Improving Mixed-initiative Collaboration between Humans and Robots when Vacuuming the Floor by Tracking Manual Cleaning

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Autonomous vacuum cleaning robots often miss small spots of dirty areas which in turn have to be cleaned manually. This leads to shortcomings of autonomous cleaning assistants. However, a robot's cleaning process can be improved by using information about which areas have been vacuumed manually. By learning which spots are repeatedly gone over by humans and can lead to a mixed-initiative interaction between the human and robots. We developed a prototype of a handheld vacuum cleaner which can track the areas which it is used it for cleaning by the very human. This work-in-progress paper contributes our mixed-initiative approach of vacuuming and a technical prototype. We also discuss further steps and evaluating the prototype.

CCS Concepts: • **Human-centered computing → Ubiquitous and mobile computing systems and tools**; • **Computer systems organization → Robotics**; **Sensors and actuators**.

Additional Key Words and Phrases: Human, robot, vacuum cleaning, indoor localization

1 INTRODUCTION AND RELATED WORK

Robot vacuum cleaners are very common in private households and sales are still increasing [6]. They support humans with taking over tedious housekeeping tasks and increase well-being, while their owners expect them to learn and adapt over time [4]. However, their work as assistants has some shortcomings: actual robots can repeatedly miss spots of dirty areas and do not clean as thoroughly as humans would do. As a result, users have to clean those areas in addition with traditional handheld vacuum cleaners.

Most related work for improving a robot vacuum cleaner focus on improving the robot itself as a standalone device. Kim et al. [7] for example propose to make the vacuuming process more human-like by manually analysing the vacuuming behaviour with a focus on path planning. Vaussard et al. [13] agree with these findings and further enrich these research. The actually manual collected data these studies are based on could be improved and automatically generated respectively renewed with our prototype. Kwon et al. [11] integrated a robot in a smart home environment and evaluate different approaches to detect when it is a good time to either start or not start a vacuuming process. Also Forlizzi and DiSalvo [4] describe that users expect robots to learn over time and adjust its behaviour.

Rather than separating floor cleaning into two distinct problems for humans on the one side and robots on the other side, we propose a mixed-initiative approach [5] for vacuum cleaning: By tracking the manually cleaned areas the autonomous robot can use this data to better assist their owners. We combine the information of both devices to improve the whole vacuuming assistance process so that the user has not to vacuum manually further. Further, users

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do not have to interact with the robots explicitly. It happens as an implicit interaction while they are vacuuming the floor as usual. The robot can adapt to the manual work. We developed a working prototype of a handheld vacuum cleaner which tracks the vacuumed areas.

In this work-in-progress paper, we propose an approach for improving human-robot collaboration with regard to vacuuming. We contribute a prototype which applies sensing to a manual vacuum cleaner for tracking human vacuum behavior. We evaluate our solution and discuss lessons learned.

2 PROTOTYPE

The main challenge of our approach is indoor localization and tracking of the manual vacuuming process. Typical outdoor techniques such as GPS can be hardly used in a building with thick walls because of the shielding [3]. Another approach is localization with Bluetooth Beacons. But they have to be installed and calibrated in the custom environment. Also their accuracy in the order of meters is accurate enough [2]. For usability reasons we want to use an approach where the users do not need to install additional equipment in their flats. Camera based approaches were also not reviewed because of the possibility of privacy violations. Furthermore we need a technique which has an accuracy of about 10cm to get usable results. So we take a deeper look at Monte-Carlo-Localization (MCL). MCL is a very common approach for indoor localization. It is a probabilistic localization approach and uses environmental sensor data combined with odometry [12].

We use a light detection and ranging sensor (LiDAR) for distance information. Here we can expect good results and it has already shown that it works for this approach because it is used in other vacuuming robots for example. The LiDAR detects the ranges in angle of 360 degrees around itself and measures the distance to the next obstacle. The LiDAR we used has a range from 7 cm up to 4.5 m.

Odometry data contains information about the movement of the vacuum cleaner itself. It contains movement along the floor and also the rotation while moving. Because we do not have an automated move control which knows by itself how it moves we have to detect this with the help of other sensors. For this we want to short introduce the approach of the Canonical Scan Matcher (CSM) by Censi [1]. We tested the ROS (robot operating system) implementation [8] of the algorithm and take a look at the generated odometry data. We found the data good enough (accuracy in order of cm) for our approach so we decided to test it with a real prototype.

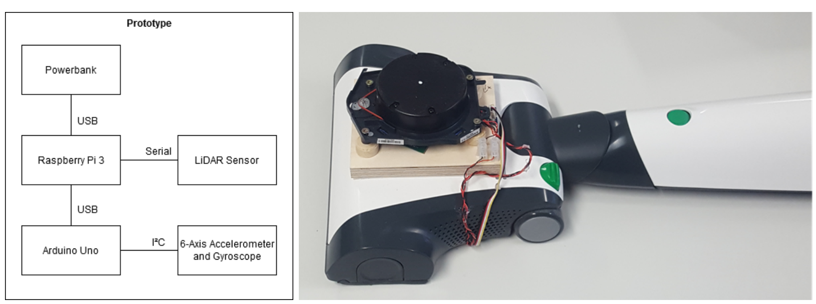

Fig. 1. Hardware components and their connections

The used hardware and connection between them is conceptually shown in figure 1. The main component of our prototype is a Raspberry Pi 3 which draws power from a usb connected power bank. There is a LiDAR sensor connected via the serial port to the raspberry. We also connected a 6-axis accelerometer and gyroscope with the help of an Arduino Uno to the Raspberry Pi. The Arduino was necessary because there was no SDK available for the sensor that fits the Raspberry Pi. So it was easier for us to connect the additional device between the raspberry and the sensor and send the data via USB to the raspberry pi. All of this hardware was mounted on the vacuum cleaner. Figure 1 shows the final prototype. The LiDAR and 6-axis accelerometer/gyroscope is mounted on the cleaning unit. From there the cables are going through the air duct to the inside of the vacuum cleaner where we removed the vacuum cleaner bags and places the raspberry pi with power supply. We figured that we got best results when placing the sensors at the center point the cleaner would turn around.

The software implementation of the prototype is based on the Robot Operating System (ROS) [9]. We used ROS version "kinetic" for our implementation. The whole software runs on locally on the Raspberry Pi. ROS is a modular system and connects so called "nodes" through synchronus communication via function calls or asynchronus communication via pub/sub on different topics. We used mostly available packages (as nodes) and also implemented some individual nodes for custom behaviour. Core of the implementation is the public available AMCL ROS-Package, which provides a probabilistic localization system. "It implements an adaptive MCL approach [...], which uses a particle filter to track the pose of a robot against a known map" [10] as described in [12]. So this package, which we started as a single node, builds the center of our application. It gets the odometry and LiDAR sensor data as well as the already generated map and publishes the calculated pose of the vacuum cleaner in real time.

3 FIRST EVALUATION

For evaluation of our prototype we build a small test area. The test area and the map, generated by the robot vacuum cleaner, is shown in Figure 2. We did a series of tests and we found that in most tries the vacuum cleaner successfully could localize itself. To give a better insight we show a example vacuuming process in the following. In each of the figures we see a picture of the room and where the vacuum cleaner is at this time. In the upper left corner we see a heatmap where the vacuum cleaner was tracked in the past since begin of the process. In the bottom right corner we see the map with the current particle cloud and estimated position of the robot.

In Figure 2(a) we can see the initial state of the localization process. Global localization was initialized so the particle cloud is spread across the whole map. At this time the device has not localized itself. Starting to vacuum the test area is showing in Figure 2(b). We can see that the particle cloud is getting smaller and focusing on the center area away from the walls. But it has not localized itself at this time. After approx. 15 seconds of vacuuming there are two separated particle clouds on the map. This regards to the symmetry of the room. The algorithm recognizes that it is with a high probability on either one or other end of the room. The position of the device is already correct visualized. This is shown in Figure 2(c). By going on with vacuuming we can see in Figure 2(d) that the particle cloud finally focuses around the real position of the handheld vacuum cleaner. The localization process was successful. We can also see that the red points in the heatmap show the positions where the vacuum cleaner was during the process.

4 CONCLUSION

This work-in-progress paper deals with improving collaboration between robots and humans in the area of vacuum cleaning. We propose to track manual vacuuming and improve robot cleaners with the information on where humans have went over the floor again or tidy very often. This leads to a more human-centric approach of robotic assistance for floor cleaning. Our work contributes a working prototype of a sensor-instrumented handheld vacuum cleaner which is capable of tracking itself inside our test area.

(a) Initial state of the test scenario

(b) Status shortly after the start of the test scenario

(c) Status 15 seconds after starting the test scenario

(d) End status of the test scenario, successfully localized

Fig. 2. Different states of the test scenario

For future work, we are planning to further improve our tracking by including odometry data from rotation sensors attached to the wheels. Further, we thought about integrating WiFi localization for localizing objects within a room. This could especially be helpful for rooms with a similar floor plan in case of global localization, especially to address the kidnapped robot problem [12].

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