Information based indoor environment robotic exploration and modeling using 2-D images and graphs

Vivek A. Sujan · Marco A. Meggiolaro · Felipe A. W. Belo

Abstract As the autonomy of personal service robotic systems increases so has their need to interact with their environment. The most basic interaction a robotic agent may have with its environment is to sense and navigate through it. For many applications it is not usually practical to provide robots in advance with valid geometric models of their environment. The robot will need to create these models by moving around and sensing the environment, while minimizing the complexity of the required sensing hardware. Here, an information-based iterative algorithm is proposed to plan the robot’s visual exploration strategy, enabling it to most efficiently build a graph model of its environment. The algorithm is based on determining the information present in sub-regions of a 2-D panoramic image of the environment from the robot’s current location using a single camera fixed on the mobile robot. Using a metric based on Shannon’s information theory, the algorithm determines potential locations of nodes from which to further image the environment. Using a feature tracking process, the algorithm helps navigate the robot to each new node, where the imaging process is repeated. A Mellin transform and tracking process is used to guide the robot back to a previous node. This imaging, evaluation, branching and retracing its steps continues until the robot has mapped the environment to a pre-specified level of detail. The set of nodes and the images taken at each node are combined into a graph to model the environment. By tracing its path from node to node, a service robot can navigate around its environment. This method is particularly well suited for flat-floored environments. Experimental results show the effectiveness of this algorithm.

Keywords Mobile robots · Localization · Map building · SLAM · Information theory

1. Introduction

In recent years, mobile service robots have been introduced into various non-industrial application areas such as entertainment, building services, and hospitals. They are relieving humans of tedious work with the prospect of 24-hour availability, fast task execution, and cost-effectiveness. The market for medical robots, underwater robots, surveillance robots, demolition robots, cleaning robots and many other types of robots for carrying out a multitude of services has grown significantly (Thrun, 2003). The sales of mobile robots are projected to exceed the sales of factory floor robots by a factor of four, exceeding US$2 billion within this decade (Lavery, 1996). And unlike the factory floor robot market, the sources for the vast majority of these machines could be U.S. companies.

Service robots for personal and private use are mainly found in the areas of domestic (household) robots, which include vacuum cleaning and lawn-mowing robots, and entertainment robots, including toy and hobby robots. If the
technology for personal service robots provides what it has promised, at a competitive price, and if there is a sufficient degree of consumer acceptance, then this can be indeed a very large market.

Due to increased computational performance, algorithm complexity has grown thus providing increased system capability (Borenstein and Koren, 1990; Khatib, 1999; Lawitzky, 2000; Nister, 2003; Wong et al., 2000). This growth in algorithm complexity has been in conjunction with growth in hardware complexity. However, the high costs associated with hardware complexity are a discouraging factor. This economic drive has been seen in the last decade, where the performance of industrial and personal robots has radically increased while prices have fallen. A robot sold in 2000 would have cost less than a fifth of what a robot with the same performance would have cost in 1990 (World Robotics, 2001). Although hardware costs have declined with respect to their sophistication, this economic trend will still require the replacement of complex hardware architectures by more intelligent and cost-effective systems.

In this work, an algorithm is developed to allow a mobile service robot to explore and build its environment model for future navigation requirements, using a limited sensor suite consisting of a single monocular camera system fixed to the mobile base, wheel encoders and contact switches. The main objective of this algorithm is to allow a low-cost robot to localize itself and navigate through a flat-floored static environment such as an office floor or apartment. The algorithm is based on determining the information present in sub-regions of a 2-D panoramic image of the environment from the robot’s current location. Using a metric based on Shannon’s information theory (Reza, 1994), the algorithm determines potential locations of nodes from which to further image the environment, traversing the graph in a depth-first manner. Using a feature tracking process, the algorithm helps navigate the robot to each new node, where the imaging process is repeated. When a node is sufficiently explored (i.e. no new exploration nodes are identified), then the algorithm uses a Mellin transform (Alata et al., 1998; Casasent and Psaltis, 1978; Ruanaidh and Pun, 1997) and tracking process to guide the robot back to a previous node. This imaging, evaluation, branching and retracing its steps continues until the robot has mapped the environment to a specified level of detail. The level of detail is application-dependent and specified before the exploration/mapping process is initiated. The set of nodes and the images taken at each node are combined into a graph to model the environment. This graph model is essentially the causal map described by Kuijpers (2000), where the panoramic images correspond to views, navigation methods correspond to actions, and nodes correspond to distinctive states. Finally, by tracing its path from node to node, a service robot can then continue to navigate as long as there are no substantial changes to the environment (even though the proposed approach is relatively robust to such changes).

Environment mapping by mobile robots falls into the category of Simultaneous Localization and Mapping (SLAM). In SLAM a robot localizes itself as it maps the environment. Researchers have addressed this problem for well-structured (indoor) environments and have obtained important results (Anousaki and Kyriakopoulos, 1999; Castellanos et al., 1998; Kruse et al., 1996; Leonard and Durrant-Whyte, 1991; Thrun et al., 2000; Tomatis et al., 2001). These algorithms have been implemented for several different sensing methods, such as stereo camera vision systems (Castellanos et al., 1998; Se et al., 2002), laser range sensors (Tomatis et al., 2001), and ultrasonic sensors (Anousaki and Kyriakopoulos, 1999; Leonard and Durrant-Whyte, 1991). Sensor movement/placement is usually done sequentially (raster scan type approach), by following topological graphs, or using a variety of greedy algorithms that explore regions only on the extreme edges of the known environment. Geometric descriptions of the environment are modeled in several ways, including generalized cones, graph models and Voronoi diagrams, occupancy grid models, segment models, vertex models, and convex polygon models. Sensing uncertainties have been investigated for single or multi-robot systems (Roumeliotis and Rekleitis, 2004). However, the focus of most of these works is only accurate mapping. They do not address mapping efficiency. Researchers have addressed mapping efficiency to a limited amount (Kruse et al., 1996), but in these cases sensing and motion uncertainties are not accounted for. Prior work also assumes that sensor data provides 3-D (depth) information and/or other known environment clues from which this may be derived.

To achieve the localization function, landmarks and their relative motions are monitored with respect to the vision systems. Several localization schemes have been implemented, including topological methods such as generalized Voronoi graphs and global topological maps (Tomatis et al., 2001), extended Kalman filters (Anousaki and Kyriakopoulos, 1999; Leonard and Durrant-Whyte, 1991), and robust averages. Although novel natural landmark selection methods have been proposed (Simhon and Dudek, 1998), most SLAM architectures rely on identifying distinct, recognizable landmarks such as corners or edges in the environment (Taylor and Kriegman, 1998). This often limits the algorithms to well-structured indoor environments, with poor performance in textured environments.

On the other hand, the algorithm proposed in this work is able to localize the robot even in textured environments, without the need of 3-D information. In the following sections, an analytical development of the proposed algorithm is provided. The three primary components of the algorithm are developed and classified as: (i) potential child node identification, (ii) traverse to unexplored child node, and (iii)