Performance Metrics for Coverage of Cleaning Robots with MoCap System

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Abstract. Nowadays there are a lot of kinds of cleaning robots which producted by different manufacturers come into people's lives. But it is still a problem that how to evaluate each robot's performance to check whether the quality is acceptable. In this paper, we make the first trial to evaluate the complete coverage path planning algorithm which is the core algorithm of a cleaning robot with Mocap system, and three simple metrics were proposed to evaluate overall performance of the algorithm. Lastly, the comparisons between different kinds of robots are presented.

Keywords: Cleaning robot · Mocap system · Coverage algorithm

1 Introduction

A robotic vacuum cleaner (or robot cleaner or cleaning robot) is a service robot [7,15] which designed to help people clean their houses efficiently, one of the popular robot cleaners is Roomba [13]. A typical robot cleaner is composed of a mobile base, cleaning units, collision sensors and attachments. Nowadays many robot cleaners are equipped with lasers, they will build a map to help them generate a more efficiently cleaning path. Robot cleaners from different manufacturers vary in price, size, motors, sensors, efficiency and so on. There are already many evaluation indexes of a robot cleaner such as price, noise, suction. However, these evaluation indexes are often performed by unofficial third party evaluation organizations, and the process of evaluation is often carried out manually and the data are not recorded for post review. Therefore, a general framework of performance evaluation of a robot cleaner is needed to address this problem.

We will focus on evaluation the performance of the coverage algorithm of a robot cleaner in this paper, because the algorithm has greatest contribution to the intelligence of the robot. It is urgent to have a general framework to evaluate the performance of a robot cleaner for the following reasons: (1) A customer wants to know which type of robot cleaner is more efficient or more suitable for their needs. (2) Currently evaluation methods rely on experience, for example,

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A tester sprinkles scraps on the ground and see how many scraps are left with eye after the cleaning robot finish cleaning, this kind of method is not scientific. (3) Different kinds of robot cleaners vary in hardware and software, therefore we can only rely on external measurement to evaluate their performance.

In this paper, we proposed a general platform for evaluating the performance of coverage of a cleaning robot. Then we discussed the three criterias for measuring the performance. Lastly, we conduct the experiments to evaluate the performance of complete coverage algorithms of three robots which manufactured by different companies.

2 Related Work

Complete coverage algorithms have applications in floor cleaning [14], and lawn mowing [1]. Obviously, the goal of the algorithm is to generate the shortest path that cover the entire area as much as possible. A large body of algorithms are developed [10–12,26]. Different kinds of coverage algorithms were compared in [11], *randomized coverage algorithms* which don't need a laser sensor are very simple but inefficient, while *sensor-based coverage algorithms* use sensors information to help the robot cleaners make a plan.

Cleaning robots in the market can be divided into two types according to whether they are equipped with laser sensors. The strategies of randomized robots are mostly pre-defined heuristic behaviors, for example, perform spiral walking in free space or following a wall detailed in [2] and so on. While laser-based robots need to build a map of the home environment, the map can be an occupancy grid map or geometry map or others which detailed in [21]. They also need to use algorithms such as those proposed in [20] to localize where they are in the map. With the sensors and computational resources, they are also possible to make high-level decision-making or long-term planning [4,25] in the future.

As a product, a cleaning robot has a lot of indexes of performance evaluation criteria as detailed in [18]. However we focus on evaluation of the performance of the coverage algorithm of different kinds of cleaning robots. Sylvia used two simple methods (percentage of coverage and distance travelled) for measuring the performance of complete coverage algorithms [22], the position of the robot is calculated by computer vision, this method has the following disadvantages: (1) The camera needs to be calibrated in advance. (2) The method cannot be carried out in real home environment. (3) The accuracy of the position of the robot can't be guaranteed. (4) The process of evaluation needs a lot of manual intervention. Therefore we use Motion Capture System (MCS) as our evaluation tool in virtual of it can provide realtime, accurate movement data of measured objects. Actually MCS has already been used in robotics in many tasks [8,9,19,27,28].

Our goal in this paper is to develop benchmarks problems for comparing the performance of different cleaning robots. Many benchmark problems have been proposed to evaluate robot systems, e.g., robot soccer [3,5], search and rescue tasks [16,17,23,24], etc. However, to the best of our knowledge, none has been proposed for the cleaning robots in the literature.

3 Performance Metrics for Coverage

Coverage task is difficult for a cleaning robot because the environment is dynamic and complex. The coverage algorithm itself is not covered in this paper, we want to evaluate the performance of the cleaning robots which can be buied off the shell. The following three performance metrics are used.

Compute the coverage rate. To compute the coverage rate of a cleaning robot, we build a map with SLAM [6] to compute the free space A_{free} and get the area A_{robot} robot covers with Algorithm 1.

$$R_{cover} = \frac{A_{robot}}{A_{free}} \tag{1}$$

3.1 Computing the Repeat Coverage Area Ratio

We record positions of the cleanning robots with MoCap while they run freely in the simulated home environment, and we de-sample the positions so that each position is at least 2 *cm* or 2 *deg* away from its neighbors. Then we compute the repeat coverage area ratio by feeding the positions to Algorithm 1.

3.2 Computing the Distance Travelled

This metric is very simple, we can compute the distance D_{robot} that the robot travelled by summing up the distance of each two adjacent positions. D_{min} is the least length which a robot travels just covers the whole filed. The efficiency of the coverage E can be calculated by:

$$E = \frac{D_{robot}}{D_{min}} \tag{2}$$

Algorithm 1. Computing the repeat coverage area ratio

Each grid of map M has two filed, $\langle covered, repetition\_time \rangle$
Let C indicate whether a grid of map is covered
Let R indicate times that a grid of map is covered
Input: Robot positions P
procedure ComputeRepetition(P)
    $I' \leftarrow \emptyset$
    for $p \in P$ **do**
        Compute indexes I that the robot covers in position p
        for $i \in I - I'$ **do**
            $C[i] \leftarrow 1$
            $R[i] \leftarrow R[i] + 1$
        $I' \leftarrow I$

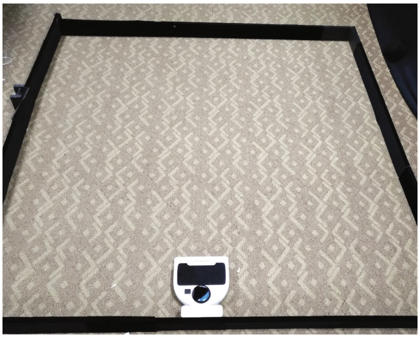

Fig. 1. Experiment site

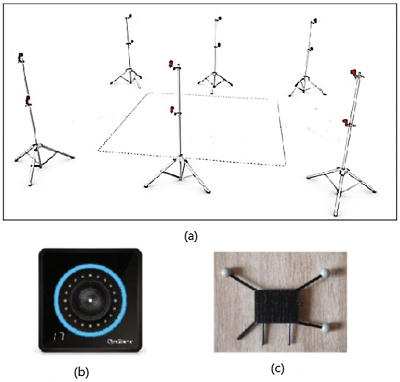

Fig. 2. (a) MoCap system (b) Optical camera (c) Markset

4 Experimental Setup

We tested three popular cleaning robots among which two cleaning robots are laser-based and one cleaning robot is collision-based. Experiment environment is shown in Fig. 1, the area of test platform is about 9.5 m^2. MoCap system shown in Fig. 2 can track markerset which fixed on the robot in realtime. The cleaning robot will run with no interference once started. Every robot performances the cleaning task several times and the trajectories are recorded.

The collected trajectories and coverage areas are shown in Fig. 3. The first row of images are the coverage areas of the three cleaning robots, the second row of pictures are the trajectories of the three cleaning robots. Obviously, robot A travelled the farthest distance to finish the task, robot C is better than robot A because it's trajectory is more ordered, and the trajectory of robot B is as ordered as robot C except that distance between sweeping lines is larger than robot C.

4.1 Result and Comparisons

We compared these three cleaning robot in travelled distance, covered area, sweeping time as shown in Fig. 4. Obviously, all robots successfully covered the whole field, robot A can't plan according to the environment in advance because it is not equipped with a laser sensor, so it travelled according it's designed behavior which is almost randomly, therefore, it waste a lot of time and it's efficiency is worst among the three robots, and robot B finishes the cleaning task with the least time among the three robots. The repetition times of the three cleaning robots is shown in Fig. 5, we can see robot B has least repeation ratio.

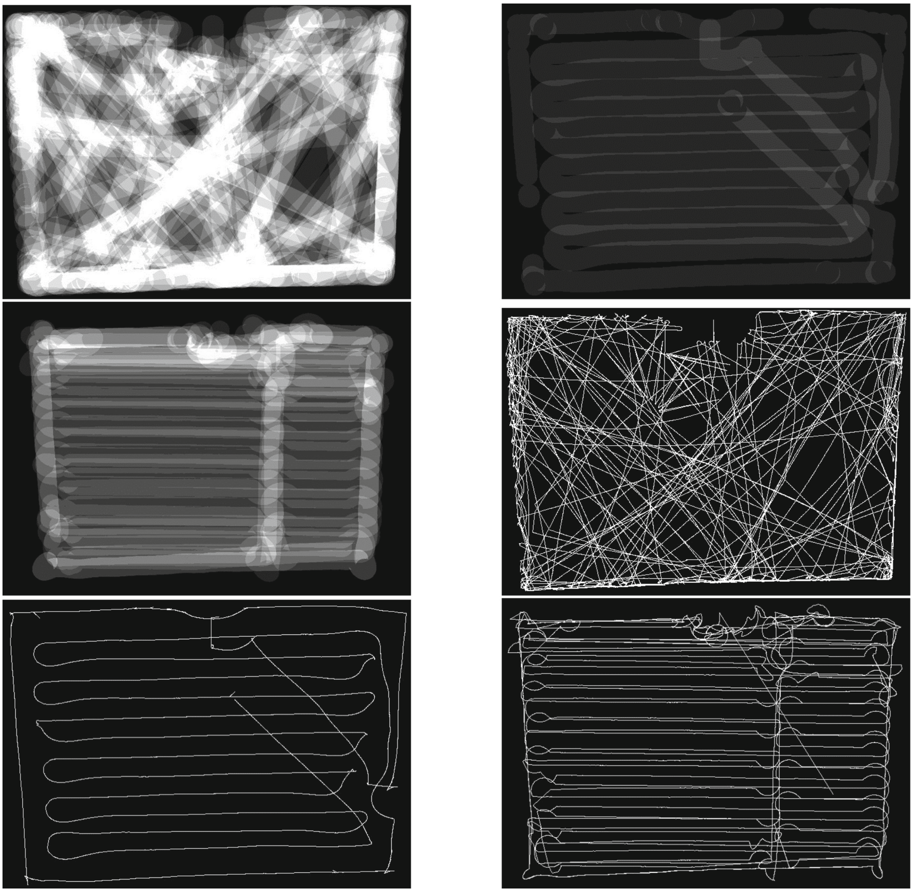

Fig. 3. Areas are in the upper row and trajectories are in the lower row, the color of the area which the cleaning robot covers many times is brighter.

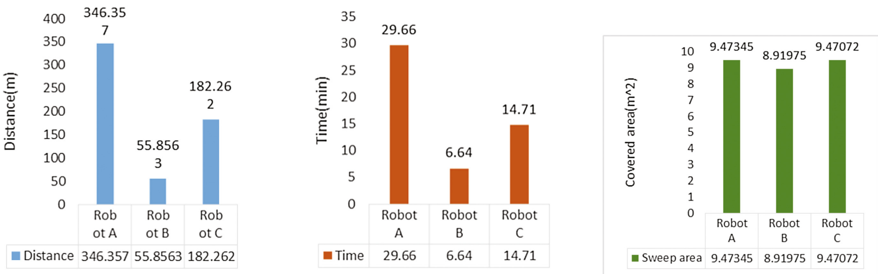

Fig. 4. Comparisons of three robots

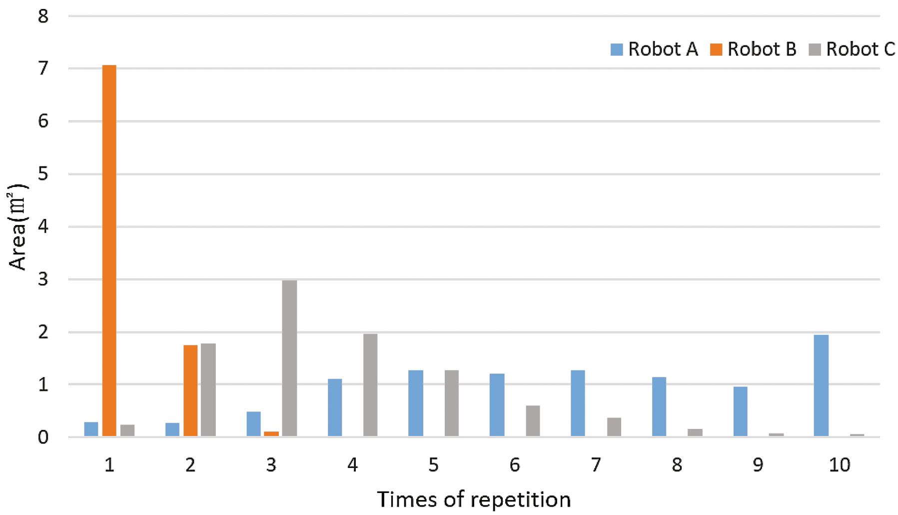

Fig. 5. Repetition times of the robots

5 Conclusions

In this paper, we proposed three performance evaluation indices of the complete coverage algorithm of a cleanning robot, they are coverage area percentage, repeat coverage area ratio, distance travelled respectively, these metrics show the performance of coverage algorithm of cleaning robots from the whole level. We use Mocap system as an external measurement because it is accurate, realtime and easy to use. Then, we test the three robots buied in market to see how well they perform actually, we can conclude that laser-based cleaning robots are better than randomized cleaning robots from the result.

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