IFT6757 Project Proposal: Closing the reality gap using Generative Adversarial Networks

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***Abstract*—Training a robot in a simulated environment has many advantages: simulators are easier to use and control than the real environment and have the advantage of allowing reproducibility. However, this comes with a major drawback which is the complex transition from the simulated world to the real world. This drawback is framed as the reality gap. In this project, we will tackle this problem by using a Generative Adversarial Networks (GAN) [1] to generate realistic data from our simulated data. We assess the performance of our generator using a Sim-vs-Real Correlation Coefficient(SRCC) [2].**

I. Addressing the problem

There exists a discrepancy between the simulation environment and the real environment that considerably reduces the performance of the robot in the real environment after being trained in simulation. Even though there are multiple factors causing this reality gap, visual perception is often the most influential component since synthetic images - images coming from simulation - do not constitute a realistic representation of the real world. They mislead the trained models in learning specific features without generalizing well. Instead of investing in extensive resources to develop a new, more realistic yet not realistic enough simulator, we propose to leverage the benefits of GAN [1].

A. GAN

GAN constitute a framework in which we simultaneously train two models: a model, that we say generative, that will try to capture the underlying distribution of the data and a discriminative model that will estimate the probability that an observation was generated by our generator or that it came from the real distribution of the data. This is an adversarial process in which the training procedure of the generator tries to maximise the probability that the discriminator will be wrong [1].

B. How will GAN help us in reducing the reality gap?

Our objective is to try to improve the synthetic images that come from the simulator by increasing their "realism". We thus need to preserve as much of the inherent features that constitute a real image, in other words a none generated image. In order to do so, we will use in the context of the framework defined above as a GAN, a deep neural network that we will call the generator and that will take as input the synthetic images, train on them and output augmented images. Since we are in an unsupervised problem setting, we do not have any labels from which we could establish a direct correspondence between synthetic and real images. We want to be able to learn the mapping between synthetic and real images using unlabeled targets. In order to do so, GANs make use of another deep neural network that we will call the discriminator which will classify the images provided to it as real or fake. Both generator and discriminator will train simultaneously in the context of an adversarial process where the generator will try to "trick" the discriminator by producing augmented images as "realistic" as possible. Once the discriminator is unable to distinguish augmented and real images, the training stops.

The augmented images produced by our GAN will serve to learn a model in simulation that will generalize well on the robot, in the real world.

II. Methodology

A. Data collection

To attain our goal, one of the major issues will be to collect the data needed to train our GAN. We will need to collect pairs of images, one corresponding to reality and the other one corresponding to the simulator image. To collect this data, two avenues are available to us. First, we can use pre-existing data from the DuckieTown logs database [3] and try to match this data to the simulated data. Otherwise, we can try to generate the real data with our robots and also generate the matching data on the simulator. The data collection will be done using the provided ROS functionalities for this goal, e.g ROS bag.

B. Assessing performance

To assess the performance of our GAN and its ability to close the reality gap, we will be using different benchmarks.

The first one will be to use the already available reinforcement learning baseline to compare the effect of an agent trained with our augmented data compared to the regular simulator images. To train the agent, the simulated image will be fed to our trained generator, and the resulting generated image will be then used by the agent. If results seem promising, the imitation learning baseline might also be used.

In addition to that, the Sim-vs-Real Correlation will be calculated like described in the article Sim2Real Predictivity: Does Evaluation in Simulation Predict Real-World Performance [2]. This evaluation metric uses the Success Path Length result of the agent in the simulated environment compared to the result in the real world setting.

Finally, we will try to run the pure pursuit routine in our augmented simulator and compare its performance to the regular simulator as well the the same algorithm on the duckiebot.

REFERENCES

[1] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, "Generative adversarial nets," vol. 27, pp. 2672–2680, 2014.

[2] A. Kadian, J. Truong, A. Gokaslan, A. Clegg, E. Wijmans, S. Lee, M. Savva, S. Chernova, and D. Batra, "Sim2real predictivity: Does evaluation in simulation predict real-world performance?," 2019.

[3] DuckieTown, *Duckietown Logs Database*, 2020 (accessed November 9, 2020).