Semantic Place Labelling Method

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Abstract:
The paper presents a method of semantic localization of a mobile robot. The robot is equipped with a Sick laser finder and a Kinect sensor. The simplest source of information about an environment is a scan obtained by the range sensor. The polygonal approximation of an observed area is performed. The shape of the polygon allows us to distinguish corridors from other places using a simple rule based system. During the next step rooms are classified based on objects which have been recognized. Each object votes for a set of classes of rooms. In a real environment we deal with uncertainty. Usually probabilistic theory is used to solve the problem but it is not capable of capturing subjective uncertainty. In our approach instead of the classic Bayesian method we proposed to perform classification using Dempster-Shafer theory (DST), which can be regarded as a generalization of the Bayesian theory and is able to deal with subjective uncertainty. The experiments performed in real office environment proved the efficiency of our approach.

Keywords: *mapping, classification, Dempster-Shafer theory*

1. Introduction

The problem of localization is essential for a mobile robot or an intelligent agent. Metric or topological localization algorithms have been described in many articles and books [6, 8, 15, 18, 25].

In SLAM (Simultaneous Localization and Mapping) approach metric information about exact position and orientation of a robot is significant [12,16] but it is less important in a framework for topological mapping. In this case exact position within a metric space is not necessary.

A topological map is represented as a graph, where nodes indicate places, edges denote their connectivity [17]. In a such representation of an environment the robot only has to decide from which node (place) the current measurement comes from. Place labelling is also natural for a human so it is necessary when the robot interacts with people. We can ask the robot to go to the kitchen or to the bedroom.

Some place recognition techniques rely on prior object identification [23]. The methods suffer from high complexity so most of the recent scene classification systems bypass this step. The authors compute various descriptors on laser range scans [13] or on images [19]. We can distinguish between methods using global features [3, 4, 14, 19] and methods using local descriptors [22]. In [3, 4] the methods of places labelling based on laser or ultrasonic scanners are presented. Mozos [13] proposed using Hidden Markov Model and AdaBoost algorithm. The work that is the closest to ours is [23] but instead of clasic Bayesian method we proposed to perform classification using Dempster-Shafer theory (DST). DST can be regarded as a generalization of the Bayesian theory and is able to deal with subjective uncertainty. We propose a procedure of place labelling which consists of the following steps:
- acquiring information about the environment,
- known object detection and classification using 3D vision sensors,
- adding information about the detected objects to the map,
- segmentation into rooms using information about doors and doorways,
- classification of the rooms based on their features and detected objects.

In next sections of the article the steps of the algorithm are described.

2. Hardware

The robot Kurier, presented in Fig. 1 is used in our system. It is equipped with a laser range scanner, cameras and a Kinect sensor which allow us to acquire information about the environment.

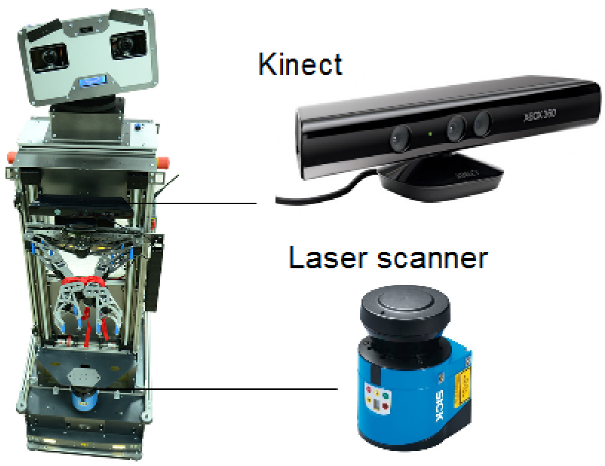
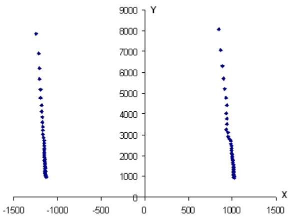


Fig. 1. The robot Kurier

The laser scanner is an optical 2D distance measuring sensor with $270°$ angle range and $0.5°$ resolution.

The Kinect is a motion controller designed for the Xbox 360 console. This inexpensive device is a very good replacement for costly advanced 3D laser scanners. The device includes vision camera and depth sensor. With the use of this device it is possible to gather visual information and 3D point cloud. Such information allows us to reproduce a 3D digital model (with colour information) of a scene seen by the robot. Fig. 2 presents the image of the environment (corridor), data obtained using laser scanner and point cloud generated by Kinect sensor.


a)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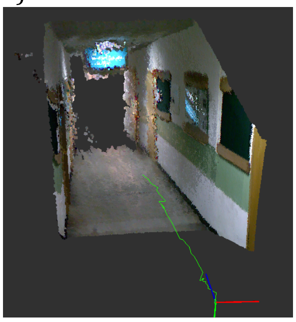

c)

Fig. 2. Sensors reading: a– the image of the corridor, b – laser scanner meauserment, c – a point cloud

3. Mapping

Algorithms which allow us to build a metric map of an environmant based on a laser scanner measurement are described in many articles [7,20,21] and are implemented in ROS system [1]. In our system ROS modules are used in order to build the metric map of the Mechatronics faculty building.

Fig. 3 presents the grid-based map of a part of the Mechatronics building. Black dots represent the parts of an obstacle, grey colour stand for unrecognized area, white dots represent free from the obstacles parts of the environment.

Once the system possesses a metric map of the building we seek for information about its functional spaces.

Automatic obtaining of such information is a more difficult task as it requires understanding of the environment on a much higher level.

The simplest source of information about the environment is a scan obtained by a range sensor. Figs. 4a, 5a present images of the environment: a corridor and a laboratory and corresponding range scans. The scan consists of a set of points $\{x_i, y_i\}, i = 1, ..., M$, where M is a number of LRF reading. The polygonal approximation of an observed area is performed using efficient implementation of Hough transform decribed

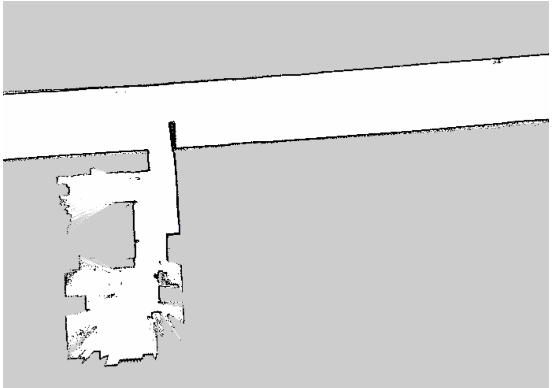
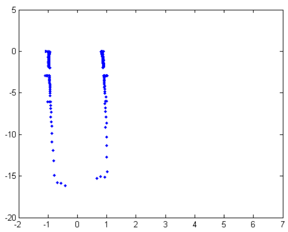


Fig. 3. Grid-based map of the environment

in [5]. Fig. 4c, 5c represent the polygons constructed on the basis of laser scans 4b, 5b.


a)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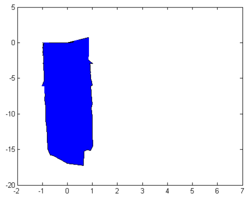
c)

Fig. 4. Data obtained by the laser range finder in the image of the corridor:
a – the image of the corridor, b – scan taken in the corridor, c – polygonal approximation of the scan

For the polygons the following parameters are computed:

- *eccentricity* – the ratio of the maximum length of the line that spans the region to the minimum length,
- *compactness* c

$$c = \frac{p^2}{A}, \tag{1}$$

where p is the perimeter of the polygon and A is its area.

- *the maximum length* of the polygon sides.

The parameters: *eccentricity*, *compactness* and *the maximum length* allow us to distinguish corridors from other places using simple rule based system.

The result of the first step of segmentation is shown in Fig. 6 areas, which are the parts of corridors are outlined in blue, areas which have not been classified are not marked.

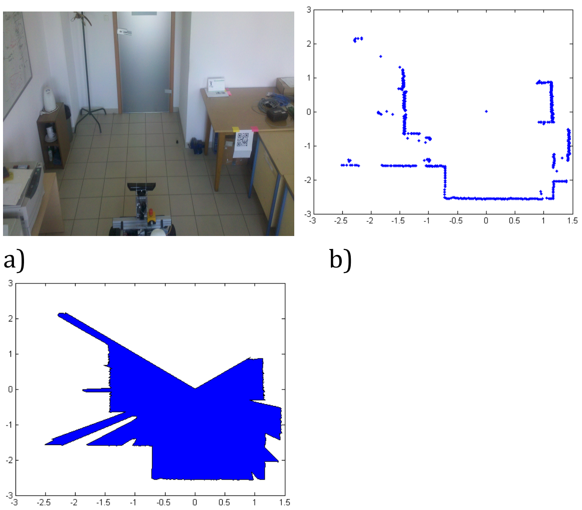

Fig. 5. Data obtained by the laser range finder: a – the image of the laboratory, b – a scan taken in the laboratory, c – polygonal approximation of the scan

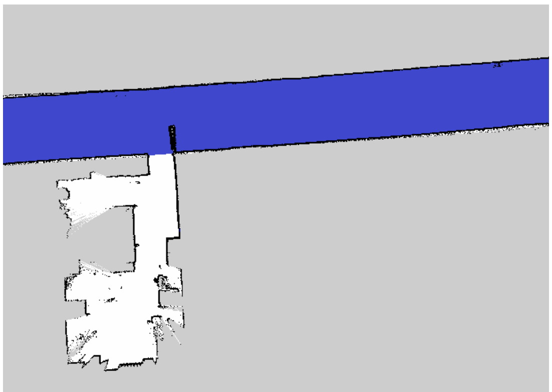

Fig. 6. Grid-based map of the environment and place classification: blue – corridor, black – obstacles

4. Object Recognition

When the objects have been detected and recognized they are marked on the grid-based map of the environment. The features usually used for object classification are, among others [21]:

- size – usually an object which is supposed to be detected is characterized by some specific size
- orientation – e.g. walls or doors are always vertical, but ceiling and floor are always horizontal, even though the other features of these surfaces are almost identical.
- topology – relations between objects are important, which is described in [9].

In our previous work [2] we presented a method which allows object classification based on shapes representation. However, recently we have developed a new, promising set of features [10, 11]. Fig. 7 presents the a part of grid-based map of the environment and recognized objects.

The Figure 8 shows how the program obtains vertical edges connected with metric information. Then

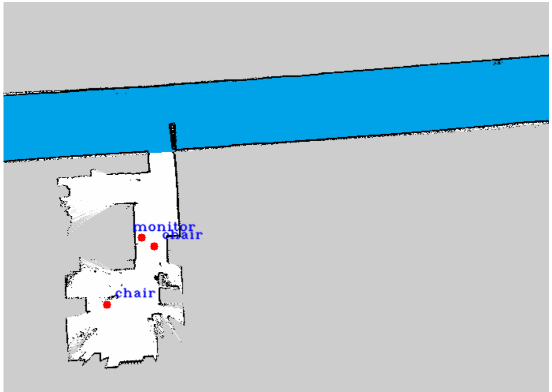

Fig. 7. Grid-based map of the environment and recognized objects

further analysis extract pairs of the edges that correspond to the door. The program detects both closed and opened door and returns their positions and states.

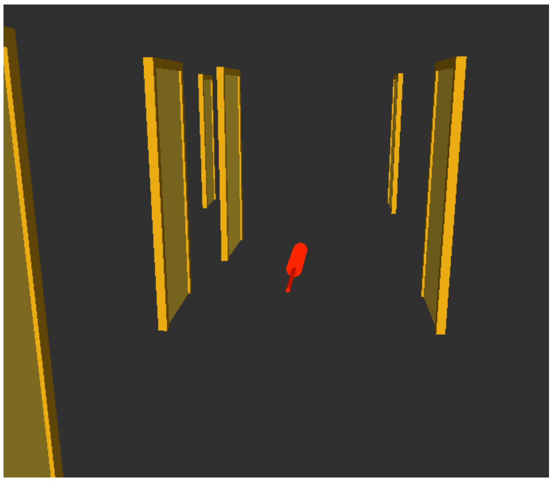

Fig. 8. Doors recognized by our algorithm

Doors recognition plays very important role during a process of place labelling, objects which are placed behind opened doors could not be used in process of place classification. When the robot go trough doorway it probably changes its state (room).

5. Places Classification Using Dempster-Shafer Theory

Each object *votes* for a set of classes of rooms, for example when washbasin is observed it support the hypothesis that it is placed in the toilet and denies the hypothesis that it is in the corridor.

In real environment we deal with uncertainty. Usually probabilistic theory is used to solve the problem but it is not capable of capturing subjective uncertainty. In our approach instead of classic Bayesian method we proposed to perform classification using Dempster-Shafer theory (DST), which can be regarded as a generalization of the Bayesian theory and is able to deal with subjective uncertainty. In this approach a degree of belief is represented as a function. Each fact can support the hypothesis in degree between 0 and 1

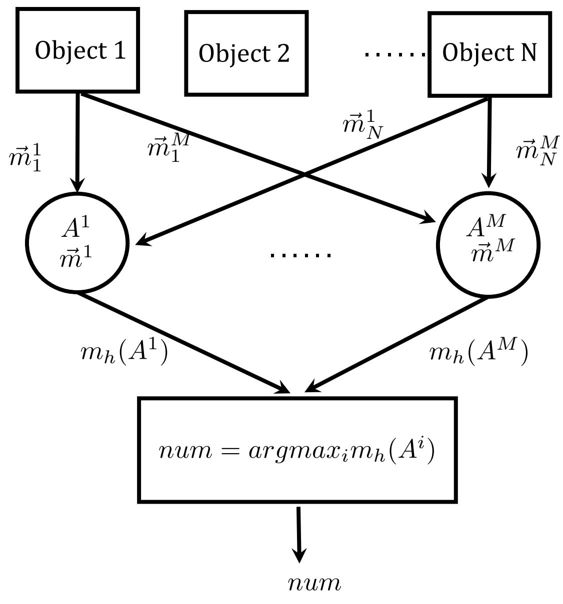

Fig. 9. Places classification using SD theory: the symbol $\vec{m}_k^j$ ***stands for*** $[m_h^k(A^j), m_{nh}^k(A^j)]$***, symbol*** $\vec{m}^j$ ***represents*** $[m_h(A^j), m_{nh}(A^j)]$

and support its negation in some degree. In comparison to the Bayesian theory the belief in a hypothesis and its negation need not to sum to 1 and both values can even be equal 0, which would mean that there is no evidence for or against the theory. Our algorithm consists of two steps:
- initialization,
- data aggregation.

The process of initialization consists of the following stages:
- a set of place labels is given: *classroom*, *toilet*, *laboratory*,....,
- a set of objects is given,
- for i-th object, $i = 1, ...N$, where N is the number of objects and each label A_k, $k = 1, ...M$, where M is the number of labels, two masses are attached $m_h^i(A^k)$ and $m_{nh}^i(A^k)$. The first one expresses the proportion of evidence that supports the claim that the current state (place) of the robot belongs to A_k while the second is a level of supporting the negation of the hypothesis. Because of uncertainty the following inequality occurs:
$$m_h^i(A^k) + m_{nh}^i(A^k) \leq 1. \tag{2}$$
- The value:
$$m_{uh}^i(A^k) = 1 - m_h^i(A^k) - m_{nh}^i(A^k), \tag{3}$$
represents the uncertainty. In this article the parameter $m_{uh}^i(A_k)$ is named an uncertainty mass.
- for each place label the initial value of parameters $m_h(A^k), m_{nh}(A^k)$ are attached. In the current version of the system the total initial uncertainty is assumed, so $\forall_{k=1}^M$:
$$\begin{aligned} m_h(A^k) &= 0, \\ m_{nh}(A^k) &= 0, \\ m_{uh}(A^k) &= 1. \end{aligned} \tag{4}$$

In the next version of our algorithm similarly to PMDs the history of the robot states will be taken into account.

Fig. 9 presents the idea behind the SD place classification.

When $i-th$ object is recognized it sends values $[m_h^i(A^k), m_{nh}^i(A^k)]$ to all nodes. The k-th node (which is represented as a circle in fig. 9) stands for the class A^k.

For all classes new values of beliefs $[m_h(A^k), m_{nh}(A^k)]$ are computed using formulas 5-6. The formulas are modification of Dempster rule of aggregation and were successfully applied in the process of grid-based map building [24].

$$m_h(A^k) = \frac{S^i(A^k)}{1 - K_i^k}, \tag{5}$$

$$m_{nh}(A^k) = \frac{S_n^i(A^k)}{1 - K_i^k}, \tag{6}$$

where:

$$\begin{aligned} S^i(A^k) = \quad & m_h(A^k) \cdot m_h^i(A^k) + \\ & + m_h^i(A_k) \cdot m_{uh}(A^k) + \\ & + m_{uh}^i(A^k) \cdot m_h(A^k) \end{aligned} \tag{7}$$

$$\begin{aligned} S_n^i(A^k) = \quad & m_{nh}(A^k) \cdot m_{nh}^i(A^k) + \\ & + m_{nh}^i(A^k) \cdot m_{uh}(A^k) + \\ & m_{uh}^i(A^k) \cdot m_h(A^k) \end{aligned} \tag{8}$$

$$K_i = 1 - m_h(A^k) \cdot m_{nh}^i(A^k) - m_{nh}(A^k) \cdot m_h^i(A^k) \tag{9}$$

Unlike the probabilistic methods there are not strict rule to obtain the mass values in Dempster-Shafer theory. In our system the masses are computed on the basis of date set and the following algorithm is applied:
- a_i^k represents the incidence of the object i-th in the class k,
- for all objects the value s_i is computed:
$$s_i = \frac{\sum_{k=1}^M a_i^k}{M} \tag{10}$$
- if for k-th class and i-th object the value:
$$a_i^k - s_i > 0 \tag{11}$$
then:
$$\begin{aligned} & m_h^i(A^k) = a_i^k - s_i, \\ & m_{uh}^i(A^k) = 1 - m_h^i(A^k), \\ & m_{nh}^i(A^k) = 0 \end{aligned} \tag{12}$$
otherwise
$$\begin{aligned} & m_{nh}^i(A^k) = s_i - a_i^k \\ & m_{uh}^i(A^k) = 1 - m_{nh}^i(A^k) \\ & m_h^i(A^k) = 0 \end{aligned} \tag{13}$$

Fig. 10 presents the result of the experiments. Black area represents the doorway and are recognized using object classification algorithm. Yellow area represents the part of the environment which is classified as a corridor based on shape descriptors. Blue area

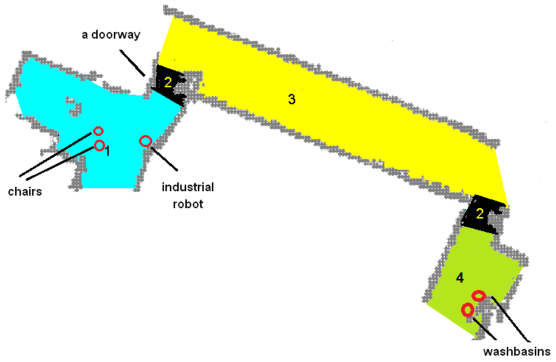

Fig. 10. Place labelling

was recognized as a laboratory and the green one as a toilet.

Our algorithm of place classification built on the basis of Dempster-Shafer theory allows us to distinguish easily between lack of information and contradictory information, in the first situation we obtained $m_{nh}(A^k) = m_h(A^k) = 0$, in the second one $m_{nh}(A^k) = m_h(A^k) = 0.5$. When the classic probabilistic approach is used it is assumed that the probability is computed basing on the large number of examples. In the problem presented in the article in order to compute the conditional probability for a given class based on an object we have to gather the data sets in which each class is represented approximately the same number of times. If the probability is computed based on small data set or the classes are represented with different incidence the computed conditional probability can be unreliable. If the Dempster-Shafer theory is used and the mass is computed based on small amount of data then the uncertainty can be increase so unreliable information has smaller influence than certain information.

6. Conclusion

In this work we have proposed a new approach to place labelling by applying Dempster-Shafer theory. DST can be regarded as a generalization of the Bayesian theory and is able to deal with subjective uncertainty. The experiment performed in real office environment proved the efficiency of our approach. In future works we intend to use a wider range of features and objects and focus on real-time performance by exploiting GPU processing power.

In general, the robot will have to remember its history of actions and observations and use this information, together with current observation to maintain an estimate of its location. The proposed method is only semantic place labelling and the total uncertainty is assumed in the beginning of the algorithm. In the future research similarly to [13] initial degrees of belief for hypothesises will be computed on the basis of history of past state of the robot and transactions between states.

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