



# An information-based exploration strategy for environment mapping with mobile robots<sup>☆</sup>

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## ABSTRACT

The availability of efficient mapping systems to produce accurate representations of initially unknown environments is recognized as one of the main requirements for autonomous mobile robots. In this paper, we present an efficient mapping system that has been implemented on a mobile robot equipped with a laser range scanner. The system builds geometrical point-based maps of environments employing an information-based *exploration strategy* that determines the best observation positions by taking into account both the distance travelled and the information gathered. Our exploration strategy, being based on solid mathematical foundations, differs from many *ad hoc* exploration strategies proposed in literature. We present: (a) the theoretical aspects of the criterion for determining the best observation positions for a robot building a map, (b) the implementation of a mapping system that uses the proposed criterion, and (c) the experimental validation of our approach.

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## 1. Introduction

The availability of maps of environments where they operate is undoubtedly one of the main requirements for autonomous mobile robots [1]. To be efficient in performing its tasks, an autonomous robot needs an effective mapping system that incrementally builds a map of an environment by determining the most convenient observation positions in the partially known environment.

This paper presents a mapping system that builds point-based geometrical maps by employing an information-based *exploration strategy* that, in the determination of the observation positions, takes into account both the distance travelled and the information gathered. The strong mathematical foundation of the implemented exploration strategy, based on the concept of *relative entropy* [2,3], is the distinctive feature of our approach and constitutes the main original contribution of this paper.

We implemented our mapping system on a mobile robot equipped with a laser range scanner, following an established practice in current mobile robotics. This sensor acquires a sequence of distance measurements, along directions separated by a programmable angle (one degree, in our case). We assume that

the robot moves on a flat 2D surface and that obstacles are at the height of the laser range scanner. The mapping system proposed in this paper iteratively performs the three following activities:

- building a *local map* that represents the portion of the environment surrounding the robot, this local map is built by taking a 360 degrees view of the surroundings and is represented as a set of points (on the 2D plane of the sensor scanning),
- updating the *global map* according to the newly acquired local map and, at the same time, localizing the robot within the global map, and
- determining and reaching the next observation position, according to the exploration strategy.

The sequence of the robot observation positions is the result of the exploration strategy. Following the mainstream state-of-the-art, a *greedy* approach is adopted: at each step, just the *next* observation position is planned. The next observation position is determined within the presently known free space, according to the current global map. We experimentally tested and validated the proposed mapping system in heterogeneous environments, both with a real and with a simulated robot.

The main original contributions of this paper are the definition of a new information-theoretical criterion for selecting the next best observation position and the comparative experimental validation of a mapping system embedding the criterion.

This paper is organized as follows. The next section surveys the exploration strategies proposed in the literature. Section 3 formulates the exploration problem the information-based strategy of Section 4 solves. In Section 5, we describe the proposed mapping

<sup>☆</sup> Preliminary versions of some parts of this paper appeared in F. Amigoni (2008) [58], F. Amigoni, V. Caglioti (2003) [61] and F. Amigoni, V. Caglioti, U. Galtarossa (2004) [62].

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system, which is experimentally validated in Section 6. Finally, Section 7 concludes the paper.

## 2. Related works

Robotic mapping addresses the problem of acquiring spatial models of physical environments through mobile robots [1]. These spatial models, or *maps*, are typically used for robot navigation and localization. In order to build a map, robots use sensors like sonars, cameras, and laser range scanners. In the system described in this paper, we employ a laser range scanner sensor (like, for example, [4–6]). Maps can be classified by the way in which the collected information about obstacles and free space is represented: maps can be topological (e.g., based on graph data structures) or geometrical (e.g., based on data structures storing grids [7,8], points [6], or line segments [4,9,10]). Point and line segment maps usually have a fundamental advantage over grid-based maps: they are a more compact representation of the environment and, thus, are easier to manage [11]. The system proposed in this paper uses a representation of the obstacles as sets of points along the obstacle contours. This approach allows for a simple update of the map as new information is acquired by the laser range scanner.

Since the ranges of the sensors used in mapping are limited, measurements are inaccurate, and occlusions may occur, mapping is usually performed by taking several measurements at different positions and by integrating them in a global map. Maps are thus built *incrementally* by integrating measurements on the basis of the (probabilistic) estimated positions of the robot [12], of the geometrical features of the maps [6,9], or of a mixture of these two approaches. In almost all cases, it is important that, during the exploration, the robot is able to localize itself not only by odometry, but also by detecting landmarks or by matching data with an existing model of the environment. For this reason, techniques for Simultaneous Localization And Mapping (SLAM) [13] and for Concurrent Mapping and Localization (CML) [14] have been extensively studied. In our approach, the robot localization is performed by matching the geometrical features of the local maps with those of the global map, starting from a pose estimation provided by odometry. This alignment operation is called *scan matching*.

At a given time  $t$  of the incremental process of map building, *exploration strategies* drive the selection of the successive observation positions, on the basis of the global map built until  $t$ . Several works in literature have been devoted to the methods for integrating in a coherent global map the successive measurements taken by the robots (see [1] for a survey, dating back to some years ago). In comparison with this very large amount of work, relatively little efforts have been devoted to exploration strategies, and in many cases the robots are manually driven to acquire the measurements used to build the map. In this paper, we aim at giving a contribution to automate the exploration process. In the following, we review the most significant results on exploration strategies that have been presented in literature, covering both papers that are explicitly devoted to exploration strategies and papers in which exploration strategies are “embedded” in more general descriptions of mapping systems. Exploration strategies can be roughly divided into three groups that are analyzed in the following subsections, from the simplest to the most complex.

### 2.1. Exploration strategies using fixed trajectories

The first group collects the simplest exploration strategies, which employ a fixed path to move in an environment. An early strategy for systematically exploring all the landmarks in an environment is presented in [15]. Some more recent examples are the

exploration strategies proposed in [16]: SeedSpreader, Concentric, FigureEight, Random, Triangle, and Star. For instance, following the Concentric strategy, the robot successively traces concentric circles starting from its initial position. These exploration strategies are used for building visual maps, namely maps that do not represent the geometry of the environment but store visual landmarks that can be used for localization. The approach has been extended in [17], where a parameterized trajectory is used to direct the exploration of a robot in an environment. In [18], a predefined trajectory similar to Archimedes spiral is proposed for exploration in grid-based environments. Another very simple exploration strategy is that used in [6], which moves the robot to a fixed distance  $d$  from the current position. Two wall-following exploration strategies are presented in [19]. Finally, some algorithms for exploring polygonal environments with idealized robots have been devised by the theoretical computer science and computational geometry communities (for example, see [20]); but, given their ideal assumptions, they are not directly applicable to real robots.

### 2.2. Exploration strategies using random movements

The second group contains exploration strategies that are slightly more complex than those based on fixed trajectories discussed in the previous subsection. Typically, using these strategies a robot moves randomly and follows complex paths without explicitly evaluating the worthiness of observation positions. An exploration strategy of this kind is presented in [21], where a robot explores an environment by following a random walk that is biased toward frontier between explored and unexplored areas. Another exploration strategy of this group has been proposed in [22]. It is based on a set of behaviors (including Random Cruise, Local Door Driving, and behaviors for obstacle avoidance and wall following) that enable a robot to explore an environment and to build topological maps.

### 2.3. Exploration strategies evaluating the observation positions

The exploration strategies of the third group evaluate some observation positions to determine the next *best* observation position. The exploration strategy we propose in this paper belongs to this group. These exploration strategies usually aim at improving the efficiency of the exploration process, by reducing the exploration time and making a small number of exploration steps, and at reducing the error, by balancing the expected sensory information with the navigation cost to reach the observation positions. In general, these methods employ a greedy approach [23], that consists in moving the robot from its current location to the next location of interest. We adopt a greedy approach, since we plan only for the *next* best observation position (that could be not optimal if successive observation positions are considered). The general algorithm describing these exploration strategies can be summarized as follows.

- Generate a set of random (reachable) *candidate observation positions*. Candidate observation positions can be generated locally around the robot or globally within the known free space of the portion of the map built so far.
- Evaluate each candidate observation position  $p$  according to an *evaluation function*  $f(p)$ . The evaluation function usually considers the contribution of different components, the most common being:
  - a component evaluating the (information) *utility* of reaching  $p$ , measured in terms of the amount of expected new information about the environment that can be gained at  $p$ ,
  - a component evaluating the *cost* of reaching  $p$ ,

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