Place Categorization and Semantic Mapping on a Mobile Robot

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Abstract—In this paper we focus on the challenging problem of place categorization and semantic mapping on a robot without environment-specific training. Motivated by their ongoing success in various visual recognition tasks, we build our system upon a state-of-the-art convolutional network. We overcome its closed-set limitations by complementing the network with a series of one-vs-all classifiers that can learn to recognize new semantic classes online. Prior domain knowledge is incorporated by embedding the classification system into a Bayesian filter framework that also ensures temporal coherence. We show how semantic information can boost robotic object detection performance and how the semantic map can be used to modulate the robot’s behaviour during navigation tasks. The system is made available to the community as a ROS module.

I. INTRODUCTION

To become truly ubiquitous, mobile service robots that operate in human-centered complex indoor and outdoor environments need to develop an understanding of their surroundings that goes beyond the ability to avoid obstacles, autonomously navigate, or build maps. Truly useful robots need to be able to extract semantic information about the place they operate in [1]. Instead of merely answering the question of “Where am I?” [2] that often links to the problems of localization or SLAM, robots should also know “What is this place like?” to aid higher level decision processes, to infer high-level information about an environment, to ease robot-human interaction and to modulate the robot’s behaviour. The problem of assigning a semantic label to places or parts of the environment is often referred to as place categorization [3], [4], or – when combined with creating a map (see Fig. 1) – semantic mapping [5], [6]. To address this challenge we focus on transferable and expandable semantic place categorization and mapping for robotics. Transferable means the place categorization does not require environment-specific training. To achieve this, we leveraged the recent success of convolutional networks (ConvNets) in the computer vision community where networks were recently trained specifically for the task of place categorization [7]. In contrast to state-of-the-art semantic mapping systems in robotics [3], [5], [8], [9] these networks generalize well and do not have to be re-trained or fine-tuned for specific environments. However, ConvNets can only recognize the classes they have been trained on. This closed-set constraint is ubiquitous in computer vision but poses an important limitation for robotics applications that aim at long-term autonomous operations and life-long learning. We overcome the closed-set limitation and present a novel expandable classification system by complementing the ConvNet with one-vs-all classifiers that are computationally cheap to train and can learn to recognize new classes online. In typical benchmark applications in computer vision each image is treated individually. In this paper we exploit the fact that robots see a temporally coherent stream of image data and embed the semantic classifier in a Bayesian filter framework. This allows us to correct spurious misclassifications and incorporate prior knowledge. We demonstrate that more coherent results are achieved when interpreting semantic classification as a probabilistic estimation problem with first order Markov properties. In addition to applying a state-of-the-art ConvNet-based classifier on a robot, and showing that no environment-specific training is required for robotic place categorization, our paper provides the following contributions:

1) We overcome the closed-set limitation of the ConvNet
classifier by training computationally cheap additional one-vs-all classifiers that can learn to recognize new classes online.

2) To benefit from the temporal coherence between consecutive camera images, we integrate this dual classification system in a Bayesian filter framework.

3) We combine the place categorization with a robotic mapping system and test it in real-time on a large dataset in a variety of indoor and outdoor places.

4) We demonstrate that semantic place information can boost object detection and recognition on a robot.

5) We demonstrate how a semantic map can be used to modulate robotic behaviour in navigation tasks.

6) We provide the complete system to the community as a ROS module.

To the best of our knowledge such a comprehensive robotic semantic mapping system has not been proposed before. In the following we discuss related work in the field in Section II before introducing our system in Section III. Section IV presents the experimental setup and the dataset used for evaluation. Finally we draw conclusions and discuss future work in Section VII.

II. RELATED WORK

The topic of vision-based semantic scene categorization has been explored both in the robotics and computer vision community. The SUN (Scene UNderstanding) challenge initiated by Xiao and Torralba et al. has driven this field of research forward and resulted in a number of benchmark papers, e.g. [4], [10]. Very recently, [7] achieved a significant improvement of place semantic categorization on the SUN benchmark by training a convolutional network for this task.

A. Semantic Mapping in Robotics

Wu et al. [11] defined the visual place categorization problem for robotics using a purely appearance-based method based on CENTRIST features [9]. Their system has been trained on image sequences collected in six different apartment houses and was able to distinguish between typical semantic room categories like living room or bathroom. A similar system has been proposed by [8] and was tested on the same dataset. In contrast to [11] they use SIFT features extracted in a dense grid. Although both papers use a leave-one-out approach for training and testing (i.e. training on data collected in 5 of the 6 houses, and testing on the 6th), the visual similarity between the apartments and therefore the similarity between training and testing data is high. In contrast to the aforementioned purely vision-based methods, Zender et al. [12] combine laser-based place categorization with vision-based object detection and a "commonsense ontology" to build a so called conceptual map of the environment that contains semantic information. In [3], Pronobis et al. examined another place classification system that combined sensor data from a camera and a 2D laser range finder to assign semantic labels like corridor, office or meeting room in an office building. They combine this with a metric SLAM system to accumulate class labels over time and generate a semantic map of the environment. Although the authors separate their training and testing environments by using different floors of the same building, the visual similarity between the training and testing instances is very high. In later work [5], the same authors extended their system to include more sensor modalities like object information, or human input in addition to the visual scene appearance and the geometry information obtained by the laser. Again they separate training and testing environment by using different floors in the same building. Unfortunately, their dataset is not publicly available, so no benchmarking against their results was possible. Apart from appearance based methods, other authors explored semantic mapping that relies on the detection of objects to infer semantic information about the current place (e.g. a cereal box is more likely to be spotted in a kitchen, while a stapler indicates being in an office). An early example is [13]. Another research topic that is closely related to semantic mapping is the discovery of places as recently demonstrated by Murphy and Sibley [14] as well as Paul et al. [15], [16]. In contrast to the semantic mapping methods described above, this research focussed on finding meaningful clusters in the sensor data acquired by a robot over longer periods of time and did not assign semantic labels to them. These summaries of perception or experience over time can ease the generation of annotated training data over time.

B. Features for Semantic Classification

A commonality between all of the aforementioned vision-based systems is that they rely on a fixed set of hand crafted features that are extracted from the images and then used for classification. For example [8] uses dense SIFT, [11] uses CENTRIST [9], [5] relies on SURF and CRFH and so on. However, a recent trend in computer vision, and especially in the field of object recognition and detection, is to exploit learned features using deep convolutional networks (ConvNets). The most prominent example of this trend is the annual ImageNet Large Scale Visual Recognition Challenge where for the past two years many of the participants have used ConvNet features [17]. The concept of convolutional networks is not new and was proposed by LeCun et al. [18] to recognize hand-written digits. Their popularity has risen ever since algorithmic improvements such as dropout and rectified linear units [19], [20] and the widespread availability of GPUs to train these models. Several research groups have shown that ConvNets outperform more classical approaches for object classification or detection that are based on hand-crafted features [21–25]. Recently [7] used ConvNets to beat all competing approaches on the task of semantic place categorization.

C. The Closed-Set Limitation

An important limitation of ConvNets and many other classifiers is the implicitly built in closed-set assumption. The classifier is trained on a fixed set of classes and is never presented a new or unknown class during test time. While this constraint is widespread in many computer vision
and machine learning benchmarks [26], it is not a realistic assumption to make in long-term robotics applications. Overcoming this limitation is currently an active field of research in machine learning and computer vision [26–28], but did not yet converge to a widely accepted solution.

D. Summary

Despite the large body of work on semantic mapping and scene classification in the robotics community, most research systems lack a clear separation between training and testing data which makes their transferability and generalizability questionable. Also, to the best of our knowledge, the combination of a convolutional network, a set of computationally cheap one-vs-all classifiers for online learning of new classes, and a Bayes filter that enforces temporal coherence has not been explored for vision-based semantic mapping before.

III. SYSTEM OVERVIEW

Our proposed place categorization and semantic mapping system consists of four main parts:

1) a convolutional neural network that classifies each image individually,
2) one-vs-all classifiers that recognize scene classes the network was not trained on,
3) a Bayesian filter to exploit temporal coherence and remove spurious false classifications, and
4) the mapping subsystem that gradually builds a map using the resulting place labels.

We describe each part in the following, before presenting experiments and evaluations in the next section. We provide the complete system as a ROS module for download on our website http://tinyurl.com/semantic-mapping-QUT.

A. Transferable Place Categorization

To classify each camera image individually, we leverage the recent successes of Convolutional Networks for various visual recognition tasks. We use the Places205 network recently published by Zhou et al. [7] since it is the state of the art in place categorization and outperforms all competing methods on various benchmark datasets. The Places205 network follows the same principled architecture as AlexNet [21] but was trained specifically for the task of place categorization. The training dataset comprised 2.5 million images of 205 semantic categories, with at least 5,000 images per category. The images originated from several internet sources such as Google Images, Bing, and Flickr. The images were labeled by human workers using Amazon Mechanical Turk. The large number and variety of the training dataset ensures that the resulting classifier generalizes well and does not need to be retrained or fine-tuned when deployed in environments it has not seen during training. This ensures that our semantic mapping system is transferable and can be deployed on any robot in a variety of environments. The input to the Places205 ConvNet are RGB images that are resized to $227 \times 227 \times 3$ pixels, independent of their initial aspect ratio. The network’s output layer prob represents the discrete probability distribution $p(x_i | \mathcal{I}_t)$ over all 205 known classes $x_i$, given the current image $\mathcal{I}_t$. The network processes a single image in approximately 30 ms on a Nvidia Quadro K4000 GPU which is more than sufficient for typical robotics applications.

B. Expandable Place Categorization

A major difference between the computer vision community and robotics is the closed set assumption. Most object detection or scene classification benchmarks in computer vision assume that all classes are known during training, and that the classifier is presented only images of one of the known classes during testing [7], [17]. This is called closed set classification. However, research in robotics aims at life-long operations and long-term autonomy over extended periods of time. Inevitably, the robot will be faced with scene categories that were not part of the initial training set, but are important for the robot’s mission. Being able to extend the classification framework with new classes during deployment therefore is crucial. We show how the place categorization based on the Places205 network can be expanded by a set of new classes $y_i$ that are not part of the original training set: We propose to train a one-vs-all classifier that distinguishes the new class $y_i$ from the already known classes $\{x_0, ..., x_{n-1}\}$. The advantage of this approach is that it is not necessary to retrain the ConvNet, which would be computationally expensive (typical training times are in the order of days) and would require a lot of training images (in the order of hundreds or thousands) of the new class. In contrast, a Random Forest one-vs-all classifier can be trained in under a minute using only a few (in the order of 10-100) training images. We let the classifier use the output of the fc7 layer of the Places205 network as a feature vector. The fc7 layer is the last generic (i.e. class independent) fully connected layer in the network. The layers fc8 and prob have 205 output neurons since they are specifically tailored for the task of recognizing the 205 classes from the training dataset. As mentioned before, $p(x_i | \mathcal{I}_t)$ – the discrete probability distribution over $n = 205$ class labels $x_i$ – is the classification result of the Places205 network, given the current image $\mathcal{I}_t$. Now $p(y_i | \mathcal{I}_t)$ denotes the result of one of the one-vs-all classifiers that is trained to classify the new class $y_i$. Let

$$\mathbf{x} = (x_0, x_1, ..., x_n, y_0, ..., y_m)$$ (1)

1In an earlier version of this paper we trained a nonlinear SVM on the fc7 layer of the AlexNet provided by Caffe [29]. This system achieved a top-1 accuracy of 46.2% on the SUN-397 benchmark, thus achieving state-of-the-art performance, only beaten by [30] at that time which achieved 47.2%. While this paper was in preparation, [7] published their specialized Places205 network which achieves 54.3%, thus outperforming all previous approaches by a large margin. We therefore decided to switch to Places205.

2The same is true for object recognition tasks, where the 1000 object classes in ImageNet might not be sufficient or specialized enough for robotics tasks.
denote the combined vector of class labels. Then we define the combined likelihood \( \mathcal{L}(\mathcal{I}_t | \hat{x}_t) \) as

\[
\mathcal{L}(\mathcal{I}_t | \hat{x}_t) = (p(x_0 | \mathcal{I}_t), \ldots, p(x_n | \mathcal{I}_t), p(y_0 | \mathcal{I}_t), \ldots, p(y_m | \mathcal{I}_t))
\]

(2)

Re-normalization distributes the probability between the \( n \) classes known to the ConvNet classifier and the \( m \) additional classes known to the one-vs-all classifiers in a natural way. Notice that this assumes independence between the class labels \( x_0 \ldots n \) and \( y_0 \ldots m \) as well as pairwise independence between any \( y_i \) and \( y_j \).

C. Bayesian Filtering over Class Labels for Temporal Coherence

Typical computer vision benchmarks for place categorization or object detection treat each image individually [7], [17]. In contrast, most of the observed sensor data in robotics have a temporal dimension. Knowing that two images were observed consecutively can be a strong source of information that can be exploited by using Bayesian filtering techniques. We interpret the robotic place categorization problem as a probabilistic estimation problem and estimate the discrete distribution \( p(\hat{x}_t | \mathcal{I}_{0:t}) \) over all possible place labels \( x_t \), given all the observed images \( \mathcal{I}_{0:t} \) from the past until now. Assuming first order Markov properties, this leads to the following well-known Bayesian filter step:

\[
p(\hat{x}_t | \mathcal{I}_t) = \mathcal{L}(\mathcal{I}_t | \hat{x}_t) \cdot p(\hat{x}_{t-1} | \mathcal{I}_{t-1})
\]

(3)

where \( \mathcal{L}(\mathcal{I}_t | \hat{x}_t) \) is the combined likelihood defined in (2).

D. Incorporating prior knowledge

Interpreting place categorization as a Bayesian estimation problem allows us to incorporate other sources of information in a very natural way. For instance we might know that many of the 205 categories Places205 can recognize are unlikely or even impossible to be observed in the environment the robot is deployed in. This kind of knowledge \( p(\hat{x}) \) can be easily incorporated by an additional prior term:

\[
p(\hat{x}_t | \mathcal{I}_t) = p(\hat{x}) \cdot \mathcal{L}(\mathcal{I}_t | \hat{x}_t) \cdot p(\hat{x}_{t-1} | \mathcal{I}_{t-1})
\]

(4)

E. Semantic mapping

The place categorization component described in the previous section creates a probability distribution \( p(\hat{x}_t | \mathcal{I}_t) \) over the known class labels, given the current camera image \( \mathcal{I}_t \). This continuous stream of classification results is the input to the semantic mapping component, along with a laser range scan which aids the map building. To build a combined semantic and metric map of the environment, we apply the occupancy grid mapping algorithm and maintain one map layer per semantic category. Fig. 2 illustrates this concept. Instead of expressing the probability of being occupied or free, each cell in these semantic layers expresses the probability of belonging to a certain semantic category. This is achieved by propagating the class probability \( P(l_t | z_t) \) along the laser rays that are within the field of view of the camera and updating the penetrated map cells using the usual recursive Bayes filter update method [31] for occupancy maps. This way, all unoccupied cells that are within 5 meters of the robot’s position and within the camera’s field of view are updated with the currently observed semantic label. The probability that a cell \( k \) is representing a place category \( \hat{x}_i \) given the classification result \( z_{1:t} \) are:

\[
p_k(\hat{x}_i | \mathcal{I}_{1:t}) = \left[ 1 + \frac{1 - p_k(\hat{x}_i | \mathcal{I}_t)}{p(\hat{x}_i | \mathcal{I}_t)} \right]^{-1}
\]

(5)

where \( p_k(\hat{x}_i | \mathcal{I}_t) \) is the probability that cell \( k \) is of place category \( \hat{x}_i \) given the currently observed image \( \mathcal{I}_t \), while \( p_k(\hat{x}_i | \mathcal{I}_{t-1}) \) is the previous estimate and \( p(\hat{x}_i) \) is a prior probability. For better performance, our implementation uses a log-odds representation, which results in the following simple update equation [32]:

\[
\mathcal{L}_k(\hat{x}_i | \mathcal{I}_{1:t}) = \mathcal{L}(\hat{x}_i | \mathcal{I}_{1:t-1}) + \mathcal{L}(\hat{x}_i | \mathcal{I}_t)
\]

(6)

where \( \mathcal{L}(\hat{x}_i) = \log \frac{p(\hat{x}_i)}{1 - p(\hat{x}_i)} \). Finally, a clamping step ensures that \( l_{\min} \leq \mathcal{L}(\hat{x}_i | z_{1:t}) \leq l_{\max} \). Notice that spurious false classifications do not permanently corrupt the map since the probabilities within the cells are adapted gracefully and can be corrected with later observations. The resulting map can be used in a variety of tasks. For instance for path planning different traversal costs can be assigned to different labels to make the robot avoid busy places during certain times of the day (e.g. the food court during lunch time).

IV. EXPERIMENTS, EVALUATION AND RESULTS

A. Place Categorization on a Real Robot

We demonstrate and evaluate the place categorization performance of our proposed system on a real robot on our university’s campus. We use the MobileRobots Research GuiaBot shown in Figure 3 and test the system on the images of three types of cameras that are mounted on the robot: 1) the RGB camera from the Microsoft Kinect (version 1) sensor; 2) Point Grey Grasshopper monochrome camera and 3) the front facing camera of the Ladybug2, a spherical camera. The test dataset was collected by teleoperating the robot across nine different and versatile environments on our campus and recording the images from all three cameras as
Fig. 3: The Guiabot robot used to evaluate the system and example images from all three cameras in a variety of places: Kinect RGB (color), Grayscale, and Ladybug (portrait format). Notice that all images are resized to a fixed size of $231 \times 231$ before calculating the ConvNet features. While the change in aspect for the RGB and Grayscale images is minor, the Ladybug image gets squeezed significantly. Also notice the low quality of the Ladybug image.

| Environment   | RGB  | Grayscale | Ladybug |
|---------------|------|-----------|---------|
| corridor      | 100.0% | 98.4%    | 98.2%   |
| office S11    | 94.4% | 96.4%    | 97.0%   |
| parking garage| 90.8% | 86.0%    | 98.0%   |
| foodcourt     | 84.2% | 65.6%    | 48.2%   |
| cafe outside  | 66.6% | 62.2%    | 53.1%   |
| shop          | 53.3% | 56.3%    | 45.9%   |
| lobby         | 49.1% | —        | 31.2%   |
| lecture theater| 44.5% | 38.0%    | 35.2%   |
| outdoor       | 33.3% | 3.3%     | 55.9%   |
| weighted average | 67.7% | 61.6%   | 59.8%   |

TABLE I: Accuracies for the different cameras in the QUT Gardens Point Campus dataset. The bottom row gives the average accuracy weighted by the number of recorded frames for each environment. Notice that there were no grayscale images recorded for the lobby environment.

well as laser scans and odometry. The traversed environments are listed in Table I. Since we know the robot is operating on the campus, only the following set of semantic classes could possibly be encountered: $\hat{X} = \{\text{corridor, classroom, office, parking_lot, restaurant, food_court, kitchen, kitch-enette, lobby, supermarket, clothing_store, botanical_garden, coffee_shop}\}$. We incorporated this prior information as described in Section III-D. The prior probabilities of all classes not in $\hat{X}$ were set to zero. We measure the top-1 classification accuracy for each of the nine environments separately for the images captured by the three different types of cameras on the robot. The classifier results were checked by a human expert and the resulting accuracies are summarized in Table I. The RGB camera (from the Kinect 1 sensor) produces the best results, presumably because the camera characteristics are more similar to the cameras the training set was captured with. Our system performed well with grayscale images, with average accuracy 6.1% below that of the RGB camera and only performing much worse on the outdoor dataset. This indicates that color is not an important cue for scene classification in many indoor environments. The ladybug camera performed worst. We account that to the extreme deformations that occur (see Fig. 3) when squeezing the Ladybug’s upright format images into a squared input image for Places205.

B. The Effect of the Bayes Filter

Fig. 4 illustrates the positive effects of the Bayes filter that enforces temporal coherence and incorporates prior knowledge. The maximum a posterior solution is much more stable than the maximum likelihood solution alone. Spurious results are smoothed out, reducing false classifications. The bottom plot shows the maximum likelihood solution when not incorporating prior domain knowledge, and using a uniform prior probability over all 205 class labels instead.

C. Semantic Mapping Results

Fig. 5 shows the output of our semantic mapping system using the RGB images in the nine different tested environments on campus. The map are color coded where the only the winning labels are rendered. The percentage values given in the figure correspond to the fraction of correctly classified images listed in Table I, but do not necessarily reflect the correctly classified map area. Each place has a main category label that describes the place in general, however, all the nine places contain mixed categories of places. For example, the office environment, as shown in the left middle in Fig. 5 contains actual offices (orange) that are connected by a long corridor (light green) and a kitchen area (brown). Similarly, not all areas in the supermarket...


environment have been assigned the label supermarket (yellow). A large area in the lower right can be seen colored in dark blue, representing a clothing store. Manual inspection confirmed this classification result, since the store actually sells clothes and has them on display in this part of the shop. Towards the top and the right of the supermarket map, large windows lead out to the open campus. The system created incoherent classifications and assigned the labels botanical garden and parking lot. Another particular challenging map is that of the food court. The classifier correctly assigned the label the restaurant (purple) in areas with tables and chairs and food court (pink) when the robot faces the actual food stalls. The transition areas have been labeled as lobby. Given that our test dataset contained many very challenging and cluttered scenes, we are very content with the classification and mapping results produced by our system.

D. Expanding the Classifier with New Classes

As discussed in Section III-B, the ability of adding new classes to the classification system is crucial for long-term operation. We expanded our system by adding a new class door that Places205 cannot detect. We randomly selected 80 positive examples from the elevator-door\(^3\) category of the SUN-397 dataset [10], and 26,000 negative images from other categories. Training the classifier on a standard desktop machine using Python’s scikit-learn implementation takes only 57 seconds on a desktop machine. Although the one-vs-all classifier was trained on elevator doors, it reliably detects the doors that are typically found in offices and corridors and so on. We tested this on another dataset (1332 images) we collected in our office environment, where the robot was driven through multiple offices and corridors. The system detected 8 of the 10 doors in the environment and produced two false positive detections. The two false negatives can be accounted to rapid camera motion (the door was only visible for 4 frames) and extremely bad lighting conditions (the door was at the end of a long unlit corridor). For one of the two false positive detections the classifier responded to a wooden plank on the wall.

V. Case Studies: Applications of Semantic Information in a Robotics Context

A. Semantic Place Information Boosts Object Detection

The semantics of a place provide valuable information that can boost the performance of object detection and recognition on a robot. We demonstrate this by running an object detection pipeline inspired by [24] that consists of an object proposal step (using EdgeBoxes [31]) and a ConvNet classifier (AlexNet [21] as implemented in Caffe [29]). Similar to Places205, AlexNet provides a discrete probability distribution over the 1000 object classes it was trained on. We denote this as \(p(c|x)\), where \(c\) is the image patch the classifier is applied on. Depending on the semantic context, different object classes are more likely to be observed than others. E.g. in a kitchen we expect to see cups and mugs, but not a motor bike. We propose to exploit such knowledge in a naive Bayes classifier:

\[
p(c|x, \hat{x}^*) \propto p(c|\pi) \cdot p(\pi|\hat{x}^*)
\]

where \(\hat{x}^*\) is the maximum-a-posteriori solution of the semantic place category for the currently observed scene and we assumed independence between \(\pi\) and \(\hat{x}^*\) and uniform prior probabilities. The terms \(p(c_i|\hat{x}^*)\) express the likelihood to observe an object of class \(c_i\) in a scene with label \(\hat{x}^*\). We learned these priors from the NYU2 dataset [34] by analysing the ground truth labels and building statistics over the relative occurrences of object classes for every scene type. Non-occurring object classes or classes that do not appear in both the NYU2 and the ImageNet datasets were given a small but non-zero default prior probability. We tested the combination of our semantic place categorization and object detection on a robot in a kitchen environment. We found the robot was more accurate in its object classifications when it had the additional semantic information available and could apply equation (7). Fusing both streams of information increased the top-1 accuracy of correctly detected objects from 0 % to 54 % and the top-5 accuracy from 15 % to 100 % in this experiment. Examples of the boosted object detection results are shown in Fig. 6.

B. Path Planning on a Semantic Map

We demonstrate how the semantic map created by our system can modulate the behaviour of a robot in an indoor
Fig. 6: Case study I: Semantic place information significantly boosts object recognition performances. The examples illustrate how the top-5 classification results by AlexNet on objects in a kitchen scene can be improved by incorporating prior knowledge that is conditioned on the current semantic scene class. Left: original results, right: results when exploiting the semantic mapping system and boosting the object classifier with prior probability \( p(c_i | \hat{x}^*) \). See text for details.

navigation scenario. In our example a robot has to navigate from its current position to another place in a workplace environment with offices and corridors. During working hours the robot should try to avoid disturbing humans in their office spaces and rather take longer detours through the corridors. During night times, the shortest path is always preferable. Such scenarios can be easily implemented when performing the path planning in the semantic map. Different class labels in the map can be assigned different cost values that are used by a path planner. Fig. 7 compares the results of an A* path planner when avoiding offices and when preferring the shortest path.

VI. THE PROVIDED ROS MODULE

We provide the semantic place categorization system and the semantic mapper as a ROS module to the community. The module consists of two nodes. One node subscribes to an image topic and interfaces the Caffe framework [29] that implements the Places205 ConvNet. The network provides a probability distribution over the 205 known scene types. On a Nvidia Quadro K4000 GPU, this operation takes 0.031 seconds for a 320 \( \times \) 240 image. During the classification process, features from layer fc7 are extracted and passed through the one-vs-all classifiers to detect additional classes. This step requires additional 3 ms per classifier using a Python implementation of a random forest classifier on a desktop machine. After passing the combined likelihoods through the Bayes filter, the posterior probability distribution is published as a ROS topic. A second node subscribes to this topic, the data of a laser range finder, the robot pose estimate and a grid map created by a SLAM system such as gmapping. Our node fuses all these information and creates a 3-dimensional map structure (based on OctoMap) where each layer contains a probability map for a specific semantic class. The complete system can be downloaded from http://tinyurl.com/semantic-mapping-QUT, where additional information and documentation can be found. This ROS package provides a readily usable semantic categorization and mapping system to the community that can be deployed without environment-specific training.

VII. CONCLUSION AND FUTURE WORK

Our paper introduced a novel transferable and expandable place categorization and semantic mapping system that requires no environment-specific training, can be expanded with new classes, and is embedded in a Bayesian filter framework that allows the incorporation of prior information and ensures temporal coherence of the classification results. Semantic information about the environment is an important enabler of more advanced robotic tasks, especially for human-robot collaboration. Humans describe places, goals, and objects using semantic categories and it is natural for them to formulate tasks using these categories. We demonstrated how semantic information can influence robotic navigation tasks in a workplace, making robot operations more compliant with human needs. A second case study demonstrated how semantic information supports robotic object detection and
increases the performance of this equally important visual recognition problem. In future work we will extend the system to support multi-scale or sub-scene categorization, i.e. assigning labels to parts of the scene. We will also explore how semantic mapping can guide visual place recognition by partitioning the search space to similar semantic places and apply the system to various robotic tasks in the real world.

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