# Incremental, on-line topological map building with a mobile robot

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## ABSTRACT

We present a behavior-based technique for incremental on-line mapping and autonomous navigation for mobile robots, specifically geared for time-critical indoor exploration tasks. The experimental platform used is a Pioneer AT mobile robot endowed with seven sonar transducers, a drift-stabilized gyro, a compass and a pan-tilt color camera. While the thrust of our work is the autonomous generation of real-time topological maps of the environment, both metric and topological descriptions of the environment are created in real time, each preserving its unique representational power and ease-of-use. We also present initial results on multi-robot cooperative topological mapping.

The building blocks of the topological map are corridors, junctions and open/closed doors, augmented with absolute heading and metric information. Since the robot does not begin with an *a priori* map, all environmental features have to be evaluated at run-time to ensure safe navigation and efficient exploration. Our enhanced dead-reckoning algorithm is backed up by the cyclic nature of indoor environments that provides additional hints for self-localization corrections. In addition, domain knowledge (such as perpendicular hallways) is used to actively correct maps as they are built on-line. All navigation, exploration, map building and self-localization capabilities are implemented as tightly-coupled behaviors, run by the onboard CPU.

**Keywords:** Autonomous robots, Topological maps, Mobile robots

## 1. INTRODUCTION

The task of enabling mobile robots with autonomous navigation capabilities has been the subject of much research over the past decades.[1,2] Heavy instrumentation of the environment with positioning devices in which the robot is expected to navigate curtails flexibility, and therefore is the least practical solution for dynamic indoor spaces, typically shared with humans and other robots. Yet, purposeful navigation usually requires more than a random selection of actions. In the light of these requirements, an important body of research has arisen, devoted entirely to autonomous modeling of the environment, referred to as mapping.

Mapping techniques broadly fall into two categories: metric and topological maps. Metric maps[3] are commonly implemented via occupancy-grids[4–7] that divide the area to be mapped into smaller units. Each of these units carries an attribute that indicates the degree to which the corresponding physical space is filled.

On the other hand, topological maps represent the world as a collection of interconnected landmarks.[8–14] Both the position of the robot and the connections between the landmarks have been modeled as probability distributions as studied in.[15–17]

In this paper, we present a behavior-based technique for incremental on-line mapping and autonomous navigation for mobile robots, specifically geared for time-critical indoor exploration tasks. The experimental platform used is a Pioneer AT mobile robot endowed with seven sonar transducers, a drift-stabilized gyro, a compass and a pan-tilt color camera. While the thrust of our work is the autonomous generation of real-time topological maps of the environment, both metric and topological descriptions of the environment are created in real time, each preserving its unique representational power and ease-of-use. We also present initial results on multi-robot cooperative topological mapping.

The rest of the paper is organized as follows. Section 2 presents a brief description of the underlying physical platform used in the experimental work, and focuses on navigational and mapping capabilities. In section 3, results

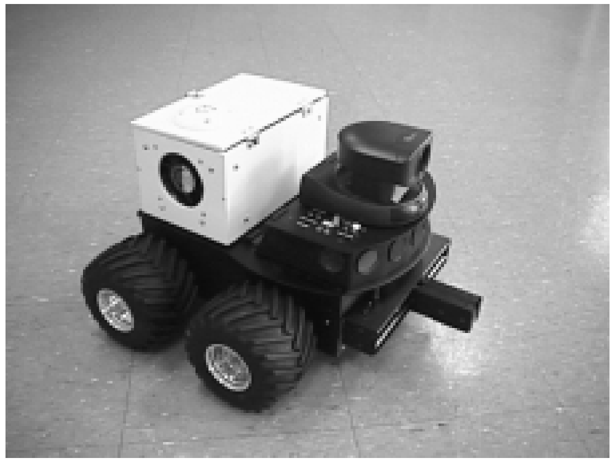

**Figure 1.** Pioneer AT Mobile Robot

of extensive mapping tests are presented for three different indoor environments. Finally, section 4 highlights our first multi-robot mapping experiments and preliminary results.

## 2. SYSTEM DESCRIPTION

### 2.1. Hardware Architecture

Our experimental platform is the Pioneer AT, a four-wheeled mobile robot shown in Figure 1. The robot's sensor suite includes 7 sonar transducers pointing to the sides and front, a Pan-Tilt-Zoom color camera connected to a Cognachrome FastTrack vision system, and wheel encoders that provide left and right translational velocities. An electronic compass with a resolution of 2 degrees is also available. In addition, a relatively inexpensive gyroscope (QRS14-64-109 from Systron Donner) has been added to improve the robot's odometry.

The processing power on board is provided by a PC-104 stack, composed of a 486DX4-100 CPU board with 40 MBs of solid state hard disk. A PCMCIA Ethernet card connected to Wireless Ethernet Desk Station (DS132 from WaveAccess) establishes high-bandwidth wireless communication at approximately 1.6 MBit/sec with various nodes of the network such as other mobile robots and the portable computer on which the graphical user interface is running. QNX is the underlying operating system on all computers.

### 2.2. Mapping Approach

The objective of our mapping system is to enable users to efficiently acquire an overall view of the main characteristics of the interiors of a building, consisting of basic topological features such as corridors, junctions, and corners. This basic set is then enriched by specialized features such as closed doors. The incremental nature of the approach allows the user to view the most up-to-date map displayed at any time. As the robot proceeds to explore, it constantly estimates its position and orientation and updates the map in real-time.

#### 2.2.1. Behavioral Organization

Our robot control and mapping algorithm is entirely composed of behaviors, which are specialized, light-weight processes that run in parallel.[18,19] Each of these behaviors is responsible for a well-defined robot control (e.g., obstacle avoidance, target following, etc.) or data processing (e.g. feature extraction, map updates, etc.) task. From the perspective of control flow, the sense-decide-act loop is typically executed to completion at every cycle of these behaviors, their outputs serving as inputs to others. Data is passed from and to behaviors through communication channels (i.e., ports), set up as required by the behavioral organization.

The navigation scheme used by the robot is simple: it traverses corridors while avoiding obstacles, turning only when the path is blocked. For the sake of simplicity, right turns are preferred to left turns, and U-turns are performed at dead-ends. This scheme results in paths which tend to travel deep into the building (relative to the entry point)

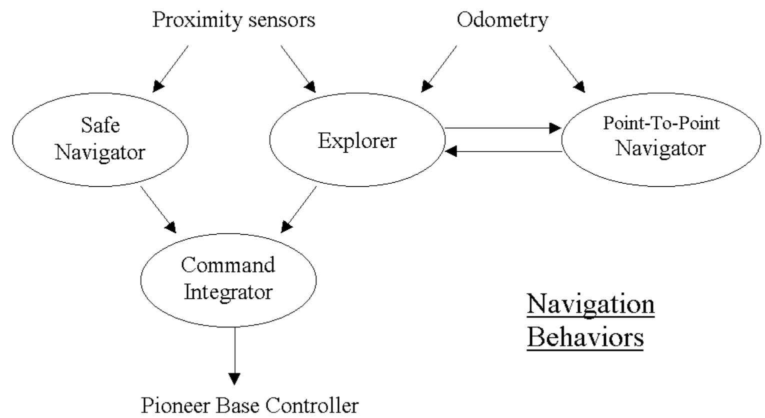


**Figure 2.** Organization of Navigational Behaviors

rather than thoroughly mapping the nearby rooms. The exploration algorithm is independent of the other modules (basic navigation skills, mapping, etc.), and can be replaced easily. Figure 2 depicts the behaviors involved in the navigation system and their connections: **Safe Navigator** is responsible for avoiding obstacles based on readings from proximity sensors, in that objects too close to the robot cause it to move away from them. **Explorer**, on the other hand, only cares about successfully following corridors or moving along walls, which requires a particular heading to be tracked. The **Point-To-Point Navigation** module accomplishes short, open-loop navigation tasks solely based on odometry. The **Command Integrator** gives priority to **Safe Navigator** whenever the latter is active.

### 2.2.2. Topological Map Elements

The topological map consists of a graph, whose nodes represent landmarks of interest such as T-junctions, corners, dead-ends and closed doors. Each node is connected to others by links augmented with distance, bearing and raw compass information as well as an attribute describing its nature (open space, barrier, door, etc.). Figure 3 shows a variety of these features encountered in a typical indoor environment. In addition, each landmark has two associated counters indicating how many times it was detected and actually visited. As to links connecting the nodes, the number of traversals is updated as the robot explores the environment.

### 2.2.3. Landmark Detection

The identification of topological landmarks is accomplished by feature detection behaviors that run independently from each other, at frequencies determined by the sensor modality in question. The building block of sonar-based feature detection algorithms is a line segment: Given the physical location and direction of sonar transducers, five separate buffers (one left, one right, and three frontal) are defined, each updated with projections of proximity readings onto the robot's two dimensional global coordinate system. If the buffers get full, or too much deviation is registered between consecutive sonar readings, a Least Squares line fitting algorithm is applied to the buffer in order to produce a line segment along with a quantitative measure of the fit. Line segments with poor fit rates are ignored. Also, a weak orthogonality condition is required between the buffer's average direction and the wall segments heading. Extracted line segments are immediately communicated over to sonar-based feature detectors, and expire within seconds of their creation. This scheme does not rely on global accuracy of the underlying odometry capability, and is only meant to support local feature extraction.

The **Opening Detector** is designed to watch for discontinuities in consecutive line segments originating from left and right sonar buffers. A good candidate for corridor openings or open doors is a gap between two wall segments on the same side of the robot with matching headings. The **Corridor Detector** seeks sufficiently long, and overlapping right and left wall segments with approximately matching bearings, and outputs their average heading. The **End-Of-Corridor** detector looks for frontal wall segments that are orthogonal to the corridor being traversed. The **Door**

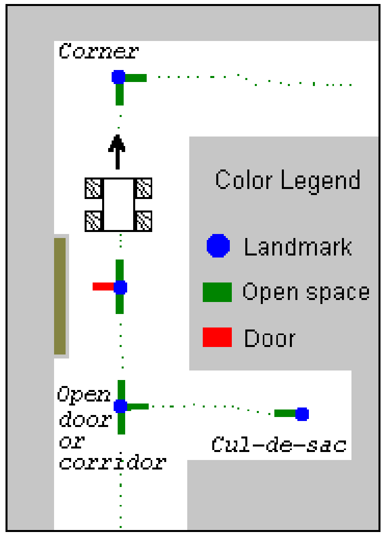


**Figure 3.** Symbols indicating topological landmarks and their attributes

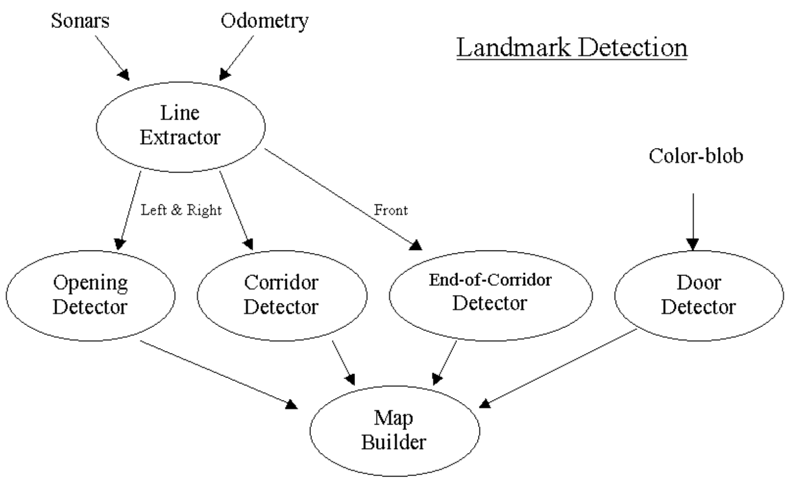


**Figure 4.** Landmark detection and Map building behaviors

**Detector** processes visual color blob information provided by the underlying vision system, examines the shape of perceived colored objects, and recognizes a closed door by its width and height. Figure 4 summarizes the organization of feature detection modules and their roles.

## 2.3. Concurrent Localization and Mapping

Since the robot starts with no *a priori* given map, it is not only required to have a sufficiently good position tracking system in order to distinguish nearby landmarks, but it should also be able to close large loops which are present in cyclic indoor environments. This section explains the interplay between position tracking that bootstraps topological map building, and the process of relocalization that refers to the partial map at hand to keep position estimation errors bounded.

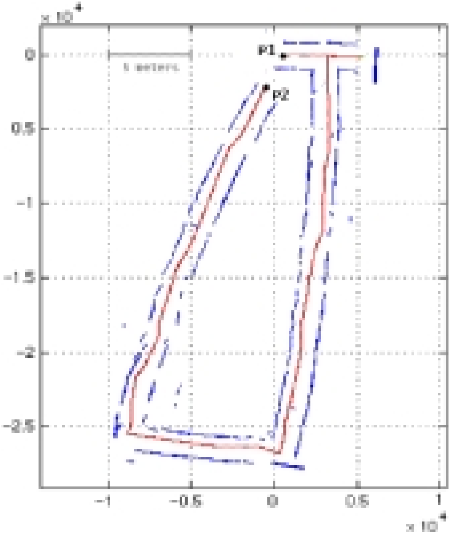


**Figure 5.** The effect of unmodeled gyroscope drift on odometry and mapping

### 2.3.1. Position Tracking

Earlier work to enhance a Pioneer mobile robot's odometry[20] resulted in substantial improvement in position estimation. A Kalman Filter incorporated wheel velocities and the output of a relatively inexpensive gyroscope using a calibrated kinematic model of the mobile platform. However, the gyroscope's contribution for measuring the yaw rate was overshadowed by the difficulties to successfully determine its bias. Figure 5 depicts a typical case of gyroscope drift, constantly affecting the robot's odometry during a mapping process and causing an error of approximately 15% of the distance traveled. At the end of this experiment, the robot had just reached P2, which is the other end of a 10 meter long corridor, where it had started at P1. Yet, under the influence of the gyroscope, straight corridors were deformed into banana-shapes on the map.

As a general technique for enhancing the robot's odometry for indoor environments, two assumptions were made, namely 1. the corridors are straight and 2. the corridors are orthogonal to each other. Corrections based on these constraints were suggested by the **Odometry Correction** behavior in an on-line fashion, based on the discrepancies in most recently detected corridor stretches and landmarks. Figure 6 shows a series of position corrections that took place while the robot traveled down the hallway. At points P1 through P5, corrections caused jumps in the robot's estimated trajectory, and recent wall segments were rotated to match with the corridors general heading. To help visualize the correction process, both old and newly rotated walls segments are shown.

Figure 7 shows the complete behavior set involved in position tracking. Note that **Corridor Detector** is the very same one discussed in an earlier section on landmark detection. The **Position Integrator** keeps track of heading and x-y offset corrections.

### 2.3.2. Relocalization Using Landmarks

In this work, landmark-based localization is used for position corrections (up to 10 meters), and is integrated into the existing position tracking system described above. The underlying idea is to search through the existing topological map for nodes that match a newly acquired landmark, and to suggest position corrections when there is a unique and strong match. The criteria for matching include the node's approximate coordinates, the headings and attributes of its connecting links, and if available, compass readings. Corrections based on corridors that come to an end (corners, T-junctions) are ranked higher because they involve physical constraints that are relatively less prone to false alarms.

## 3. EXPERIMENTAL EVALUATION

Figure 8 shows an exemplar screenshot of the map obtained at the Salvatori Computer Science Center in USC. In this experiment, the robot autonomously completed four tours around the building with no *a priori* knowledge about

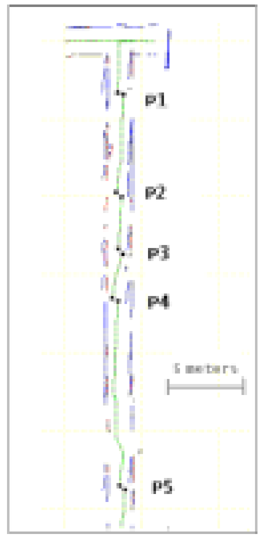


**Figure 6.** Straight and orthogonal corridor assumption at work

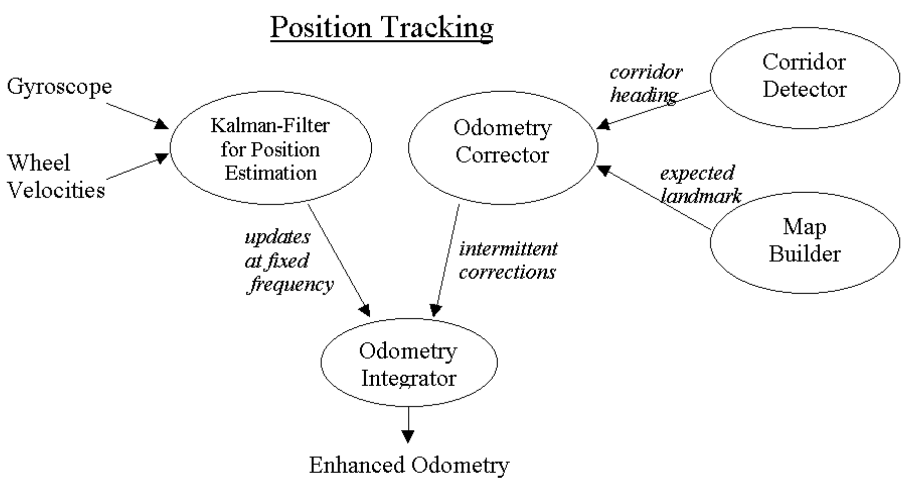


**Figure 7.** Position tracking behaviors

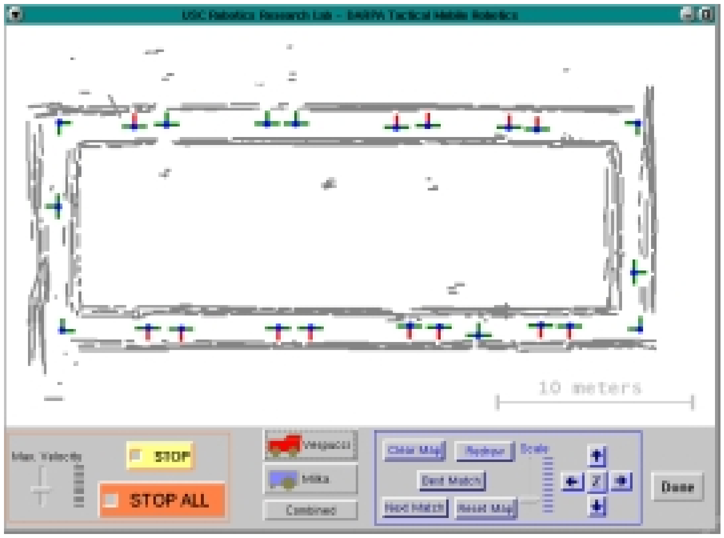


**Figure 8.** Map of the USC Salvatori Computer Science Center

the environment or its location in it. This corresponds to over 300 meters traveled at an average speed of 30 cm/sec. Note that the purpose of our mapping scheme is specifically not to perfectly align all wall segments accumulated during multiple traversals of the same corridor. The wall segments are shown only as additional information to the user, whereas the topology extracted from it is all that the robot needs and uses.

For the period of March-June 1999, the length of accumulated practice traversals exceeded 2.6 kilometers in the same building, and Table 1 shows statistical data obtained for landmark detection rates.

**Table 1.** Landmark detection rates for the USC Salvatori Computer Science Center. (2.6 kilometers)

| Sensor Modality | Total Number of Features | Correct Detection (%) | Missed Feature (%) | False Alarm (%) |
|---|---|---|---|---|
| Sonar | 300 | 81 | 19 | 20 |
| Color Vision | 180 | 92 | 8 | 3 |

Our mapping algorithm was also tested in other buildings: Figure 9 shows the map built during a DARPA demonstration in May 1999, at the TACOM site in Detroit.

More recently, our mapping algorithms were tested in an empty hospital building in Fort Sam Houston, San Antonio for the DARPA Tactical Mobile Robotics experiments in July 1999. Approximately 1 kilometer was traveled by our robots, during which sonar-based detection modules performed almost as well as they did at home. This is summarized in Table 2.

**Table 2.** Landmark detection rates for the hospital building in Fort Sam, San Antonio. (1 kilometer)

| Sensor Modality | Total Number of Features | Correct Detection (%) | Missed Feature (%) | False Alarm (%) |
|---|---|---|---|---|
| Sonar | 230 | 75 | 25 | 23 |

In Table 1 and 2, Correct Detection (%) is the ratio of correct detections to the total number of features, whereas False Alarm (%) is the ratio of false alarms to the total number of detections.

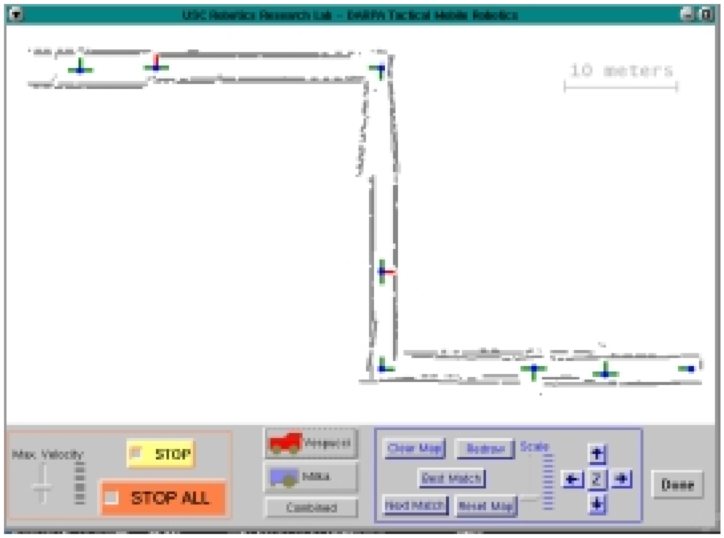


**Figure 9.** Map of the conference building at the TACOM site, Detroit

## 4. DISCUSSION AND FUTURE WORK

We have presented a topological mapping scheme that has been fully implemented on physical robots and extensively tested for robustness. Future work will include the use of probability distributions for position information, and the extension of the mapping algorithm to the multi-robot case. Preliminary results show the adequacy of topological descriptions for cheap and efficient map sharing across multiple robots.

### 4.1. Multi-Robot Case

Our most recent work extends the described mapping approach to a cooperation scheme for two independently mapping mobile robots, which are unaware of each other's initial position in absolute and relative coordinate frames. To provide an insight into our approach, results from the same DARPA demonstrations (Fort Sam Hospital, July 1999) are included. In this experiment, the second robot was a Pioneer 2DX indoor mobile platform, equipped with sonars and a SICK laser scanner, enabling it to detect closed doors.

Figure 10 shows the map built by Vespucci (the Pioneer AT), which began mapping the West wing of the building, reached the end of the corridor, came back to the central block of the building, and made a single tour around the elevator area. Figure 11 depicts Milka's (the Pioneer 2DX) map, which was initially located in the East wing of the same building, heading West. As Milka reached the central block, it successfully completed 1.5 tours around it. Figure 12 shows the result of combining the two maps based on topological matches only: at any time during the experiment, the user can attempt to combine the maps even though the robots have not mapped a common area. If there is sufficient evidence of areas mapped by both robots, a combined map will be displayed immediately, with shared landmarks encircled to indicate the anchoring points of the two maps. To show correctness and quality of the match, we have overlaid this map onto a floor plan of the hospital, as shown in Figure 13.

## 5. CONCLUSION

We have presented a simple, modular, and scalable behavior-based technique for incremental on-line mapping and autonomous navigation for mobile robots, specifically geared for time-critical indoor exploration tasks.

We used corridors, junctions and open/closed doors, augmented with absolute heading and metric information, as topological features, and evaluated them at run-time to ensure safe navigation and efficient exploration. Enhanced dead-reckoning, and minimal domain knowledge (the perpendicular nature of hallways) are used to actively correct maps as they are being constructed. All capabilities are implemented as tightly-coupled behaviors, and validated on numerous single- and two-robot trials.

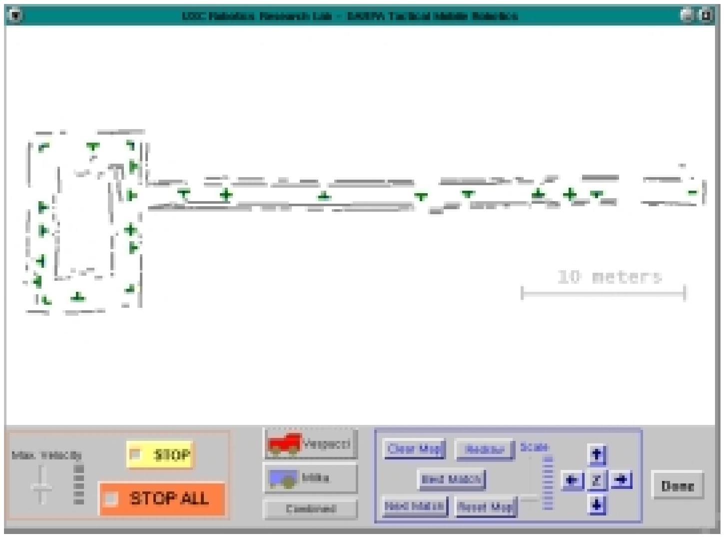


**Figure 10.** Map built by Vespucci, starting from the West wing of the hospital building

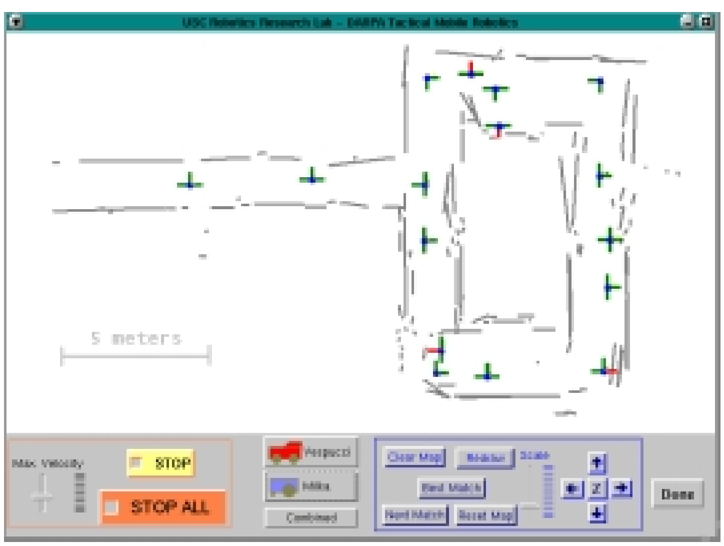


**Figure 11.** Map built by Milka, starting from the East wing of the hospital building

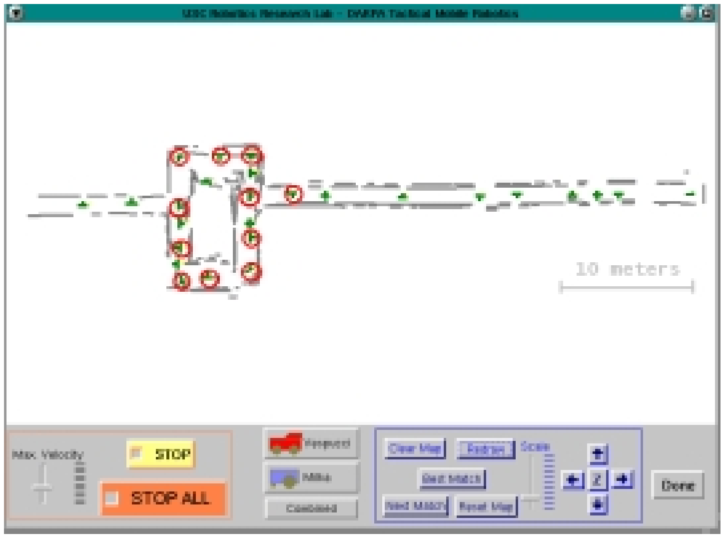


**Figure 12.** Combined topological maps of the two robots

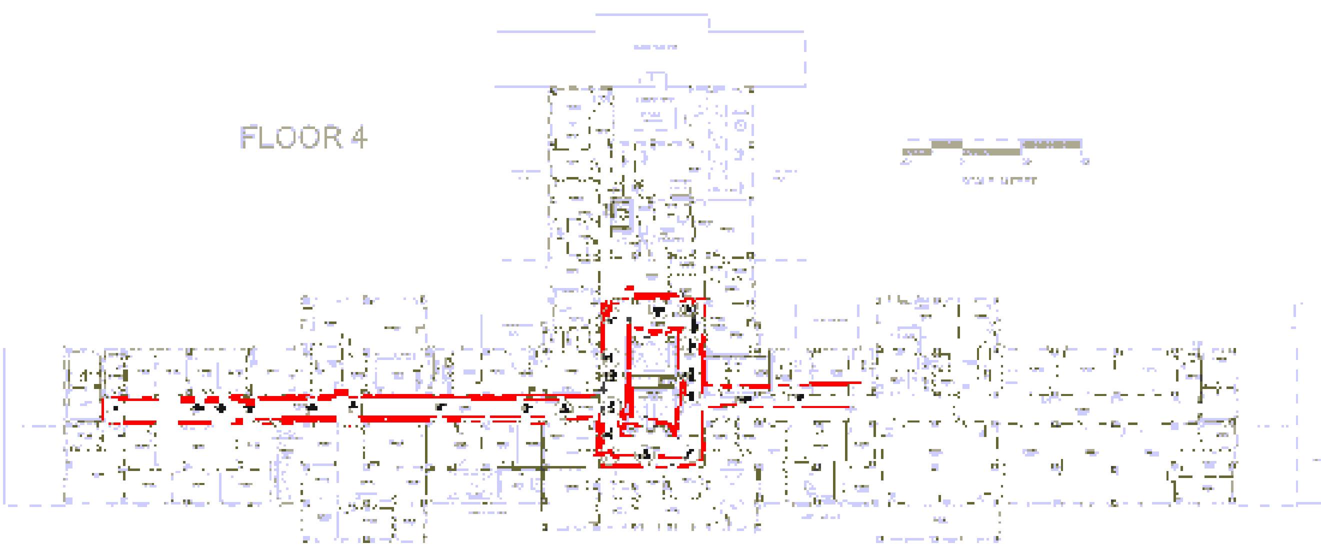


**Figure 13.** Combined topological maps laid over the floor plan

Our current work is toward scaling up the demonstrated results to large groups of concurrent autonomous mapping robots generating and fusing real-time topological maps of the environment.

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