To Go or Not To Go?
A Near Unsupervised Learning Approach For Robot Navigation
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Abstract—It is important for robots to be able to decide whether they can go through a space or not, as they navigate through a dynamic environment. This capability can help them avoid injury or serious damage, e.g., as a result of running into people and obstacles, getting stuck, or falling off an edge. To this end, we propose an unsupervised and a near-unsupervised method based on Generative Adversarial Networks (GAN) to classify scenarios as traversable or not based on visual data. Our method is inspired by the recent success of data-driven approaches on computer vision problems and anomaly detection, and reduces the need for vast amounts of negative examples at training time. Collecting negative data indicating that a robot should not go through a space is typically hard and dangerous because of collisions; whereas collecting positive data can be automated and done safely based on the robot’s own traveling experience. We verify the generality and effectiveness of the proposed approach on a test dataset collected in a previously unseen environment with a mobile robot. Furthermore, we show that our method can be used to build costmaps (we call as "GoNoGo" costmaps) for robot path planning using visual data only.

I. INTRODUCTION

Robot navigation is essential for many tasks, such as guiding people through a space [1], carrying heavy luggage for shopping [2], [3], [4], automated delivery, or environmental inspection. To successfully navigate in many of these circumstances, robots need to adapt to the presence of dynamic obstacles and changes in their environment.

Motivated by the recent success of neural network models in control and perception applications, this work explores the use of deep learning for mobile robot navigation with a single camera. In particular, we study the problem of specifying if a wheeled robot can go through a space or not. We further refer to these cases as GO or NO GO situations, respectively. Making the right decision in this problem can prevent robots from colliding with objects, injuring people, getting stuck in constrained spaces, or falling over an edge.

Building accurate neural network models often require a large amount of annotated data, but collecting this data can be both time-consuming and costly. In applications such as robot navigation, incorrect annotations made by human error can further cause serious damage to both the robot and its environment. Besides, collecting negative examples of situations in which a robot should not traverse a space can be challenging and dangerous. Some of these spaces are impossible for a robot to go through. Others may involve expensive collisions and injuries. The alternative idea is to use sensors like a bumper for collecting negative data. However, bumpers may not work well with small obstacles nor prevent the robot from falling down an edge. IR sensors can also be used as “cliff sensors, but the consequences of false detections are often too costly to depend on them.

The main insight of our work is that we can build a reliable deep model for the GO or NO GO problem using vision and an unbalanced dataset of examples. This dataset is mainly composed of positive examples that can be automatically collected safely based on the robot’s traveling experience, e.g., under human supervision. Moreover, we build this dataset using an onboard and off-the-shelf fisheye camera. This type of sensor makes our solution practical and cheap for mobile platforms in comparison to using more expensive sensors, such as LiDARs.

Inspired by prior work on anomaly detection [5], we propose two methods based on Generative Adversarial Networks (GAN) to classify the scenarios which a robot can go through or not [6], [7]. One method is unsupervised; the other, which is an extension, is near unsupervised.

The proposed unsupervised method uses GAN to train a generator function (Gen) that generates images in the manifold of the positive dataset. The difference between the real image X and the generated image X′ through the trained generator is used to classify whether the real image
is positive or not. Note that, the generator trained on the positive images can not generate negative images. Hence, it is expected that the difference between the real image and the generated image \(|X - X'\)| for the negative examples to be bigger than the positive examples. However, the two main limitations for implementing this approach on a real-time mobile robot are high computational time and low accuracy.

To solve the first limitation, we design another network as the inverse generator \((\text{Gen}^{-1})\) to produce the generated image \((X')\) corresponding to the input image \((X)\) in real time \([8]\). To address the second limitation, we propose a near unsupervised method. And use a relatively small amount of negative and positive annotated data. The annotated dataset is less than 1 percent of the whole positive dataset used for our unsupervised learning method. This small amount of data annotation is acceptable for our problem and can help to improve the performance significantly. All the components in our method are performed in a feed-forward manner and are applied in real time with high accuracy, applicable on real-time mobile robots.

In this work, we use a fisheye RGB camera image as the input \((X)\) for our method. Fisheye cameras can efficiently capture every angle of the surrounding environment. It enables the robot to see up, down, and side areas using a single camera. Moreover, the cost of a Fisheye camera is much less than a 3D LIDAR.

The rest of the paper is organized as follows. Section II first describes related work on deciding whether robot’s location is traversable or not. The proposed data-driven approach and its evaluation are then presented in Sections III and IV. The latter section we show a detailed experimental study of our method and introduce a novel costmap called GoNoGo generated by our method for the task of path-planning. Section V finally concludes this paper and discusses future work.

### II. RELATED WORK

Prior work has proposed different approaches to classify GO or NO GO situations and perform obstacle avoidance. We briefly describe these works and their connections to our method.

#### A. Measurement Methods

Different sensors have been used in the past to estimate whether a physical space is traversable or not. For example, Suger et al. \([9]\) used a 3D LIDAR to design a grid map for robot navigation. This map was built using a naïve Bayes classifier. Pfeiffer et al. \([10]\) proposed an imitation learning method to learn how a robot should navigate a space based on expert demonstrations and 2D LIDAR data. Borenstein et al. \([11]\) rather proposed a histogram method to avoid obstacles using an ultrasonic sensor, and Er et al. \([12]\) trained a neuro-fuzzy controller to mimic innate behavior using IR sensors.

Other prior methods have relied on image data for obstacle detection and avoidance. For instance, Ulrich et al. \([13]\) used a monocular camera and color differences to detect obstacles on the floor. Other efforts have used monocular cameras to estimate depth \([14], [15], [16]\), which can then be used to avoid obstacles.

Different to these lines of work, we propose to use a single RGB fisheye camera for the GO or NO GO problem. This type of camera can capture every angle of the surrounding environment and is significantly cheaper than a LIDAR. Furthermore, our results suggest that depth information is not necessarily needed for this problem.

#### B. Deep Learning Techniques

Nowadays, deep learning techniques have been successfully extended to many fields such as robotics, computer vision \([17]\), modeling \([18], [19], [20]\), control \([21]\), voice recognition and so on. We can divide previous works on the obstacle avoidance into two categories, 1) imitation of human behavior, and 2) Near unsupervised and supervised learning.

1. **Imitation of human behavior**: LeCun et al. \([22]\) train neural networks to mimic human behavior for autonomous vehicles. The steering input of the human drivers is collected for their supervised learning techniques. S. Ross et al \([23]\) trains DAgger \([24]\) to imitate a human being’s behavior for obstacle avoidance using a drone. Tai et al. \([25]\) uses neural networks to mimic the traveling velocity and turning angular velocity from the joystick control of a wheeled robot. Huang et al. \([26]\) proposes an approach to solve the problem of autonomous mobile robot obstacle avoidance using reinforcement learning neural networks. Giusti et al. \([27]\) trains a network to decide go straight, turn right or turn left for a drone. The camera images with annotation are collected by a trail in a forest. However, referenced human motion in these methods often includes not appropriate behavior for the training, which may cause an accident. As opposed, we only collect a positive dataset that is automatically annotated by the robot’s own experience (without any errors) and do a classification task. Therefore, our method can suppress the possibility to learn the wrong behavior and reduce the risk of an accident significantly.

2. **Near Unsupervised and Supervised Learning**: Gandhi et al. \([28]\) collects negative images ("NO GO") by crashing drones into obstacles and uses a neural network to classify scenes into GO or NO GO. However, in our problem there are many situations that the wheeled robot can not have a crash, e.g. falling from an edge. Elkan et al. \([29]\) proposes the PU learning method to distinguish between positive and negative samples only using a positive and unlabeled dataset. Schlegl et al. \([5]\) applies an unsupervised learning approach based on GAN for anomaly detection. These approaches \([5, 29]\) don’t need to have the annotation process for the negative dataset. However, it is difficult to apply current PU learning methods \([29]\) to our problem because they work well in the scenarios where the distribution or the domain of positive and negative examples are limited and simple. On the other hand, the calculation speed and the accuracy of most methods such as \([5]\) are not enough for the real-time mobile robot. We evaluate the performance of this baseline in more details in the later section.

To address the performance and computation costs of the baseline methods, we propose an unsupervised and a near unsupervised learning method. We also avoid the time-consuming and costly annotation process.

### III. LEARNING TO “GO” OR “NO GO”

#### A. Overall Architecture

Figure 2 shows the overall architecture of our proposed approach. First, our approach tries to generate an image \(X'\).
which corresponds to the real input image \( X \) through the manifold of the positive dataset. The generator function \( \text{Gen} \) is trained by a GAN and outputs images in the manifold of the positive examples. \( \text{Gen}^{-1} \) is the inverse generator to search for the appropriate latent vector \( z \) to express \( X \). We apply \( \text{Gen}^{-1} \) to decrease the computational load instead of the iterative back-propagation method used in previous baseline methods [5].

We then extract the following three features from \( X \) and \( X' \) to classify the scene observed in the input image as GO or NO GO:

- (R) **Residual Loss:** \( \| X - X' \| \),
- (D) **Discriminator Loss:** \( \| f(X) \) \( - f(X') \| \),
- (F) **Feature by Discriminator:** \( f(X) \),

where \( f \) is the last convolution layer features of our GAN’s discriminator. Because \( \text{Gen} \) and \( \text{Gen}^{-1} \) are trained only on positive data samples [5], our method expects that the residual loss “R” and the discriminator loss “D” are large when the input image is a negative example. However, for some negative examples, \( R \) and \( D \) are not discriminative enough for accurate “GO”, “NO GO” classification. Thus, we modify the weight of salient areas as shown in section III-D. To improve the performance of our method furthermore, we train an FC layer with a small amount of annotated data.

**B. Manifold of “GO” Image**

Figure 3 depicts our GAN, which is constructed by two adversarial modules, a generator, \( \text{Gen} \) and a discriminator, \( \text{Dis} \). Here, \( z \) is the noise generated by a normal distribution. \( \text{Dis} \) is trained to decide whether the input is real or generated image. On the other hand, \( \text{Gen} \) is trained to fool \( \text{Dis} \). \( \text{Dis} \) and \( \text{Gen} \) are simultaneously trained by the following a two player min-max game:

\[
\min_{\text{Dis}} \max_{\text{Gen}} V(\text{Dis}, \text{Gen}) = E_{X \sim p_{\text{data}}(X)}[\log \text{Dis}(X)] + E_{z \sim p_{z}(z)}[\log(1 - \text{Dis}(\text{Gen}(z)))] ,
\]

where \( p_{\text{data}} \) and \( p_{z} \) are the distribution of \( X \) and \( z \), respectively. The training dataset \( X \) is composed of images with positive labels only.

In the proposed approach, \( \text{Gen} \) and \( \text{Dis} \) are designed as standard Convolutional Neural Networks (CNN) listed in Table I and II. Here, “FC” is a fully connected Layer, “Dconv” is a de-convolutional layer, and “Conv” is a convolutional layer. Batch normalization is applied after each convolutional layer. Table I and II list the parameters of the generator \( \text{Gen} \) and the discriminator \( \text{Dis} \), respectively.

**C. Training of the Inverse Generator**

To generate an image similar to the input data, an adequate value for the noise \( z \) has to be found. Prior work by Schlegl et al. [5] applies an iterative back-propagation procedure for 500 times to minimize the following cost function under the fixed \( \text{Gen} \) and \( f \):

\[
L(z) = (1 - \lambda) \cdot L_R(z) + \lambda \cdot L_D(z) ,
\]

where the residual loss \( L_R(z) \) and the discriminator loss \( L_D(z) \) are defined as follows:

\[
L_R(z) = \| X - \text{Gen}(z) \| ,
\]

\[
L_D(z) = \| f(X) - f(\text{Gen}(z)) \| .
\]

The parameter \( \lambda \) in eq. (2) is a weighting factor for \( L_R(z) \) and \( L_D(z) \). Unfortunately, the computational load of the iterative back-propagation procedure used to minimize \( L(z) \) is too expensive and it’s not applicable on a real-time mobile robot.

In order to speed up this process, we train and apply the inverse generator \( \text{Gen}^{-1} \) to find the appropriate noise \( z \), as shown in Fig. 4 [8]. The structure of the network corresponding to \( \text{Gen}^{-1} \) is listed in Table III. This is the same design as \( \text{Dis} \) except for the last FC5. The output size of FC5 in our \( \text{Gen}^{-1} \) is set as 100, in order to match the size of \( z \). \( \text{Gen}^{-1} \) is trained only on positive data by minimizing the cost function \( L(z) \) under a fixed \( \text{Gen} \).

**D. Weighting for Unsupervised Learning**

The base line method uses the following score \( A(x) \) for classification:

\[
A(X) = (1 - \lambda) \cdot R_s(X) + \lambda \cdot D_s(X) ,
\]
TABLE III
PARAMETERS OF INVERSE GENERATOR Gen⁻¹.

| filter size | stride | output size | function |
|-------------|--------|-------------|----------|
| Input -     | -      | 128 × 128 × 3 | -        |
| Conv1 4 × 4 | 2      | 64 × 64 × 64 | Elu[30]  |
| Conv2 4 × 4 | 2      | 32 × 32 × 128 | Elu      |
| Conv3 4 × 4 | 2      | 16 × 16 × 256 | Elu      |
| Conv4 4 × 4 | 2      | 8 × 8 × 512  | Elu      |
| FC5 -       | -      | 100         | linear   |

where the residual score $R_s(X)$ and the discriminator score $D_s(X)$ are defined as $\mathcal{L}_R(z)$ and $\mathcal{L}_D(z)$, respectively. $z_t$ is the latent space vector representing the input image. The base line method classifies the scene as GO or NO GO by thresholding $A(X)$ as follow:

$$t_d = \begin{cases} 
1 & \text{“GO”} \quad (X < a_{th}) \\
0 & \text{“NO GO”} \quad (X \geq a_{th}) 
\end{cases}, \quad (6)$$

where $t_d$ is decision flag for GO (=1) or NO GO (=0). The threshold value $a_{th}$ is set to 0.17. The base line method can not precisely distinguish between positive and negative images. To address this problem, we modify $R_s(X)$ and $D_s(X)$. Basic idea is weighting the salient areas of the image more instead of simple L2 norm of the difference in (3) and (4) as follows:

$$\mathcal{L}_R(z) = ||W_R \circ (X - Gen(z))||,$$

$$\mathcal{L}_D(z) = ||W_D \circ (f(X) - f(Gen(z)))||,$$

where $W_R \in \mathbb{R}^{3 \times 128 \times 128}$ and $W_D \in \mathbb{R}^{512 \times 8 \times 8}$ are the weighting matrices, and $\circ$ indicates pointwise product function. Using cross validation we found that the salient area for classifying GO or NO GO is the bottom area on the image, which corresponds to the close area on the floor in front of the robot. Thus, we gave more weight to one eighth bottom area of the image.

IV. EXPERIMENTAL RESULTS

A. Robot Platform

Left side of Fig.1 depicts the robot used for our experiments. This is a “Turtlebot 2” platform [31] with a “THETA S” fish eye camera by Ricoh [32]. Turtlebot 2 is a common research platform that is easy to use with the Robot Operating System (ROS) [33].

Ricoh’s THETA S can efficiently capture every angle of the surrounding environment around the robot with a full HD resolution (3 × 1920 × 1080) at 15 fps. It enables the robot to have full visibility of the area above, below and around it with a single camera. This wide view is very important to capture the environment and decide to GO or NO GO.

B. Data Collection

Figure 6 shows the map of the engineering quad at Stanford University. Here, the red rectangles indicate the buildings where data was collected for the training set, and the blue rectangles indicate those where the test set was gathered. The length of the video collected per location for training and evaluating the proposed approach is shown beside the highlighted rectangles.

In each building, we controlled the robot using a gamepad and collected videos at 3 fps. Although the THETA S has 2 fisheye cameras, one in front and one in the back, we only used the front camera. The total duration of the data collected for the experiments was about 7.2 hours.

The recordings led to a dataset of 78,711 useful images for the present evaluation. The images were cropped and resized.
Algorithm 1 Automatic labeling of positive dataset

1: for $i = 0$ to $N$ do
2: if $v(x) > v_{th}$, $\forall x \in [i - p, \ldots, i + f]$ then
3: label of $X(i)$ is positive
4: else
5: label of $X(i)$ is not defined (unlabel)
6: end if
7: end for

Fig. 6. Amount of data captured per location for our experiment. The information was overlaid on a view of the campus from Google Maps [34].

C. Annotation

We used the robot’s velocity to automatically identify situations in which the robot could traverse the space in front of it. More specifically, the images that were captured within a time window in which the robot’s velocity $v$ was bigger than a threshold value $v_{th}$ were automatically labeled as positive examples in our dataset. This procedure is detailed in Algorithm 1. The hyper parameters $v_{th}, p$ and $f$ were set to 0.3 m/s, 5, and 3, respectively. This resulted in 53598 and 17968 positive images for training and testing, respectively.

In addition, two small datasets of positive and negative annotated images are required, one for training the FC layer and other for evaluation of our overall method. For the positive dataset, we randomly select 400 images from the annotated images using Algorithm 1. The negative annotations are given by hand. A candidate set of negative images were randomly chosen from the unlabeled dataset. And 400 images from these candidates were hand labeled by the authors. The above process was done both for training and test data. The amount of hand-labeled data for training the FC layer (near supervised method) was less than 1% of the overall positive training dataset used for training our GAN (unsupervised learning method).

D. Training

There are three steps for training our method. Two of them only use positive data (unsupervised learning) i) GAN in Fig.3 and ii) inverse generator $Gen^{-1}$ in Fig.4. The third step is part of the supervised learning method which is training the FC layer in Fig.5 to improve the accuracy of our near unsupervised learning method. We implemented and trained all our methods using “chainer” deep learning framework [35]. For training, we use a mini-batch size of 100 and the optimization method is ADAM[36].

E. Visualization

1) Performance of the trained $Gen$ and $Gen^{-1}$ models:
In order to verify the performance of trained $Gen$ and $Gen^{-1}$, Fig.7 shows a set of real images ($X$) in [a], and the corresponding generated images ($X'$) in [b] for the positive images. Similarly, Fig.8 shows the real images ($X$) and the corresponding generated images for the negative images. The images in Fig.7 and 8 are randomly chosen from the test set.

As we can see in Fig.7[a] and [b], the generated images $X'$ are similar to their corresponding real images $X$ for the positive dataset, except some small differences. For example, a person in the upper center image, a windows frame in the middle left image, and a small white box in the bottom center image in $X$ are partially removed in the generated images $X'$. However, the general look and the color of the images is almost same.

On the other hand, Fig.8 depicts the big difference between $X$ and $X'$ for the negative dataset. The generated images in Fig.8[b] look like corridors or hallways, which are the typical in the positive dataset, although the inputs were negative images. The obstacles, like trash box, wall, fence, stairs, wooden furniture, and chair are disappeared in the generated images $X'$, because $Gen$ is the manifold of the positive images and can not generate NO GO situations.

Note that in some cases, the difference between the negative image that was input to our system and the one it generated is not very large. For example, in the scenario depicted in the bottom left corner of Fig. 8, some of the stairs get washed out in the generated image $X'$. However, the overall look of the input and the generated images is similar. Or, in the bottom right image, the brown box in $X$ is turned into a brown corridor in $X'$. Thus, relying solely on an unsupervised learning method to distinguish between positive and negative examples just by comparing $X$ and $X'$ can be hard. As we show in our ablation study in the next section, the final FC layer of our model can handle these situations robustly.

2) Saliency map: We visualize the behavior of our overall trained neural network using a saliency map[37]. Figure 9[a] is the mean of all the saliency maps for the positive class. Almost all the white area (most salient) is shown inside of the red lines. The center and upper area of the image are not that important for predicting the GO or NO GO classes. In particular, the upper area of the input images was typically the ceiling of the room where the robot navigated through, while the center area was typically a space farther away from the robot. In contrast, the bottom area was often occupied by the floor in front of the robot. The right and left sides were often a wall of the room or the corridor in the vicinity of the robot. These areas are the most important part of the image to look.

We also visualized the weights for the residual loss of the FC layer in Figure 9[b]. Four corners and center area is
almost black, while inside of two red curves is white, which has bigger weight to predict GO or NO GO. This result indicates that the residual loss R gives a positive effect to the whole system of our proposed approach.

F. Ablation Study

Table IV shows the results from our evaluation on the test set using different sets of components: (R) Residual loss, (D) Discriminator loss, and (F) Features by the discriminator. The table also shows results for unsupervised [5] and supervised [38] baseline methods.

We use accuracy, recall, precision, and f1 score as metrics to evaluate our performance. Also, the frequency, which corresponds to the calculation speed, and memory size are also listed to understand whether these techniques are applicable on a real mobile robot. For the measurement of frequency and memory size, we ran our experiments on a Geforce GTX TITAN X GPU. We further describe the baselines used in our evaluation and discuss the results presented Table IV in the following sections.

1) Unsupervised learning: We use [5] as an unsupervised baseline method. Our method for the unsupervised learning is using inverse generator $Gen^{-1}$ to search the appropriate noise $z$ and to apply weighting modifications shown in the section III-D.

As shown in Table IV, our method performs better than the unsupervised baseline method. Moreover, the computation speed is improved by the inverse generator $Gen^{-1}$. However, an accuracy of 72.5% with unsupervised learning is low for practical purposes. The problem is that sometimes the
### TABLE IV
**Analysis of our method on the test set using different set of components (R) Residual loss, (D) Discriminator loss, and (F) Feature of Discriminator.**

| Model         | Accuracy [%] | Recall [%] | Precision [%] | F1 score | Hz    | Memory [MB] |
|---------------|--------------|------------|---------------|----------|-------|-------------|
| base line method [5] (unsupervised learning) | | | | | | |
| R             | 57.25        | 66.75      | 56.09         | 60.95    | 0.127 | 323         |
| D             | 59.75        | 58.50      | 60.00         | 59.24    | 0.127 | 323         |
| R+D           | 60.00        | 72.25      | 58.03         | 64.36    | 0.125 | 323         |
| our method (unsupervised learning) | | | | | | |
| R             | 67.88        | 66.75      | 69.81         | 73.46    | 175.18 | 339         |
| D             | 72.00        | 77.50      | 69.81         | 73.46    | 102.381 | 352         |
| R+D           | 72.50        | 68.50      | 74.46         | 71.35    | 93.07  | 354         |
| base line method [38] (supervised learning) | | | | | | |
| ResNet 50     | 91.63        | 95.75      | 87.64         | 91.52    | 34.46  | 705         |
| ResNet 152    | 92.25        | 94.75      | 90.23         | 92.44    | 12.21  | 1357        |
| our method (supervised learning) | | | | | | |
| R             | 85.38        | 83.50      | 86.75         | 85.10    | 175.17 | 338         |
| D             | 91.63        | 94.50      | 89.36         | 91.86    | 103.17 | 356         |
| F             | 92.25        | 95.50      | 89.67         | 92.49    | 94.11  | 358         |
| R+D           | 91.63        | 94.00      | 89.74         | 91.81    | 96.41  | 357         |
| D+F           | 93.00        | 96.50      | 90.19         | 93.24    | 96.41  | 357         |
| R+D+F         | 93.13        | 95.00      | 91.56         | 93.25    | 119.99 | 348         |
| base line method [38] (supervised learning) | | | | | | |
| ResNet 50     | 91.63        | 95.75      | 87.64         | 91.52    | 34.46  | 705         |
| ResNet 152    | 92.25        | 94.75      | 90.23         | 92.44    | 12.21  | 1357        |
| our method (supervised learning) | | | | | | |
| R             | 85.38        | 83.50      | 86.75         | 85.10    | 175.17 | 338         |
| D             | 91.63        | 94.50      | 89.36         | 91.86    | 103.17 | 356         |
| F             | 92.25        | 95.50      | 89.67         | 92.49    | 94.11  | 358         |
| R+D           | 91.63        | 94.00      | 89.74         | 91.81    | 96.41  | 357         |
| D+F           | 93.00        | 96.50      | 90.19         | 93.24    | 96.41  | 357         |
| R+D+F         | 93.13        | 95.00      | 91.56         | 93.25    | 119.99 | 348         |

[a] mean of saliency map  [b] weight for Residual loss

Fig. 9. Visualization of proposed neural network.

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difference between $X$ and $X'$ is not informative enough for classification purposes. For positive input images, the generator sometimes washes out small, but important details. For some negative input images, the difference between $X$ and $X'$ can be small, as discussed in the previous section.

2) **Near supervised learning**: We chose pre-trained ResNet 50 and 152 on ImageNet [38] as the supervised baseline method for our near unsupervised learning approach. We extracted features from ResNet and trained the last FC layer to decide GO or NO GO using this features. We only trained the FC layer because training the whole neural network on the small dataset of positive and negative examples would lead to over-fitting.

As can be seen in Table IV, our method (R+D+F) outperforms the baseline supervised methods. In addition, the baseline ResNets need 2 to 4 times more memory and significantly more computation time than our method (R+D+F). Our approach can run at 89.69 Hz, which is much faster than the camera’s frame rate of 15 fps.

**G. Cost-map GoNoGo**

One of the practical applications of our approach is building cost-maps for navigation. For example, Figure 10 shows a cost-map that was generated for static objects in the environment of the robot. This cost-map was built by tele-operating the robot and placing high-cost obstacles in its cost-map whenever the view from its camera detected a NO GO situation. These obstacles correspond to the magenta parts of the map in the right image of Fig. 10. The surrounding of the obstacles (considering a fixed radius for inflation) was set to a lower, but still considerable cost for navigation (blue and light blue areas in the map). Note that any automatic exploration method, such as Frontier exploration [39], could have been used as well to generate this cost-map.

With the proposed approach, it is also possible to build cost-maps of dynamic environments. For example, Fig.11 shows the path planned for the robot (green line) based on a
cost-map that was generated in real-time using the output of our classifier. In this experiment, we placed a trash box in front of the robot, in between its location and a destination goal. The robot then adjusted its planned trajectory to avoid the obstacle and reach the desired goal. Note that for these experiments, we used the Ricoh THETA camera only and no other sensors.

V. CONCLUSION

We proposed an unsupervised and a near unsupervised learning approach to classify GO and NO GO scenarios observed from a fish eye RGB camera on a robot. Our approach outperformed baseline methods regarding performance (accuracy, recall, precision, and f1 score) and on computational requirements (calculation speed and memory footprint). We also showed that our method could be used to generate cost-maps for robot navigation.

In terms of future work, more experiments are needed to validate the effectiveness of the proposed approach in other scenarios not considered in the present work, like outdoor environments. We would also like to test our method on other robots and further evaluate obstacle avoidance.

VI. ACKNOWLEDGEMENTS

We appreciate TOYOTA Central R & D Labs., INC. for the financial support to Noriaki Hirose as visiting scholar in Stanford University. In addition, we appreciate Fei Xia and Kazuki Kozuka for the helpful discussions.

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