Image Based Exploration for Indoor Environments using Local Features

(Extended Abstract)

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ABSTRACT

This paper presents an approach to explore an unknown indoor environment using vision as the sensing modality, thereby building a topological map of images. The contribution of this paper is in a new approach that identifies the next best place to move from a node in the topological graph. This decision is taken locally at a node by choosing the next best direction, when there are open spaces before the robot, and globally by choosing the next best node to branch off a new exploration, when there are no open spaces before the robot. We propose a method to assign weights to nodes for this purpose. Weight is defined as a function of the depth of local descriptors of images, and the number of times they were seen across different nodes. The efficacy of the approach to explore office like environments is verified through several experiments on a P3DX robot.

Categories and Subject Descriptors

I.2 [**Robotics**]: Commercial Robots and Applications

General Terms

Algorithms, Experimentation

Keywords

Robot exploration, Image based navigation, topological mapping

1. INTRODUCTION

Mobile robot exploration is a vital cog in the automation of the mapping process. In recent years, lot of work has been done on image based navigation along the lines of appearance based mapping [3] and topological SLAM [4]. Image based navigation algorithms such as [5, 2] have shown through visual servoing or otherwise, a framework for navigating from one node to another in a topological map based on images. However these methods do not describe in detail the process of automating map construction.

While range sensor based exploration has been well understood, the amount of literature on vision based exploration is indeed sparse. In the available literature on vision based exploration [1, 2], this problem was tackled in the context of identifying frontiers (similar to laser based exploration) as the next best places to explore. In contrast to [1] which requires the depth computation to be accurate to build a metric map, we build a topological map of images. And, our work is different from [2] by incorporating local and global decision making in our exploration strategy.

We propose an exploration algorithm which does not rely on accurate depth computation and also provide a termination condition. Our two part strategy consists of the following: 1) selection of next best direction(*local decision*) for immediate exploration, and 2) selection of a next best node(*global decision*) in the topological graph to branch off a new exploration. This strategy relies on the relative depth of local features and their association across different nodes.

2. METHODOLOGY AND RESULTS

At each node in the topological graph, the robot takes images in 3 directions(0^o, 120^o, 240^o) to get a 360^o field of view.

2.1 Part 1 : Local decision making

Decision is taken locally at a node, when there are open spaces before the robot. Open space is identified by the depth of the local features seen in the current image. Local decision making aims at increasing information of neighbouring nodes to the current node in the graph. *Information is defined in terms of feature association across images in different nodes. The information about a feature is proportional to the number of times it gets associated across different nodes.* Hence to increase information, the robot has to move in such a way that it can see the features it has seen already. This is be done by computing the depth of all features in an image and moving towards the farthest feature. The assumption here is that, the farthest feature lies in the proximity of far features which is generally the case in our experiments. This decision would thus result in an information gain of other far features too. After finding the farthest feature, the robot orients(θ) towards it and moves a distance δ. A new node is added in the graph and the (θ, δ) relationship between the current node and the previous node is stored in the graph.

$$\delta = \min(1m,\ depthofNearestFeature/2) \qquad (1)$$

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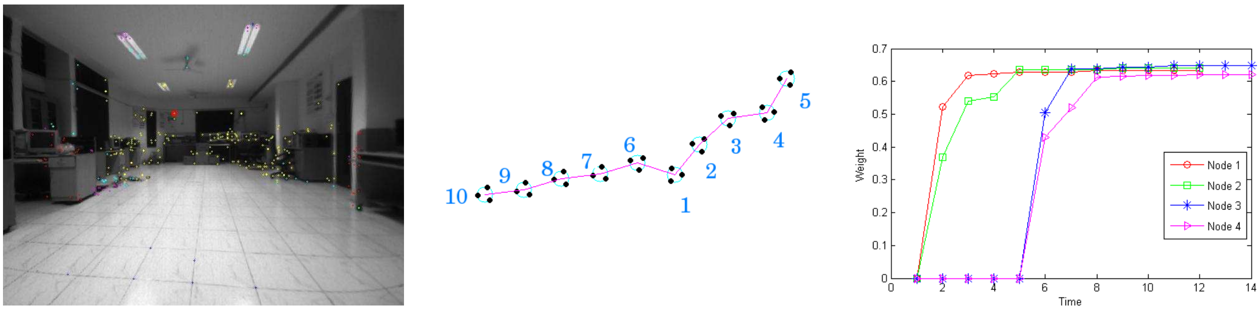

(a) Far feature based direction selection (b) Topological map built by the roobt (c) Weight change during exploration

Figure 1: Image based exploration

2.2 Part 2 : Global Decision making

Global decision making finds the next best node in the graph, to branch off a new exploration. The next best node refers to a direction(among 3 directions 0^o, 120^o, 240^o) in a node which is best to branch off a new exploration. Henceforth, it is understood that next best node always refers to a particular direction in a node.

Decision is taken globally when the robot comes to a dead end. Weights are defined for nodes for this purpose and the node with the least weight is chosen as the next best node to explore. A common feature table(k-d tree) is used to assign weights to nodes. The global feature table maintains two attributes for each feature 1) *count*, which maintains the number of times the feature was seen across all nodes. 2) *minimumDepth*, which maintains the minimum depth at which the feature was seen. Features seen at every node are associated with the features seen already(in the common feature table) based on euclidean distance metric. New features are added to the table if they don't get associated.

Defining Weights : Weight is defined as a function of i) the number of times the features of a node were seen across different nodes, and ii) the nearest depth at which the features in the node were seen across different nodes. We use *count*, *minimumDepth* attributes in the global feature table for computing weights.

$$\text{Weight } w = max(\sum_i \alpha_i * cnt(i), \sum_j \beta_j * depth_j) \quad (2)$$

cnt(i) is the number of number of features in that node with *count* *'i'* in the global feature table, and $depth_j$ is the depth of the jth feature in that node. α_i is higher for higher values of i so as to give more weights to features which were seen many times. β_i is higher for lower values of depth, thus giving more weights to features which were seen at a close range. The second part of weight update dominates the first part when the robot is near to the corner of a room.

The next best node to explore is the one with least weight, and exploration continues in this fashion until the weights of all nodes saturate. The weight change across selected nodes during exploration is shown in figure 1(c).

2.3 Comparison

Table 1 shows a comparison across different strategies to explore. The comparison is shown in terms of the number of nodes in the topological graph by the end of exploration. Results presented here are averages of several experiments conducted in two rooms. The strategies used for comparison are i) Our method, using next best direction and next best node (NBD-NBN) ii) Randomly selecting a direction for immediate exploration and using weights to identify the next best node on reaching a dead end (RD-NBN) iii) Using far features for immediate exploration and randomly selecting nodes to explore on reaching a dead end (NBD-RN) iv) Boustraphedon like paths.

Table 1: Comparison across different strategies

Exploration strategies	Room 1	Room 2
NBD-NBN	11	6
RD-NBN	21	9
NBD-RN	25	14
Boustraphedon	28	18

3. CONCLUSION

We have presented a novel method for exploring indoor environments with images only. This is one of the first methods to explore indoor environments autonomously based on images. This method uses local and global decision making from time to time to identify the next best place to move at every decision point. A termination condition to stop the exploration was discussed. Results were provided to justify the efficiancy of our approach.

4. REFERENCES

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