LARGE-SCALE FEATURE IDENTIFICATION FOR INDOOR TOPOLOGICAL MAPPING

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Abstract

This paper describes a new approach to creating a map of the environment for a mobile robot by identifying large-scale indoor features directly from sonar observations. Current research in creating environmental maps for mobile robots use grid-based representations, use small-scale features to construct larger entities for topological maps, or use combinations of these approaches. These methods do not identify directly features on the scale of corridors, alcoves, and intersections that have high semantic content for people and provide a compact representation of the topology of the environment. We present a simple rule-based technique to differentiate and identify a set of large-scale indoor features. The rule-based approach is used to demonstrate the potential of our method. The experimental results show that processor intensive techniques such as pattern recognition/signal processing, neural networks, or clustering algorithms may not be required for successful, direct large-scale feature identification.

1 Introduction

To perform useful tasks a mobile robot needs a “model of the near world” [18] that represents the world's configuration and the robot's location within this environment. Using a model of its surroundings a robot can avoid obstacles, identify changes in the environment, and navigate its way to a specified location. A map is a symbolic construction and is meant to describe discrete entities, objects or places in the environment [6]. The model, or map, that a robot maintains must provide the information needed for the robot to perform properly.

One of the most popular methods for creating a map of a robot's surroundings is to collect sonar data via ultrasonic sensors. This sonar data is then be used to construct grid-based representations or to construct topological representations where the data has been manipulated to produce simple geometric shapes that describe the environment [4] [14][16][23]. Typically, multiple readings are used to construct larger features such as planes, corners, and doorways.

This paper presents a topological approach to identify large-scale indoor features, such as corridors and intersections, directly from sonar observations and uses these observations to construct a map of the environment. Our approach identifies these large-scale features based upon sonar readings taken at a single position using a circular array of sensors. Our emphasis on identifying directly the large-scale features that represent salient environmental information instead of the construction of planes and corners from multiple readings distinguishes this research from other approaches currently being pursued.

Our approach has the advantage of using features that have semantic value to humans as the building blocks (primitives) of the environmental representation. Grid-based and small-scale topological approaches generally have low semantic content for people. Maps and descriptions using large-scale features are a primary means used by humans to provide meaningful directions. The use of higher-level abstractions and concepts provides a simpler and more compact way of representing and communicating information. This allows a high-level interface to the robot that is more closely related to the way humans perceive and interact with the environment while being based on constructs that robots can successfully identify directly from sensor data.

A person will be able to provide directions to, and receive directions from, a robot using features that are naturally present in human navigational directions. Using such features for maps will have significant advantages over representations that may have more precise distance information but are more restrictive and have low semantic content. This capability could be used in two modes: with a map and without a map. In both cases the robot would be provided with directions to the desired location. In the case where the robot does not currently have a map it can identify large-scale features to arrive at the location indicated by the directions. Using a map, a person could indicate the destination on the map itself. The robot would use current sensor readings and the stored map information to localize itself and navigate to the goal.

The large-scale features to be identified are geometrically simple, angular, and rectilinear, as would be expected for an indoor environment. Each feature is represented by a set of rules that are matched against the sonar readings taken by the robot. The feature with the highest match percentage is identified as the feature the robot is traversing. If necessary, a tie-breaking algorithm is used that is based on the likelihood that a particular feature exists in the environment. A number of sonar readings can also be averaged together and used for feature identification. This helps to eliminate erroneous readings due to multiple bounce reflections or the transition to a different feature.

2 Related Research

Prior work in environmental modeling for mobile robots has focused on grid-based representations and topological representations that synthesize environmental characteristics from small-scale features. Grid-based methods usually use one of two algorithms: Bayesian statistics or Dempster-Shafer reasoning. Several excellent papers describe grid-based approaches that use Bayesian statistics [7][15][16][23]. Dempster-Shafer methods are described in [17][20]. Lim and Cho [15] described modifications of these two techniques. Howard and Kitchen [9] used the Histogramic In-Motion Mapping (HIMM) approach (see [2] for a description of HIMM). The space and computational complexities of grid-based approaches are addressed in [11] and [18] by using tree structures to reduce the amount of data needed to represent an environment. Only Moravec [16] described the possibility of identifying objects directly from the grid representation.

Topological models usually provide a more compact representation of the environment than grid-based approaches [6][23]. A topological map could be a simple list of features [18] but more commonly the underlying implementation is a graph [3][6][23]. Some research has translated grid-based maps into topological maps [7][23]. Janet, et al., [10] used a combination of neural networks and hyper-ellipsoid clustering to create a topological map and discuss assembling large-scale indoor features such as corridors or rooms. Chong and Kleeman [4] used a grid map and a topological map in concert. Features were classified as planes, corners, edges, or unknown.

Bulata and Devy [3] used a hierarchy of models to build a topological representation of an environment similar to [7] and [23], but did not use grid-based maps. Dudek [6] also used a hierarchy of models to develop a representation of the environment. Dudek mentions that large-scale features could be generated but are not because this would require domain specific assumptions about the environment. Our approach uses rules very much like those mentioned in [6] for identifying large-scale features in an office building.

Kunz, Willeke, and Nourbakhsh [13] presented a method that constructs a topological map mainly based on the movements of the robot, not on direct usage of sensor data. The approach described in [13] did identify large-scale features. These features fell into three categories: intersections, hallways, and open areas. Among the surveyed research, this work is most closely related to our research.

Barshan and Kuc [1] presented a method for distinguishing a planar feature, such as a section of wall, from a corner. This work is extended in [12] and [21]. Ohya, et al. [19] presented work that is very similar to [1] and [12] but focuses on identifying walls. Horst [8] gave an algorithm to convert a certainty grid representation into object boundary curves that were used to detect corners, curves, and lines. Chong and Kleeman [4] identified partial planes and corners and then used a Julier-Uhlmann Kalman Filter (JUKF) to merge these elements into a map of the environment. Lacroix and Dudek [14] associated the arcs of sonar scans with a set of real world primitive features. This approach had the robot rotate in place for a number of revolutions to collect sonar data. In contrast, the approaches in [1][4][12][19][21] identified small-scale features by taking data from a single position or multiple positions and then applied a squared error or Kalman Filter method to the data. Work has also been done in the area of feature identification for Autonomous Underwater Vehicles (AUVs) [22].

3 Approach

Our research utilizes a mobile robot with a suite of ultrasonic sensors to detect the features of an indoor environment. The features to be identified are large-scale or complete features of an indoor environment as opposed to small-scale components of the large-scale features such as walls and corners. The sonar data obtained by the robot is used directly in identifying features without filtering or manipulation.

Ultrasonic or sonar (SOund Navigation And Ranging) sensors are commonly used on mobile robots that are intended to operate in an indoor environment [5]. There are sixteen Polaroid 6500 ultrasonic sensors spaced 22.5° apart around the circumference of the robot used in this work. The indoor environment that the robot operates in is assumed to be orthogonal and rectilinear, therefore only data from the four ordinal direction sonar sensors is used for feature identification. The four sensors used are the forward, backward, left, and right positions on the sonar ring.

The movement and data collection of the robot and the feature identification algorithm are implemented using C++ on a host computer running Linux. The robot is commanded to traverse a corridor and collect sonar data at fixed distance intervals. In some of the experiments, the raw sonar data sets are collected into groups of a specified size and are averaged together. The sonar data is matched against sets of rules that uniquely identify one feature from another. As features are detected the position data and the sonar data used for identification are associated with the feature. The detected features are logged and a report of the data collected is generated when the robot reaches the distance it was commanded to travel.

The set of features to be identified encompasses knowledge of the environment that the robot will be operating in. If the robot detects a feature that does not satisfy any of the available rules then the feature is identified as unknown. While there is no *a priori* map that the robot can refer to, there is *a priori* knowledge about the type of environment in which it will be operating [22]. Figure 1 shows the set of features that were expected in the environment. The features in this set are geometrically simple and rectilinear since the environment we selected was a typical building without non-orthogonal features.

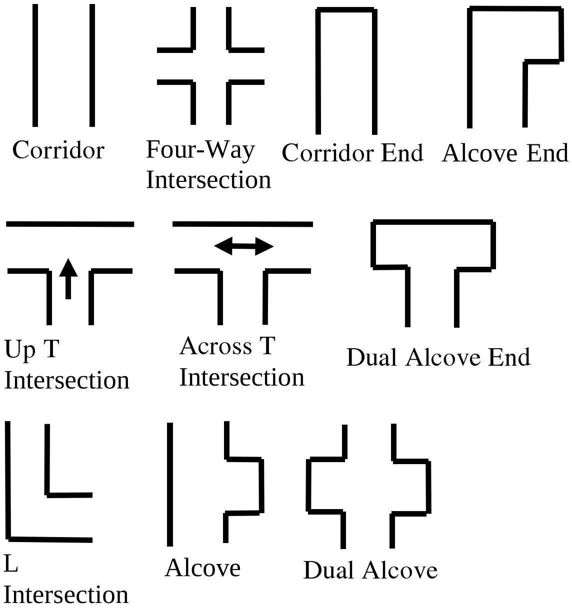


Figure 1 Feature set

Features are recognized by using sonar readings taken by different sensors from approximately the same time and the same location. A set of rules is applied to match the sonar data to the features. The feature with the highest "matching percentage" is identified as the current feature. The matching percentage for a feature is determined by dividing the number of satisfied rules by the total number of rules the feature contains. Thus, if the sonar data satisfies all the rules for a particular feature, it will have a matching percentage of 100.

$$\text{Match \%} = \frac{\text{\# of rules matched}}{\text{\# of rules}} \qquad (3.1)$$

When there is more than one feature with the highest matching percentage, a simple tie-breaking algorithm is used. If one of the best matches is a corridor, it will be identified as the feature. If one of the best matches is a four-way intersection it will be selected unless one of the other candidate feature patterns is a corridor. Otherwise, the first feature detected with the highest matching percentage is identified as the feature. This tie-breaking approach was designed to reflect probability distribution of the types of features in the environment of the robot.

The rules used to distinguish one feature from another are rather simple in nature. The majority of rules compare a predetermined threshold distance to the linear distance reported by a specific sensor. The one exception to this pattern is the corridor rule. This rule compares the length of the feature it is traversing to the feature's width. The rules are composed into sets that represent each of the features in Figure 1. Table 1 illustrates how the rules map to the features.

Table 1: Rule to Feature Mapping

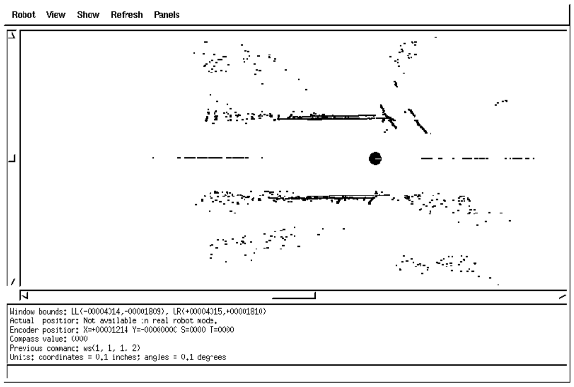
Rule	Feature
BackLongRule	Corridor Four Way Intersection Up T Intersection Across T Intersection L Intersection Alcove Dual Alcove Corridor End Alcove End Dual Alcove End
CorrRule	Corridor
FrontLongRule	Corridor Four Way Intersection Across T Intersection Alcove Dual Alcove
FrontShortRule	Up T Intersection L Intersection Corridor End Alcove End Dual Alcove End
SideInterRule	Alcove Alcove End
SideLongRule	L Intersection Across T Intersection
SideShortRule	L Intersection Alcove Alcove End
TwoSideInterRule	Dual Alcove Dual Alcove End
TwoSideLongRule	Four Way Intersection Up T Intersection

Table 1: Rule to Feature Mapping

Rule	Feature
TwoSideShortRule	Corridor Corridor End

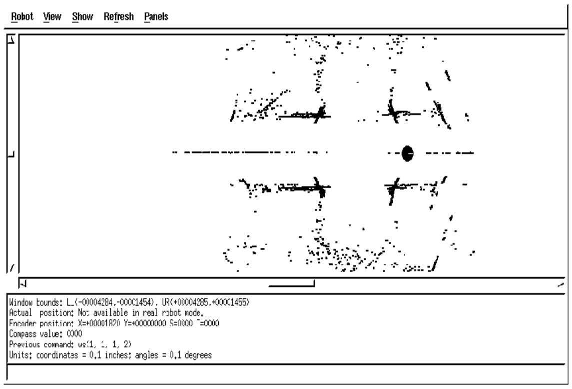
4 Results

The purpose of this work is to demonstrate the feasibility of identifying large-scale features in an indoor environment using ultrasonic sensors. To accomplish this goal the method must be able to distinguish typical environmental features from one another. The algorithm must also be able to determine whether it is traversing a feature it "knows" based on the *a priori* knowledge implicit in the rule set or if it is traversing a feature that is not accounted for. All the features in the feature set were correctly identified and distinguished from each other. Identification of features was achieved not only during tests to detect and identify one type of feature but also in tests that had the robot traverse areas of a building that had multiple features in them. Figure 2 and Figure 3 show the sonar plots for two of the features that were expected in the environment: a corridor and a four-way intersection. Figure 4 and Figure 5 are graphs of predicted and actual sonar readings for a corridor and a four-way intersection.



```
Window bounds: LL(-00004014,-00001809), UR(+00004015,+00001810)
Actual  position: Not available in real robot mode.
Encoder position: X=+00001214 Y=-00000000 S=0000 T=0000
Compass value: 0000
Previous command: ws(1, 1, 1, 2)
Units: coordinates = 0.1 inches; angles = 0.1 degrees
```

Figure 2 Sonar plot of a corridor



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Window bounds: LL(-00004284,-00001454), UR(+00004285,+00001455)
Actual  position: Not available in real robot mode.
Encoder position: X=+00001820 Y=+00000000 S=0000 T=0000
Compass value: 0000
Previous command: ws(1, 1, 1, 2)
Units: coordinates = 0.1 inches; angles = 0.1 degrees
```

Figure 3 Sonar plot of a four-way intersection

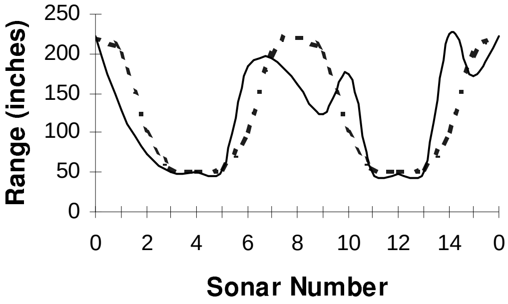


Figure 4 Predicted & actual sonar data for a corridor

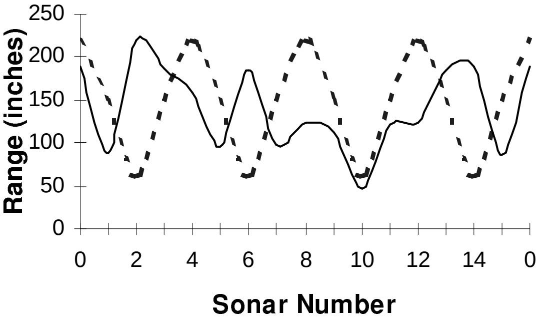
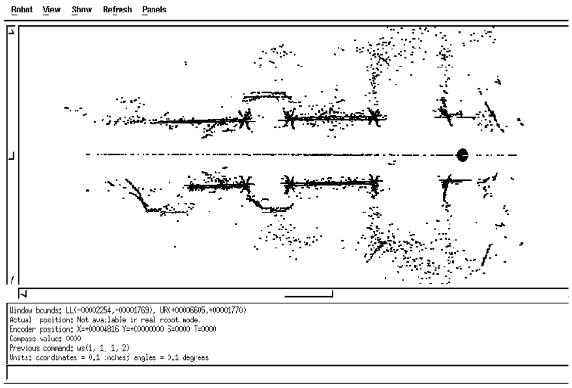


Figure 5 Predicted & actual sonar data for a four-way intersection



```
Window bounds: LL(-00002254,-00001769), UR(+00006605,+00001770)
Actual  position: Not available in real robot mode.
Encoder position: X=+00004816 Y=+00000000 S=0000 T=0000
Compass value: 0000
Previous command: ws(1, 1, 1, 2)
Units: coordinates = 0.1 inches; angles = 0.1 degrees
```

Figure 6 Sonar plot of multiple features

Misidentification of features did occur but was minimized by relatively minor changes to the logic and threshold settings of the software. Incorrect identifications were restricted to areas where two features met or where the sensors could not "see" the correct feature initially, leading to transitional misidentifications.

We investigated if averaging a number of sonar readings together would improve upon the correct identification rate and eliminate some of the transitional misidentifications. The tests were conducted with the robot traversing a section of a building that was composed of multiple features. Figure 6 is a sonar plot from one of the test runs.

The averaged data runs did demonstrate an improved correct identification rate over the raw data tests. This performance difference is even greater if single or transient feature identifications are discarded from the runs. Table 2 compares the number of correct feature identifications to the total number of feature identifications performed for runs using raw and averaged data. Table 3 lists the features identified in the experiments with transient features discarded.

Table 2: Feature Identification Performance

Data Type	Number of Identifications	Number Correct	Percent Correct
Raw	388	339	87
Average	63	59	94

Table 3: Raw & Averaged Data Feature Identification Results

Actual Feature	Reported Features using Raw Data	Reported Features using Averaged Data
Alcove	Alcove	Alcove
Corridor	Corridor	Corridor
Dual Alcove	Alcove Dual Alcove Alcove	Dual Alcove
Corridor	Corridor Corridor End Corridor	Corridor
Four-Way	Across T Four-Way	Four-Way
Corridor	Corridor Corridor End	Corridor Corridor End

Our approach makes use of an “off-the-shelf” robot with simple sensors. The robot's sensors and the software's algorithms are sufficient to correctly identify the large-scale features of an indoor environment. A set of simple rules is grouped into subsets to allow identification of the different features. The only filtering performed involves averaging six data sets together and using this averaged data set to identify features. This averaging did have the effect of reducing some misidentifications. Misidentification of features was caused by two sources: the physical layout of an area such that the sonar sensors on the robot could not “see” the correct feature initially and sonar range readings that did not represent the distance to an obstacle correctly.

5 Conclusions

This paper details the use of a simple rule-based technique for identifying large-scale features from sonar observations taken by a moving mobile robot. Experimental results demonstrate the efficacy of our approach. All features that were included in the feature set were correctly identified and distinguished from each other. Identification of the features was achieved for one-feature tests and for tests where the robot traversed areas of a building that were composed of multiple features. Misidentifications did occur but were reduced by averaging the sonar data and by minor changes to some of the rules used to identify features.

6 Future Work

Several possible improvements exist for this technique. Initially, we plan to investigate a neural network approach for learning to discriminate features, especially in environments with more diverse feature sets. We also intend to add a user interface that will utilize a simple, natural language for giving directions to, and receiving directions from, people. Conceptually, this interface will allow descriptions of the form: “Go to the end of the corridor, turn left, and go to the third door on the left past the atrium.” Finally, we will investigate alternative forms of topological graph maps. Both weighted graphs (using distance travelled) and unweighted graphs are possibilities. Furthermore, graph edges can either be transitions between features or can be some base feature, such as corridors, that dominate the environment but do not typically take part in the description of paths and directions.

7 References

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