Semantic Grid Map Building

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Abstract

Conventional Occupancy Grid (OG) map which contains occupied and unoccupied cells can be enhanced by incorporating semantic labels of places to build semantic grid map. Map with semantic information is more understandable to humans and hence can be used for efficient communication, leading to effective human robot interactions. This paper proposes a new approach that enables a robot to explore an indoor environment to build an occupancy grid map and then perform semantic labeling to generate a semantic grid map. Geometrical information is obtained by classifying the places into three different semantic classes based on data collected by a 2D laser range finder. Classification is achieved by implementing logistic regression as a multi-class classifier, and the results are combined in a probabilistic framework. Labeling accuracy is further improved by topological correction on robot position map which is an intermediate product, and also by outlier removal process on semantic grid map. Simulation on data collected in a university environment shows appealing results.

1 Introduction

Semantic grid map is a novel concept where a conventional occupancy grid map is incorporated with labels of places while keeping occupied and unoccupied cells. This map can be used for common representation of high level information which can be effectively and efficiently shared between humans and robots. Therefore the humans have a better understanding of the robots and the robots can eventually have the capability of carrying out complex tasks interacting with humans. The supporting technology used in building the semantic grid map is semantic labeling of places, which enables a robot to perceive and analyse the environment.

Most popular sensors that have been used in semantic labeling of places are cameras and laser range finders. Many prior works propose environment classification algorithms using features like lines and objects extracted from vision data [Shi and Samarabandu, 2006] [Viswanathan *et al.*, 2009]. Some researchers working on similar topics utilize laser range data [Mozos *et al.*, 2005] [Sousa *et al.*, 2007], and some others use multi-sensor based approaches [Pronobis *et al.*, 2010]. However, our belief is that the potential use of the laser range data has not yet been well exploited. Therefore, in this paper, our aim is to semantically label places based only on laser range/bearing data.

In this research area, Poncela et al [Poncela *et al.*, 2008] adopted Principal Component Analysis to classify the objects as walls or doors based on laser range data. Buschka et al [Buschka and Saffiotti, 2002] proposed a rectangular-fit algorithm to incrementally extract room-like nodes and automatically segmented the space into room and corridor regions. Their approaches rely on the invariant width and length parameters of a certain space. Tapus *et al.* [Tapus *et al.*, 2004] proposed a Bayesian approach for topology recognition and door detection with a complex implementation. Mozos *et al.* [Mozos *et al.*, 2005] extracted variety of simple features from laser range data and made use of AdaBoost classifier to label indoor environments as rooms, corridors, doorways and halls. In a similar approach, Sousa *et al.* [Sousa *et al.*, 2007] classified places using Support Vector Machines (SVM). In both cases, only the positions of the robot rather than the obstacle points were labeled.

In this paper, we firstly perform the classification task using logistic regression as a multi-class classifier and three features as dominant features; the classification results can be used to label either the observer's positions or the occupied grid cells. Then we adopt the independent opinion pool approach to fuse the semantic probabilities assigned to the same occupied grid cells detected by different observations, resulting in a semantic grid map. The labeling accuracy of the semantic grid map is improved in two ways through topological corrections (on robot position map, which is an intermediate product) and outlier removal process. Thereafter these techniques are combined to construct an exploration and labeling framework, which allows a robot to explore a relatively unknown environment and build accurate labeled maps.

Remainder of the paper is organized as follows: Section 2 discusses the details of the machine learning issues used in semantic labeling of places including classifier and the feature selection method. Data fusion and correction approachs are discussed in the Section 3. The idea of exploration and labeling is introduced in Section 4. In Section 5, experimental results are presented, and Section 6 concludes the paper.

2 Classification

2.1 Logistic Regression

Logistic Regression is an approach to learn functions of the form $P(y \mid \vec{x})$ in the case where y is discrete-valued, and $\vec{x}$ is any vector containing discrete or continuous variables [Mitchell, 2005]. It assumes a parametric form for the distribution $P(y \mid \vec{x})$ while directly estimating its parameters from the training data [Mitchell, 2005].

For binary classification, given data $\vec{x}$ and parameters or weights $\vec{w}$, the parametric model is:

$$P(y = \pm 1 \mid \vec{x}; \vec{w}) = \frac{1}{1 + \exp(-y \cdot \vec{w}^T \cdot \vec{x})} \tag{1}$$

Let the training samples be $(y_i, \vec{x}_i)$, where $\vec{x}_i$ is the feature set and $y_i \in \{+1, -1\}$ is the label of a certain training sample. Then the objective of the training task is to minimize the negative log-likelihood,

$$\min_{\vec{w}} \left(\sum_{i=1}^{m} \log\left(1 + \exp\left(-y_i \cdot \vec{w}^T \cdot \vec{x}_i\right)\right) \right) \tag{2}$$

However, overfitting is a potential risk of logistic regression especially when data is with high dimensions and training data is sparse [Mitchell, 2005]. Hence, regularization which encourages the fitted parameters to be small is usually employed to reduce overfitting [Ng, 2004]. L2 regularization is commonly used for this purpose by encouraging the sum of squares of the parameters to be small [Ng, 2004].

L2-regularized algorithm solves the following problem.

$$\min_{\vec{w}} \left(\frac{1}{2} \vec{w}^T \vec{w} + C \sum_{i=1}^{m} \log\left(1 + \exp\left(-y_i \cdot \vec{w}^T \cdot \vec{x}_i\right)\right) \right) \tag{3}$$

where $C > 0$ is a penalty parameter.

Although logistic regression is originally a binary classifier, it has also been extended by applying strategies such as one-against-all and one-against-one to deal with multi-class problems [Fan *et al.*, 2008].

2.2 Semantic Labels

In a typical university building, some commonly observed areas are *office rooms*, *lecture rooms*, *corridors* and *doorways*. Among these areas, doorways serve as transit areas which are difficult to be recognized due to the ambiguity of definition and the dependency on the state of the door (open/closed). Therefore, in our research, *office room*, *lecture room* and *corridor* are finally adopted as semantic labels.

2.3 Feature Selection

In supervised machine learning problems, feature selection issue directly affects the generalization ability, overhead and overfitting of the system.

As is suggested that a small subset of features is sufficient to represent the target well [Ng, 2004], finding the dominant features becomes a key issue for most classification problems. Some classifiers like AdaBoost [Freund *et al.*, 1999] and Support Vector Machines (SVM) [Burges, 1998] are prominent to handle these problems effectively. AdaBoost constructs a strong classifier as a linear combination of many weak classifiers, and SVM performs classification in a high-dimensional feature space and has the advantage of dealing with sparse training samples.

Generally speaking, different functional areas have different gross shapes and sizes in blueprints. However, these design schemes would not be observed by laser range finder directly because of the presence of various furniture causing the laser range/bearing data to be in complex appearance [Thrun *et al.*, 2005]. Therefore, environment classification based on few trivial features, such as the gross shape of a place will be erroneous.

There are various features that could be used for semantic classification of places. Mozos *et al.* [Mozos *et al.*, 2005][Mozos, 1998] derived two sets of simple features from laser range data. One set was extracted from raw range data and the other was from polygonal approximation of the observed area. They employed about 150 single-valued features (considering different thresholds) of 22 kinds, and fed these features into a multi-class AdaBoost classifier. In a similar manner, Sousa *et al.* [Sousa *et al.*, 2007] selected 14 single-valued features to train a binary SVM classifier.

As the above mentioned geometric features are often used in shape analysis, we selected some combinations of them based on their performances evaluated by a L2-regularized logistic regression classifier. As shown in the results section, only three dominant features are adopted in our application.

3 Data Fusion and Correction

In this section, we describe the process of building a semantic grid map based on the classification results.

3.1 Independent Opinion Pool

In this application, observations are made independently from unduplicated positions. The observations are processed to produce probabilistic opinions on their labels. As this happens while the observer is moving, temporal data can be fused for improving the accuracy.

In the perspective of data fusion, the output of a sensor could be in the form of either likelihood $P(z \mid x)$ or opinion $P(x \mid z)$, where z is an observation and x is the semantic state of the target. Three common approaches to combine these probabilistic evidences are linear opinion pool, independent opinion pool and independent likelihood pool [Berger, 1985][Raol, 2010][Siciliano and Khatib, 2008]. Based on the structure of this application, independent opinion pool is an appropriate method to solve the problem.

The independent opinion pool can be described as follows:

$$P(x \mid z_1, \ldots, z_n) = \alpha \cdot \prod_{i}^{n} P(x \mid z_i) \tag{4}$$

where z_i is the i^{th} observation of an occupied grid cell, x is the semantic state of the cell, and α is a normalizing factor. In this application, all possible semantic states (classes) of an occupied grid are exclusive, i.e. the posterior probabilities of the point belonging to a certain semantic state sum up to one.

Equation (4) can be further rephrased in a recursive way:

$$P(x \mid z_1,...,z_n) \propto P(x \mid z_1,...,z_{n-1}) \cdot P(x \mid z_n) \tag{5}$$

3.2 Semantic Grid Map Building

With the availability of temporal data, it is possible to update and improve the grid map based on equation (5), resulting in a semantic grid map. As the classifier grossly label the whole laser range/bearing scan as belonging to a particular class, the generated semantic grid map has poor labeling results because the laser can "see" occupied grid cells in multiple area types with opened doors. Therefore, if the occupied grids detected in a single scan can be further discriminated into different regions and processed separately, the accuracy of the final semantic grid map can be improved.

3.3 Outlier Removal

Here inliers are defined as the laser range/bearing data belonging to a particular area type and outliers are belonging to another area type. For example, if a robot in an office room detects occupied grid cells both in the same office room and in an adjacent corridor, then the former are called inliers and the latter are called outliers. By discriminating inliers and outliers, it is possible to improve the semantic grid map.

One way to discriminate inliers and outliers is to find the doors directly. There are many door detection techniques proposed in the literature based on the assumption of a fixed door width [ElKaissi *et al.*, 2007], dynamic door states [Anguelov *et al.*, 2004] and fuzzy temporal rules [Carinena *et al.*, 2004]. Here, we combined some of the above thoughts to build a door detector using the following heuristics.

- Door is presented by two break points (door frame points), which are supported by "walls"
- The distance between the two break points should be within a certain range (a reasonable door width)
- All obstacle points seen through doors are belonging to another area type

Another approach for outlier detection is to filter the data based on the intuition that most of the indoor spaces can fit into a rectangle. The rectangle is based on a polygonal area approximated by the laser range/bearing data in a particular scan. The proposition of the hypothesis is that most of engineered closed spaces can be represented by rectangles, and the properties of inliers rather than that of outliers reflect the correct label.

The rectangle filter algorithm is implemented as follows:

- Extract line features from a single laser scan and find the main direction
- Find all possible rectangles of the same area as that is enclosed by a laser scan polygon, and align them in the main direction, as depicted in Figure 1.
- Among these rectangles, choose the one that contains the maximum number of obstacle points

This algorithm provides a conservative inliers prediction mechanism.

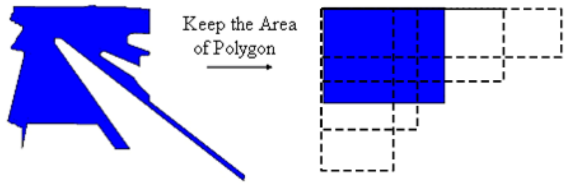


Figure 1: Basic concept of the rectangle filter

Moreover, we can also filter the laser data based on a range threshold. Intuitively it could be perceived that most probably the short range data belongs to inliers and it is further supported by statistics showing that in this application only 1% of outliers lie within 2.5m of the laser ranges. Therefore, we only concern about the occupied grids which are within a certain distance to the observer.

3.4 Correction Based on Topology

Different from outlier removal approaches which work on laser based observations, the semantic grid map can be further improved indirectly by correcting robot position map based on topological information such as room to corridor transition is more common than that of room to room or corridor to corridor transitions.

In this stage, it is assumed that adjacent robot position grid cells with the same semantic labels can be jointed to form a bigger region. After the robot's positions are corrected, the new information will be applied to the occupied grid cells observed in these positions to correct the semantic grid map.

In this application, the following topological heuristics of connected domain are defined:

- Corridor: borders of the corridor should contain obstacles (like wall or furniture) and at least one other environment type (like office room)
- Office room/Lecture room: boarders of office rooms or lecture rooms should contain obstacles (like wall or furniture) and at least one corridor

The algorithm treats connected domains as segments and generates a *segment and neighborhood table*, which is used for correcting based on above heuristics. All segments that do not comply with the above heuristics are merged to their largest semantically meaningful neighbor. The algorithm will iteratively update until it reaches a stopping criteria. Finally, corrected robot positions can be reused to correct semantic grid map.

4 Exploration and Labeling

The process of exploration and labeling is shown in Figure 2, and it consists of two sub-processes, which are actual and virtual exploration stages. In actual exploration stage, the robot explores an unknown space based on any exploration algorithm and comes up with an occupancy grid map. Once an OG map has been computed, a virtual exploration stage is carried out. In virtual exploration, the

OG map is virtually visited generating large number of robot poses and related sensor readings. Previously learned model is used to classify and label the robot's positions as belonging to different semantic labels to build a robot position map, which will be further improved by applying the topological heuristics defined in section 3.4. Finally, data fusion and outlier removal algorithms mentioned before are applied on virtual laser range data to generate a semantic grid map, which is analogy to a labeled occupancy grid map.

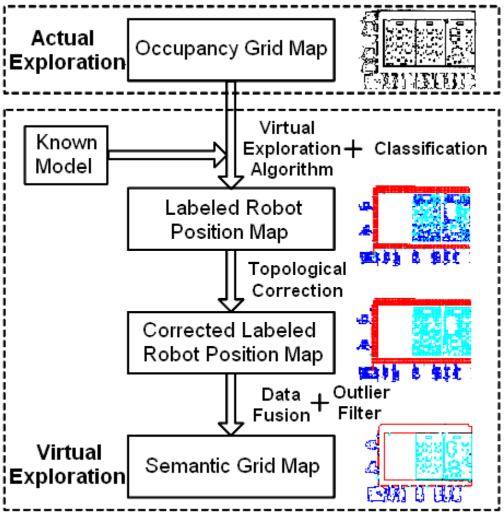


Figure 2: Block diagram of exploration and labeling scheme

5 Results

5.1 Feature Selection

Analysis of different feature combinations and their performance is carried out based on a published dataset (including raw laser scan and feature data) of a robot operating in an office like environment [Mozos, 2009]. As mentioned before (Section 2.3), Mozos *et al.* [Mozos *et al.*, 2005][Mozos, 1998] derived two sets of features from raw range data (which is called B series) and from polygonal approximation of the observed area (which is called P series). With regard to the definition of these features, please refer to literature [Mozos *et al.*, 2005][Sousa *et al.*, 2007][Mozos, 1998].

In this experiment, a L2-regularized logistic regression classifier is employed to classify environments into three classes based on different combinations of features. Many different feature combinations are tested and compared, and most prominent results are listed in TABLE I.

TABLE I
PERFORMANCE OF DIFFERENT FEATURE COMBINATIONS

Feature Combination	Testing Error	Execution Time
All 150 features	1.97 %	15292ms
All 21 single-valued features	2.09 %	2517 ms
All 11 single-valued P series	2.40 %	1175 ms
All 10 single-valued B series	2.57 %	1243 ms
3 selected features	2.12 %	361 ms

In the last row of the TABLE I, the three selected features extracted from a single laser scan are as follows:

- The standard deviation of the difference between the lengths of consecutive ranges
- The standard deviation of ranges
- The area of polygonal approximation

TABLE I indicates that feature selection is a tradeoff between accuracy and computational complexity. Given due regards to real-time performance of the system, the three selected features are adopted to be used in the classification.

5.2 Classification Results

In this section, a simulated dataset collected using a robot equipped with laser range finders operating in an indoor environment (Level 6, Building 2 of the University of Technology, Sydney) is used for the analysis.

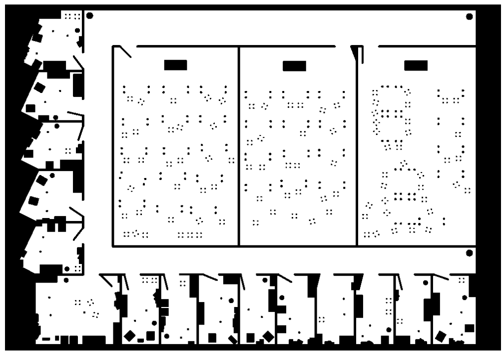


Figure 3: Map of the environment

As shown in Figure 3, the space is consisted of 3 long corridors, 3 lecture rooms with tables and chairs inside and 15 office rooms of different shapes with furniture inside. Two laser range finders were attached back to back to provide 360° laser range scans.

In this experiment, observer's positions are classified into various semantic labels and the performance of classifier is evaluated. For this purpose, 2957 scans have been used as the training dataset (corresponding robot's positions are manually labeled and shown in Figure 4 (a)), and another 2956 scans have been used as the testing dataset. Classification is carried out using L2-regularized logistic regression as a multi-class classifier and the output is in the form of probability estimation. Performance of the classifier and corresponding confusion matrix are shown in TABLE II and TABLE III respectively, and the testing result which is in the form of labeled robot positions on entire testing dataset is visualized as shown in Figure 4(b).

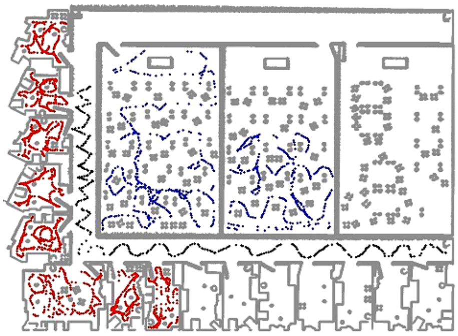
TABLE II
PERFORMANCE OF CLASSIFIER

Item (samples, composition)	Error
Training Error (2957 cases, Mixed)	1.2 %
Testing Error (401 cases, Corridor)	0.5 %
Testing Error (746 cases, Lecture Room)	2.8 %
Testing Error (1809 cases, Office Room)	0.0 %

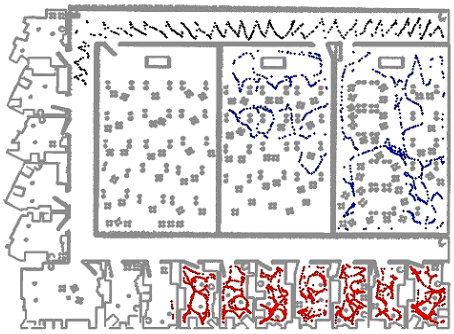
TABLE III

CONFUSION MATRIX [Witten *et al.*, 2005]

		Predicted Class		
		Corridor	Lecture Room	Office Room
Actual Class	Corridor	399	2	0
	Lecture Room	2	725	19
	Office Room	0	0	1809



(a)



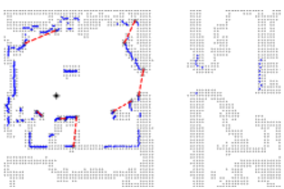
(b)

Figure 4: (a) Training dataset and (b) Testing dataset represented by robot's positions. The grey grids depict the background map as a reference. Red, black and blue points are observer's positions which are labeled as in office rooms, corridors and lecture rooms respectively (training dataset is manually labeled and testing dataset is labeled by classifier).

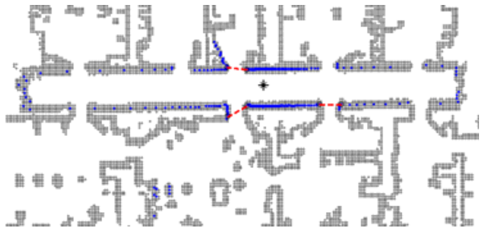
5.3 Outlier Removal

In this section, three approaches to remove outliers as mentioned in (Section 3.3) are tested and compared.

The door detection approach is carried out using heuristic rules, and the results are shown in Figure 5. In the corridor scenario (Figure 5, (b)), the door detection is reasonable due to the lack of foreign objects like furniture. However, there are few possible candidate doors (false detections) detected in the office room scenario (Figure 5, (a)). This is due to the presence of various furniture providing similar features to doors.



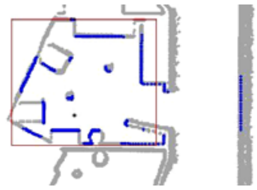
(a)



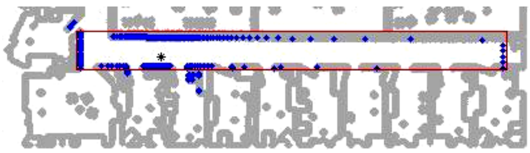
(b)

Figure 5: Performance of door detection: The observer marked as a star is in (a) an office room environment and (b) a corridor environment. The grey grids depict the background map as a reference. The blue grids are the laser based observations. Red lines indicate the potential doors.

In the second approach, rectangle filter is utilized based on the hypothesis that most of the inliers lie within a rectangle, which is restricted by the area of polygonal approximation of all obstacle points. The results of rectangle filter shown in Figure 6 indicate that the approach provides a reasonable gross classification of inliers and outliers.



(a)



(b)

Figure 6: Performance of rectangle filter: The observer marked as a star is in (a) an office room environment and (b) a corridor environment. The grey grids depict the background map as a reference. The blue grids are those detected by laser range finder. Grids inside the red rectangle are supposed to be inliers.

Although the door detection algorithm executes faster than the rectangle filter approach, it is not robust under complex environments like office rooms; the rectangle filter is effective but searching for the optimized rectangle is a time-consuming task, which makes it unsuitable for online implementation. In addition, its hypothesis has limitations in environments like corridor intersections due to shape complexity.

The third approach which only regards nearby occupied grid cells as inliers is not visualized here because it is relatively simple. Compared with other two approaches, this method is the fastest. However, on the other hand it also conservatively sacrifices some information, which is one of its disadvantages.

Eventually, the third approach is adopted in our application because of its simpleness and lower computational complexity.

5.4 Exploration and Labeling

This experiment implements the idea of exploration and labeling as described in (Section 4) based on simulation.

The aim of this idea is for a robot to construct an accurate semantic grid map of the environment, through an actual exploration and a virtual exploration (calculation) afterwards.

For the actual exploration stage, we adopt wall following algorithm as an example to generate an OG map as shown in Figure 7. Some spaces are inaccessible because of the setting of robot's size.

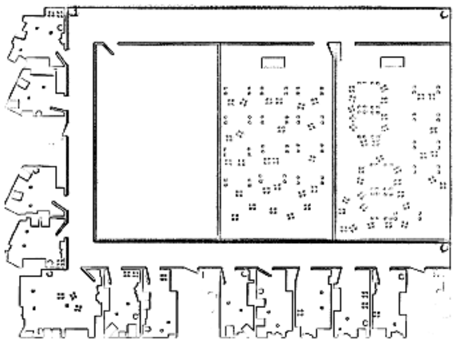


Figure 7: OG map generated by wall following exploration.

Once an OG map is generated, a virtual exploration is carried out to build a robot position map. We assume that the open space can also be represented by grids and the size of grid cell is determined by the physical dimension of the robot. Robot can start at any position and virtually move one adjacent free grid cell in one move towards all four directions (front, back, left, and right) avoiding target grids with obstacles inside; No nonholonomic constraints or kinematics of the robot are considered here. Two variable-length buffers are maintained by the AI program of robot: one is used to store unvisited free grids, and the other is used to store visited grids. During virtual exploration, the robot virtually visits all accessible open space, labels its positions and builds a labeled robot location map as shown in Figure 8.

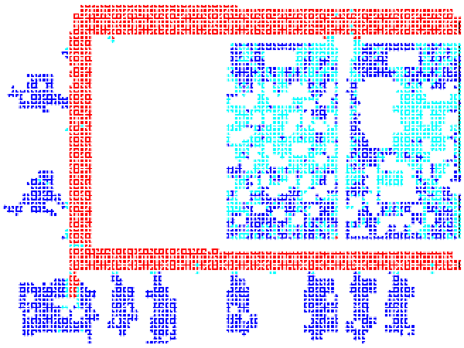


Figure 8: labeled robot position map built during virtual exploration. Blue, cyan and red grids are observer's positions labeled as belonging to office rooms, lecture rooms and corridors respectively.

The robot position map can be further improved by topological correction. Figure 8 can be represented in a topological form, which is a table recoding the neighbourhood relationship of segments (a segment means a connected domain consisting of robot positions with the same labels). The table will be processed according to the topological heuristics. The topological correction works on the table, checks from the smallest segment and iteratively updates the table. Unreasonably small segments will be merged by their largest neighbours, until all segments are reasonably in compliance with heuristics like: a corridor should have obstacles and different kinds of segments as neighbours; a lecture room or an office room should have only obstacles and a corridor as neighbours. As a result, a corrected robot position map which is an intermediate product is built as shown in Figure 9. Then the robot can generate a semantic grid map as shown in Figure 10 based on corrected robot position map. In the process of semantic grid map building, data fusion strategy (Section 3.1) and range-based outlier removal approach (Section 3.3) are implemented.

Simulation results show that by employing the topological corrections, the error rate in labeling the robot positions is reduced from 5.56% to 0.62%, and the semantic grid maps generated based on uncorrected/ corrected labeled robot location maps lead to error rates of 9.60% and 1.25% separately. This clearly shows that the topological correction approach dramatically improves the accuracy of the final semantic grid map.

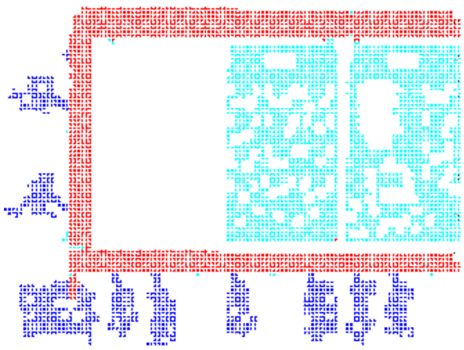


Figure 9: Corrected robot position map. Blue, cyan and red grids are observer's positions labeled as belonging to office room, lecture room and corridor respectively.

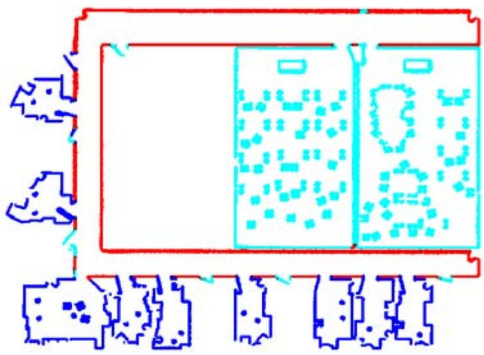


Figure 10: Semantic grid map built based on corrected robot position map. Blue, cyan and red grids are occupied grids labeled as belonging to office room, lecture room and corridor respectively.

6 Conclusion

In this paper, we presented an approach to classify the environment based on 2D laser range data. The classification results are firstly adopted to build a robot position map which is then further improved by topological heuristics. The refined robot position map was used to generate a semantic grid map which was enhanced by outlier removal algorithm. Experiments on university indoor environments with lecture rooms, offices and corridors show that the results are convincing with low labeling error on the final semantic grid map.

We are currently in the process of relaxing the heuristics and formulating problems in a probabilistic framework.

Acknowledgements

This work is supported by the ARC Centre of Excellence programme, funded by the Australian Research Council (ARC) and the New South Wales State Government.

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