GI_Forum 2018, Issue.1
Page: 152 - 161
Full Paper
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DOI: 10.1553/giscience2018_01_s152

Indoor Mapping for Human Navigation – A Low-Cost SLAM Solution

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Abstract

This paper introduces a low-cost Simultaneous Localization And Mapping (SLAM) implementation for generating geodata for human-navigable maps. In contrast to prevalent thinking, we maintain that navigation by people who are not mobility-impaired does not need accurate maps down to millimetres or even centimetres. Basically, there is a need only to map the boundaries of spaces and to highlight walkable places and areas of potential decisions. The SLAM system presented here consists of an Arduino-based robot and controlling SLAMTerminal software. A case study conducted at the University of Augsburg, Germany shows that the proposed SLAM implementation is capable of producing a map suitable for helping pedestrians to navigate.

Keywords:

SLAM, low cost, indoor navigation, places, spaces

1 Introduction

In navigation research, indoor systems have been attracting more attention. Whilst there are an increasing number of papers being published specifically on indoor navigation and positioning methodologies (Becker et al., 2009; Schnitzler et al., 2016; Werner et al., 2014; see also LBS and IPIN conferences), the lack of maps and/or spatial data suitable for use in navigating through indoor environments is striking. This might be one of the reasons why the number of systems applied successfully in real-world environments is still very low, especially in Europe, where different languages and cultural environments compound the problem.

Many different solutions have been put forward to accurately map indoor spaces for a variety of applications, including human orientation and navigation (Huang et al., 2010; Vanclooster et al., 2016). However, the geodata needs in terms of the accuracy of the mapped spaces differ widely depending on the type of application and its tasks. For example, the accuracy of data needed to navigate successfully using a wheelchair is much higher than that needed by pedestrians who are not mobility-impaired. While it might be desirable to have highly accurate data, we argue that we should adopt a 'good-enough' approach, producing data for pedestrians without mobility impairment and refining it where and when necessary for higher accuracies (e.g. doors and corridors in hospitals to allow for wheelchairs and trolley beds, or where a specific pre-defined path needs to be followed). This approach has the potential to speed up the data-gathering process. We focus solely on mapping spaces that allow walking, making sure that the connectivity to other walkable spaces is perceived correctly. Walkable spaces are connected by places of potential decisions. As stated by Rüetschi et al., (2004), open spaces do not necessarily need specific networks. Consequently, this work assumes that non-impaired individuals only need hints as to when a specific decision might lead to a grave error.

In this paper, we report on an experimental setup, using a robot, geared towards producing maps of indoor spaces for non-impaired human navigation. The aim is to present another possibility for creating a base for indoor navigation applications. Simultaneous Localization and Mapping (SLAM) allows the rapid generation of navigable outlines that may be converted into navigable spaces and thus maps. Due to the complexity and size of indoor spaces, it is impractical to use manual methods for mapping indoor environments (Worboys, 2011). Thus, we focus on SLAM as a (semi-)automatic repeatable method for data collection. Traditional SLAM (Aulinas, 2008) has been applied mainly in the area of robot navigation, requiring a relatively high precision of SLAM output in order to be usable for maps for robot movement. This has sparked research on better and faster sensors, measurement approaches and post-processing of measurement data. But every increase in accuracy has been accompanied by higher equipment and/or processing costs.

With human navigation in mind, we are convinced that it is not necessary to provide high-accuracy SLAM output requiring a host of post-processing steps. Therefore, the questions we set out to explore in this research were: When adopting a 'good-enough' approach, is the output produced by a low-cost SLAM solution sufficiently accurate to allow for pedestrian navigation in buildings? Which post-processing steps are necessary to produce a reliable map of navigable spaces?

In the following sections, we will first review recent developments in SLAM, look at SLAM in the context of human navigation, introduce our low-cost SLAM solution, and describe and discuss how SLAM results may be used for pedestrian indoor navigation. We conclude by answering our original questions and describing future research.

2 Recent Developments in SLAM

According to Cadena et al. (2016), SLAM research can be divided into three periods. Lasting from 1986 until 2004, the classical age of SLAM was dedicated to probabilistic formulations dealing with topics like Bayesian filters, maximum likelihood estimation, or data association. 2004 to 2015 saw the algorithmic analysis phase. Fundamental properties of SLAM like consistency, convergence and observability were the focus of researchers during this period. Another development during this same period was the provision of open-source SLAM solutions for a wide community. Cadena et al. (2016) argue that there is a further period of development, which they call 'the robust-perception age'. Therefore, factors such as robust performance, high-level understanding, resource awareness and task-driven perception will be urgent topics in future research.

Current SLAM-related research is highly multidisciplinary. Figure 1 presents an overview of SLAM research topics.

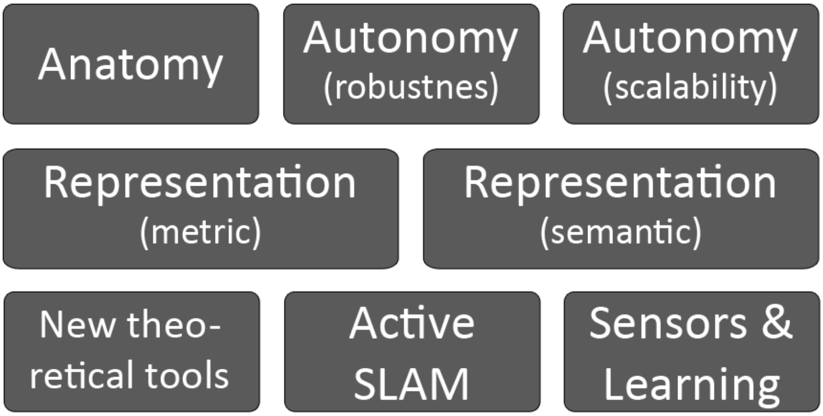

Figure 1: Current SLAM research fields.

The literature assignable to the sub-domain of the anatomy of a SLAM system includes Mourikis et al., (2007), who implement a SLAM system based on a modified extended Kalman filter. In the field of the autonomy of SLAM systems, researchers such as Wolcott et al. (2014) work on topics related to the robustness of the systems. Literature addressing the scalability of SLAM implementations includes the work of Cieslewski et al. (2015) on decentralized maps. The field of representation is concerned with metric and semantic map models. Soatto et al. (2016) review possibilities for achieving optimized visual representations. Establishing performance guarantees is one of the main aspects of research into new theoretical tools. Carlone et al. (2016) have published an approach addressing the duality of SLAM results. Active SLAM addresses the autonomy of a mobile robot while the robot is performing SLAM. The work of Wahlström et al. (2015) discussing deep learning also falls into the category of active SLAM. Using new kinds of sensors and computational tools has always been a driving force for the development of SLAM implementations. Soatto's (2011) paper discussed the dependencies of sensors on the parameters of their algorithm as well as on the environment.

3 Introducing a low-cost SLAM implementation

The research field of robotics provides various configurations for SLAM systems. Fernández-Madrigal (2012) is a good reference for technical aspects concerning the construction of SLAM robots. Taking into account our main aim expressed in section 1 (the rapid generation of navigable maps for humans), several robotic configurations are available for SLAM tasks.

We chose a two-wheel differential system was chosen as driving unit for the robot. This configuration lets the system move and turn without an additional steering actuator. An approved positioning framework for this kind of kinematic configuration is the non-holonomic model with one increment and one angle. Technically, movement at a time step k can be represented using a state vector Xk and an action vector uk. While the current state consists of position (xk, yk) and angle (øk), action is described by the distance travelled Δuk and the change in direction $\Delta\beta$k. For processing SLAM results, there are several possibilities. Mapping occupied places within the environment using point features is one recognized approach (Fernández-Madrigal 2012).

Figure 2 illustrates an example of a robotic configuration for SLAM tasks. Different units provide the functionality needed for creating maps for indoor navigation. The most important features are outlined below.

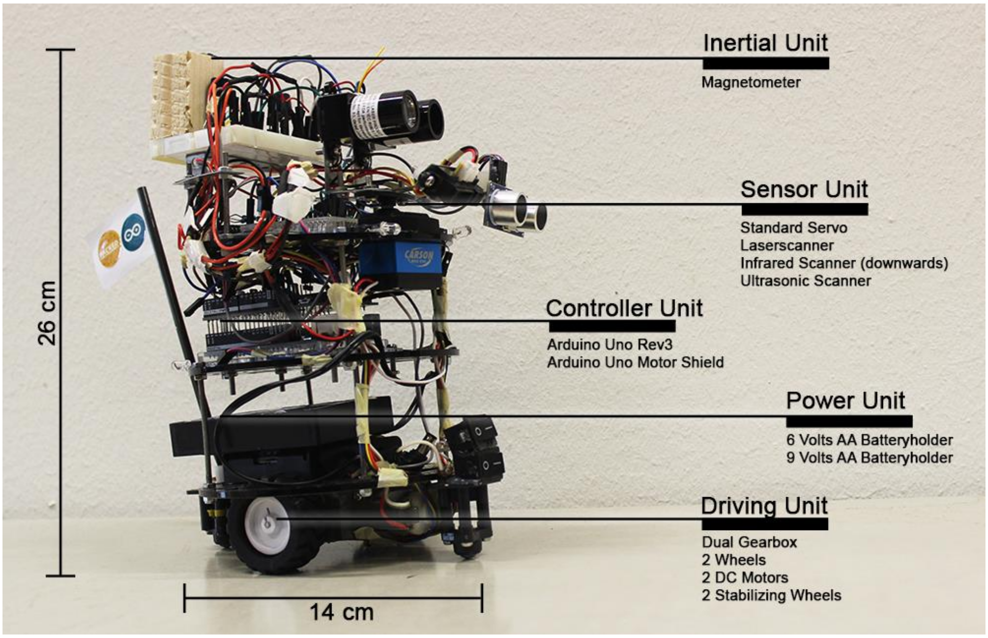

Figure 2: Configuration and dimensions of the SLAM robot.

A power unit provides the necessary energy for the controller unit, which supervises any action performed by the robot. As a powerful low-cost solution, the Arduino Uno micro controller equipped with a suitable motor shield was used. In order to move the robot in directions X and Y, a driving unit is required. In practical terms, this was accomplished utilizing a dual gearbox equipped with two brushed DC motors. Two additional ball caster wheels provided stability while driving.

We used several sensors in order to track the progress of the robot: as well as a speed encoder mounted on one of the wheels, an inertial sensor for sensing the alignment of the robot was required. In our case, a digital magnetometer provided information about the current heading of the SLAM robot.

To sense the environment, a sensor unit is required. In order to achieve a suitable field of vision, the unit was mounted on a rotating servo motor. Depending on environmental circumstances, several types of sensor can be used. In this case, a low-cost LIDAR device was used to measure the distance to any obstacle. Because laser-based sensors cannot detect glass elements, an ultrasonic range finder was also used. In order to detect changes in floor level (for example where there are stairs), an additional device pointing downwards by 45 degrees is recommended.

The wiring scheme for this particular robotic configuration is shown in Figure 3. Because of the specifications of the sensors, voltage dividers and capacitors were included (not shown in Figure 3).

Some software development is also required. In addition to the Arduino sketch controlling the hardware parts of the robot, a program processing raw output data and visualizing it as a map is needed. For this implementation, a simple python-based software, SLAMTerminal, was developed. This program is capable of controlling the movement of the robot and therefore no additional Bayesian filter was implemented. The points sensed by the range-finding devices are processed and visualized in a matplotlib diagram.

The whole SLAM system costs approximately 300 euros, and about 10 hours of development time were needed for the software.

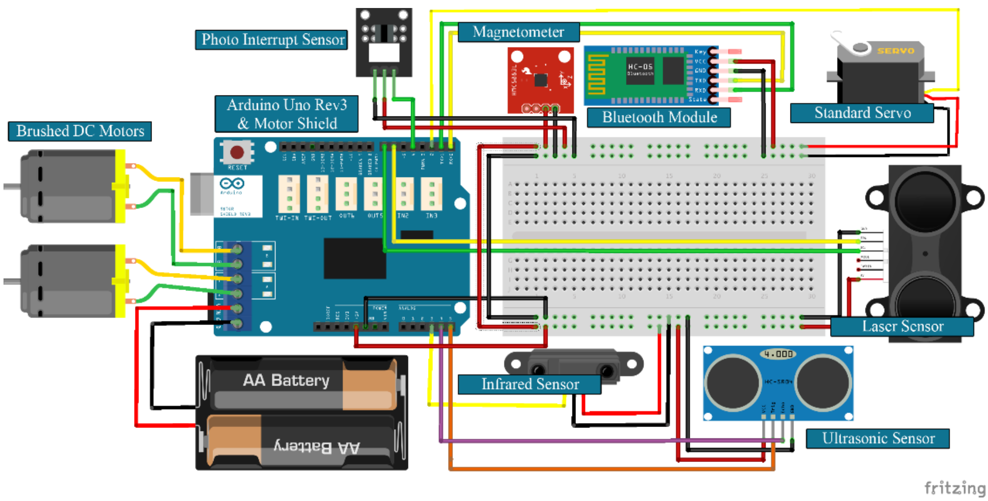

Figure 3: Wiring scheme for the SLAM robot.

The following section describes a case study that used the SLAM system described above.

4 Creating Human-Navigable Indoor Maps Using SLAM

The foyer of the Institute of Geography at the University of Augsburg, Germany was chosen as the research area. Figure 4 shows the surroundings.

Figure 4: The research area.

Before we carried out the experiment, we identified a number of physical or structural difficulties in the research area itself. In the middle of the foyer is a staircase, leading both up and down, which is challenging for the SLAM robot's sensors and actuators. There were also some glass elements, such as the main entrance door, which might prove invisible to the sensors or cause reflections that produce false data points. Finally, it was thought that a number of small holes in the floor surface might cause problems for the robot's movement.

The experiment was carried out on Monday, 16 October 2017. Traversing the research area for about 20 minutes, the SLAM robot produced the map shown in Figure 5 (white dots). In order to evaluate the results, the figure was enriched with the actual floor plan of the foyer (yellow dots).

As can be seen, nearly every feature perceptible on the floor plan was sensed. Furthermore, the driving unit was powerful enough to cover the whole area. The holes in the floor's surface proved not to be a problem. However, in places there are blank spaces because many glass areas were incompletely detected. Another weakness of the mapping is that it does not show the staircase leading down. This kind of feature cannot be picked up using the current robotic setup; the device would have had to follow the stairs directly parallel to the lowering. The warping of the walls is another indicator of error. The maximum error in comparison to the actual floor plan is about 70 centimetres.

Figure 5: Result of the SLAM measurement compared to the actual floor plan.

There are several solutions for correcting the measurement errors that occurred. The problem with the glass elements is due to the fact that a laser-based sensor does not detect transparent features properly. The sensor fusion approach applied to the sensing unit would have to be reconfigured in order to obtain better results. A possible improvement might result from a more frequent use of the ultrasonic device, which is capable of sensing glass. Computationally reconfiguring the sensor unit would be a solution for detecting the complete staircase. Using a downwards-facing range-finder would be a good approach, though the detection would have to be implemented algorithmically within the software. The warped features in the output map are an indicator for odometry errors. Since the positioning algorithm did not use any Bayesian localization filter, this finding is not surprising. Localizing the robot is just an approximation of the reality taking many possible errors into account. Hence, including a computational solution like an extended Kalman Filter would influence the results beneficially. Another consequence of the localization errors is the loop-closure problem: some features are not satisfactorily connected to their neighbouring points. This phenomenon emerges initially between two single measurements with diverse localization errors.

The following section discusses the usability of the map for human indoor navigation tasks.

5 Discussion of Methodology and Results

With a budget of 300 Euros and software development time of 10 hours, our SLAM system can be said to be low cost. Depending on their accuracy specifications, other SLAM systems generally cost several thousand Euros. However, the question arises of whether the output generated is 'good-enough' to allow pedestrians who are not mobility-impaired to navigate. As discussed in Section 1, a certain level of error in SLAM result maps is acceptable. Since the output generated is for use by people who are not mobility-impaired, small failures do not affect the results significantly. As we have seen, the case study produced a map close to the real situation, with some errors. To evaluate the results, Figure 6 gives an approximation of some of the most striking differences between the resulting map and the actual floor plan.

Some features are mapped quite accurately, while there are also some failures. As seen in Figure 6, error values vary between 0 and approximately 70 centimetres. Whilst the upper part of the map shows good accuracy, features detected on the lower left side tend to show errors. Chronologically, points with the highest error values were detected later than the highly accurate features. This is due to technical issues concerning the localization process presented in Section 4.

Due to the inaccuracies, the SLAM implementation presented here is not suitable for robotic navigation tasks. Furthermore, the output is not appropriate for wheelchair navigation. However, since the accuracy requirements for people who have no mobility impairment are not very high, our implementation does have some level of capability. While some of the walls are placed a little inaccurately within the environment, walkable spaces are clearly perceptible. All in all, therefore, we consider that the proposed SLAM implementation is suitable for generating the basis for maps for non-impaired human indoor navigation.

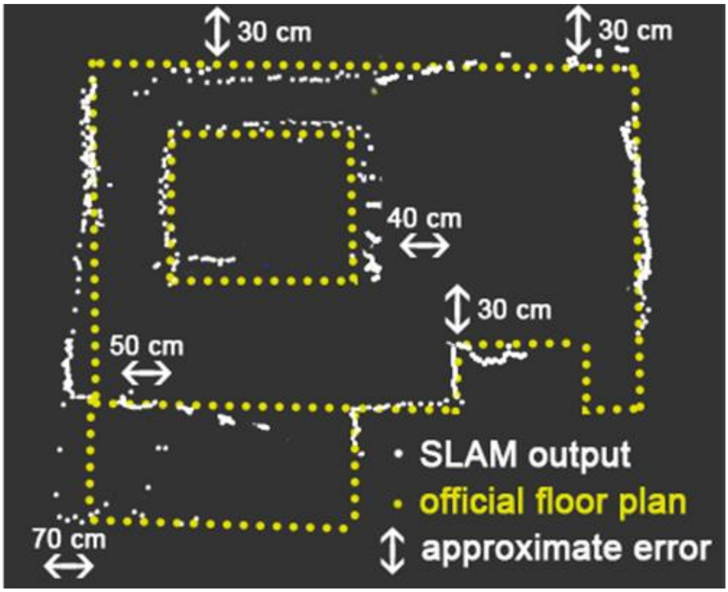

Figure 6: Approximate differences between SLAM result and actual floor plan.

6 Conclusions and Further Research

The aim of this research was to introduce a low-cost SLAM implementation allowing the rapid generation of a basis for navigable maps for indoor environments. As discussed, there are several types of use cases requiring varying levels of accuracy linked with indoor maps, including (among others) non-impaired pedestrians, wheelchair users and robots. We chose the use case of non-impaired pedestrians as the group with the lowest accuracy requirement. For a total cost of 300 Euros, a robot was constructed for taking LIDAR-based SLAM measurements. The SLAMTerminal program was developed for controlling the robot's actions and visualizing the scans. As a trial environment, we selected the foyer of a university building. The outcome of the experiment is a fairly accurate map for many parts of the environment. Nevertheless, there are some errors for some of the features. Since the maximum error did not exceed 70 centimetres, we consider the implementation to be capable of generating the basis for maps for human navigation. We can therefore tentatively answer in the affirmative the first of our research questions: 'When adopting a good-enough approach, is the output produced by a low-cost SLAM solution sufficiently accurate to allow for pedestrian navigation in buildings?'. The results of the study could be used for various applications, e.g. as the basis for indoor navigation systems in large complex environments such as airports or hospitals. It could also be used to map unknown, hazardous indoor environments, for example ones where gas or smoke are present.

Improving the processing part of the software is an aim of future research. A Bayesian filter would make the localization process more accurate. According to Fernández-Madrigal (2012), using an extended Kalman filter is an appropriate approach for SLAM applications. This would eliminate warped features within the output map as well as any loop-closure problem. Thus, the output map would also be improved. This answers our second research question, 'Which post-processing steps are necessary to produce a reliable map of navigable spaces?'.

Furthermore, the requirements for mapping changes in floor level, such as staircases, need to be implemented. In many indoor environments, staircases are prominent features. However, their physical characteristics prevent mapping them properly. Reconfiguring the sensor unit of the SLAM robot and doing further computational work on the processing code will improve this. In order to evaluate the output of the SLAM robot properly, further case studies need to be conducted. Various types of feature present in indoor environments are challenging for the robot's sensor technology. Furthermore, experiments in larger and more heterogeneous environments than the one in this case study will need to be carried out.

Finally, there is a need to conduct further experiments utilizing the actual outputs of SLAM measurements generated in the manner presented here. For example, in order to evaluate the results, test persons should use some of the output maps to navigate through specific indoor environments. Doing so, they may answer the question of whether the SLAM system is capable of generating maps for navigation by people who are not mobility-impaired.

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