# Semantic Localization through Propagation of Scene Information in a Hierarchical Model

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***Abstract*—The success of mobile robots, and particularly these coexisting with humans, relies on the ability to understand human environments. Representing the world and analysing spaces in a similar way to humans will enhance their comprehension and enable higher abstraction capabilities and interactions. The purpose of this work is to develop a localization framework that takes into account the different scenes common in a human environment and a hierarchical model of the environment. A probabilistic model for recognizing scenes is employed to determine the scene in which the robot is located. To allow that, the information about the objects and the relationships between them are considered. Besides that, a hierarchical model formed by different topological representations according to different levels of abstraction is proposed. Localization is performed at different levels to improve the localization accuracy. In this work, scene information is used to improve the localization of a mobile robot in a hierarchical model using hidden Markov models. The experiments of our framework working in real environments uphold the usefulness of the inclusion of the understanding and abstraction of the environment in localization.**

***Index Terms*—Semantic localization, robot localization, scene recognition, hierarchical modelling.**

## I. INTRODUCTION

Robot localization depends greatly on the quality of the data collected and its comprehension of the environment. In order to localize properly, the gathered data has to be trustful and accurate. A more precise and rich understanding of the environment will lead to a better localization for the robot. The main motivation of this work is to localize a mobile robot in an indoor area using the understanding of its surroundings: a hierarchical model of the environment and scene recognition.

When we talk about a robot localizing itself in human environments, we are implicitly assuming the robot knows the same information as humans do: the place where it is, the things that are in that place and their positions. The detection of certain types of objects in a place can determine the scene type (e.g. a living room, a bathroom or an office, among others) and this can affect the localization process.

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In the same way, the importance of modelling the environment lies in representing the world in an intelligent way so the maximum amount of information is included but the model is understandable for robots and humans. Hierarchical models represent the environment in an organized and intuitive way at different levels. Each level includes the required information, serves different purposes and is internally related to the other levels of the model. With regards to localization, knowing where the robot is located at every level of the model decreases the localization uncertainty and helps to solve situations where the robot may get lost. We show how abstraction of a hierarchical model using probabilistic techniques improves localization. The main contributions of this work are:

- The development of a probabilistic interpretation of the abstraction in a hierarchical model to localize a robot at different levels of the model.
- The inclusion of semantic scene and object information in order to improve the localization of a mobile robot.
- The evaluation of the semantic localization on a real-world experiments with a mobile robot.

The paper is organized as follows. Related work in hierarchical models and scene recognition for localization is presented in Section II. Section III and IV describe the environment and scene recognition models. Section V explains the inclusion of semantic information in the localization process. Finally, Section VI and VII present the experimental results, conclusions and future work.

## II. RELATED WORK

Although localization has been widely studied by the robotics community, not many authors focused on the improvement of localization processes using semantic information. Many approaches, as [1], [2], use landmarks or objects for localization. However, they do not normally consider their semantic meaning. In [3], authors use the semantical information gathered from object detection for global localization but they do not consider adding the scene information.

During the last decades, vision approaches have emerged for robot localization thanks to the technological improvements and the vast amount of useful information that a camera can provide. Many approaches have incorporated object information for the localization task, while more recent works try to solve the problem by adding more contextual information through scene recognition. In [4], the authors presented a localization method combining semantic and geometric understanding of the 3D world. They proposed a generative learning model that given a part of a scene predicts the complete scene.

Through this, it was possible to estimate accurate camera poses under challenging environmental conditions.

In [5] an approach for vehicle localization based on topological maps and scene recognition was presented. The authors proposed a technique to detect the node information and construct the topological map based on omni-directional image sequences. To do this, they combine feature-based and content-based image retrieval descriptors and then extract the SURF key points for the matching phase. Other approaches such as [6] proposed a robot localization model based on known maps using object detection. Object heatmaps are computed by the combination of two types of local image features, histograms of normalized gradient energies (HOGE) and histograms of quantized colors (HQC) to obtain the likelihood of the object being present in the image. Using this prior information about the objects, the 2D position and orientation is estimated applying particle-based localization. The authors in [7] developed an indoor topological localization method using the detection of steady objects as landmarks. They implement a convolutional neural network to classify objects and a topological matching algorithm based on hidden Markov model. They use semantic information of the objects to represent locations, and their occurrence order is used for localization through matching against the topological map. Other works such as [8] combine object and scene information into a topological localization methodology for large-scale outdoor scenarios. The authors use a deep neural network to obtain semantic observations of the environment and a topological map to store the semantic observations and calculate vehicle's pose.

Regarding hierarchical models, it is a topic that has caught the attention of many authors. This attention is due to the need of structuring the information and maintaining different representations for different tasks as localization or navigation. Most of the researchers have focused on the hierarchies that relate different representations and focus their work on geometric dependencies. In [9], the model of the environment is divided in three levels: geometrical, symbolic and topological. Localization is performed at the geometrical level while the others are used to group the information. Symbolic and sensor-based representations are considered in [10] to link the spatial and semantic information. They perform semantic localization to infer the type of place. Other authors have focused their hierarchy on topological representations, such as [11], where a multi-hierarchical model is used to provide an autonomous robotic wheelchair with an internal representation of the world to interface with the human driver. In that work, each level corresponds to a topological graph.

More recently, a mapping system to enable spatial understanding was proposed in [12]. Authors divided the model of the environment in four layers: sensory, place, categorical and conceptual layers. In [13], the idea is that local metric maps are represented as nodes of a scalable topological map. In this approach, a tree-like structure is used for sorting landmarks from global to local.

When dealing with hierarchical models, localization is usually performed only at one level while other levels serve to different tasks such as interaction. However, some authors have also mentioned the need of localizing a robot at several hierarchical levels. In [14], the authors present a hierarchical model composed by a global adjacency graph and local metric maps. Localization is performed on the local metric maps, but stochastic consistency is also maintained at the upper level.

In contrast with the previously mentioned works, we use both object and scene semantic information to improve localization at several levels of a topological hierarchical model.

## III. MODEL OF THE ENVIRONMENT

In order to navigate in human indoor environments, the robot builds a hierarchical model where knowledge is distributed at different levels. The construction of the hierarchical model depends on a map-building algorithm based on autonomous exploration that is beyond the scope of this paper. We define a hierarchical topological map as a graph representation that includes information at different abstraction levels. A group of nodes of a hierarchical level is abstracted to a single node of the next higher level, which is its supernode. In this paper, for simplicity we are just considering two hierarchical levels in the model of the environment: *Observations adjacency graph* and *Topological map*, as shown in Figure 1. In order to localize the robot at both levels a stochastic algorithm based on hidden Markov models (HMMs) is used.

*Observations adjacency graph* level. This level is structured as a topological graph based on movements: a graph in which connections between nodes do not imply a strict spatial correspondence between the real environment and the representation, but rather a qualitatively relation based on adjacency.. In the case of the environment used for the experimental results (Figure 5), the associated Observations adjacency graph is shown in Figure 1 (a). Nodes correspond to visited objects and multiple event types can be associated to them. In this work, an event is a detection of an object (black) or a transition (red). Nodes of the Observations adjacency graph are grouped at the higher level, the Topological map.

*Topological map* level. A node of the Topological map, which will be referred to as a supernode in the sequel to differentiate it from Observations adjacency graph nodes, corresponds to a semantical entity (e.g. a room). Each supernode establishes spatial constrains as it is associated with all the nodes that belong to that semantical entity. In this hierarchical level, edges include the information of the node that enables the transition between the supernodes. For example, in Figure 1 (b) if the robot moves from supernode 0 to supernode 2, it has to traverse door 2 (which in this case is the transition between supernodes).

Supernodes are semantical entities, however, considering only the model of the environment, their semantical meaning is not clear. In this paper, we have developed a Scene recognition system that gives meaning to the supernodes (e.g., Supernode 2 in Figure 1 could be associated to the classroom scene).

### A. Managing the Uncertainty of the Model for Localization

The robot uses a discrete localization algorithm based on HMMs presented in our previous work [15]. It calculates the

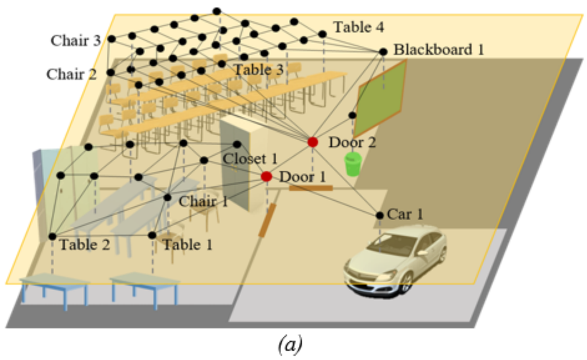


Fig. 1: Graph representations of the environment. (a) shows the Observations adjacency graph where each dot corresponds to a node of the graph and lines establish the edges between nodes. Black dots represent variable events (corresponding to detection of objects) and red dots represent invariable events (corresponding to detection of doors). (b) shows the Topological Map where each supernode is represented with a bubble, in this environment there are three supernodes.

probability of being in each node of the Observations adjacency graph using the prior information about the environment and the observations received while navigating. States of the HMM are related to nodes of the Observations adjacency graph. Observations for the HMM (which do not necessarily coincide with the nodes of the Observations adjacency graph) are the objects perceived while the robot moves. The calculation to define the current state of the robot is shown in Equation 1. State probabilities $P(s_i|b)$ are calculated as the probability of being at state $i$ given the observation $b$ at each time step; $s$ denotes the possible individual states and $a$ are the transition probabilities between the nodes. In order to reduce the localization uncertainty, the Geometric Uncertainty Coefficient (GUC) was included. GUC offers a correlation between the expected orientation to see an object and the real orientation where the object is seen. It is extensively explained in our previous work [15].

$$P(s_i|b) = \frac{(\sum_{j=0}^{N} P'(s_j|b') * a_{j,i} * GUC_{j,i}) * P(b|s_i)}{\sum_{j=0}^{N} P(s_j|b)}, \quad (1)$$

where $b'$ refers to the observation in the previous time step and $P'(s_j|b')$ to the corresponding probability. For simplicity, we denote the probabilities $P(s_i|b)$ as $P(s_i)$ in the sequel.

As supernodes are groups of nodes from the Observations adjacency graph, the probability of each supernode $P(S_i)$ can be abstracted as the sum of the probabilities of the nodes, $P(s_i)$, that belong to each supernode. The supernode probability is obtained using Equation 2.

$$P(S_i) = \sum_{j=0}^{n_i} P(s_j \in S_i) \quad (2)$$

$S$ and $s$ refer to the possible supernodes and nodes, and $n_i$ to the number of nodes in supernode $i$. Supernode estimator is calculated using maximum posterior criteria as the maximum value among all supernode probabilities $\max(P(S_i))$.

Equations 1 and 2 define the probabilistic localization of the robot in two layers of the hierarchical model, taking into account the observations and the relations between the layers. In the following sections, the inclusion of semantic scene information in the localization process is explained.

## IV. SCENE RECOGNITION

Scene recognition can be defined as the process of identifying a place taking into account objects, actions and interactions between the environment, humans and robots. The objects in a given scene are bound by certain relationships, some actions can be performed and it can lead to certain interactions between them. Scene recognition detects the generic type of a place, if the environment consists in several places of the same scene type the scene recognition system by its own will not be able to distinguish in which one the robot is.

In our case, we use a Probabilistic Scene Recognition Model presented in our previous work [16] in order to acquire the information about the environment. This model (Figure 2) includes the information of the objects in the scene as prior knowledge to generate the final estimate of being in a certain place.

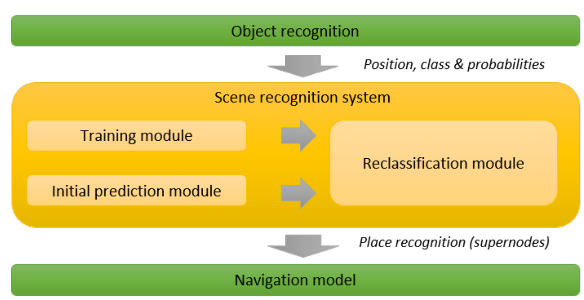


Fig. 2: General representation of the scene recognition model. The model takes the information of the object recognition system as prior information to update the outcomes of the scene recognition model. This information represents the inputs for the model of the environment (supernodes).

Simultaneously, the scene recognition model interacts with an object recognition system. This system has been developed in [17] and it is based on machine learning using SVMs as a classification algorithm. The idea is to identify some objects in a typical scene in a real everyday environment. Also, the model incorporates the information about the probability of the detected objects. Figure 3 (a) shows the main outputs of the model that represent the data used for scene recognition.

The final information about the objects is encapsulated into a message that contains the information of the class of the object, its probability and its position related to the camera.

The scene recognition model incorporates uncertainty information considering the errors generated in the sensor measurements. The calculation of uncertainty is essential for the evaluation of the accuracy of the system. The scene model has been developed using support vector machines (SVM) as a classification method in three stages:

- Training module: this is an offline process that involves building the dataset, selecting the parameters to adjust the classifier and generating the model of each scene. Training is performed using the Kyushu University Indoor Semantic Place Dataset [18].
- Initial prediction module: this stage is carried out online and involves the initial decision of the place where the robot is. The classification process is based on supervised learning and uses local features of the scene to predict the place where the robot can be.
- Reclassification module: in this real-time stage the information of the objects and their relationships is taken into account to update the probabilities of each scene.

The core of the scene recognition model is the reclassification module in which the relationship between the detected objects and a specific type of a scene are established. A strategy of reclassification has been implemented, with the idea of readjusting the probability values both in objects and scenes. This strategy is based on a model of rules based on learning to determine the frequency of occurrence of an object in a specific scene. To do that, we calculate the co-occurrence probabilities using the SUN397 dataset [19]. Reclassification allows the definition of a relation that improves the probabilistic results of the detected scenes.

This relation has been established through the Bayes' theorem by which the conditional probability is calculated. Equation 3 shows the probability to be in a scene $\xi_k$ given an object $O$ of class $s$ in this scene.

$$P(\xi_k|O_s) = \frac{P(O_s|\xi_k) * P(\xi_k)}{P(O_s)} \tag{3}$$

$P(O_s|\xi_k)$ represents the probability of finding an object $O_s$ in a scene $\xi_k$, which can be looked up in the co-occurrence matrices. $P(\xi_k)$ is the prior probability of being in a scene of class $k$ obtained from the initial prediction module. And finally, $P(O_s)$ is the probability of finding an object $O_s$ in any scene, which can be calculated using Equation 4.

$$P(O_s) = \sum_{\xi_k} P(O_s|\xi_k) * P(\xi_k) \tag{4}$$

Figure 3 (b) shows the results of the scene recognition model after the reclassification process.


(a) (b)

Fig. 3: Scene recognition outputs. (a) Object recognition including the information of the object class and its position. (b) Output of the scene recognition system in the classroom environment. The system gives the information of the most probable scene considering the objects present in the scene.

The information of scene and object estimates and uncertainties is used to improve the localization system, giving the robot the ability to understand the environment.

## V. SEMANTIC LOCALIZATION

Using a hierarchical model, we are localizing a robot according to its position in the Observations adjacency graph and the Topological map. For example, we can determine that a robot is at node 11 in supernode 2, but what does supernode 2 mean? Integrating the information from the Scene recognition system, we can conclude that it is at node 11 in supernode 2, which is a classroom. This connection between the understanding of the robot and the understanding of humans adds extra information to the localization decisions.

Each supernode of the Topological map is assigned a scene type the first time it is visited. Ten measurements of scene probability are used to calculate their joint probability and select the maximum as the most probable scene. Afterwards, when moving through the environment, the probability of being in one supernode is calculated according to Equation 2. In the meantime, the most probable scene is continuously calculated by the scene recognition model considering the detected objects and features in the environment, as shown in Equation 3. Combining the localization result for supernodes with the scene estimation, semantic information is included in the localization of the robot. Figure 4 shows this integration.

The semantically improved supernode estimation is shown in Equation 5. $P(S_i^G)$ refers to the global supernode probability (including scene information); $P(S_i)$ refers to initial supernode probability, as calculated in Equation 2; and $P(\xi_k|O_s \in S_i)$ refers to the probability of the scene type corresponding to supernode $i$, as calculated in Equation 3. Finally, $M$ refers to the number of supernodes.

$$P(S_i^G) = \frac{P(S_i) * P(\xi_k|O_s \in S_i)}{\sum_{j=0}^{M}(P(S_j) * P(\xi_k|O_s \in S_j))} \tag{5}$$

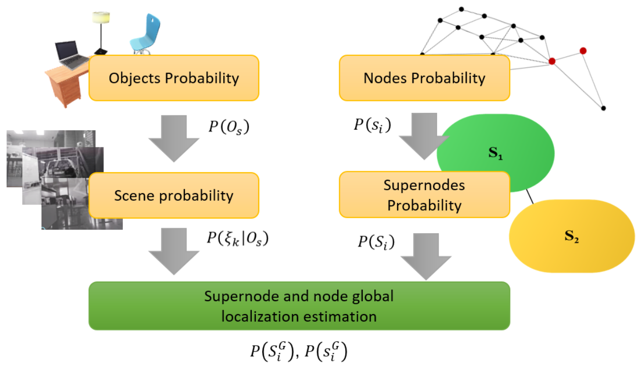


Fig. 4: Integration of semantic information to the localization process. Scene and object probabilities combined with nodes and supernodes probabilities improve localization results.

Using the semantically improved supernode probability we can improve the fine-grained node localization. A propagation between initial supernode probability and global supernode probability is proposed. Propagation maintains the probability distribution between nodes of the same supernode but strengthens the nodes that belong to the most probable supernode. The calculation of the semantically improved node probability, $P(s_i^G)$, is included in Equation 6.

$$P(s_i^G) = \frac{P(s_i) * P(S_i^G)}{P(S_i)} \tag{6}$$

Adding the understanding of the environment through scene recognition and hierarchical models improves the final localization result. In the experimental results, qualitative comparison between localization without semantic information (baseline) and localization with semantic information is presented.

## VI. EXPERIMENTAL RESULTS

The proposed algorithm operates in real-time on MOB-E. MOB-E is a differential robot equipped with an Asus Xtion camera for recognition tasks. Localization and recognition run in ROS and are developed using C++ and OpenCV libraries.

In order to evaluate the proposed method, real-world experiments were conducted at the University Carlos III of Madrid. In Figure 5, the scenes in the environment (captured by the robot) are shown. The hierarchical model for this environment is shown in Figure 1. Localization and scene recognition run autonomously while the robot is teleoperated.

### *A. Combining Hierarchical Model and Scene Recognition in a Localization Experiment*

Results for localization integrating the model of the environment and the scene recognition system are presented. Localization combines node, supernode and scene probabilities.

In Figure 6, we are presenting the evolution of the probabilities while the robot moves (from left to right the probability according to time is shown). At each instant three probabilities (corresponding to the columns of the graph) are shown: supernode probability, $P(S_i)$; scene probability

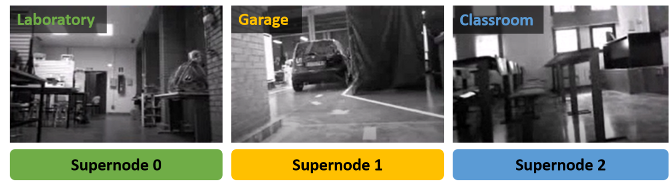


Fig. 5: Three scenes present in the environment (laboratory, garage and classroom) that relate to the three supernodes.

$P(\xi_k|O_s \in S_i)$; and global supernode probability $P(S_i^G)$. Vertical axis represents the estimated probabilities and the bottom panel shows the real scene where the robot is. The maximum estimated probability corresponds to the real scene and an improvement is observable between global probability and single supernode and scene probabilities. It is remarkable that the scene classification errors are overcome, as the laboratory which at some instants was misclassified as a classroom.

Global node probabilities including semantic information $P(s_i^G)$ are calculated and compared to initial node probabilities using HMMs localization $P(s_i)$. Single-step and continuous improvement have been computed. In Figure 7, single-step improvement for two time steps is shown. The first graph shows a situation where the most probable node and the improvement are very clear. On the contrary, in the second graph there are two most probable nodes if the semantic information is not considered. This tie is solved with semantic information. In Figure 8, continuous improvement is shown. Most probable node with and without semantic information are compared. The average improvement of including semantic information for the node probability is 7.72 %.

With this experiment we uphold the improvement of localization results when perceptual information is included and the usefulness of modelling the environment hierarchically as it offers different perspectives to link the information.

## VII. CONCLUSIONS

As the localization capability of a robot depends greatly on its comprehension of the environment, it is crucial to set recognition and understanding among the key aspects of a localization problem. In this work, propagation of scene information is used to improve the final localization. Our main contributions are the abstraction in a hierarchical model to localize a robot at different levels and the inclusion of semantic scene and object information in order to improve its localization. The system proposed solves ambiguities among localization results (as shown in the experiments) and improves the performance of algorithms based on localization.

The experiments support the enhancement of the localization results and the usefulness of incorporating semantic information. Results also show how the localization process can be improved with the abstraction and propagation in a hierarchical model. An average improvement of 6,18 % for supernodes and 7,72 % for nodes was achieved. Also, it has been shown how the relationship between objects and scenes can influence the final probabilities of being in a place.

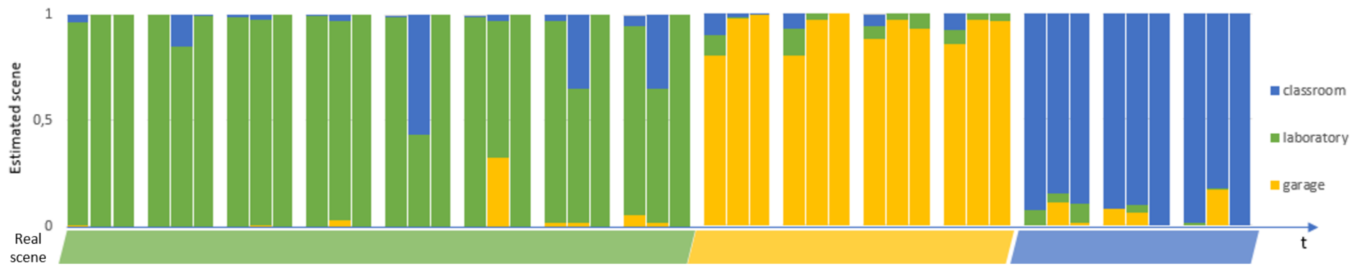


Fig. 6: Stacked chart of the localization result using scene information. Columns represent the estimated probabilities along the time that correspond to the real scene. Each group of three columns corresponds to the same instant of time and each column represents: Initial supernode probability, $P(S_i)$; scene probability $P(\xi_k|O_s \in S_i)$; and global supernode probability, $P(S_i^G)$. Different colours correspond to different scenes: green for laboratory, yellow for garage and blue for classroom.

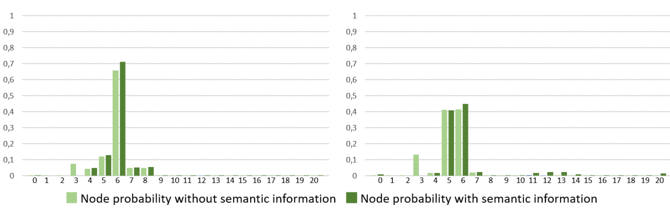


Fig. 7: Node probability distributions at two times steps. Values for the 20 nodes are included. Dark green columns show single-step improvement due to semantic information.

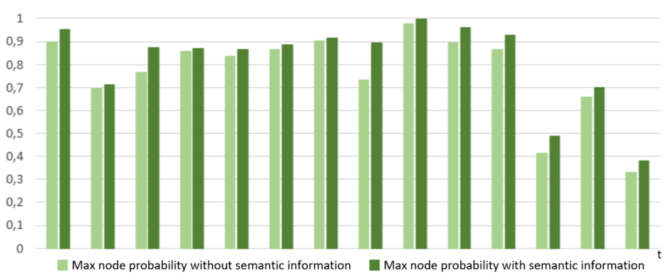


Fig. 8: Most probable node probability along the time without semantic information (light green) and with semantic information (dark green).

In the future work, we want to consider the information of several objects at the same time and to incorporate other topological and geometric information to improve the accuracy and robustness of the scene model. Another future line is to extend localization to more levels of the hierarchical model.

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