Mobile Robots Navigation in Indoor Environments Using Kinect Sensor

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***Abstract* — This paper presents the development of a perception system for indoor environments to allow autonomous navigation for surveillance mobile robots. The system is composed by two parts. The first part is a reactive navigation system in which a mobile robot moves avoiding obstacles in environment, using the distance sensor Kinect. The second part of this system uses a artificial neural network (ANN) to recognize different configurations of the environment, for example, path ahead, left path, right path and intersections. The ANN is trained using data captured by the Kinect sensor in indoor environments. This way, the robot becomes able to perform a topological navigation combining internal reactive behavior to avoid obstacles and the ANN to locate the robot in the environment, in a deliberative behavior. The topological map is represented by a graph which represents the configuration of the environment, where the hallways (path ahead) are the edges and locations (left path and intersection, for example) are the vertices. The system also works in the dark, which is a great advantage for surveillance systems. The experiments were performed with a Pioneer P3-AT robot equipped with a Kinect sensor in order to validate and evaluate this approach. The proposed method demonstrated to be a promising approach to autonomous mobile robots navigation.**

I. INTRODUCTION

AUTONOMOUS mobile robots have been assuming an important role along with modern society. A relevant type of autonomous mobile robots is directed to the surveillance and indoor safety tasks. Besides being able to navigate and avoid obstacles, this particular kind of robot must perform monitoring tasks, for example, intruder's detection.

For the development of autonomous mobile robots, several aspects must be taken into consideration, such as the type of application and the basic robot platform and sensors adopted, which compose the robot's hardware [1] [2]. Furthermore, a very important component of a robot consists of its control and navigation system, which is the software of the robotic system [3].

Sensors are used to collect information about the robot and the environment. The intelligent control deals with three main problems in mobile robotics: the mapping of the environment, localization and navigation of the robot [4]. A robotic system requires an environment map (the mapping) to plan its route and navigate through it, and information about its position on the map (the localization) in order to navigate from its current location to any other location represented in the environment map.

In this context, an interesting point to study is the possibility of creating autonomous mobile robots at a lower cost and compatible with the various applications currently available on the market [5] [6]. The use of Kinect sensor may represent a significant reduction of a robot costs, as this sensor has been showing that it can replace with large advantage the use of other sensors, including very expensive laser sensors, like the Hokuyo laser [7].

Although robotics has been evolving for decades, most of the existing indoor surveillance robots are not autonomous and reliable yet. Also, in most cases they are not commercial applications. Therefore, we want to propose methods which can be applied to different robotic solutions and that allow the creation of autonomous mobile robots with appropriate cost and great autonomy, ensuring that they can be applied to different problems and tasks.

This paper presents the partial results of the development of an environment perception system**,** composed by two subsystems responsible for: (I) autonomous mobile robots' navigation for monitoring and surveillance tasks in indoor environments, (II) global localization of the robot in an environment represented by a topological map (see Fig. 1). The integration of both subsystems is in progress.

The complete system is a robot directed to vigilant use on a closed structured environment, for example a storehouse. The environment can be characterized by classrooms and hallways and by the presence of several static obstacles (furniture, materials, general objects). The robot must navigate in the environment, being able to avoid collisions and damage.

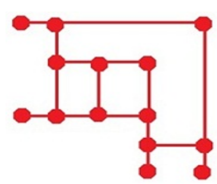

Fig. 1 – Example of a topological map of an indoor environment represented by a graph.

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The next topics of this paper are organized as follows: Section II presents a review of some important related works; Section III presents an overview of the system development; Section IV presents results obtained from tests in the indoor environments of subsystems; Section V shows the conclusion and future works.

II. Related Works

Some important reasons for the development of security vigilance robots in indoor environments can be related to bringing security to the human vigilant, providing accessibility in harmful and inaccessible places to humans and even executing tedious jobs. Although the creation of surveillance robots to indoor environments is not a totally new application [8], this area of research has been increasing [9] [10] [11], allowing a growth in security applications for indoor robots.

Besides the commercial robots, there are many robots used for research in mobile robotics safety. Some examples are the Pioneer and Seekur, manufactured by MobileRobots[1], and the SRV, from Surveyor Corporation[2]. Researches involving these robots, though, still need to earn enough maturity to enable commercial products to employ their technology, doing justice to the robotics goals of contributing to the human safety and comfort.

Among the objectives of this work is the development of a system that must navigate autonomously and safely in an indoor environment. In order to accomplish this, it is necessary to consider some methods for the navigable regions recognition and to avoid collisions with the environmental elements.

Several approaches have been used for navigation using different types of sensors (eg. laser, sonar, GPS, IMU, compass), either individually or combined [4] [12] [13]. One of the most used approaches is the computer vision-based navigation [14], a method that uses video cameras as the main sensor. The cameras have proved to be very suitable for tasks requiring navigation and obstacle avoidance due to its low weight and power consumption [15]. Furthermore, an image can provide many different types of information about the environment at the same time without the need to work with the merging of various different sensors. By using cameras rather than other types of sensors, it is also possible to reduce costs [16].

The implementation of computer vision-based approaches is already common in navigation systems working into structured or semi-structured environments [17] [18] [12] [19] [20]. These systems classify the image by segmenting the region of track and identifying the available path area in front of the vehicle, indicating a safe area for navigation.

Although the solutions mentioned are performing well, the field of view of a conventional camera is quite narrow, and many implementations require the merging of data with laser sensors (eg. Sick LIDAR, Ibeo and Velodyne), radar and/or special vision systems, such as omnidirectional cameras [18] [12] [13]. This fusion becomes necessary especially when one wants to process data related to the depth, which is a kind of information not originally obtained by a conventional camera. In this context, the use of a sensor as Kinect enables the development of low-cost solutions compared with melting methods of sensors.

Kinect is a low-cost 3D sensor developed by Microsoft[3] for the XBOX 360 console which allows the player to use his own body as the game controller. It consists of an RGB camera associated with an infrared transmitter and receiver, which permits to estimate the distance of the elements taken from the environment. The main advantage of the Kinect sensor is the possibility of building depth maps, which provides a fairly accurate estimation of the distance of different kinds of obstacles detected in front of the robot. the The depth map provided by Kinect is a 632 x 480 pixels grayscale image in which each pixel stores the distance from the scene elements to the sensor.

Due to the use of infrared, the sensor is able to create the depth map even at environments with total absence of light. Once its potential as a sensor was detected, several independent studies have emerged in order to exploit the advantages of this equipment in other applications, ranging from healthcare to robotics [5] [6] [7].

In the work [21], a topological navigation system based on artificial neural network and finite automaton is presented. In this work, a robot must move by an indoor environment with a known topological map, represented by a finite automaton, which describes the locations and actions the robot should take. To set the current context and the robot's location, the system uses a trained artificial neural network (ANN) on data from a laser sensor to recognize indoor environment situations, such as open doors to right, left corridors and intersections.

The input data for the ANN used for classification is captured by the laser-based distance sensor Sick LIDAR (Light Detection and Ranging). The disadvantage of this application is the high cost of the main sensor used, a laser sensor that offers only the depth information for a planar cut (detection in two dimensions). The solution using Kinect offers, in addition to extremely lower cost, more complete and accurate information about the environment, since a tridimensional detection is carried out besides the conventional image processing.

[1] MobileRobots – Web: http://www.mobilerobots.com/
[2] Surveyor Corporation – Web: http://www.surveyor.com/
[3] Microsoft Corporation – Web: http://www.microsoft.com/

III. System Overview

The system in development is composed by two main parts. Each of these parts were built and tested in two separate systems in order to validate the methods. The perception system (I) gets information from the sensor (3D depth map from Kinect sensor) to create a map for local navigation. This map is created to make the robot move into the environment while avoiding collisions with obstacles. The second subsystem (II) applies image processing and artificial intelligence techniques over the Kinect sensor data to classify the environment settings, and then contextualize (i.e., locate) the robot within the topological map during navigation. So, the proposed approach combines the system (I), a simple topological navigation reactive control with system (II), to allow the robot to safety navigate through the environment, and simultaneously patrol.

A. Reactive Anti-Collision System

The reactive behavior is the one in which a robot receives information form sensors and reacts by generating commands to the actuators. Using the depth map generated by using the OpenCV library [22] and Kinect, a reactive navigation system was developed to make the robot move in the environment avoiding collisions ahead.

To perform obstacles detection, portions of the image are analyzed (depth map) to define which are very close to the robot. The image is divided into five vertical sections, where three (left, front and right) are analyzed by pixel intensity in order to determine the absolute minimum and maximum distances between sensor and elements (or obstacles) of the environment. At this moment, an analysis is performed to characterize the current situation according to the distance values found for each section. When the minimum distance of a section is less than 60 cm then it is considered that the robot is facing an obstacle.

We defined 8 situations (described in Fig. 2) and 4 speed commands given to the robot: FRONT, RIGHT, LEFT and STOP. For the first command, FRONT, a linear velocity is pre-defined forward. The other two controls, RIGHT and LEFT generate a predetermined angular velocity at which the robot turns on its axis to the RIGHT and LEFT, respectively. The last command sets the zero speed.

The FRONT command is executed when the robot faces the situation shown in Fig. 2(a), which is completely free of obstacles (considering the minimum distance of 60 cm). In situations of Fig. 2(b) and Fig. 2(c) the command executed by the robot is LEFT, since there are obstacles to the right and center section of depth map. The RIGHT command is executed when there are obstacles to the left only or to the left and ahead the robot, as shown in Fig. 2(d) and (e). In the situations described in Fig. 2(f) (obstacles ahead), (g) (obstacles on the sides) and (h) (obstacles to the front and sides), the robot will decide (which may be random) between the RIGHT and LEFT commands to be executed.

B. Corridors Recognition System Using Artificial Neural Networks

The second part (subsystem) of our navigation robotic system is a classifying system trained and used to recognize all possible situations of an indoor environment using data collected previously with Kinect sensor. This section presents the construction and evaluation of this part of the system.

During the navigation, a topological map (graph) must be available to enable the robot to maintain its location, i.e., knowing on which edge or vertice of the graph it is in.

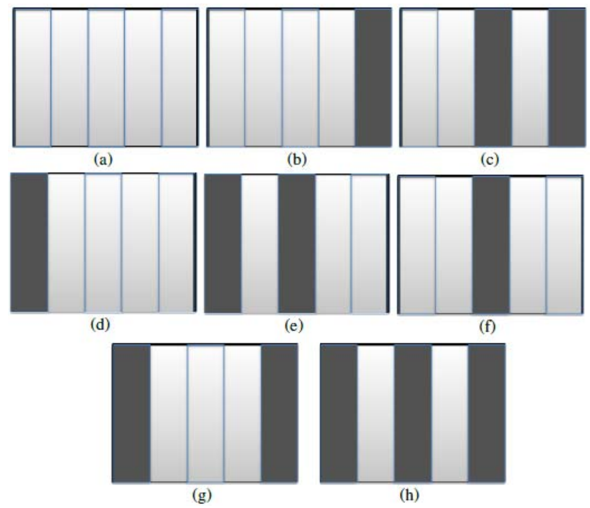


Fig. 2 – Situations in depth map of the reactive system. The portions of darker color image represent obstacle that may be forward, right or left.

We developed a classification system using artificial neural networks implemented with JavaNNS [23], a program which simulates the ANN. The system must be able to read a depth map of the indoor environment (characterized by corridors and open doors) to classify the image in 8 cases (see Fig. 3). The situations are: “path ahead”, “left path”, “right path”, “left and right path”, “path ahead and left”, “path ahead and right”, “blocked path” and “intersection”. Associating these 8 situations to the topological map, we can relate the “path ahead” situation to an edge in the graph and the other ones to vertices.

The data used for the artificial neural network training and subsequently for classifying are provided by the depth map from Kinect. Each attribute from an input pattern of the ANN is a distance value which is the average of 80 rows of the same column. In total, there are 632 values, which is the horizontal resolution of the depth map. The number of rows used and the form of feature extraction of information were chose empirically and can be modified.

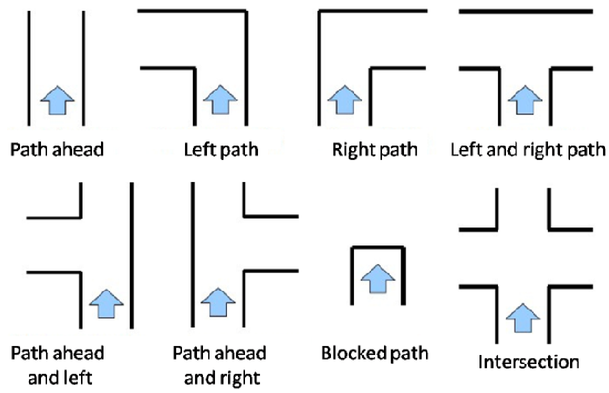


Fig. 3 – Situations of an indoor environment.

IV. Experiments and Results

To test the system implemented, experiments were conducted in a real environment using a Pioneer P3-AT robot connected to a computer, which was responsible for the processing tasks and the reception of data from Kinect, the single sensor device. The tests were performed in closed environments with lights on and off, in order to validate the system's potential for both environment conditions. The operation of subsystems (I) and (II) is presented below.

Fig. 4 (a) shows the reactive system (I) in action. Fig. 4 (b) and (c) show the commands to be followed by the robot, and also the minimum and maximum distances of each section in the depth image. In the situation depicted, the minimum distance measured in the left section is equal to 58 cm (less than 60 cm), therefore the command given to the robot was "RIGHT".

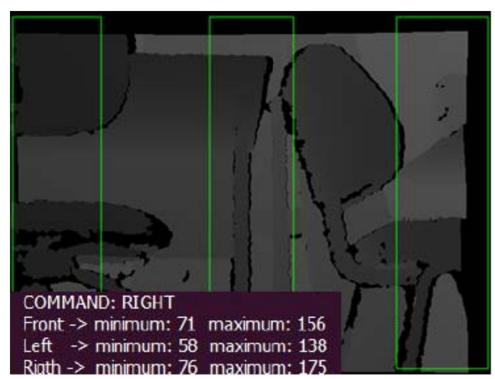
As expected, similar results were obtained in tests performed in dark environments, since the distance sensor does not depend on ambient lighting.

Subsystem (II) uses an artificial neural network to classify the environment configuration in some pre-defined situations. To gather the training data for the network, we took approximately 1400 depth images, while operating the robot remotely. The network training itself was conducted using various network topologies, in order to permit us to choose the best configuration - the one with the lowest error rate. The chosen topology has 632 entries, 316 neurons in the hidden layer and 8 neurons in the output layer.

After the training, tests in real environment were performed still using teleoperation, but this time running the ANN. Using data captured in real time, the classifier should then recognize the situations faced by the robot within the environment. This implementation provided very good results, with more than 92% accuracy on classification.

(a)

(b)

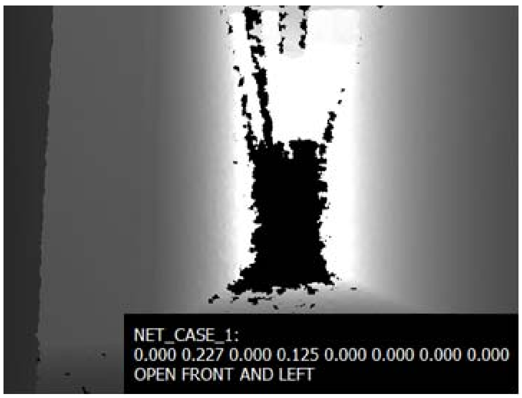


(c)

Fig. 4 – Robotic system during execution in a lighted environment. (a) the of robotic system; (b) the color image provided by Kinect; (c) depth image provided by Kinect.

The classification program run is shown in Fig. 5. Fig. 5 (a) presents the color image captured by the RGB camera and Fig. 5 (b) shows the depth map captured by Kinect. In this case, the situation is classified as "path ahead and left", because the robot is in a corridor with a door to its left.

(a)



(b)

Fig. 5 – Robotic system using ANN during execution. (a) the color image; (b) depth image provided by Kinect.

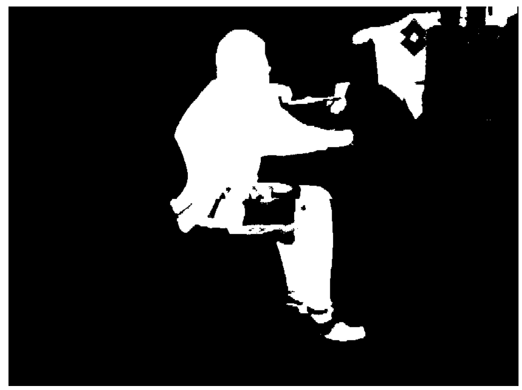
V. Conclusion and Future Works

This paper has presented the preliminar results of the construction of a surveillance system. Two subsystems were developed. The reaction system was effective to provide a safe navigation for the robot and the classification system for indoor situations has shown very good results (92% of accuracy using the ANN classifier).

This work contributes for the development of intelligent control and navigation systems for autonomous mobile robots, which is a very relevant topic to the national and international research contexts. The system can be retrained to recognize additional situations and, besides patrolling tasks, can be applied to many other purposes, such as the exploration of unknown locations.

Furthermore, both subsystems presented in this paper will be integrated as components of a complete surveillance system. Another work in progress is development of the human detection subsystem, which will use images captured by a thermal camera (see Fig. 6 (a) and Fig. 6 (b)) and the Kinect sensors (see Fig. 7).

(a)



(b)

Fig. 6 – Human recognition using a thermal camera. (a) original thermal image; (b) the segmentation image of a human.

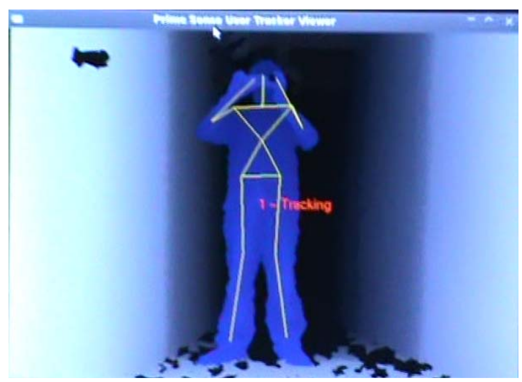


Fig. 7 – Human detection using the Kinect sensor.

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