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Finding Anomalies with Generative Adversarial Networks for a Patrolbot

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Abstract

We present an anomaly detection system based on an autonomous robot performing a patrol task. Using a generative adversarial network (GAN), we compare the robot's current view with a learned model of normality. Our preliminary experimental results show that the approach is well suited for anomaly detection, providing efficient results with a low false positive rate.

1. Introduction

Typical surveillance systems consist of multiple cameras providing visual coverage of an area of interest, and result in a large cognitive load placed on a human operator. In this work, we automate the surveillance task using an autonomous robot which continuously patrols an environment looking for anomalies: as the robot patrols, it compares its current view of the world with a previously learned model of normal objects within the given environment.

We use a generative adversarial network (GAN) as a per-environment model of normality. We do not explicitly perform object detection, but, rather, our GAN learns objects in the context of the given environment. Like previous anomaly detection on autonomous robots [2], our GAN learns its normality models in an unsupervised fashion eliminating the need for extensive human labeling of large training corpora, resulting in scaling to arbitrarily large environments.

We construct our GAN by first tele-operating the robot within a given environment (e.g., hallway, cubicle area, outdoors) collecting images. A shifted grid is then used to partition all the images into patches, which are used to train the GAN. During testing, we use the same shifted grid to partition the input image, and then compare the bottleneck features for the generated patch with the bottleneck features from the actual patch. If the difference is significant, we call the patch anomalous.

We present preliminary results on anomaly detection in the hallway of an office environment. Our primary contribution is demonstrating the usefulness of GAN bottleneck features to locate anomalies in indoor environments. This eliminates the need to store or register background images to find anomalies. Finally, the approach runs efficiently, and can be deployed on resource limited robotics platforms.

2. Methodology

Network Architecture Key to this approach is the ability to learn a normative model for each environment by navigating through them with a mobile robot. The robot learns normative models by building a separate GAN for each environment. We use the DCGAN approach as suggested by [1], adopting an architecture that is similar to what was proposed by [3]. Like [4], we minimize the use of dense layers, using a single dense layer as the bottleneck between encoder and decoder. It has been our observation that a dense bottleneck converges quickly and is more useful for related tasks such as semi-supervised learning. Unlike [4], we use an autoencoder-style with a bottleneck size of 4096. Experimentally, we have found that when using an autoencoder, larger bottlenecks generate better images. We use an Adam optimization scheme with a learning rate of 0.0001 and $\beta_1 = 0.5$ for both the discriminator and generator.

Running in real-time on a resource limited robot makes it necessary to extract object proposals efficiently. For this reason, we use a sliding window where each patch is a fixed size $N \times N$ with a small step size M. In our experiments, we set $N = 150$ and $M = 50$ for training and $M = 75$ for evaluation. During training, each image produces 144 patches, resulting in 243,584 training patches for the hallway environment. Additionally, for testing and training, each patch is resized to 128×128.

Locating Anomalies We hypothesize that the GAN will perform better when generating images from previously seen objects (i.e., present during training) than it will be when generating images of objects it has never seen before.

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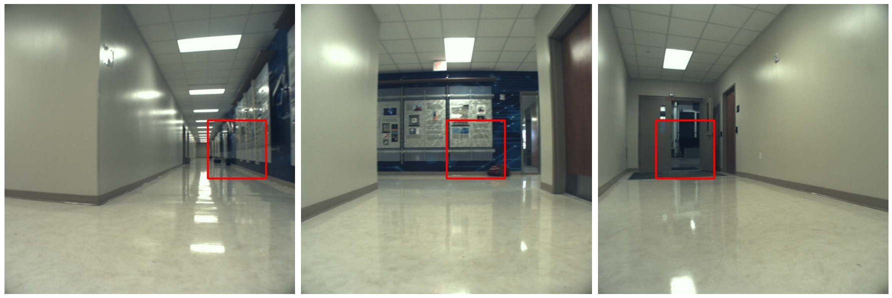

Figure 1. Results of performing anomaly detection; anomalies are highlighted with a red bounding box. In the left image, the trashcan has been knocked over. In the middle image, a backpack has been abandoned. In the right image, the door has been left open.

See Fig. 1 for detected anomalies and Fig. 2 for examples of reconstructed anomalous patches.

"Bottleneck features" in the GAN represent important visual features in the image patch. We use these features to determine whether the generated image differs from the input image in some significant way. To do this, the original image patch $\mathbf{x_i}$ is presented to the generator of the GAN, which produces bottleneck features $\mathbf{z}$ and a reconstructed image $\hat{\mathbf{x_i}}$. Then, the reconstructed image $\hat{\mathbf{x_i}}$ is fed to the encoder of the GAN producing bottleneck features $\hat{\mathbf{z}}$.

The l_2 norm of the difference between these two features, shown in Eq. 1, represents a measure of how much the generated image deviates from the original image. High values of d_p indicates that the patch did not reconstruct all of the content, which is indicative of an anomaly, i.e. the dominant object in the patch was not seen at training time.

$$d_p = \|\mathbf{z} - \hat{\mathbf{z}}\|_2^2 \tag{1}$$

3. Experimental Results

We mounted a Carnegie Robotics S7 camera at 1024×1024 resolution at 15 FPS atop a Pioneer 3AT mobile robot. The S7 camera projects a circular image on a square field; so we crop a centered middle square of 750×750 pixels. Fig. 1 shows experimental results.

During evaluation, we ignored images where over 80% of the image is detected as anomalous to account for motion blur and dynamic lighting. Dynamic lighting changes were the result of the camera's auto-iris, which is normally disabled, but on an autonomous robot, the auto-iris allows the system to perform better in poorly lit areas. Using the GAN approach results in a false positive rate of 0.42% compared to our previous work which reported a false positive rate of 4.72% [2].

4. Discussion

We present an anomaly detection approach for a mobile autonomous robot based on a GAN. In an unsupervised manner, our approach uses the GAN to learn a model of normality for a given environment, and then uses this learned model to find things that do not belong in the environment. Our approach scales to arbitrary environment sizes and is efficient enough to run on a mobile platform. In practice, the approach presented runs at 2 Hz. Our future work centers around testing in additional environments, exploring architectural variations and learning the relationship between detection accuracy, patch size, and bottleneck features size.

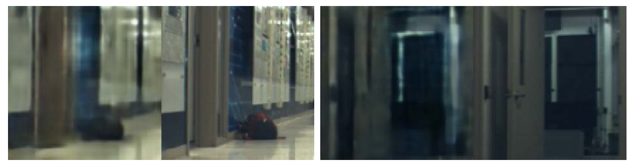

Figure 2. Two examples of detected anomalies. Each image pair shows a generated image on the left and actual image on the right. In the left pair, note that the generated backpack is a different color; in the right pair, note that the generated door has no doorknob.

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