Enhancing Door Detection for Autonomous Mobile Robots with Environment-Specific Data Collection

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Abstract—Door detection represents a fundamental capability for autonomous mobile robots employed in tasks involving indoor navigation. Recognizing the presence of a door and its status (open or closed) can induce a remarkable impact on the navigation performance, especially for dynamic settings where doors can enable or disable passages, hence changing the actual topology of the map. In this work, we address the problem of building a door detector module for an autonomous mobile robot deployed in a long-term scenario, namely operating in the same environment for a long time, thus observing the same set of doors from different points of view. First, we show how the mainstream approach for door detection, based on object recognition, falls short in considering the constrained perception setup typical of a mobile robot. Hence, we devise a method to build a dataset of images taken from a robot's perspective and we exploit it to obtain a door detector based on an established deep-learning object-recognition method. We then exploit the long-term assumption of our scenario to qualify the model on the robot working environment via fine-tuning with additional images acquired in the deployment environment. Our experimental analysis shows how this method can achieve good performance and highlights a trade-off between costs and benefits of the fine-tuning approach.

I. INTRODUCTION

The operational environments of indoor autonomous mobile robots, that nowadays are used to perform several tasks in public, private, and industrial workspaces, are particularly complex. One of the reasons of this is because environments are highly dynamic, and their features can rapidly and frequently change, e.g., due to the presence of human beings [1].

During a time span of several hours or days, one of the things that can change frequently is the topology itself of the indoor environment, since doors may be either open or closed. This fact impacts the capability of autonomous mobile robots to navigate and to succeed in performing their task. Consequently, door detection, namely the capability to detect the presence and the status (open or closed) of a door, is critical, as it could be used by the robot to distinguish between the parts of the environment that are reachable, from those that are not.

Recently, some works as [2], [3] have shown how the availability of a model that describes the status of doors across a long time span allows the robot to improve its performance by predicting the changes in the environment topology due to the fact that a door could be either opened or closed. Intuitively, by using such a model, a robot can plan in advance the path to execute by predicting whether a room will be reachable or not at that moment.

To model the door status of its working environment, a robot needs the capability to perceive the presence and status of the doors in it. In this way, a robot can acquire additional knowledge about the status of doors it encounters while navigating for performing other tasks.

In this work, we propose a module for allowing autonomous mobile robots to detect doors and identify their status (open or closed) from RGB camera images. The doors detector we present is based on DETR [4], a deep end-to-end architecture for object detection. An important feature of this module is the capability to distinguish doors (and their status) even in a setting where the robot does not have a...
clear view of the door, as in the example of Fig. 1.

Popular datasets employed to train such deep learning detectors [5], [6], do not correctly model the typical uncertainty in which a robot operates as well as the constrained perception of the environment due to the robot’s physical characteristics [7]. Consequently, we propose a method for acquiring a visual dataset in batch from multiple photorealistic simulated environments taking into account the robot navigation paths. Models adopted to perform tasks of object detection, such as door detection, are commonly trained in advance using standard datasets, thus building a general detector that can work in every previously–unseen environment. Such a model is saved once and later used in a target environment for evaluation. However, in a typical long–term deployment scenario, an autonomous robot is commonly used in the same environment and operates inside it for a long time, sometimes even for its entire life cycle. In this case, the robot eventually observes the same doors over and over again, in different conditions, and from different points of view. Moreover, the doors that are found inside the same environment may present a similar visual aspect (e.g., the same door model is repeated in multiple locations).

In such a situation, an end–to–end object detector, trained to be suitable in any context of use, can be qualified to increase its accuracy in a target environment. Following this intuition, we propose to qualify the door detection model on the target operational environment of the robot, thus creating a qualified detector, whose performance can improve with the increase of the robot experience, and which is based on the fine–tuning [8]–[10] of the general detector. Our approach aims to specialize a general pre–trained door detector with new examples (obtained, for instance, in the initial setup phase of the robot) to increase its accuracy in detecting doors in a single environment. We evaluate both the performance of the general detector and qualified detector in 10 environments obtained from photorealistic simulation [11], [12]. We show how, while the performance of the general model is adequate to allow the robot to distinguish the location and status of doors even in challenging examples (Fig. 1), the qualified model, targeted for the own working environment of the robot, allows a substantial performance increase. In a long–term deployment, the availability of the qualified model may allow the robot to obtain knowledge of the door status to build a robust model of the traversability of door, thus improving its capability to plan its tasks.

In summary, the main contributions of this work are the following.

- We provide a method to obtain a dataset of semantically–labelled images perceived from a robot perspective.
- We create a general door detection module using a deep–learning object–detection method.
- We show how to qualify such a model in the robot operational environment, assessing the performance improvements and discussing the limitations of such an approach.

II. RELATED WORKS

The detection of doors and their status has been considered one important ability needed by a robot to operate in indoor environments, as the fact that a door may be open or closed impacts the traversability of the entire environment. The detection of the door location could be useful for several tasks, as room segmentation [13], i.e. to divide the map of the environment into semantically meaningful regions (rooms), to predict the shape of unobserved rooms [14], or to do place categorization [15], [16], which assigns to the rooms identified within the occupancy map a semantic label (e.g., corridor or office) according to their aspect.

Recent studies [2], [3] exploit the benefits of having a model to estimate environments traversability in long–term scenarios to optimize localization and navigation of autonomous agents. They show how the door status affects the navigation capability of robots, and how the understanding of door status improves performances. In [3] an approach for mapping a dynamic environment in a long–term run to model the periodic environmental changes is proposed. The work presented in [2] proposes a navigation system for robots that operate for a long time in indoor environments with traversability changes.

Detecting doors in RGB images is a computer vision problem typically addressed as an object detection task. Classical methods are based on the extraction of hand–crafted features [17]–[19]. Examples include edges [20] or corners [21] with which the typical rectangular shape of a door can be described. The need to define and compose such features clearly represents a limit of these approaches, preventing them to achieve suitable levels of robustness and adaptability when used with highly–variable images gathered on the field.

Deep learning end–to–end methods [22] provide significant improvements thanks to their capability of automatically learning how to characterize an object class, robustly to scale, shift, rotation, and exposure changes.

The work of [23] describes a method for door detection with the goal of supporting and improving the autonomous navigation task performed by a mobile robot. A convolutional neural network is trained to detect doors in an indoor environment and its usage is shown to help a mobile robot to traverse passages in a more efficient way.

The work proposed in [24] focuses on robustly identifying doors, cabinets, and their respective handles in order to allow grasping by a robot. The authors use a deep architecture based on YOLO [10] to detect the Region Of Interest (ROI) of doors. This allows to obtain the handle’s location by focusing only on the area inside the door ROI.

The above works are representative examples of methods addressing the door detection problem within a mobile robotics domain. However, with respect to the long–term reference scenario we consider in this work, they fall short at integrating two characterizing environmental features. The first one is given by the fact that training examples do not explicitly consider the challenge of the typical point–of–view
of the mobile robot. A second limit is that the aforementioned works do not take advantage from the fact that the robot is deployed in the same environment for several weeks or months.

III. BUILDING A DOORS DATASET FOR MOBILE ROBOTS

One of the key prerequisites to exploit deep learning in synthesizing an effective door detector for a mobile robot is the availability of a dataset of training examples where images with and without doors need to be consistent with the constrained perception setup of a robot autonomously navigating in an indoor environment, as those shown in Fig. 1. A naïve, but impractical and time-consuming, way to achieve this would be to deploy a platform (equipped with a camera) on the field and having it exploring different environments while acquiring image samples of doors. The overheads of collecting such data in real-world runs are well-known; to mitigate such issue, an alternative is to rely on realistic simulation frameworks [25].

In this work, we use the widely used framework of Gibson [12], which provides providing highly-realistic visual perceptions. The framework of Gibson is used in conjunction with Matterport3D [11], a RGB-D dataset of 90 virtual environments where scans are tagged to obtain an instance-level semantic segmentation of regions and object categories.

Despite the remarkable advantages provided by the above tools, defining an effective data-acquisition procedure to extract samples from the virtual environments consistent with the perception made by a robot in that same environment is still a non-trivial task.

First, we extend the simulation framework based on Gibson and Matterport3D to allow for batch acquisition of visual perceptions from arbitrary poses settled inside a virtual environment. Then, we define an algorithm to determine a set of relevant poses that could describe plausible points of view from which a mobile robot might happen to perceive the environment while carrying out autonomous navigation. These are poses that must be compatible with a set of principles describing a typical indoor navigation behaviour. The key ones include lying in the free space (feasibility), ensuring a minimum clearance from obstacles, and being along the shortest paths between key connecting locations in the environment’s topology. The algorithm works in three phases: grid extraction, navigation graph extraction, and pose sampling.

The grid extraction phase aims at obtaining a 2D occupancy grid map, similarly to those commonly used by mobile robots for navigation. We start from the environment’s 3D mesh, and we aggregate obstacles as identified in multiple cross-sections of the 3D mesh performed with parallel planes, starting from a few centimeters over the floor’s heights. The result is then manually checked for inaccuracies and artefacts produced during the procedure. An example of the obtained results is shown in Fig. 2 where we provide an example of an environment’s 3D mesh (2a) with the associated grid map extracted from it in this phase (2b).

The navigation graph is a data structure we use to represent the topology of those locations on the grid map that correspond to typical waypoints a robot occupies while travelling in the environment. To compute this graph we perform a Voronoi tessellation of the grid map by using obstacle cells as basis points (an established approach widely adopted in robot navigation [26]), extracting graph edges from those locations that maintain maximum clearance from obstacles. An example result of this step is shown in Fig. 2c.

In the last phase, we perform pose sampling on the navigation graph. The method extracts from the graph a list of positions keeping a minimum distance $D$ between them (this parameter controls the number and the granularity of the samples). An example of the result is shown in Fig. 2d.

To build the dataset we acquire an image from the points of view of a robot’s front-facing camera simulating its perceptions in the virtual environment from the sampled poses (the red dots in Fig. 2d). Specifically, in each pose on the grid map, we acquire perceptions at two different height values ($0.1 \, \text{m}$ and $0.7 \, \text{m}$ – to simulate different robot embodiments) and at 8 different orientations (from $0^\circ$ to $315^\circ$ with a step of $45^\circ$). Each acquisition includes the RGB image, the depth information, and the semantic data from Matterport3D.

Data cleaning and labelling are performed with a semi-automatic procedure exploiting the semantic information inside the acquired images. The positive examples where the robot was too close (average robot–door distance is less than $0.3 \, \text{m}$) or too far from a door are also discarded. Specifically, if the image does (not) have at least $2.5\%$ of its pixels tagged as door, it is marked as positive (negative). After this pre-processing phase, a human operator checks positive examples, fixes the doors bounding boxes extracted from semantic data (correcting possible noise from the Matterport3D dataset), and specifies the door’s status as open or closed.

In the experimental campaign we shall discuss later, we sampled poses in 10 different Matterport3D environments (small apartments or large villas with multiple floors and a
heterogeneous furniture style) by setting $D=1\, \text{m}$. The final dataset we obtained is composed of 9363 examples, 5457 of which are positives and 3906 negatives. Note how our process for obtaining the dataset for door detection could be easily generalized to create any visual indoor dataset for mobile robots by changing the image classification step.

IV. DOOR DETECTION IN LONG–TERM DEPLOYMENT

In this section, we describe our method for building and deploying a vision–based door detector. We tackle this problem from the perspective of an autonomous mobile robot deployed in a long–term setting. In practice, this means that the physical environment $e$ where the robot has to perform this vision task, will not change in its core features for the whole operational time of the robot (ideally spanning over weeks or months). As an example, the door position and aspect are fixed, while their status changes.

Within the scope or door detection with robots, the long–term scenario implies a relaxed requirement for generalization among different physical environments. More importantly, it opens for the opportunity to boost the performance by qualifying the detector towards the specific environment $e$, exploiting additional data that the robot might gather during its initial setup or operational time. The approach we propose in this work builds upon this idea by exploiting the well–known technique of fine–tuning, which has proved of being effective in several object classification tasks performed through vision [4], [8]–[10]. In the following, we describe our method composed by the synthesis of a general deep–learning door detector ($\text{label GD}$) and by the assessment of how its qualification of it on $e$ (label $QD$) could introduce advantages on a long–term deployment in $e$.

A. General Door Detector

The doors detector we devise is based on DETR [4] (DEtection TRansformer), a recent approach based on deep learning to perform object detection. The method combines a CNN backbone based on ResNet [8] to produce a compact representation of an image and a transformer [27] to find complex relationships between the extracted features.

We used a pre–trained version of the [4], which was trained on the COCO 2017 [5] dataset. To adapt it to the door detection task at hand, we chose the smallest configuration provided by authors. It is composed of a ResNet–50 backbone, a transformer, and a 4–layers perceptron, for a total of 41 million parameters. We tuned the hyper–parameter $N$ determining the number of predictions (given by bounding boxes) produced by the model for each image, hence defining the maximum number of detectable objects per frame. We use a minimum confidence threshold $\rho$, for accepting a predicted bounding box among the $N$ as provided by DETR.

To obtain the detector, we fix the first two layers of the backbone with the weights provided in the pre–trained model and we re–train the rest of it with images taken from the dataset described in the previous section. In this phase, we also run a simple data augmentation procedure by applying a random horizontal flip followed by a random resize operation from randomly selected images (each image of the dataset is independently selected for data augmentation with probability, chosen after a number of trials, of 0.5).

B. Qualification of Door Detector on a Target Environment

The qualification of the general detector becomes relevant for our reference scenario, where the robot is assumed to be operative in the environment $e$ for a long time. We envisage a situation where the robot, during this time, gathers images from $e$ as it carries out tasks involving autonomous navigation. These images are then labelled with the bounding box and a label identifying the presence and status of doors. Notice that images collected on the field cannot be used to re–train the model as soon as they have been collected. Post–processing steps, analogously to what described in Section III, are required to prepare the data with cleaning and labelling being the most important tasks. Such operations might be carried out by a technician during the robot’s first installation and testing in $e$. Alternatively, data autonomously collected by the robot can be uploaded to a remote server during idle times and then post–processed in a separate phase. The bottom line that these examples highlight is that collecting and preparing data for fine–tuning a qualified detector brings a cost that, ideally, we would like to minimize. In the following section, we provide an empirical assessment of how the performance in door detection might vary with the fine–tune approach. Moreover, we study the trade–off between performance and the cost of collecting data samples from $e$. Note how, while we focus here on a specific model $GD$ based on DETR [4], our method to obtain a qualified detector $QD$ is rather general, and can be applied to other detectors and methods [9], [10].

V. EVALUATION

A. Experimental Setting

To evaluate the methods introduced in this work, we start by performing a set of preliminary experiments to assess the performance of the general door detector described in Section IV–A on a publicly available dataset used to test door detection methods from RGB images, which is less challenging than our proposed one. We exploit the DeepDoors2 dataset [28], that contains 3000 labelled RGB images of doors with different textures and sizes. The dataset contains images of doors that are sometimes obstructed by obstacles (e.g., furniture or persons) but the labels are assigned only for those doors that are totally contained in the frame and close enough to be sharply distinguishable. Clearly, this cannot properly represent the real view typically encountered by a mobile robot, which actually tends to provide additional challenges made by, for example, nested doors (see, for example, Fig. 3a) and partial views (Figs. 3b and 3c). To fix this, we manually re–labelled the entire dataset including bounding boxes also for those challenging doors exemplified in Fig. 3.

In this first evaluation assessment of our door detector, we use the enriched DeepDoors2 dataset as test set to compare our method with a baseline from the literature working
the presence and status of doors from an environment by a mobile robot that has to recognize impact of the fine-tune paradigm (Section IV-B) when the status (open or closed).

performance in recognizing the door presence as well as its term. This evaluation, that involves training, fine-tune, and testing, exploits the dataset collected in the context of this work (Section III). We denote the dataset as $D = \{D_{-e}, D_e\}$, where $D_e$ denotes all the instances acquired from poses sampled in environment $e$ while $D_{-e} = D \setminus D_e$. To further specify subsets of the dataset we shall use superscripts $P$ and $N$ to indicate positive (with at least a door) and negative examples, respectively. So, for example, $D_{e}^P$ shall indicate the positive examples obtained by poses sampled in environment $e$. To better denote our different experimental setups, we partition this last subset as $D_{e}^P = \{D_{e,1}^P, D_{e,2}^P, D_{e,3}^P, D_{e,4}^P\}$, where each $D_{e,i}^P$ contains approximately a randomly selected $25\%$ of all $e$’s positive instances in the dataset.

We use this dataset structure to perform a series of experiments where we vary the deployment environment $e$ (recall from Section III that in our dataset we have images acquired from 10 different Matterport3D environments). First, we train a general door classifier on $D_{-e}^P$ (the positive examples not belonging to $e$), this will be our general door detector denoted as $GD_{-e}$. We shall test it on $\{D_{e,1}^P \cup D_{e,2}^N\}$ ($25\%$ of the positive examples and all the negative ones, both taken from $e$). Then, we perform a series of fine-tuning rounds to obtain three new environment-qualified detectors $QD$. Specifically, we fine-tune $GD_{-e}$ using these three additional subset of data instances: $\{D_{e,1}^P, D_{e,1}^P, D_{e,2}^P, D_{e,2}^P, D_{e,3}^{P}\}$. We call the obtained qualified detectors $QD_{25}^P$, $QD_{20}^P$, and $QD_{15}^P$, respectively. Here the superscript denotes the percentage of data instances from $e$ that are required to fine-tune the general door detector. Notice that this value is also an indicator of the data acquisition/preparation costs that has to be carried out in $e$ in order to obtain a particular qualified detector for that environment. We set $N = 10$. This value was conservatively chosen after assessing that the maximum number of doors in an image from our dataset is 4. Moreover, after preliminary validation tests, we set the minimum confidence threshold $\rho_c$ for not discarding a predicted bounding box to $50\%$.

The source code of our simulation framework (Section III), the door detectors (Section IV), and all the datasets are maintained in a freely accessible repository.

### B. Evaluation Metric

To evaluate the performance in door detection, we adopt the average precision score (AP) used in the Pascal VOC challenge [6]. To get more refined values, we used a finer interpolation of precision/recall curve than that of [6]. To accept a true positive, the prediction must have an intersection over union area with one true bounding box above a threshold $\rho_a$ (empirically set to $75\%$). We evaluate the performances in detecting an image without doors with a slightly different pipeline: the bounding boxes with an above-threshold ($\rho_c$) confidence value that are mistaken for doors are counted as false positives, they are accepted as true positives otherwise.

### C. Results

The comparison result against the baseline are reported in Tab. I. The baseline’s hyper-parameters have been set empirically, by seeking acceptable performance in a series of preliminary experiments (the actual configuration is included in the repository). We randomly split our relabelled version of DeepDoors2 into a train ($80\%$) and test set ($20\%$) and learn a generic detector, denoted here as $GD$, on the former by running 40 epochs with a batch size of 1. Notice that the baseline method, seeking the rectangular shape of doors with features like edges and corners, achieves very poor performance with semi-open and open doors. For this reason, we report results only for closed doors, indicating the number of positives from the labelled dataset as well as the number of true and false positives achieved by each method.

| Method       | N. Positives | TP  | FP  |
|--------------|--------------|-----|-----|
| Baseline [19] | 198          | 39  | 3981|
| $GD$         | 198          | 169 | 33  |

**TABLE I:** Comparison with the baseline [19] (closed doors).

We also evaluate the capability of $GD$ in detecting doors’ status. In Tab. II we report the AP score obtained by the detector for each door status.

| Label     | AP | N. Positives | TP  | FP  |
|-----------|----|--------------|-----|-----|
| Closed    | 90 | 234          | 214 | 45  |
| Semi-open | 83 | 198          | 169 | 33  |
| Open      | 85 | 243          | 214 | 66  |

**TABLE II:** Performance on door status.

This first evaluation shows how our method outperforms the baseline based on handcrafted features. The number of
false positives found by the baseline highlights the challenging characteristics of the dataset. Moreover, the results in Tab. II show that our detector performs well in the task of detecting doors and their status.

In the second part of our experimental phase, we evaluate the performance of $GD_{-e}$ on our dataset, namely the general door detector that will be deployed in environment $e$.

Our dataset is more challenging than DeepDoors2 because it has been acquired by simulating the real constrained perception of a mobile robot. Due to this fact, the AP scores are significantly lower than those obtained with the DeepDoors2 dataset, in which the model is trained considering all the doors types. Note how, despite being less challenging, DeepDoors2 presents doors with a status (semi–open door) which is not contained in our dataset due to constraints in the simulator. Future work will investigate how to remove such a limitation.

After that, we qualify this model through fine–tuning over new examples collected from $e$. For each environment $e$, we train a general detector $GD_{-e}$ for 40 epochs, while the 3 fine–tuned modules ($QD_{25}^e$, $QD_{50}^e$, $QD_{75}^e$) are trained for 20 epochs, with a batch size 1. Tab. III reports the mean AP scores (averaged over the 10 environments) reached by the 4 detectors divided by label (no door, closed door, and open door), the average increments (with respect to the detector immediately above in table) obtained with fine–tuning, and the standard deviation ($\sigma$). We also report the AP scores for every single environment on closed and open doors in Fig. 4.

| Exp. | Label | AP  | $\sigma$ | Increment | $\sigma$ |
|------|-------|-----|----------|-----------|----------|
| $GD_{-e}$ | No door | 74  | 5 | – | – |
|       | Closed  | 39 | 14 | – | – |
|       | Open | 60 | 8 | – | – |
| $QD_{25}^e$ | No door | 79 | 4 | +7% | 9% |
|       | Closed | 61 | 10 | +75.5% | 66% |
|       | Open | 70 | 7 | +16% | 14% |
| $QD_{50}^e$ | No door | 78 | 5 | –1% | 5% |
|       | Closed | 69 | 12 | +13% | 9% |
|       | Open | 73 | 6 | +5% | 5% |
| $QD_{75}^e$ | No door | 79 | 5 | +1% | 4% |
|       | Closed | 72 | 11 | +6% | 10% |
|       | Open | 76 | 6 | +5% | 5% |

TABLE III: Average performance before and after fine–tuning.

The evaluation of the proposed detector on the dataset collected in this work (reported in Tab. III) suggests that the detector obtains acceptable performance also with any knowledge about the final environment in which the robot is deployed, as can be seen from the doors recognized by $GD_{-e}$ in the examples of Fig. 5.

Despite this, the obtained results show that, through the fine–tune paradigm, a detector can be successfully qualified by learning directly from a new operational environment, increasing the AP of an initially general door classifier. The performance in recognizing doors continues to rise with more examples, except for the no door category, which benefits only from the first fine–tuning step. Another outcome is

that the best performance increase is reached with the smallest fine–tune operation (performed using the 25% of the examples from environment $e$). Fig. 6 shows qualitative examples of the performance increase due to fine–tuning (in this case $QD_{25}$, bottom row) when compared to the performance of the generic detector (top row). It can be seen how the qualified detector $QD$, even when fine–tuned with a few examples, better distinguish doors in challenging images as nested doors, partially observed doors, and reduces false positives. This demonstrates that the lowest effort for data acquisition/preparation ensures a satisfactory increment in detection accuracy, suggesting that the number of examples that have to be collected on the field can be limited.

VI. CONCLUSIONS

In this work, we have presented a door detection method for autonomous mobile robots. Our method, based on a deep learning architecture, allows robots to distinguish between open or closed doors also in challenging images, as partial view of (nested) doors detected. To train our model, we built a dataset of labelled images from photorealistic simulations, from the point of view of a mobile robot moving in that environment. We show how our model is able to detect doors...
Future work will investigate how to quantify and reduce the effort for labelling the new examples to qualify a general detector. Furthermore, we will study approaches to perform online fine-tuning reducing the need of human intervention to obtain new labelled examples. In this way, a robot can learn with experience to better distinguish features, such as doors, in its operational environment.

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