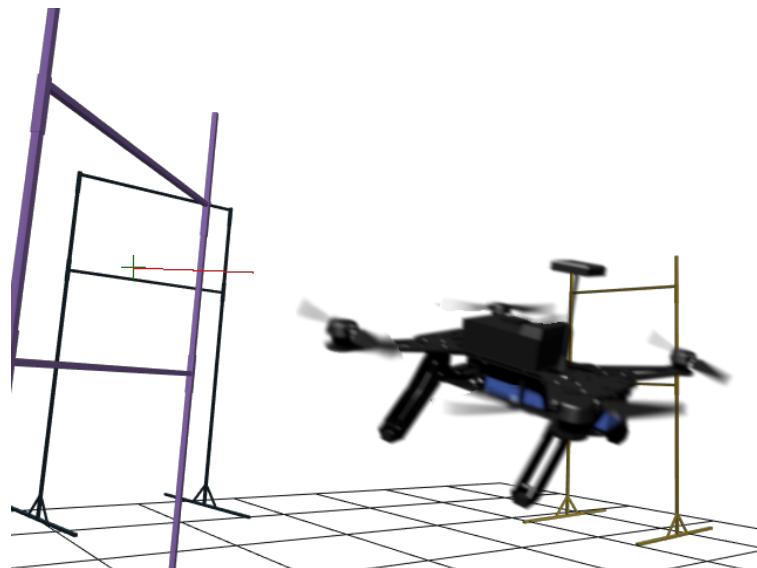




AARHUS
UNIVERSITY

DEPARTMENT OF ENGINEERING



Generating synthetic images to train convolutional neural networks for autonomous drone racing

Transferring knowledge from a semi-synthetic domain into the real world for trajectory planning

Master's thesis in M.Sc. Computer Engineering

Théo Morales

MASTER'S THESIS 2019:NN

Generating synthetic images to train convolutional neural networks for autonomous drone racing

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Department of Engineering
Control and Automation Laboratory
AARHUS UNIVERSITY
Aarhus, Denmark - 2019

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Using synthetic images to train convolutional neural networks for autonomous drone racing
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Theo Morales

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Abstract

The focus of this research will be on developing a robust and generalized vision algorithm for detecting obstacles in a configurable manner and regardless of their shape and color, such that the race gates can be specified prior to the training of the algorithm, and thus tailored to the challenge itself. The end goal is to greatly facilitate the learning of the vision-based detection model, by automating the tedious and long process of collecting and annotating a large dataset required to train the object detection algorithm using Deep Learning.

Indeed, this task is often the most time-consuming part of training convolutional neural networks, mostly because each image must be annotated to be used in supervised learning. By removing this weight off researchers' shoulders, much more time is left to focus and experiment on the *planning* and *acting* problems of the robotic paradigm .

In this work, the efficiency and robustness of tailored dataset generation for Deep Learning-based computer vision algorithms, for the specific case of autonomous drone racing, is analysed and discussed. A simple approach to solving the *planning* challenge is also undertaken, which supports the praises of the proposed solution.

reference to the diagram above

Keywords: drones, autonomous, dataset, deep learning, cnn.

Acknowledgements

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Theo Morales, Aarhus, June 2019

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Introduction

Each year, the robotic community gathers at conferences such as IROS (International Conference on Intelligent Robots and Systems), where they exhibit their discoveries and achievements in the field. For the year 2019, the Drone Racing League will be hosting a series of races which autonomous drones will compete and attempt to outperform a professional drone pilot.



Figure 1.1: Drone racing arena at IROS 2016.

The company Lockheed Martin is sponsoring the event and offering a prize of 2 million USD for the winning team. Teams of university students and other drone enthusiasts shall present innovative approaches on vision-based systems for unmanned aerial vehicles: hence, they showcase their progress through racing.

1.1 What is drone racing?

As in any race, competitors measure their skills at maneuvering their vehicle, from within or at distance, against the clock or against themselves, in an attempt to complete a circuit before everyone else.

In drone racing, the circuit is comprised of a set of obstacles, static or dynamic, usually arranged in a loop. For the case of classic drone racing, huge futuristic-looking arenas are used as a playground for extremely skilled pilots, who make the race look impressive and dynamic by the use of FPV goggles to fly the drones at very high speed, reaching 120mph [<https://thedroneracingleague.com/learn-more/>].

For the case of autonomous drone racing, up until the *Drone Racing League* announced their autonomous competition of 2019, arenas looked much more like a laboratory than a glowing circuit, as it can be seen on Figure 1.3 showing the AiR Lab in Skejby (Aarhus, DK), with its gates built and painted for this work. These obstacles were inspired of the previous competitions organized by IROS, as seen on Figure 1.1 which also shows the typical type of drones used in this research area: consumer drones for the larger audience. This kind of drones is not made

cite image
<https://homegadgets.tech-news/the-drone-racing-league-has-set-a-new-world-record-for-the-fastest-drone-around-113641968811>

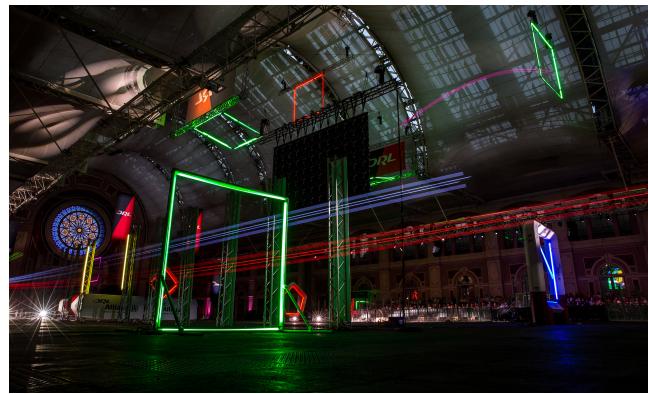


Figure 1.2: Drone Racing League arena in London (Steven Paston/PA)

for sportive flight, but mostly for an easy hands-on experience, providing a relatively slow but stable flight.



Figure 1.3: The AiR Lab and the custom built obstacles around the author in Skejby

The goal is to complete a given amount of turns as fast as possible, but since it is still the early days of drone racing and the costs of a potential crash would be too high, each drone races against the clock, one after another. Ultimately, autonomous drones will be racing against skilled pilots, as the *Drone Racing League* seems to encourage it by giving a total prize of 2 millions USD for the race of 2019.

1.1.1 Stakes

1.1.2 Beyond the hype and into reality

1.1.3 Challenges

Most robotic system's operation can be modeled by the commonly known *Sense, Plan, Act* paradigm:

- **Sense:** gather information using sensors (camera, IMU, sonar...).
- **Plan:** create a world model using all the information, and plan the next move.
- **Act:** carry out the actions that the plan calls for.

Talk about the predictions for in drone racing and drones in general for the future

Talk about Amazon Prime Air food delivery, driverless taxi

Add custom act, sense, plan paradigm pic

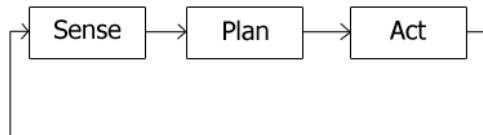


Figure 1.4: The Sense, Plan, Act robotic paradigm.

This thesis will be focused mainly on the sensing of the drone control, and more precisely using computer vision algorithms along with machine learning concepts. However, an important part of the trajectory planning directly follows the sensing phase, therefore those two first phases of the control loop can be included in the scope of the project.

To this day, most drones in the robotic research field are running *Robot Operating System* (ROS), which is a set of "libraries and tools to help software developers create robot applications". Add citation

The implementation of the computer vision algorithms will be constrained within ROS, and cooperate with the different control components provided by the project team.

1.2 Litterature review

1.3 The modern approach

As Deep Learning has known an exponential growth during the past decade, computer vision applications tend to exploit the power of convolutional neural networks more and more. Thanks to their impressive accuracy in specific problem solving, CNNs are becoming the main choice for tasks such as: object detection, object segmentation, object recognition, *etc...*

In drone racing, the latest works, which are often the best performing, tend to employ CNNs for the sensing part, or even as an all-in-one solution (refer to).

Talk about why CNNs are used more and more in drone racing and basically it is the chosen approach, which leads to tackle the dataset generation problem.

refer to litter review

1.4 The chosen approach

The solution will be implemented iteratively, by gradually increasing the complexity of the vision algorithms, such that progress can be made even if the end goal is too difficult to achieve.

The project should attempt to fulfill the following goals:

- Recognize gates in the input image
- Detect and localize the closest gate's center
- Evaluate the closest gate's orientation and distance
- Plan a trajectory for the drone to fly across the gate center
- Refine the trajectory in real time, for an optimal flight time
- Make the drone follow that trajectory while adjusting in real time

However, the following functionalities are out of the scope and will be discarded:

- Detect any other obstacles in the input image
- Avoid obstacles that are on the drone's trajectory

- Map and localize the detected gates in world frame
- Plan a trajectory of a sequence of gates
- Apply online learning for adaptive racing

2

Perception

2.1 Convolutional Neural Networks theory

2.1.1 Advantages and applications

2.1.2 Architecture

Typical inputs

Typical outputs

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Regularization

2.1.3 Training and evaluation

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2.1.4 Common pitfalls

Underfitting

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2.2 Choice of network topology

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Control and trajectory planning

3.1 Problem statement

3.2 Robots Operating System

3.3 Proportional Integral Derivative controllers

3.4 Putting things together

3.4.1 Supervision state machine

4

Experiments and Discussion of results

4.1 Gate detection

4.2 Trajectory planning

5

Conclusion

A

Appendix 1