Affordable Robot Mapping using Omnidirectional Vision

Mohammad Hossein Bamorovat Abadi, Mohammad Reza Shahabian Alashti, Patrick Holthaus, Catherine Menon, and Farshid Amirabdollahian

***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 the visual sonars 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.**

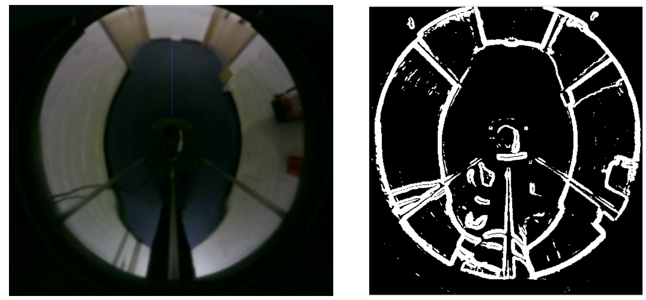
I. INTRODUCTION

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, lasers that provide a high scanning rate often cost more than £1,000 and are not always feasible. However, lasers that provide a high scanning rate often cost more than £1,000. 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]. The method can enable robot navigation when using an enhanced model that uses three individual sonars to the left, right, and front of the image to detect obstacles and another one to determine a free path simultaneously [5].

All authors are with the School of Physics, Engineering, and Computer Science, University of Hertfordshire, College Lane, Hatfield, AL10 9AB, UK. Corresponding author's email: m.bamorovat@herts.ac.uk



(a) Visual Sonar Beam (b) Sobel Edge detection

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

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 comparable to normal 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 example 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 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 d 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 and from the visual sensor for a change in pixel distance. We then use the fitting method 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 RGB-D sensor of a TurtleBot2e[1] with an RGB camera-based solution (<£50) to evaluate our approach under realistic circumstances, cf. [4]. We also mounted a rotating DS-01 laser (£150) as a high-precision alternative to compare the mapping results. 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 has been repeated 10 times to gather odometry data and sonar pixel lengths. Results indicate that the most reliable data is obtained from a calibration with a slowly moving robot (velocity: 0.0 angular, $-.05$ linear) without any obstacles in front. Moreover, a straight robot movement with minimal deviations from its path led to optimal results. Figure 2 shows the result of fitting of a polynomial using one of the most reliable calibration routines. The function $d(x)$ describes the relation between the distance d in cm and the visual sonar length x in pixels:

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

B. Mapping

With the function d and the visual sonar, we can calculate metric distances that can be used in mapping. Figure 3 shows a map that has been generated using SLAM[2] to use our visual sonar approach. As a comparison, red colour indicates the mapping of the same area that has been recorded with the high-precision 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.

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

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

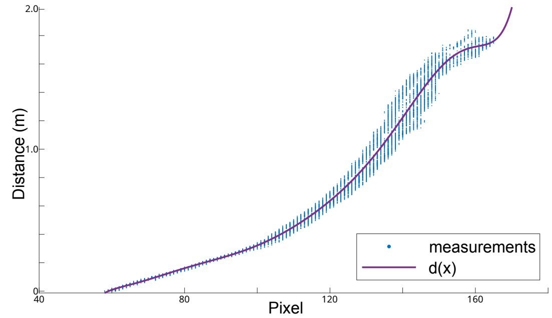


Fig. 2: Calibration and polynomial odometry fitting d

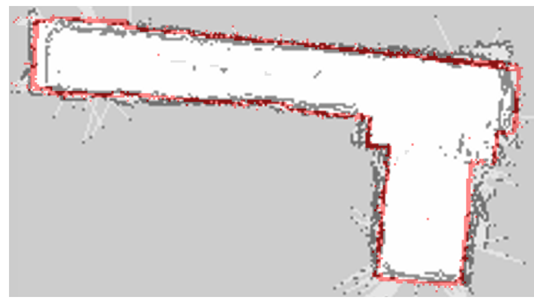


Fig. 3: Mapping result with laser comparison in red

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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