{i}^{N}\sqrt{((x_i - X)^2 + (y_i - Y)^2)} \qquad (1)$$

4. Evaluation and Experimental Results

In an ideal localization system, the robot always executes a perfect path, that is, the robot passes through all points and makes all the turns of the planned trajectory. In the real world, however, physical experiments are affected by sensors' accuracy, which in turn are prone to mechanical and systematic errors that are cumulative over time. Aiming at comparing the effect that usual combinations of some selected positioning sensors have on the accuracy of the robot´s localization system, five sensor configurations were devised for the experiment: i) encoder only; ii) encoder + Kinect; iii) Kinect + IMU; iv) encoder + IMU; and v) encoder + IMU + Kinect.

Table 1 summarizes the RMSE (linear and angular) of each sensor configuration. For the sake of simplicity, only errors taken at the fourth checkpoint, or the end of the trajectory, is shown. Since we are using relative position sensors, errors are cumulative, thus the end of the trajectory is always the worst-case scenario.

Table 1: Root Mean Square Error (Linear and Angular).

Configuration	**Sensors Used**	**RMSE Linear (cm)**	**RMSE Angular (degree)**
1	Encoder	16,37	37,20
2	Kinect + IMU	26,55	8,72
3	Encoder + Kinect	5,55	9,49
4	Encoder + IMU	4,16	6,59
5	Encoder + Kinect + IMU	2,17	3,63

The first configuration of the experiment evaluated only encoder data to estimate change in position over time. As expected, the use of a single sensor produces high linear and angular errors. On average, the robot moved 16.37 centimeters away from the last check point. Considering a trajectory with less than 300 centimeters, this configuration generates a linear error close to 5.5%. The average angular errors for the configuration with encoders only were 37.20 degrees. Considering that the robot should perform a turn of 90 degrees at the end, it represents an angular error of almost 42%. These values are unacceptable for most practical applications, which reinforces the idea that the location of robots cannot be based solely on data from encoders.

The use of more than one sensor, however, does not imply in linear and angular improvements. It all depends on the characteristics of the sensors used. The second configuration, for instance, uses data from visual odometry and inertial odometry. The linear RMSE of this configuration shows a significant degradation in the estimation of the distance traveled by the robot. On average, the robot moved 26.55 cm away from the last check point. On the other hand, the angular error of 8.72 degrees represents an improvement in the estimation of rotations when compared to the former configuration. Configuration 2 is the only configuration in our experiment that does not use data from wheels´ encoders. Thus, this configuration is very unlikely to be found in practice for robots with wheels but very likely for other types of robotic platforms such as drone and humanoids.

The third configuration carried out in the experiment is based on the technique of fusing the differential data of the wheels´ encoders and the visual odometry performed by the Kinect camera. It is possible to notice relevant changes in the linear RMSE when compared to the results obtained in the first and second configurations. On average, the robot moved 5.55 cm away from the last checkpoint of the trajectory. The RMSE angular of Configuration 3, however, shows mixed results, that is, an improvement in the orientation awareness when compared to Configuration 1, but a small degradation in the orientation when compared with Configuration 2. The mean angular errors were 9.49 degrees, an error of approximately 10.5% for the intended 90-degree curve.

The fourth configuration, like the former two configurations, uses data coming from a pair of sensors, that is, encoder and IMU. This is perhaps one of the most usual configurations found on low-cost terrestrial robotic platforms. The main reason for this is that it is the cheapest configuration, both in financial and computational costs, and it produces the smallest linear and angular errors among all configurations tested in the experiment that use only two sensors.

The fifth configuration and the last phase of the experiment used the fusion of all available sensors in the platform: encoder, IMU, and Kinect. It is natural to expect that this configuration provides significant improvements in linear and angular errors. Table 1 shows that, on average, the robot showed a 2.17 cm deviation in relation to the coordinates of the checkpoints and the angle of rotation 3.63 degrees in relation to the predicted 90 degrees, errors of about only 0,7% and 4% when compared with the ground linear and angular displacements, respectively.

The results of the experiments shown in Table 1 allow anyone to draw some conclusions about the advantages and disadvantages of the combination of sensors for the navigation of mobile robots in indoor environments. For the sake of comparison and for decision-making purposes, however, the results of the experiment are better understood when the comparisons between pairs of different configurations are made explicit. Comparisons between sensors´ configurations are more evident when a certain configuration is chosen as a reference and the gain or loss in the accuracy of the positioning system is computed with respect to this reference configuration. Table 2 indicates the variation of the RMSE linear taking every sensor configuration as a reference. At each line of the table, it is possible to see the gain or loss of precision with respect to every other configuration. Positive values (red boxes) indicate an increase in mean error and negative values (green boxes) indicate a reduction in mean error. Taking Configuration 1 as a reference, for instance, the first line of Table 2 shows the variation of the linear error of Configurations 2, 3, 4, and 5 when compared to Configuration 1. Thus, when the encoder is exchanged by a combination of IMU and Kinect sensors (Configuration 2), the RMSE linear increases by 62%. When the encoder is kept in the configuration and combined with Kinect, IMU, or both, the RMSE linear decreases by 66%, 75%, and 87%, respectively.

Table 2: Variation of RMSE linear between configurations.

Configuration / Reference	*1 -Encoder*	*2 – Kinect +IMU*	*3 –Encoder + Kinect*	*4 -Encoder + IMU*	*5 - Encoder+Kinect +IMU*
1 - ***Encoder***		+62%	-66%	-75%	-87%
2 - Kinect + IMU	-38%		-79%	-84%	-92%
3 - Encoder + Kinect	+195%	+378%		-25%	-61%
4 – Encoder + IMU	+294%	+538%	+33%		-48%
5 – Encoder + Kinect + IMU	+654%	+1.124%	+156%	+92%	

The same reasoning can be used to compare the different configurations with respect to the angular RMSE (Table 3). Considering the configuration with only the encoder as a reference, all other configurations showed improvements in the accuracy of the angular RMSE. Exchanging the encoder by the combination of Kinect and IMU, or adding to the encoder configuration an IMU, a Kinect, or using all sensors increase the accuracy of rotations by 77%, 74%, 82%, and 90%, respectively.

Table 3: Variation of RMSE angular between configurations.

Configuration / Reference	*1 -Encoder*	*2 – Kinect +IMU*	*3 –Encoder + Kinect*	*4 -Encoder + IMU*	*5 - Encoder+Kinect +IMU*
1 - ***Encoder***		-74%	-77%	-82%	-90%
2 - Kinect + IMU	292%		-8%	-31%	-62%
3 - Encoder + Kinect	327%	9%		-24%	-58%
4 – Encoder + IMU	464%	44%	32%		-45%
5 – Encoder + Kinect + IMU	925%	161%	140%	82%	

As far as navigation systems are concerned, the distance traveled by the robot is too important as the direction that the robot is facing. Thus, it is important to consider RMSE linear and angular together. Analyzing Configurations 3 and 4 as references, where the Kinect and IMU sensors were individually associated with the encoder, there is a significant gain in the accuracy of linear and angular measurements when compared with the encoder only (Configuration 1). The reduction of linear and angular errors observed in Configurations 3 and 4 are in the same order of magnitude, with a slight advantage for the configuration with IMU (Configuration 4). While Kinect reduces the linear error by 66%, the IMU achieves a 75% reduction (Table 2). For angular errors, Kinect improves the accuracy of angular error by 74% and the IMU by 82% (Table 3). Based on these results, it can be concluded that if the intention is to add just one more sensor in a system with encoders only, the best option is to use inertial sensors. Moreover, IMU sensors have an additional advantage over the Kinect sensor, they are cheaper than image sensors and require less processing power from the onboard computer to perform odometry.

Corroborating what common sense suggests, Configuration 5 (i.e., the use of all sensors) produces the best results, both in terms of linear and angular accuracy. Thus, the most important information in the comparative analysis of this configuration is the percentage of effective gain when compared to all other configurations. Regarding Configuration 1, for example, using encoders only increases the linear error by 654% (Table 2) and the angular error by 925% (Table 3). When Configuration 5 is compared with Configurations 3 and 4, an improvement in linear and angular precision in the same order of magnitude is perceived, but the improvement concerning Configuration 4 (encoder and IMU) is slightly less than the improvement concerning Configuration 3 (encoder and Kinect).

The comparison between the best combination of sensors (Configuration 5) with the worst combination (Configuration 3) produces interesting results. The linear error when removing the encoder from Configuration 5 increases by 1,124%. The angular error is less impacted, with an increase of 140%.

Based on the data from the experiment, some practical recommendations can be derived. Terrestrial robotic platforms with wheels must always install encoders on the wheels to perform odometry. When using sensors for inertial and visual odometry without the presence of encoders (Configuration 3), linear and angular errors are unacceptable for most applications.

If someone wants to increase odometry accuracy in a system that has only the encoder, it is suggested to include an inertial sensor or depth camera, with a preference for the first type of sensor. The best solution, however, is the use of the three types of sensors, since the improvement in the precision of the orientation and location of the robot, is worth the cost of implementing this solution. The improvement in linear error, when compared to the second-best option (Configuration 4) is 92%. For angular errors, this improvement reaches 82% when compared with the same configuration. As final remarks, it is important to analyze the cumulative error at the end of the trajectory. Configuration 5 presented a total linear error of 2.17 cm in a 282 cm path, which is equivalent to an accumulated error of ~ 0.75%, and a total angular error of 3.63º after performing 4 rotations of 90º (360º), which is equivalent to an accumulated error of ~ 1%. This accuracy is acceptable for many robotics applications.

5. Conclusions and Future Work

This work presented an evaluation of the localization systems for indoor environments implemented in mobile robots using the sensory fusion technique with Extended Kalman Filter. The experiments were carried out to extract information from data from wheel odometry, inertial sensors, and visual odometry. The selected data sources were based on sensors that are frequently mentioned in studies involving the navigation of terrestrial robots.

Aiming at evaluating the relative accuracy obtained by the various combinations of sensors, an experiment was carried out with five sensor configurations. The most basic configuration uses only data from the encoders (wheel odometry). The second configuration removes the encoder from the system and uses the Kinect camera and the inertial sensor to obtain the robot's location. The third and fourth configurations combine the encoder with a video camera (visual odometry) and with the IMU (inertial odometry), respectively. The last configuration incorporates the data from all the sensors previously mentioned.

The evaluation of the impact that the different sensors have on the robot's localization was analyzed in a predefined square path with a diagonal measuring approximately one meter. In this experiment, it was possible to analyze the accuracy of linear and angular movement in navigation. For analysis purposes, linear and angular mean square errors were used to evaluate navigation accuracy. These statistical indicators were used to obtain a quantitative measure of the quality of navigation in each configuration of the experiment. The results of the experiment can be used to support decision-making and cost-benefit analysis regarding the use of a certain combination of sensors.

The experiments in this study were carried out in a research laboratory, where there is a limitation of physical space to perform long trajectories. Considering this reality, this work carried out the analysis of the localization systems only in a short path. We understand that experiments over long distances are fundamental to evaluate the behavior of sensors in the long term and how the evolution of linear and angular errors evolves as the distance and the number of rotations increases.

This work has multiple possibilities for extension. As future work, it is suggested the realization of longer and more elaborate routes and to increase the number of localization sensors, incorporating different relative positioning technologies and at least an absolute localization sensor, such as the GPS.

Regarding the path taken by the robot, it is essential to increase the paths both in size and complexity. Some paths considered in the development of this research were: jagged paths, ladder paths, sinusoidal paths, circular routes, among others.

An interesting possibility to be explored as an additional sensor is the use of simple video cameras to perform monocular visual odometry [10]. Monocular odometry has the advantage of relatively inexpensive and easy to install hardware, also of not requiring high processing capacity of the on-board computer. We believe that data from monocular visual odometry can increase the accuracy of the robot's rotational movements. However, no relevant improvements in linear motion are expected, as it is difficult to infer a scale for displacement and to infer the actual distance traveled.

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