Area measurement of large closed regions with a mobile robot

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Abstract

How can a mobile robot measure the area of a closed region that is beyond its immediate sensing range? This problem, which we name as *blind area measurement*, is inspired from scout worker ants who assess potential nest cavities. We first review the insect studies that have shown that these scouts, who work in dark, seem to assess arbitrary closed spaces and reliably reject nest sites that are small for the colony. We briefly describe the hypothesis that these scouts use "Buffon's needle method" to measure the area of the nest. Then we evaluate and analyze this method for mobile robots to measure large closed regions. We use a simulated mobile robot system to evaluate the performance of the method through systematic experiments. The results showed that the method can reliably measure the area of large and rather open, closed regions regardless of their shape and compactness. Moreover, the method's performance seems to be undisturbed by the existence of objects and by partial barriers placed inside these regions. Finally, at a smaller scale, we partially verified some of these results on a real mobile robot platform.

1 Introduction

Insects provide fascinating examples of how seemingly complex problems can be solved with simple autonomous agents equipped with extremely limited sensing, computation, and actuation capabilities[2]. Biological studies revealed that utilization of stigmery[7], indirect communication through environment, often opens the way for finding simpler solutions to seemingly complex problems. An indicative example of stigmergic behavior comes from foraging ants. When an ant finds food, it lays pheromone on its way to its nest. The pheromone laid in

Figure 1 should be here.

Figure 1: Buffon's needle method. If a needle is dropped at random on a a plane with equally spaced parallel lines, what is the probability that the needle will intersect one of these lines? This problem, proposed by Comte George de Buffon in 1773, is considered to be the first problem in the field of geometric probability. In 1777, Buffon proved that the probability of intersection is $p = 2l/\pi d$, where l is the length of the needle and $d \geq l$ is the spacing between the lines. This formula allows one to estimate the value of π by making repeated experiments. If the needle is thrown N times, and in n of these throws the needle intersects a line, then $p^* = n/N$ is an unbiased estimate of p and $\pi^* = 2l/p^*d$ is the corresponding estimate for π [14]. Buffon's needle method can be adapted to measure space. It can be shown that the area of a planar surface can be estimated by $A = 2SL/\pi N$ where N is the number of intersections between two sets of lines of length S and L twisted into definite shapes on the plane [13].

the environment acts as an attractant and leads the ants leaving the nest to the location of the food.

Although stigmergy is often discussed as a mechanism to coordinate the behavior of a swarm of agents, stigmergic communication applies to single agents as well. In the foraging ant example discussed above, even if there is a single ant in the nest, stigmergic communication still exists. Upon returning to its nest, the ant itself will be able to return to the location of the food at its subsequent foraging trip. By laying a trail in the environment, the ant no longer needs to keep track of the location of the food or the trail information. Therefore, through stigmergic communication, the ant affords to solve its problem with limited perceptual and computational capability.

The idea of minimizing robot complexity by utilizing stigmergic communication is a promising approach that has not yet been fully studied. In this paper, we study the problem of how the area of large closed regions can be measured by a simple mobile robot using stigmergy. Although there have been quite a number of studies[3, 8, 20] on area coverage of arbitrary closed regions by robots using stigmergy, to the best of our knowledge, the question of how the areas of such regions can be measured has not yet been addressed.

Both the problem of area measurement and its solution are inspired from ants. In the next section, we first describe the nest assessment (where the area of the nest is one criteria) behavior of ant scouts, briefly summarize the experimental results, and the hypothesis of how these scouts are measuring the area of a potential nest.

2 Nest Assessment in *Leptothorax albipennis*

Scout ants in colonies of *Leptothorax albipennis*, a small monomorphic myrmicine ant species inhabiting small flat crevices in rocks, search and evaluate potential nest sites when their current nest becomes uninhabitable. Mallon and

Franks[9] observed that these scouts tend to make more than one visit to a new site before they attempt to initiate an emigration of the entire colony. During each visit, the scouts spent a considerable part of their time exploring the internal periphery of the site, while making seemingly random explorations of the central part of the nest.

Mugford et al.[13] found no significant differences between the duration of the visits to nests of different sizes. Mallon and Franks[9] observed that during their second visits, the scouts “briefly but significantly slow down” as they cross their first visit trails. They suggested that the scouts lay an individual-specific pheromone trail during their first visit, and that they use the intersection frequency of their path with this pheromone trail during their subsequent visits to estimate the floor area of the nest. They pointed out that, this strategy is consistent with the Buffon’s needle method (see Figure 1), and tested this hypothesis by tracing the visits of scouts to different potential nest sites in the laboratory environment. Apart from the Buffon’s needle method, they have also tested whether the ants use the internal perimeter of the nest, and the ‘mean, free-path-length algorithm’ to assess the size of the nests. However, the experiments showed that (1) scouts were able to choose a standard-size nest over a half-size one with the same internal perimeter and, (2) a partial barrier placed inside a standard-size nest did not affect the assessment of the nest.

3 Related Work

Despite the experimental results obtained from ants and the theoretical results derived in computational geometry, the use of Buffon’s needle method in the measurement of large closed regions still begs a constructivist analysis. In [17], we proposed that exploration behavior of the scouts contained at least two sub-behaviors; wall following and random exploration. We then constructed a mobile robot simulation through which we had studied the dynamics of the nest assessment process, and proved that the two sub-behaviors were conflicting; that is the wall following behavior improves the periphery checking of the nest while impairing area measurement, whereas the opposite being true for the random exploration behavior. In [16], we repeated the nest assessment experiments of ant scouts with a simulated mobile robot and showed that the results are indeed in aggreement. Both of these studies were conducted with the goal of improving our understanding of the behaviors of the ant scouts and aimed to confirm the Buffon’s needle hypothesis in a constructive way. In [10], Marshall et al. studied whether there were any evolutionary advantages over making two visits into the same nest than a single visit where both trail laying and sensing is done concurrently. Based on their preliminary simulation results, they were not able to determine the superiority of one strategy over the other.

This paper takes an constructivist view of the problem: *How can a mobile robot measure the area of a closed region that is beyond its immediate sensing range?* This problem resembles to the challenge faced a blind person (lacking a complete view of the region being measured) trying to estimate the area of a

Figure 2 should be here.

Figure 2: Sketch of the Khepera robot model. The circle represents the body (diameter 5.34cm). The two elongated rectangles placed on the left and right part of the body denote the wheels of the robot. The small rectangles around the body shows the placement of the infrared proximity sensors. The blobs emanating from the six front sensors (the two sensors placed at the back are not used) show the approximate sensing range. The concentric circles drawn at the center of the robot indicate the pheromone nozzle and detector.

large room using his hands (short-range sensing) only. Therefore we call it, as the problem of *blind area measurement*. Here, the term blindness denotes that the person (agent) cannot "see" the whole region (either because it is too large or because of objects that occlude a complete view), and that he has to use only his local and short range sensing abilities.

The blind area measurement problem poses interesting questions to someone who wishes to utilize the method on a mobile robot. In this paper we tackle some of these questions such as: How should the exploration behavior of the robot be? What's the performance of Buffon's needle method for different types of regions? How does the thickness of the pheromone and the duration of the visit affect the area measurement? Our results presented here are extended from our earlier work that was presented in [6].

In the rest of the paper, we first describe the experimental setup and the implementation of the Buffon's needle method on a simulated mobile robot. Section 6 describes the experiments conducted and presents the results. In Section 7, we presented results of experiments with a physical mobile robot to partially verify some of the results obtained in simulations. We review mapping and area coverage, as two related approaches that can be applied to the blind area measurement problem, in Section 8 and experimentally compare the performance of an area coverage method with that of Buffon's needle method. In the last section, we summarize the arguments supported by the experiments, and outline future directions for the research.

4 Experimental setup

We have chosen Webots (Cyberbotics, Switzerland) as the simulation platform and used a robot model which simulates the Khepera[12] miniature robot (K-Team, Switzerland). The simulated robot model, whose sensory readings are sampled from a real robot[11], is widely accepted as realistic. The robot has eight infrared distance sensors as sketched in Figure 2, however only the six sensors placed in the front are utilized. The robot is also equipped with a virtual "pheromone nozzle" and a virtual "pheromone detector", both located at the center of the body, the former for laying and the latter for detecting the pheromone in the simulated environment.

Figure 3 should be here.

Figure 3: Eight set of arenas used in the experiments: **(a)** circular arenas, **(b)** square arenas, **(c)** elliptic arenas, **(d)** standard size arenas with vertical barrier, **(e)** standard size arenas with cross barriers, **(f)** ring shaped arena, **(g)** plus shaped arena, **(h)** circular arena with small obstacles. In f, g, and h dashed circles show standard size arena. The dark small circles placed in the arenas indicate the relative size of the robot.

4.1 The arenas

Eight different set of arenas, shown in Figure 3, are used in our experiments. Arenas do not have an entrance (i.e. they have a closed boundary) in order to remove the possibility of the robot leaving the arena prematurely. Real nests, natural or the ones used in laboratory experiments of ants, have at least one entrance [9]. Arena walls and any obstacles inside the arenas are modeled using extruded geometric shapes. The diameter of the robot is taken as the *unit* of distance measurement. In each visit, the robot began its exploration from the central bottom part of the arena. The initial position of the robot was kept constant (~ 0.83 units away from arena boundary) except that its initial orientation was varied within ± 15 degrees of the wall.

Figure 3(a), shows the circular arenas used in our experiments. The diameter of the smallest circular arena is approximately ten times the body length of the robot. The largest arena is ten times wider than the smallest one, and other eight arenas have sizes in between. A circular arena with diameter 100 units is taken as the standard size arena. Ten square arenas in (b) are selected in such a way that area of each square arena is equal to the area of its circular counterpart. Figure 3(c), shows the standard size arena and three elliptical arenas having same area as the standard size arena but with different eccentricities (0.968, 0.994, and 0.998 respectively). The arenas in (d,e) are standard size arenas with $|$ and $+$ type partial barriers placed at the center. The length of the barriers (in horizontal and vertical directions) is varied. The arenas in Figure 3(f, g, h) also have same area as the standard size arena but are ring shaped, plus shaped and circular with small obstacles inside respectively.

4.2 Exploration behavior

Using the six front sensors, we designed an exploration behavior that is modified from the ones implemented in our earlier works[16, 17]. The behavior lies within the spirit of Braitenberg's behaviors[1] with noise added to motor activations, and short-term time dependency included to avoid abrupt changes in robot's movement. The reason behind this modification is that, Braitenberg's original obstacle avoidance algorithm moves the robot like a ping-pong ball in the environment, driving it on almost straight lines in free space, and bouncing from the objects like a ball. As a result the exploration trails tends to concentrate on certain bands in the environment and therefore, the original algorithm is not very suitable for the Buffon's needle method. Details of the implementation of the exploration behavior is given below.

The robot is controlled by setting the speed of its left and right wheels (m_l and m_r), which are calculated as

$$m_l = (1 - |\bar{r}|) * 0.25 - \bar{r}$$
$$m_r = (1 - |\bar{r}|) * 0.25 + \bar{r}.$$

where $\bar{r}$ denotes the tendency to turn. When $\bar{r} = 0$, the robot moves forward. It turns left when $\bar{r} = 1$, and right when $\bar{r} = -1$. Here, $\bar{r}$ is defined as

$$\bar{r} = \begin{cases} sign(w_r - w_l) * \bar{n} & : \sum_{i=1}^{4} I_i > 2.7 \vee I_0 > 0.95 \vee I_5 > 0.95 \\ -1 & : r + n < -1 \\ r + n & : -1 < r + n < 1 \\ 1 & : r + n > 1 \end{cases}$$

where n is a random number between -0.4 and 0.4, $\bar{n}$ is a random number between 0.3 and 1.0, w_l, w_r represent the 'perceived presence' of the wall on the right and left side respectively, r is defined as the value of the 'rotational activation', and I_i denotes the infrared readings, with a value between 0 (no object) and 1 (very close object), where $0 < i < 5$ is the index. In this formula, the first row dictates that if the robot is very close to objects, indicated by the high infrared readings around the robot, then the robot would make a turn of random size in its current turning direction. This condition prevents any collisions that may happen due to the random component of the behavior. The third row adds a random turning direction to robot's current turning direction. The second and the fourth row merely clamps the turning component into $[-1 : +1]$ range.

The change in r is calculated as

$$\Delta r = \ -0.9r + 0.3(1 - r)(w_l + 1.5I_4 + 1.2I_3) - 0.3(1 + r)(w_r + 1.5I_1 + 1.2I_2)\ .$$

The first term on the right of the equation guarantees that when no wall is perceived and the infrared readings are all zero, then any rotational activation will decay to zero in time. The second term raises the rotational activation towards 1 in proportion to the amount of wall perceived on the left side and the infrared readings from the right side. The third term tries to pull down the rotational activation to -1 in a similar way.

The variables, w_l and w_r, indicate the presence of the peripheral wall on the left and right side of the robot respectively, and the change in them are defined as

$$\Delta w_l = -0.1w_l - 0.7w_l(I_2 + I_3)$$
$$\Delta w_r = -0.1w_r - 0.7w_r(I_2 + I_3).$$

The first term on the left side causes the perceived presence of a wall to decay to zero when no objects are sensed. The second term diminishes the perceived

Figure 4 should be here.

Figure 4: Exploration patterns generated by the behavior for circular arenas of **(a)** the smallest size, **(b)** the standard size, and **(c)** the largest size.

presence of any wall if the front sensors become active, to raise the priority of avoidance. Even with obstacle avoidance in place, the robot can get stuck, particularly when its is moving straight towards the wall. The first condition of $\bar{r}$ allows robot to escape from such situations by making steep turns away from the obstacles blocking its course of movement.

The exploration behavior generates random exploration patterns within a closed region. The robot moves in a random way, while avoiding any obstacles (walls or barriers in our experiments) on its way, covering the whole arena over the long run. Figure 4 shows exploration patterns for three different circular arenas.

5 Buffon's needle method

We evaluated the Buffon's needle method, as observed in ant scouts, for blind area measurement. In this method the robot makes two independent visits to a arena using the pure random exploration behavior. The robot only lays pheromone along its path during its first visit. During its second visit, the robot senses the pheromone trail laid in its first visit without laying new pheromone trail, and counts the number of intersections. The output of the pheromone sensor (a binary value) is first filtered by a leaky integrator to remove any artefacts that may have occurred due to a pixellized implementation of the pheromone trail and then thresholded. *Buffon's count (BC)* is defined as the number of pheromone trail crossings (low-to-high transition of thresholded value).

For a given arena, three parameters affect the Buffon's count: 1) the duration of the first visit, 2) the duration of the second visit, and 3) the thickness of the pheromone trail. For the experiments reported below, unless otherwise stated,

- the duration of the first and second visits are fixed to 50000 simulation steps (the resulting trail length has a mean of 1680, and a variance of 0.76 units), and
- the width of the pheromone is taken as 0.1, i.e. one tenth of the body length of the robot.

In order to discount the effect of the second visit, we define *normalized Buffon Count* (*nBC*) as the Buffon count normalized by the length of the visit in which pheromone sensing task is executed. In the rest of the discussion, *nBC* is used as a measure for the area of the arena.

Figure 5 (a) should be here. **Figure 5 (b) should be here.**

(a) **(b)**

Figure 5: **(a)** The nBC values of the circular and square arenas are plotted for different arena sizes. The error bars drawn indicate the interquartile range for the nBC values. **(b)** The median nBC values of circular arenas are plotted against median nBC of square arenas.

6 Experimental results

Using the experimental setup and Buffon's needle method described in the previous section, we have conducted systematic experiments to evaluate this method for blind area measurement. We have measured nBC 100 times for each of the arenas shown in Figure 3.

6.1 Size

Figure 5(a,b) plots the median nBC values obtained from circular and square arenas using the two-pass strategy. The error bars denote interquartiles, that is the range in which 50% of the data lies, equally split on each side of the median. In Figure 5(b), median nBC values measured from circular and square arenas are plotted side-by-side for different sizes. Four points worth mentioning:

1. nBC values for square and circular arenas are approximately the same for all sizes except the two smallest arenas. The nBC values of circular arenas are plotted against median nBC of square arenas in Figure 5(b). As it can be seen clearly, most of the points lie on the $y = x$ line, and in Figure 5(a) plots almost overlap for arenas of equal area showing that nBC is a good measure of area for circular and square arenas.

2. The error bars, indicating the interquartile range of the nBC measurements show that 50% of the measurements lie within a narrow band of the median for a wide range of arena sizes. The plot clearly indicates that nBC provides a robust measure for area.

3. nBC values of the two smallest arenas (with area 348 and 1392 $unit^2$) obtained are lower than expected. This is due to the blending of trails (the merging of multiple trails such that they are no longer distinguishable as individual trails) in these two small arenas. Since the trail density at the periphery is different for square and circular arenas (due to the interaction between the boundary and the robot as produced by the exploration behavior), the amount of blending is different. As a consequence of the nBC values for these two arena sizes show more discrepancy, which is marked by the two slightly off-axis points in Figure 5(b).

Figure 6 should be here.

Figure 6: Median nBC values versus compactness (r_1/r_2) for elliptic arenas. The error bars indicate the interquartile range of nBC.

6.2 Shape

In the experiments reported above, we have shown that nBC promises itself as a good measure for area. In order to evaluate the effect of shape when area is kept constant, we evaluated nBC for the set of arenas shown in Figure 3(c-h), where each arena covers the same area as the standard circular arena.

6.2.1 Compactness

Figure 6 plots the median nBC values for elliptic arenas obtained with respect to compactness value defined as r_1/r_2 where r_1 and r_2 denote the large and small radii of the ellipse. The baseline denotes the median nBC value for the standard circular arena with compactness $r_1/r_2 = 1$. It can be seen that nBC values remain approximately the same despite the change in the compactness of the arena. As the arena becomes less compact, the variance in the nBC values obtained using two-pass strategy increase (indicated by the growth in the error bars) also affecting the median value. Also mean nBC values increase, possibly due to different levels of blending at arena boundary.

6.2.2 Barriers and Irregular Shapes

The experiments reported so far have used convex arenas. In order to analyze the affect of non-convexity, we conducted experiments on five sets of arenas containing partial barriers and obstacles of irregular shape (Figure 3(d-h)).

Figure 7(a,b) plots the median nBC with respect to varying barrier length (percentage of the arena diameter) for both types of barriers obtained using two-pass strategy. Again, the baseline denotes the median nBC value for the standard circular arena with no barriers. The plots clearly show that, the partial barrier inside an arena has no significant affect on its size measurement. The slight increase in nBC is possibly due to the non-zero size of the barriers. Although the barriers, themselves, do not take up much space, the robot's exploration behavior tends to keep the robot "a sensing distance away" from the barriers, hence shrinking the area being explored.

We should note that, as the openings between the barriers and the walls reduce down to a couple of robot's diameter, it becomes more difficult for the robot to pass from one lobe to the other, causing the robot to remain stuck in some of the lobes. As a result of this, the variance the error bar corresponding to the the largest barrier length is increased.

Figure 8 plots the median nBC values obtained for different arena types, Figure 3(a,f-h). Areas of all three arenas are equal to the area of the standard

Figure 7 (a) should be here.
(a)

Figure 7 (b) should be here.
(b)

Figure 7: Median nBC values versus barrier length (percentage of the arena diameter) are shown for arenas with **(a)** | and **(b)** + barriers. The error bars indicate the interquartile values.

Figure 8 should be here.

Figure 8: Median nBC values measured from (a) standard, (b) ring shaped, (c) plus shaped, and (d) circular arena containing small obstacles. The error bars indicate the interquartile values.

arena. The plots clearly show that nBC remains almost invariant with respect to arena shape.

6.3 Pheromone thickness

As mentioned before, the thickness of the pheromone trail being laid can affect the value of nBC. Figure 9 plots the median nBC values of circular arenas for different pheromone thickness values. It can be clearly seen that as the thickness of the pheromone increases, blending (which can be seen by smaller-than-expected nBC values for small arenas) affects larger arenas.

In the following section, we present our studies with a physical mobile robot.

7 Experiments with a physical robot

We used the Hemisson robot platform, see Figure 10, to conduct experiments with a physical robot to partially verify some of these results obtained through simulations.

The experiments are conducted in three different arenas, as shown in Figure 11. The areas of the arenas are $1m^2$, $2m^2$, and $4m^2$ respectively. The first and second arenas are square shaped, and the last arena is a nonuniform hexagon with a circular obstacle inside. The circle and the arrow inside indicate the initial position and the orientation of the robot. Similar to the simulation experiments, the arenas do not include any openings in order to prevent early escape of the robot.

The Hemisson robot has the ability to hold a pen stuck at its center, allowing it to leave a trail on the floor. It also has two infrared sensors facing the floor

Figure 9 should be here.

Figure 9: Median nBC values measured from circular arenas are plotted side-by-side for different thickness of the pheromone trail. The error bars drawn indicate the interquartile range for the nBC values.

Figure 10 (a) should be here.
(a)

Figure 10 (b) should be here.
(b)

Figure 10: **(a)** The Hemisson robot is a small differential drive robot with a diameter of 12cm (K-Team, Switzerland). **(b)** The sketch of the robot. On the sketch, only the sensors and actuators used in experiments are shown. The two elongated rectangles denote the wheels, the small black rectangles represent the position, and the direction of the front infrared sensors. Emanating blobs from the infrared sensors roughly indicate the sensing range of these sensors. The circle at the center shows the position of the felt-pen.

Figure 11 should be here.

Figure 11: Three different arenas are used in experiments with the Hemisson robot. The dark circle inside the largest area represents a circular obstacle. See text for details.

for detecting lines. Unfortunately, our preliminary experiments showed that the lines drawn by the robot on the floor are too thin to be detected by the downward facing infrared sensors. Therefore the experiments were conducted by having the robot visit a closed arena twice, leaving its trails with different colored felt-pens. After the second visit, the number of intersections between the two different trails were manually counted. Since the robot has no odometry sensor, the trail length were not measured. Therefore the results presented in this section are in units of BC rather than nBC.

We adapted the exploration behavior, described in Section 4.2, to the Hemisson robot. When compared with Khepera, whose simulated model is described in Section 4, Hemisson is twice in size, and the locations of sensors are slightly different. We conducted the experiments at night, with controlled uniform lighting in the environment due to the sensitivity of the infrared sensors to ambient light in the environment. Each visit of the robot lasted 7 minutes. The trails left after two visits of the robot in the arena, shown in Figure 12(a), can be seen in Figure 12(b). Note that, the trails produced by the Hemisson are rather similar to those produced by the simulated Khepera robot model, seen in Figure 12(c).

Figure 12 (a) should be here.
(a)

Figure 12 (b) should be here.
(b)

Figure 12 (c) should be here.
(c)

Figure 12: (a) A snapshot of the $4m^2$ arena after two visits. (b) A zoomed copy of a partial view of the arena. The blue trail is laid down during the first visit and the red trail during in the second visit. (c) A zoomed copy of a partial view of the trails obtained in the simulated arena.

Figure 13 (a) should be here. **Figure 13 (b) should be here.**
(a) **(b)**

Figure 13: **(a)** BCvalues from 5 experiments conducted with the real Hemisson robot in arenas of size $1m^2$, $2m^2$, and $4m^2$. **(b)** BCvalues from 100 experiments conducted with the simulated Khepera robot in arenas of size $0.198m^2$, $0.396m^2$ and $0.792m^2$. The relative size of the arenas with respect to the robot sizes are kept constant, that is $\frac{1}{12^2} = \frac{0.198}{5.34^2}$. The error bars drawn indicate the interquartile range for the BCvalues. Note that the BCvalues in (a) are consistently smaller than the ones in (b). This is probably due to the different sensing range characteristics of the two robots. Although we scaled the arenas with the body size of the robot, it was not possible to do such a scaling for the proximity ranges of the robots.

7.1 Results

We conducted five experiments with the Hemisson in each arena and counted the BC. The results are plotted in Figure 13(a) which clearly shows that $1m^2$, $2m^2$, and $4m^2$ arenas are clearly distinguishable by the BC value. In order to partially verify the validity of our results obtained from simulation, we also conducted a similar experiment in using the simulated Khepera robot model. In these simulations, the ratio of the length of the simulated arena to the radius of the simulated Khepera robot was kept equal to the length of the actual arena to the radius of Hemisson robot. The duration of the visits in simulation was also chosen to produce trails of approximately equivalent length trails. For each arena, we ran 100 simulations and plotted the result. The resulting BC values are shown in Figure 13(b). It can be seen that, despite the use of completely different robot platforms, real and simulated, the method can clearly distinguish arenas with different sizes and shapes, producing similar BC values for both. This results confirms our argument that the method is not specific to a certain robot model, and provides robust area estimations.

Our experiments with the real robot aimed to provide partial verification of the experiments conducted in simulation and therefore are limited. There remains a number of practical and theoretical justifications for this approach. First, laying a trail and detecting it are still competences that are difficult to find in mobile robots. The most common form of laying trail has been through sticking a pen to a mobile robot to mark the floor. Sensing the trail, which tends to be rather thin, has proven to be a difficult task. In [15], a robot was equipped with two arrays of proximeters to detect the trails laid. However, such solutions are rather rudimentary, and that advances in this competency will be driven mainly by marker/sensor technologies, rather than robotics. Second, large regions, on the order of the ones that are used in simulation, are logistically difficult/impossible to get access to. Third, as the first one on this problem, we believe that, it is important to present a study that evaluates the method in its most plain form without putting question marks due to implementation.

8 Comparison with related approaches

The blind area measurement problem, posed in this paper, has not been explicitly studied by other methods, making it difficult to make performance comparisons. We believe that there are two lines of research that can be considered relevant against the proposed method: map making and area coverage.

Mapping, which can be defined as creating a model of environment using the sensor data collected during exploration, has been one of the fundamental problems of autonomous robotics[18]. Existing mapping methods can be categorized into three groups based on the type of the map that they generate: metric, topological, and hybrid (combining metric and topological maps). In particular, one can consider metric and hybrid mapping methods to make area estimations of closed environments. However, to the best of our knowledge, most of the mapping methods, like SLAM[4], rely on the existence of uniquely identifiable landmarks in the environment. Therefore they will not be suitable in "dull arenas", which do not contain such landmarks or landmark-like structures, that were used in our studies. Mapping methods that match locally created maps[5] (mostly by accumulating sensor readings using odometric measurements) as a pattern on the global map being built, will not work either, again due to the dullnes of the environmet. As a result, any mapping method will be reduced down to the accumulation of sensor readings on a metric map, using odometric information to position them. Such an approach, we claim, would not produce any meaningful results under realistic odometric errors. Also, using such methods, it is not even guaranteed that the robot would ever stabilize its map.

Area coverage [3] is defined as the problem of sweeping a closed region with a robot, by passing over (almost) all points of the region. It has many real world applications, such as floor cleaning, lawn mowing, mine hunting, and surveillance. The area coverage methods that are relevant to our discussion are the ones designed for robots with simple sensing abilities, lacking self-localization. The simplest class of such methods are known as *Randomized Search (RS)* [3] method, i.e. the robot moves randomly in the environment sweeping the region underneath its body. The *Probabilistic Covering (PC)* method presented and analyzed in [19] is one good example. In these methods, one can estimate the area of a region as the total area covered by the robot. However, this approach has two main drawbacks; *(i)* complete coverage can not be guaranteed, and *(ii)* it may take a long time since various parts of the region may be visited repeatedly.

There are also more complex area coverage methods, such as *Mark and Cover (MAC)*, which systematically covers a closed region while avoiding previously covered (marked) areas, or *MAC-PC*, a hybrid of *MAC* and *PC* methods[19]. Heuristic real-time search methods also enable one or a more robots to overcome the limitations of randomized search method. Various real-time search algorithms basicaly differ on how the value of new markings are determined and more detailed discussion can be found in [3]. These methods, although proved to provide a better performance, require more complex robots. The marking is assumed to be multiple valued, rather than binary as in our approach, and the intensity of the marking being laid, depends on the sensing of existing markings. Furthermore, the robot needs to sense not only the space that it currently occupies, but also its immediate vicinity to determine the direction of movement.

In the experiments described below, we compared the proposed method against the *RS* area coverage method, since it would allow us to keep as many aspects of the problem same as possible, for a fair comparison.

8.1 Comparison of Randomized Search with Buffon's needle method

We compared the area estimation performance characteristics of *RS* area coverage method with Buffon's needle method. In *RS*, the robot explored the environment using the same exploration algorithm, and the duration of the exploration is set to be equal to the the sum of two visits used in ours method. Different from the robot model used in our method, we assumed that the robot can sense and mark the whole region underneath its body, instead of a narrow trail. In addition to this, the robot is assumed to mark only the "unmarked" areas underneath its body and that the amount of marker used after the exploration is taken as the area estimate.

In Buffon's needle method, the area estimation is done through the measurement of a unitless value *nBC*. This value needs to be translated into area estimations, to be able to compare the results with those obtained from *RS*. An example of the relationship between *nBC* and area can be seen in Figure 5(a). This relationship indicates that, excluding the regions where blending occurs, the relationship between *nBC* and the area can be obtained by fitting a curve to the data points, based on the *nBC* values of a limited number of arenas of different sizes. The area of an arbitrary arena can then be estimated using the *nBC* measurement obtained by the robot.

We split the set of circular arenas into two disjoint groups; the first group consists of arenas with diameters 30, 50, 70 and 90 units, and the second includes arenas with diameters 40, 60, 80 and 100 units. Starting from a first visit trail length of 168, at regular intervals (every 168 units), *(i)* *nBC* values of all arenas are found, *(ii)* a function that maps *nBC* value to area is generated by fitting a curve to *nBC* values of arenas in the the first group only, and *(iii)* area estimates for the arenas in the second group are calculated using this function. In the curve fitting phase, we obtained best results with two-term power equation, $a + bx^c$. We would like to note that, the use of data from other experiments and the curve fitting step is needed only when one needs an absolute area estimation. This process should be seen as an optional calibration step for the Buffon's needle method, rather than as a weakness.

Figure 14 plots the area estimates of the four arenas in the second group, obtained both from the *RS* and our method, with respect to trail length. The area estimates obtained from the area coverage method, shows that, one needs to increase the trail length with the size of the arena being measured for a reliable estimate. Real-time search algorithms that use admissible marking rules, such as Learning Real-Time A*, are shown to have polynomial cover time with respect

Figure 14 (a) should be here. **Figure 14 (b) should be here.**
(a) **(b)**
Figure 14 (c) should be here. **Figure 14 (d) should be here.**
(c) **(d)**

Figure 14: Area estimations obtained from the *RS* method and the Buffon's needle method for four different arenas with radii **(a)** 40, **(b)** 60, **(c)** 80, and **(d)** 100 units. In these plots, the vertical axis is the area whereas the horizontal axis is the total trail length. The horizontal solid line drawn marks the actual area of the arena.

to area. Algorithms with simpler but non-admissible update rules, such as node counting, are also known to perform well in practice, although theoretically their worst case behavior can be exponential[3]. Similarly, time requirement of MAC is proved to increase linearly with area [20]. This means that even if more complex models are employed, the area estimates obtained using area coverage methods would depend on exploration time, at best linearly. On the contrary, the results indicate that, Buffon's needle method provides reliable area estimates for even short trail lengths, showing little dependency to the size of the arena. We believe that this makes it an appealing approach especially for time critical applications. Finally, we would like to note that, Buffon's needle method would require a simpler robot for area measurement than any of the area coverage methods.

9 Conclusions and Discussion

In this paper, we put forward the problem of *blind area measurement* as a challenging problem for the mobile roboticists. We presented a simple generic exploration behavior which is shown to generate trails that can be used for the Buffon's needle method on different simulated and real robot platforms. We have conducted systematic experiments and analyzed the performance of the method. We have also compared the performance of the method against the Randomized Search area coverage method and identified the relative pros and cons of the two methods.

The results obtained shows that the Buffon's needle method provides a very powerful, and robust way to measure closed regions. The experiments, conducted in large and rather open arenas, indicate that *nBC* is a good measure of area for such regions: *nBC* of a region is *(i)* independent of its shape, *(ii)* independent of the compactness of the region, and *(iii)* independent of the barriers (or objects) placed inside the region. However we should also make the limitations of the method explicit. First, based on the results presented here, it is not possible to generalize these claims to highly split regions such as a house with many rooms. Area coverage methods briefly reviewed in Section 8, would probably be more appropriate to be used in such environments. Second, Buffon's needle method measures a unitless value, called *nBC*, and that an additional set of experiments are needed to convert this value into an area estimate. Although, area coverage methods do not have such a conversion problem, it should be noted that, the measurement of area based on the amount of marking used by the robot would require an additional technical challenge for the approach.

We believe that there are many open questions with the method that needs to be investigated such as: How should the length (duration) of the first visit determined for maximum robustness? Can the first visit's duration be determined on-line, that is during the visit? How can the Buffon's needle method be improved by making the exploration behavior influenced by the pheromone that was laid before?

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