Machine Learning Engineer Nanodegree
Capstone Proposal

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Proposal - Situational Awareness System for Autonomous Vehicles

Domain Background

Goal and preface: Goal of this project to provide situational awareness for Autonomous Vehicles or more preceisly to detect few key classes of objects that could potentially be unsafe for an autonomous flying vehicle. The approach applied relies on computer vision and machine learning methodologies. Situational Awareness System for Autonomous Vehicles could be thought of also in terms of famous sense-and-avoid systems for drones. Their goal is to detect obstacles and avoid them in real time during flight to allow for safe drone operation and for successful mission. In this project the goal however is not to avoid obstacles but simply to detect them and define their position within a frame of a video stream.

Background information and key motivation: Sense and avoid systems have been pursued for a long time in industry and they are one of the key technologies missing to enable fully autonomous operations of drones. In order to perform fully autonomous operations in the air it is necessary to have a situational or environmental awareness around the vehicle. This is relevant to know where the "flyiable" space is around the aircraft so that safe operations without crushing into obstacles or terrain is possible but also it requires to understand where mission relevant objects or places are in the vehicle environment such as a potential landing spot or an object to be followed and tracked. Many approaches have been adopted to detect obstacles on the flight path and most of them directly relied on sensing of the environment and some signal processing using active radar, laser, optical sensor, sonar or passive radars. Recently more and more demos from the academics and industry relies on computer vision and camera approaches. Till this day however there is no high reliability sense and avoid system on the market, few companies are making good strides towards that but this key technology is still missing today. More information and sense and avoid market solutions can be found in the article: http://droneanalyst.com/2016/09/22/sense-and-avoid-for-drones-is-no-easy-feat/

How the problem could and should be solved: Recent progress in computer vision approaches based on machine learning could perhaps enable to solve the problem of sense and avoid and in particular of the situational awareness. This work is an attempt to detect a small subset of objects namely aeroplanes and birds in a frame of a video stream from a flying aircraft. If however this problem is to be fully solved then this approach should be further extended into other objects; into sensor fusion (perhaps with radar, or other sensors); maps could be added as well; small transponder devices and air traffic management solution should be studied or finally Vehicle to Vehicle communication could be also considered. This project is just the first building brick for detecting a subset of objects using CV.

Academic research:

1. Sense and avoid aircraft detection using computer vision:

- Vision4UAV Research Group from Technical University in Madrid (http://138.100.76.11/visionguided2/?q=node/349) have produced work with sense and avoid using computer vision. Their dataset of few movies is used for demonstration of the results in this work:

  - [1] "A Ground-Truth Video Dataset for the Development and Evaluation of Vision-based Sense-and-Avoid Systems"; Adrian Carrio, Changhong Fu, Jesus Pestana, Pascal Campoy; 2014 Technical University in Madrid

  - [2] "SIGS: Synthetic Imagery Generating Software for the Development and Evaluation of Vision-based Sense-And-Avoid Systems"; Adrian Carrio, Changhong Fu, Jean-Francois Collumeau, Pascal Campoy; 2015

- Carnegie Mellon University - overview of the sensor technologies and Sense and Avoid requirements from 2008-2009 as well as passive system for long range vision based detection of objects without the machine learning approach:

- [3] "Prototype Sense-and-Avoid System for UAVs"; Christopher Geyer, Debadeepta Dey, Sanjiv Singh; 2009 Carnegie Mellon University

- [4] "Avoiding Collisions Between Aircraft: State of the Art and Requirements for UAVs operating in Civilian Airspace"; Christopher Geyer, Sanjiv Singh, Lyle Chamberlain; 2008 Carnegie Mellon University

- [5] "Passive, long-range detection of Aircraft: Towards a field deployable Sense and Avoid"; Debadeepta Dey, Christopher Geyer, Sanjiv Singh, Matt Digioia; 2009 Carnegie Mellon University

- Korea Aerospace Research Institute and KAIST - Department of Aerospace Engineering research on vision based sense and avoid using computer vision but without machine learning approaches but particle filters instead:

- [6] "Vision-Based Sense-and-Avoid Framework for Unmanned Aerial Vehicles"; SUNGSIK HUH, SUNGWOOK CHO, YEONDEUK JUNG, DAVID HYUNCHUL SHIM; 2015 Korea Aerospace Research Institute and KAIST - Department of Aerospace Engineering

- Ecole Polytechnique Federale de Lausanne EPFL - sense and avoid using both appearance and motion cues but no classification performed using machine learning approaches:

- [7] "Detecting Flying Objects using a Single Moving Camera"; Artem Rozantsev, Vincent Lepetit, and Pascal Fua; 2015 Ecole Polytechnique Federale de Lausanne EPFL

2. Sense and avoid market overview:

- Overall market overview here: http://droneanalyst.com/2016/09/22/sense-and-avoid-for-drones-is-no-easy-feat/

- Iris Automation (http://www.irisonboard.com) - Startup backed by Y Combinator to solve the sense and avoid with the help of computer vision. For now however they have not produced a demo to show their technology.

3. Birds detection using computer vision and machine learning:

- The University of Tokyo study for birds detection near wind turbines with CNN networks but on a limited static dataset of up to 70 images and with a static perspective:

- "Evaluation of Bird Detection using Time-lapse Images around a Wind Farm"; Ryota Yoshihashi, Rei Kawakami, Makoto Iida, and Takeshi Naemura; The University of Tokyo

- "Detection of small birds in large images by combining a deep detector with semantic segmentation"; Akito Takeki, Tu Tuan Trinh, Ryota Yoshihashi, Rei Kawakami, Makoto Iida and Takeshi Naemura; The University of Tokyo

Personal motivation:

As an aerospace engineer by trade I am also interested in the autonomous vehicles taking flight beyond the line of sight and furthermore into fully or almost fully autonomous operations. Reliable sense and avoid systems as well as good situational awareness are key technologies and machine learning approaches applied to computer vision hold a good promise to solve this problem.

Problem Statement

- detect and identify birds and aircraft in a frame of a video taken from a Point of View of another flying aircraft as a part of a sense and avoid system for autonomous vehicles.

- problem can be measured by detections indicators in three classes (aircraft, bird, everything else). This allows to measure the performance of models and reproduce the results

- goal is to create bounding boxes around the first two classes of aircraft and birds

Datasets and Inputs

There is no good dataset existing for proper and reliable sense and avoid systems. Some partial datasets exist, for some very specific problem approach with normally very few samples. Apart from complexity and diversity of the problem this is probably why there is still no good sense and avoid system out on the market. In this work the problem is divided into specific sub-problems for which a separate dataset was obtained to train and test the models as well as to create final demos.

Goal of these three datasets is to combine them with particular labels for aircraft, bird(s) and other-class. The combined datasets will be used for training and for testing of the algorithms. Most probable split of the dataset into training and testing samples is 80-20% which means 80% of the data to be used for training and 20% for testing. Some experiments might be performed to do also 90-10 ratio.

1. Aircraft class dataset - collected from Google Images + ImageNet data (http://image-net.org) – see Figure 1

Google dataset size: total of 1346 images (935 Airline Jets and 411 General Aviation light airplanes)

2. Birds class dataset - collected from Google Images + ImageNet data (http://image-net.org) – see Figure 2

Google dataset size: total of 1233 images (516 Single birds, 176 images with up to 5 birds, 541 images with more than 5 birds (formation, flock etc.))

Figure 1 Sample image from a dataset of class aircraft

Figure 2 Sample image from a dataset of class bird

Demonstration datasets: goal of the datasets 3 and 4 is only for demonstration purposes. Testing and metrics for aircraft in an image detection will be performed on and extracted from combination of the datasets 1, 2 and 3.

3. Demo for aircraft detection - videos are provided from Vision4UAV Research Group from Technical University in Madrid as described in references [1] and [2] with the permission of authors. Videos contain an aircraft with a camera on its tail with simulated either Boeing 737 or a Cessna 172 flying into the field of view at different angles – see Figure 3.

4. Demo for birds detection - YouTube videos - one of a flock of birds and the second one of a single or few birds in the line of sight – see Figure 4

Figure 3 Screenshot of a movie with an approaching aircraft

Figure 4 Screenshot of a movie with birds

Solution Statement

- solution of the problem is detected aircraft and birds in each image of the test set. For ease of identification they can be marked with a bounding box around detected objects.

- for demonstration purposes two video streams will be shown with aircraft and birds detected correspondingly

- performance of the model can be measured by the rate of correct detections as well as by the number of false detections or outliers.

- model to be tried is based on Support Vector Machine for the benchmark performance and an additional method to be used to see potential improvement in performance is based on the Convolutional Neural Networks CNN using Keras in TensorFlow.

Benchmark Model

- measure of the benchmark are correct detections of aircraft and birds classes as well as the number of false positives, outliers.

- unfortunately it is difficult to compare exactly the dataset to already existing models entirely as it also depends on the dataset used and the data used in this problem is an ImageNet dataset quite heavily augmented by google images.

- as a benchmark two solutions shall be compared, one simpler based on Support Vector Machines and the more complicated one which is estimated to outperform the simpler solution to be based on Convolutional Neural Networks implemented in Keras in TensorFlow.

Evaluation Metrics

- measure of the benchmark are correct detections of aircraft and birds classes as well as the number of false positives, outliers.

- the metrics will be available in a format of a confusion matrix of TP (True Positives)/TN (True Negatives)/FP (False Positives)/FN (False Negatives)

- as additional metrics some extra parameters shall be calculated such as precision and recall where precision P = Tp/(Tp+Fp) and recall R = Tp/(Tp+Fn) or in other words precision (P) is defined as the number of true positives (T_p) over the number of true positives plus the number of false positives (F_p). Recall (R) is defined as the number of true positives (T_p) over the number of true positives plus the number of false negatives (F_n).

Project Design

<u>Step 0:</u> Compile the dataset - download and compile all relevant datasets from [1] to [4] as indicated above.

<u>Step 1:</u> Explore the dataset - review the dataset, its consistency and diversity, its suitability for this task

<u>Step 2:</u> Images data import - import images from datasets [1] and [2]

<u>Step 3:</u> Images preprocessing - process the images into workable format, perhaps standardize, perform basic feature extraction such as gradients or color histograms, split the dataset into training and testing ratio of perhaps 0.8 to 0.9

<u>Step 4:</u> Model training & testing - train and test the model using appropriate data sets (algorithms considered are based of course on supervised learning including Support Vector Machines and Convolutional Neural Networks)

<u>Step 5:</u> Compile and plot the performance metrics & results - plot the actual validation and test error metrics (Confusion Matrix of TP/TN/FP/FN as well as precision and recall)

<u>Step 6:</u> Prepare the demonstration videos based on datasets [3] and [4] - compile two videos with detected objects of classes aircraft and birds in them