

# Sensing Planning for Mobile Robot Localization - Use of Learning Bayesian Network Structure -

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**Abstract**— In this paper we propose a novel method to solve a kidnapped robot localization problem. A mobile robot plans its sensing action for localization using learned Bayesian network’s inference. Concretely, we represent the contextual relation between the local sensing results, actions and the global localization beliefs using the Bayesian network. The Bayesian network structure is learned from complete environment information data using *K2* algorithm combined with GA. The mobile robot actively plans its sensing action to obtain sensing information event by taking into account the trade-off between global localization belief and the sensing cost. We have validated the learning and planning algorithm by simulation experiment in an office environment.

**Key Words:** Bayesian network, Structure learning, Sensor planning, Mobile robot, Localization

## 1. Introduction

We propose a novel localization method which models the local sensing results, global localization and actions in a Bayesian network<sup>1</sup>(*BN*). The mobile robot plans the efficient sensing actions to localize itself in this *BN*. The *BN* predicts the possible actions and associate some possible sensor data according to these actions, then uses these predicted actions and sensor data to evaluate the actions by a criterion of sensing efficiency (the balance of the global localization belief and the sensing cost). The structure and the parameters (CPTs) of the *BN* are learned from the environment information data without heuristics.

## 2. Gathering Environment Information Data

We performed simulation experiments in an office environment (Fig.3). In order to obtain the complete environment information, the mobile robot must pass all of the corridors and intersections. To solve this problem, we employ a framework of the *Chinese postman problem*(Fig.1).

The mobile robot is driven by a potential method in corridors. A laser rang sensor is assumed to be used, and we obtain 180-direction distance information in front of the mobile robot. The mobile robot is guided by the command at each intersection from a command list which was generated by the *next node algorithm*<sup>2</sup> beforehand. The labels (*A, B, ..., L* of Fig.3) of intersection are given by human while the mobile robot arrives each intersection. The landmarks (hollow in our experiments) are detected by filtering the range data in two sides of the robot. To simplify the problem, uncertainty of the *local distance*, i.e., the

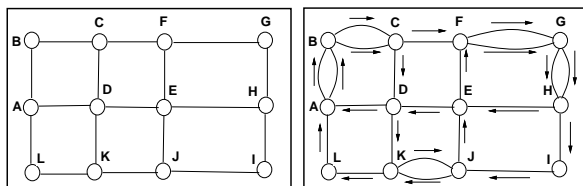
local distance between two neighboring landmarks or between a certain intersection and its neighboring landmark, is ignored in current system. The geometrical features of the intersections is recognized by a supervised learning algorithm, *support vector machines* (SVMs).

We define the environment information between two neighboring intersections to be an information *segment* (*Sg*). One *segment* involves (1)two intersection labels, (2)landmarks’s information between the two intersections, (3)the geometrical features of intersections that are read when the mobile robot is entering each one, and (4)action that how the mobile robot enters this *segment*. The environment data of two neighboring *Sg* is recorded as one data case, and the recorded sensing data is used to learn the *BN*’s structure and parameters.

## 3. Learning Bayesian Network Structure from Data

We apply a score based search method, named *K2* algorithm<sup>3</sup>, for structure learning of *BN*. In order to decrease the search scope, the best structure searching of *K2* algorithm is based on ordering of nodes (i.e.,the causal attributes of an attribute should appear earlier in the order). We apply a *genetic algorithm*(GA) to search the best ordering as in Ref<sup>4</sup>, and based on this ordering, *K2* can learn the best structure form environment information data.

As an example, 13 variables are defined as nodes of a Bayesian network. The nodes *Head(H)*, *Mid(M)*, *Tail(T)* denote order of the intersections<sup>1</sup>. Number of the probabilistic variable of intersection labels is 12 (*A, B, ..., L*). The nodes *Action1(a<sub>1</sub>)* and *Action2(a<sub>2</sub>)* denote the actions when the mobile robot enters two *segments* of one case, respectively. Probabilistic variables of actions are *go forward*, *turn left*, *turn right*. The nodes *Hf*, *Mf*, *Tf* are defined by geometrical features of intersections that are sensed when the mobile robot enters each one. Number of probabilistic variables of intersection types is 6, for example,  $\perp$ ,  $+$ ,  $\top$  and so on. We denote the landmarks in each *segment* by nodes  $m_{h1}, m_{h2}, m_{t1}, m_{t2}$ , and the nodes also include the *local distance* information. We



**Fig.1** (left) A graph representing an office. (right) A path as a solution of Chinese postman problem.

<sup>1</sup>*Head(H)* is the first intersection of two neighboring *Sg*, *Mid(M)* is the middle intersection, and *Tail(T)* is the last one.

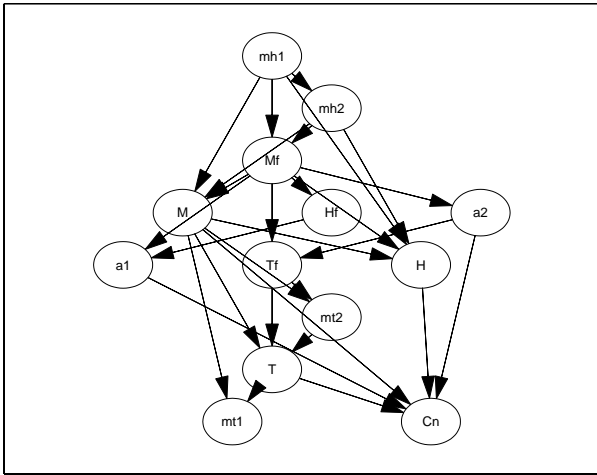


Fig.2 Learned *BN*'s structure by K2 and GA.

can represent a landmark as a vector (*geometrical feature, local distance*), probabilistic variables of the landmarks take four values. We also define a *mediating variable* by label of every data case, it has 138 probabilistic variables. After 100 generations of the GA searches, we obtained the *best* ordering. Using the *best* ordering, K2 algorithm generates a *BN* structure as shown in Fig.2.

#### 4. Sensor Planning for Localization

The planning system consists of three phases: (1)*inference for localization*, (2)*prediction for sensor planning*, and (3)*sensor planning for localization*. Initially, the mobile robot moves in a certain corridor. While the mobile robot gets a new sensing information, the system uses *BN* to infer the *global localization belief*. At some intersection, if the gathered sensing information is not sufficient for localization, in other word, the *global localization belief* can not exceed a certain *threshold*, the system will predict some action and associate some sensing information in the Bayesian network. Using these information the robot selects an optimal sensing action to perform active sensing and localize itself.

#### 5. Experiments

Initially, the mobile robot starts from intersection *D*, and perceived two hollows from two sides of the corridor (from *D* to *K*). The *global localization belief* is inferred by the learned *BN*. The probability of *Head(H)*, *Mid(M)* and *Tail(T)* is shown in Fig.3. We find the belief of each intersection is too ambiguous to localize the mobile robot(Fig.3(a)). The sensor planner runs at *K*. The predicted actions are *turn left* and *turn right*, the sensor planner tests the *global localization belief* and sensing cost using each predicted actions and some predicted sensing information according to the action. If the mobile robot *turns left*, the mobile robot can not get enough sensing information for *global localization* until it moves to the **Tail** intersection (**J**), and if the mobile robot *turn right*, the mobile robot can obtain enough belief(Fig.3(b)) with lower sensing cost. Therefore, the optimal action at the intersection *K* is determined as *turn right*.

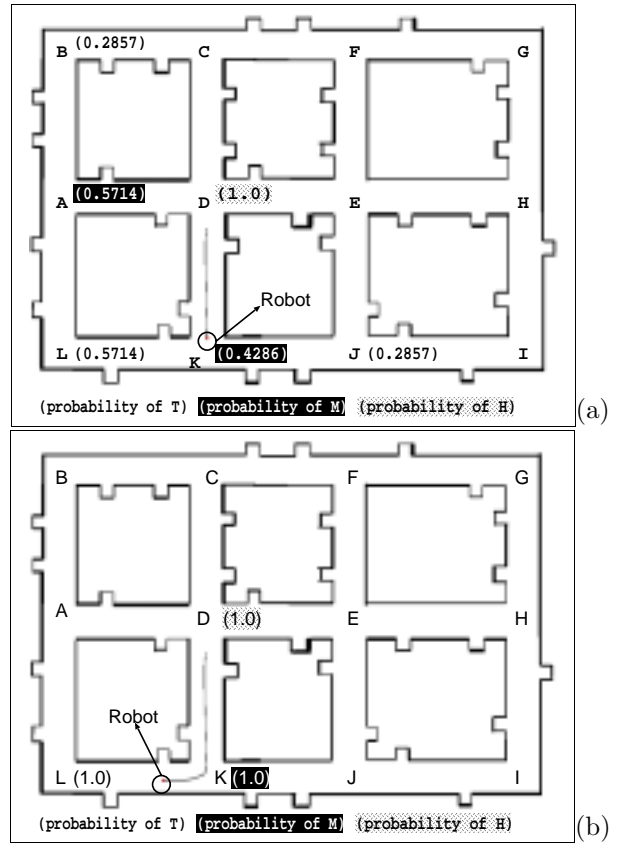


Fig.3 An example of the experiments of sensor planning for the mobile robot localization.(In the figure, the real numbers in ( ), ( ) with black square, ( ) with hatched square represent probability of node T, M, H respectively.

#### 6. Conclusion

In this paper, we propose a novel sensor planning method for the mobile robot localization using a Bayesian network. The *BN* structure is learned from environment data based on K2 algorithm combined with GA. The sensor planner predicts possible actions and some sensing information according to these actions at a certain ambiguous intersection, and selects optimal plan of sensing action for *global localization* by taking into account the trade-off between *global localization belief* and the sensing cost. In the future, we will validate the system using a real mobile robot.

#### Reference

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