Affordable Robot Mapping using Omnidirectional Vision

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Abstract—Mapping is a fundamental requirement for robot navigation. In this paper, we introduce a novel visual mapping method that relies solely on a single omnidirectional camera. We present a metric that allows us to generate a map from the input image by using a visual sonar approach. The combination of this metric with the robot's odometry enables us to determine a relation equation and subsequently generate a map that is suitable for robot navigation. Results based on visual map comparison indicate that our approach is comparable with the established solutions based on RGB-D cameras or laser-based sensors. We now embark on evaluating our accuracy against the established methods.

Index Terms—Visual Sonar, Omnidirectional Vision, Visual Mapping.

I. INTRODUCTION

Mobile robots require a navigation algorithm to move in a goal-directed manner. A good understanding of the environment is thereby key for a successful navigation. There are many methods of obtaining this information, such as using a variety and combination of sensors as input. Most popular solutions include a laser range finder to generate highly accurate maps for simultaneous localisation and mapping (SLAM), cf. [1]. However, this method is costly and not always feasible. There are other affordable solutions that use, for example, RGB-D cameras to provide the navigation system with input. However, these are usually limited in their field of view due to the opening angle. Our approach, by contrast, uses a single omnidirectional RGB camera capable for gathering information about the entirety of the robot's surroundings. Our research further identifies a metric for generating a map from the input image using a visual sonar approach to find obstacles around the robot. Data from visual sonar sensors is used to determine a metric distance between the robot and these obstacles. These distances are then used to generate a map that a robot can use for navigation.

II. PREVIOUS WORK

Our approach builds on top of existing work that uses monocular vision instead of a laser sensor to find the obstacles around a robot with the help of edge detection and so-called visual sonars [2]. This approach has been modified to be used with an omnidirectional vision system [3]. It has also been extended to determine a free path by varying the number of sonar beams to identify their ideal range and shape [4]. This method is further capable of mobile robot navigation when using an enhanced model that uses three individual sonars to the left, right, and front of the omnidirectional image to





(b) Sobel Edge detection

Fig. 1: (a) Omnidirectional image with a visual sonar. (b) Result of the edge detection and thresholding algorithm.

detect obstacles and another one to determine a free path simultaneously [5].

III. METHOD

One key characteristic of the previous approach is that it is non-metric. In comparison, we present an omnidirectional vision system for mobile robot navigation that generates a metric map. Our method consists of two steps: (A) visual preprocessing to find edges that represent obstacles and to calculate the sonar beams and (B) a fitting step to relate the pixel distance to real-world lengths.

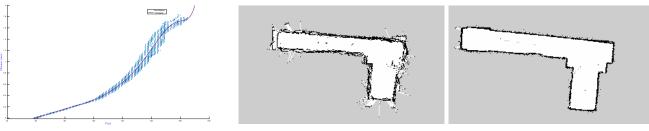
A. Visual processing

First, a sobel operator is used to detect edges in the image. We further apply a black and white threshold to remove noise (cf. Fig. 1b). In parallel, we use an algorithm to identify and mask surface reflections to prevent them from being incorrectly identified as obstacles [4]. We then generate visual sonar beams that measure distances to obstacles in a similar way as standard sonar technology. Instead of using acoustic signals, visual sonar works on the preprocessed image and results in pixel-based distances [6]. That is, the beams originate at the centre of the image and extend outwards until they reach an edge. Figure 1a shows an exemplary beam (blue) on an omnidirectional image.

B. Sonar Fitting

In this section we present a novel method to calculate the metric distance between robot and obstacles, taking into account the pixel-based characteristics of visual sonar. Each sonar beam forms a vector of visual sonar consisting of a group of pixels. The length of this vector is the number of pixels. For instance, the sonar between robot and the wall in Figure 1a has a length of 158 pixels. This distance corresponds to a metric length, which can be identified using the robot's odometry, i.e. by moving the robot around between defined places. A relationship can be found using a fitting method that relates changes in the robot's position to changes in the pixel distance that originates from the visual sonar. Since all visual

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(a) Calibration and Curve Fitting Plot

(b) Visual Sonar Model Map Fig. 2: Calibration and Mapping Results

(c) Laser Map

sonars start from the centre of the omnidirectional image, a single sonar sensor can be considered alone to identify this relationship, which can then be used for the other sensors. A dense calibration is necessary to find the correlation function f between the sonar pixels and their real-world distance. We have designed a routine that begins with the robot placed sufficiently close to a wall so that the sonar vector's first pixel can be detected. The robot is then moved back. Information is gathered from the odometry to obtain a real-world distance. We then use the fitting model described above to determine the metric distance from the visual sensor, obtaining from this fitting method an equation that takes pixel input and outputs the metric distance.

IV. EVALUATION

We replaced the standard RGB-D sensor with an omnidirectional camera on top of a TurtleBot2e¹ to evaluate our approach under realistic circumstances, cf. [4]. We also mounted a DS-01 360 laser distance sensor to map the environment for ground truth data. Our experiments, all of which were performed at University of Hertfordshire's Robot House, consisted of two parts: calibration and mapping.

A. Calibration

A successful calibration is the prerequisite for applying our approach to a robot's navigation system. We, therefore, performed a series of tests moving the robot backwards at different speeds. Each of these tests have been repeated 10 times to gather odometry data and sonar pixel lengths. Results indicate that the most reliable data is obtained from calibration tests in which the robot moved slowly (velocity: 0.0 angular, -.05 linear) and the front was free from obstacles. Moreover, a straight robot movement with minimal deviation from its intended path led to the most optimal results. Figure 2a shows the result of fitting of a polynomial using one of the most reliable calibration routines. The following function d = f(x)describes the relation between the distance d in cm and the visual sonar length x in pixels:

$$\begin{split} f(x) &= (0.0125 * x^7) + (0.0552 * x^6) + (0.0533 * x^5) \\ &- (0.0910 * x^4) - (0.1683 * x^3) + (0.0784 * x^2) \\ &+ (0.4732 * x) + 0.5147 \end{split}$$

¹A platform specification can be found at turtlebot.com/turtlebot2

B. Mapping

With the function f(x) and the visual sonar, we can calculate metric distances that can be used in mapping. Figure 2b shows an exemplary map that has been recorded using SLAM² on a modified TurtleBot2e to use our visual sonar approach. As a comparison, Figure 2c shows the same area recorded with the high precision DS-01 360 laser. The visual sonar method has generated a map that is not as precise as the one generated with a laser and contains some artifacts but it is suitable for navigation tasks as we were able to successfully use it for driving the robot.

V. CONCLUSION

We have presented a novel method for calculating the metric distance between a robot and obstacles based on a visual sonars. It correlates pixels from an omnidirectional image and the robot's odometry by fitting a function that determines the relationship between the sonar's length in pixels and a real-world distance. We have demonstrated that this method produces comparable results visually. For future work, we aim to revise the edge detection algorithm and plan to integrate regression learning to further improve results. Moreover, we plan a study to compare the approach's performance to other methods and technologies, such as RGB-D cameras and laser sensors and to calculate their precision and computation time.

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²We used the standard ROS gmapping suite from wiki.ros.org/gmapping