

Runway Recognition

Michael Hardt mwhardt@stanford.edu Carlos Querejeta carlosq@stanford.edu

Grzegorz Kawiecki kawiecki@stanford.edu

https://youtu.be/bKq6iCp_MAw

1. Introduction

- Autonomous aircraft will require redundant and robust solutions for navigation.
- Without GPS or other aids, need new tools to rely upon its camera for landing.
- Assume the runway's position is known, but the aircraft doesn't know its position
- Question: Is the runway in view in the forward-looking camera?
- If so, how large is the runway, what is its relative angle within the image?
- Use Deep Learning to answer. From camera calibration and barometric altitude, one can determine aircraft position relative to the runway and then plan for landing.

2. Data

- Two data sources: Google Earth and osgEarth.
 Google Earth images are high quality, but need
- manual preparation.
 osgEarth transforms satellite orthoimagery from
- free, online databases to any camera location and perspective which we automated.
- 16 single runway airports selected, 1186 random samples of camera positions: 83% viewing runway, 17% negative samples without runway.
- Pixel masks calculated.
 1024x768 resolution scaled and padded to 416x416.
- Dataset split: 80%-10%-10% for training / dev / test sets.

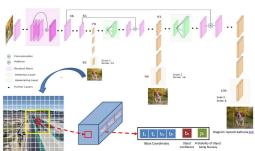
mAP vs # of trained laver



3. Methods

- Yolo (v3) model
 106-layer fully convolutional architecture
- Multilabel classification
- Residual blocks & skip connections for bigger network
- Parallel object detections on 3 scales
- 416 x 416 native resolution
- Tiny-Yolo also tested
- Enhanced detection of small objects

Train loss, LR=0.00



4. Results

- Successful application of Transfer Learning of Yolo and Tiny-Yolo pretrained on COCO dataset to runway recognition task.
- Hyperparameter search conducted with following results:
- o number of trained layers: all
- o learning rate: 10-4
- o batch size: 8
- Excellent runway detection capability: mAP = 0.94
 on test set. Even detected unexpectedly multiple runways
 which were not initially labeled, and some runways at a
 large distance that even a human can't easily recognize.
- Tiny-Yolo also did well with a mAP = 0.72 with only about a third of the number of layers of the full Yolo.
- Semantic segmentation attempted which classifies each pixel in image and indicates shape, but no conclusive results obtained.

5. Conclusions

- Yolo achieved excellent, promising results. Its detection capability in some cases beat the human eye!
- Now need to validate model on real flight imagery and check its
 consist in the various conditions in a lighting torsion dictance.
- sensitivity to varying conditions, i.e. lighting, terrain, distance.

 How does Yolo answer the initial question? Yolo tells us first if
- the runway is in the image.
 Then, in all but very few cases when the aircraft is already perfectly aligned with the runway, the runway appears as a diagonal of the bounding box. So the diagonal length gives the



Still need the runway orientation. Our current plan is to extend Yolo with a binary variable or probability which indicates whether runway appears as left or right diagonal.