

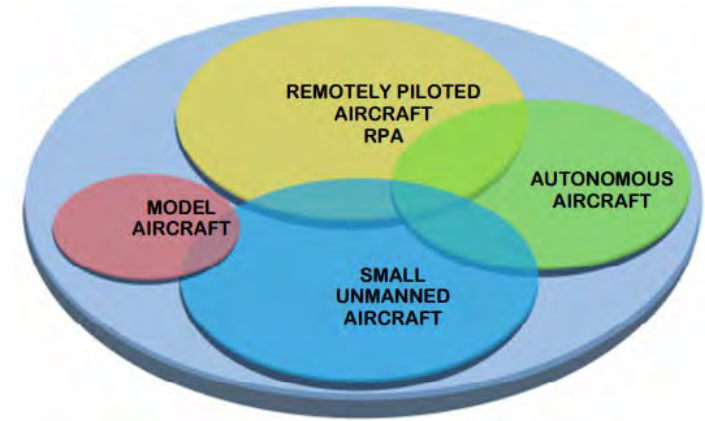
On Emerging Technologies

9.11. 2018.

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I. Overview

- **Recent emerging technologies in civil aviation**
 - **Advent of AI**
 - **Application to Civil Aviation**
 - **Certification of AI**
 - **Future of AI applications and adoptions**
 - **Legalization of UAVs**
 - **UAM and Beyond**



II. Advent of AI and Robotics

- Machine learning became very successful recently.
- Image classification is one of the most successful application of machine learning.
- Latest ML-based image recognition outperforms humans, which indicates AI will can do a vigilance for Detect-and-avoid task without getting tired or distracted.
- As with AlphaGo case, AI can make better strategic decisions.
- With its faster computing and enormous amount of data storage, an AI-powered autopilot can be of a great help for civil aviation.
- When not safety-critical, AI is adopted at a extremely fast pace.
 - iPhone's FaceID, AI speakers, China's facial ID system, and more
- **However, for civil aviation, where safety is of utmost importance, AI system cannot be simply introduced.**



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ImageNet Large Scale Visual Recognition Challenge

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Abstract The ImageNet Large Scale Visual Recognition Challenge is a benchmark in object category classification and detection on hundreds of object categories and millions of images. The challenge has been run annually from 2010 to present, attracting participation from more than 500 institutions.

This paper describes the creation of this benchmark dataset and the advances in object recognition that have been possible as a result. We discuss the challenges of collecting large-scale ground truth annotations, highlight key breakthroughs in categorical object recognition, provide a detailed analysis of the current state-of-the-art in the field of large-scale image classification and object detection, and compare the state-of-the-art computer vision accuracy with human accuracy. We conclude with lessons learned in the five years of the challenge, and propose future directions and improvements.

Keywords Dataset, Large-scale, Benchmark, Object recognition, Object detection.

1 Introduction

Overview. The ImageNet Large Scale Visual Recognition Challenge (ILSVRC) has been running annually for five years (since 2010) and has become the standard benchmark for large-scale object recognition. ILSVRC follows in the footsteps of the PASCAL VOC challenge (Everingham et al., 2012), established in 2005, which set the precedent for standardized evaluation of recognition algorithms in the form of yearly competitions. As in PASCAL VOC, ILSVRC consists of two components: (1) a periodically available dataset, and (2) an annual competition and corresponding workshop. The dataset allows for the development and comparison of categorical object recognition algorithms, and the competition and workshop provide a way to track the progress and discuss the lessons learned from the most successful and innovative entries each year.

* In this paper, we will be using the term object recognition loosely to encompass both image classification (a task requiring an algorithm to determine what object classes are present in the image) as well as object detection (a task requiring an algorithm to localize all objects present in the image).

inf:arXiv:1409.0575v3 [cs.CV] 30 Jun 2015

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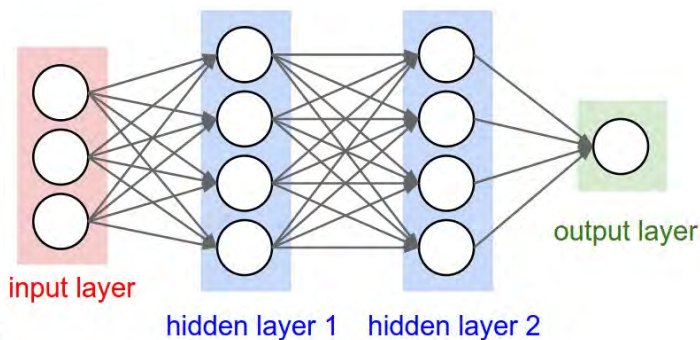
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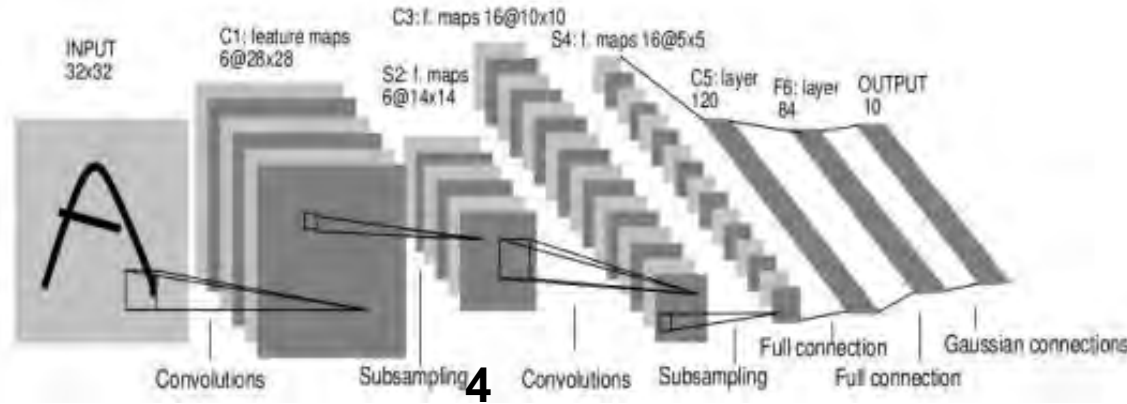
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II. Advent of AI and Robotics

- Some insights on AI:
 - Deep learning-based approach is drastically different from previous AI systems.
 - Deep learning requires huge amounts of data: no data, no learning.
 - Currently, AI can be applied to relatively simple tasks such as image recognition.
 - AI does not constantly learn: typically learning is done offline as it takes tremendous amount of computing power.
- It is true that the inner working of deep learning is not clearly known.
- AI-based systems are different from adaptive systems.
- Deep learning based systems can be quite sensitive to small changes (brightness change, some disturbances in images)



▲ Neural network example



▲ Convolutional neural network example

A Study and Comparison of Human and Deep Learning Recognition Performance Under Visual Distortions

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Abstract—Deep neural networks (DNNs) achieve excellent performance on standard classification tasks. However, under image quality distortions such as blur and noise, classification accuracy becomes poor. In this work, we compare the performance of DNNs with human subjects on distorted images. We show that, although DNNs perform better than or on par with humans on good quality images, DNN performance is still much lower than human performance on distorted images. We additionally find that there is little correlation in errors between DNNs and human subjects. This could be an indication that the internal representation of images are different between DNNs and the human visual system. These comparisons with human performance could be used to guide future development of more robust DNNs.

I. INTRODUCTION

Recently deep neural networks (DNNs) have attained impressive performance in many fields such as image classification [1], semantic segmentation [2], and image compression [3]. The performance of these deep networks has begun to exceed human performance in many tasks. Human top-5 classification error rate on the large scale ImageNet dataset has been reported to be 5.1% [4], whereas a state-of-the-art neural network [1] achieves a top-5 error rate of 3.5%.

Most existing works assume that the input images are of good quality. However in many practical scenarios, images may be distorted. Image distortions can arise during acquisition or transmission. In acquisition, the image sensor can exhibit noise in low light conditions. Motion blur can occur if the camera is moving. In transmission, packet-loss could cause missing regions of the image, or missing frequencies, depending on how the image is encoded. As machine learning has begun to see popularity as a cloud-based service, these issues have become more relevant.

It has been shown that neural network performance decreases under image quality distortions [5]. The degradation is particularly evident for additive noise or blur distortions. Given that networks equal or exceed human performance on undistorted images, it is interesting to ask: do networks still achieve equal or greater performance as compared to humans on distorted images? If human and DNN performance are similar on distorted images, then distorted images may be inherently difficult to recognize. Conversely, if it is shown that humans exceed DNN performance on distorted images, then



Fig. 1: Human vs DNN predictions on distorted data. We show several example stimuli from our tests, and the predictions given by > 90% of human subjects compared with the predictions from a fine-tuned VGG16 network.

there is some representational capacity present in the human visual system that is lacking in DNNs.

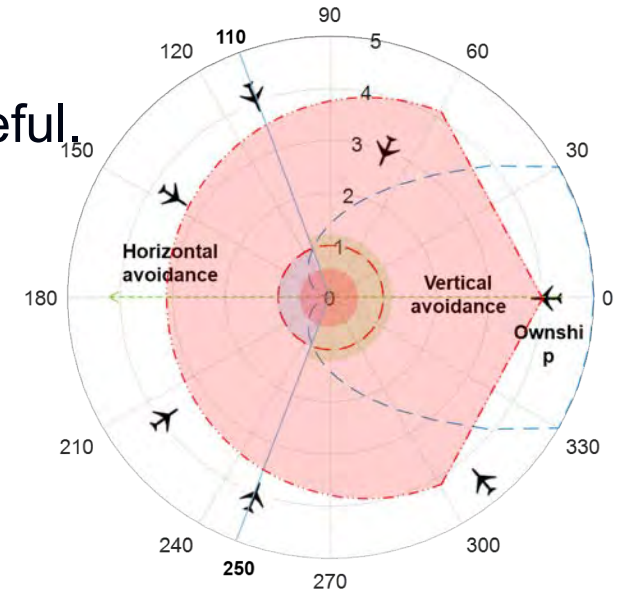
To answer this question we perform classification experiments with 15 human subjects. We ask the subjects to classify images that are distorted with varied levels of additive Gaussian noise and Gaussian blur. We find that human subjects are able to more accurately classify images under blur and noise distortions compared with DNNs (Figure 1). Furthermore, we find that at high distortion levels the correlation in the errors between deep networks and human subjects is relatively low. This could indicate that the internal models of the DNNs are quite different from the human visual system. These results could be used to guide future research into more robust learning systems. It may be useful to take motivation from the human visual system to achieve good performance on distorted images.

A. Related Works

Comparing the performance of machine learning systems with human subjects has attracted interest because it may give insights on how machine learning systems can be improved.

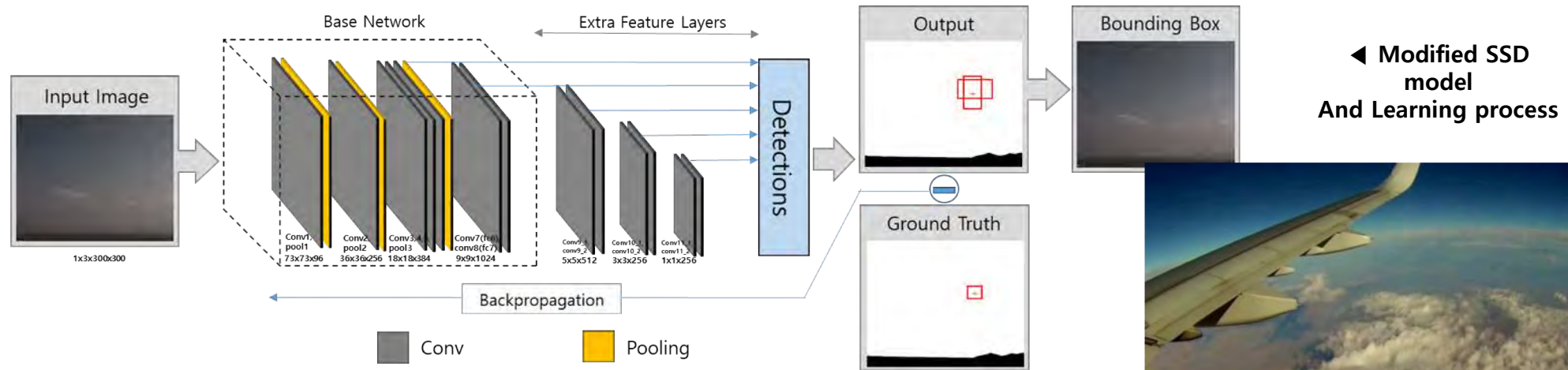
II. Advent of AI and Robotics

- Application of Deep Learning for Civil Aviation
 - When RPAS flies in VFR condition, visual detection can be very useful.
 - Being the best image classifier now, DL can be used for visual airplane detection for DAA
 - Using a large annotated set of data, a neural network can be trained for airplane detection
 - Using the latest GPU technology, a real-time detection can be performed.
 - There are a number of research activities on this topic, including my own lab's.
 - As an early result, the detection accuracy is not satisfactory, but there is a great potential for further improvement.



II. Advent of AI and Robotics

- **Modified SSD(Single-shot Detector) model for DAA technology**
 - AlexNet-like base network: 7 convolutional layers and 3 max-pooling layers
 - Modified : Less extra feature layers than that of original SSD but better speed and result
 - Original SSD model has 23 conv. layers but modified model has 13 conv. layers
 - 88.19% detection success rate in positive frame while it tested using 17,651 frames



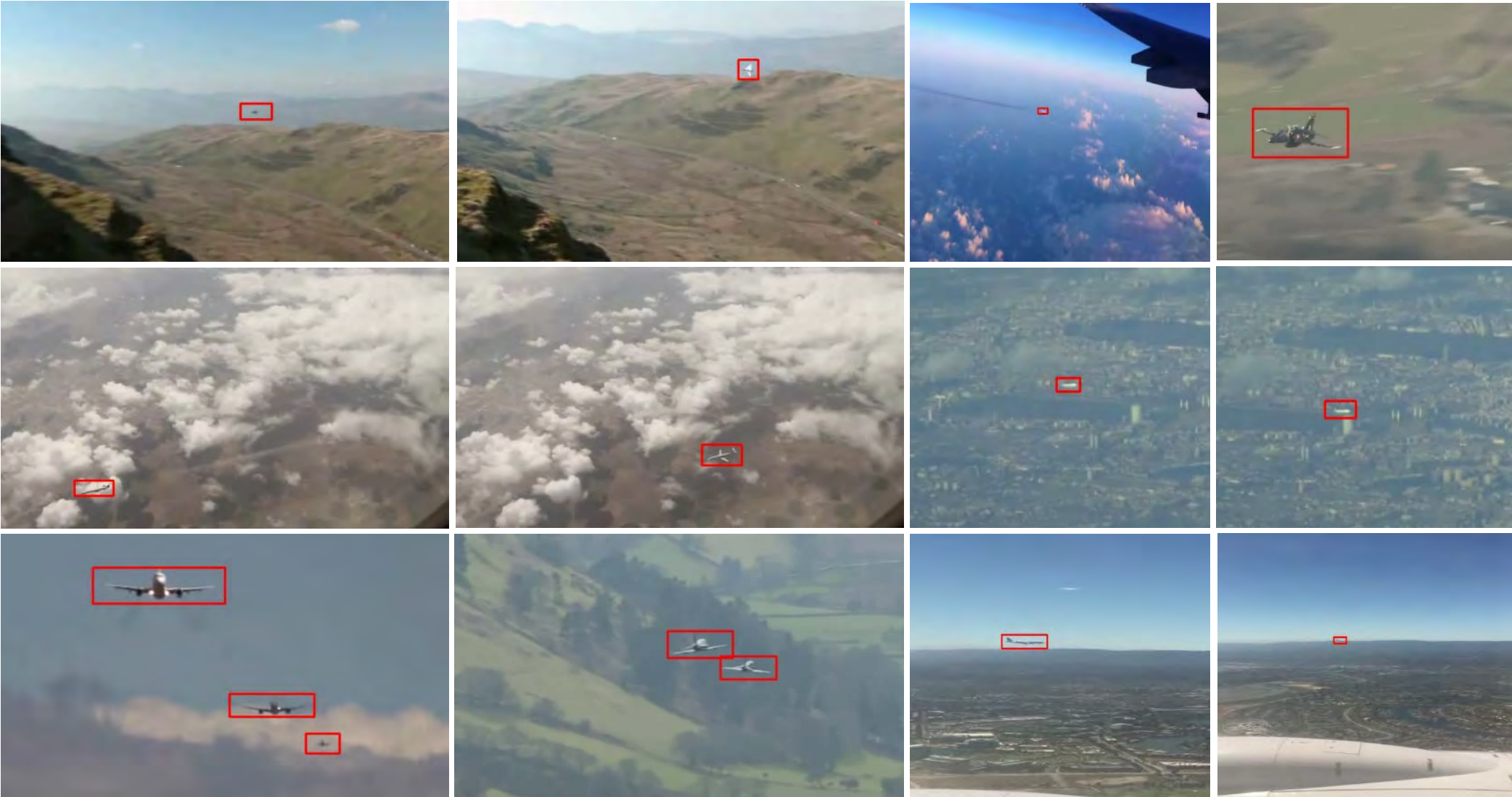
Total	Number of Frames					Detected size	
	Positive	Negative	Detected	Missed	False alarm	Min	Max
17,651	7,984(45.2%)	9,667(54.8%)	7,041(88.19%)	943(11.81%)	205(2.6%)	28 px	29,666 px

ref) Hariharan, B., Arbeláez, P., Girshick, R., and Malik, J., "Hypercolumns for object segmentation and fine-grained localization," *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2015, pp. 447–456., Long, J., Shelhamer, E., and Darrell, T., "Fully convolutional networks for semantic segmentation," *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2015, pp. 3431–3440., Zhou, B., Khosla, A., Lapedriza, A., Oliva, A., and Torralba, A., "Object detection emerges in deep scene cnns," *arXiv preprint arXiv:1412.6856*, 2014.



II. Advent of AI and Robotics

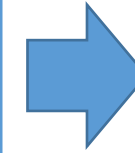
- Application of Deep Learning for Detect-and-avoid



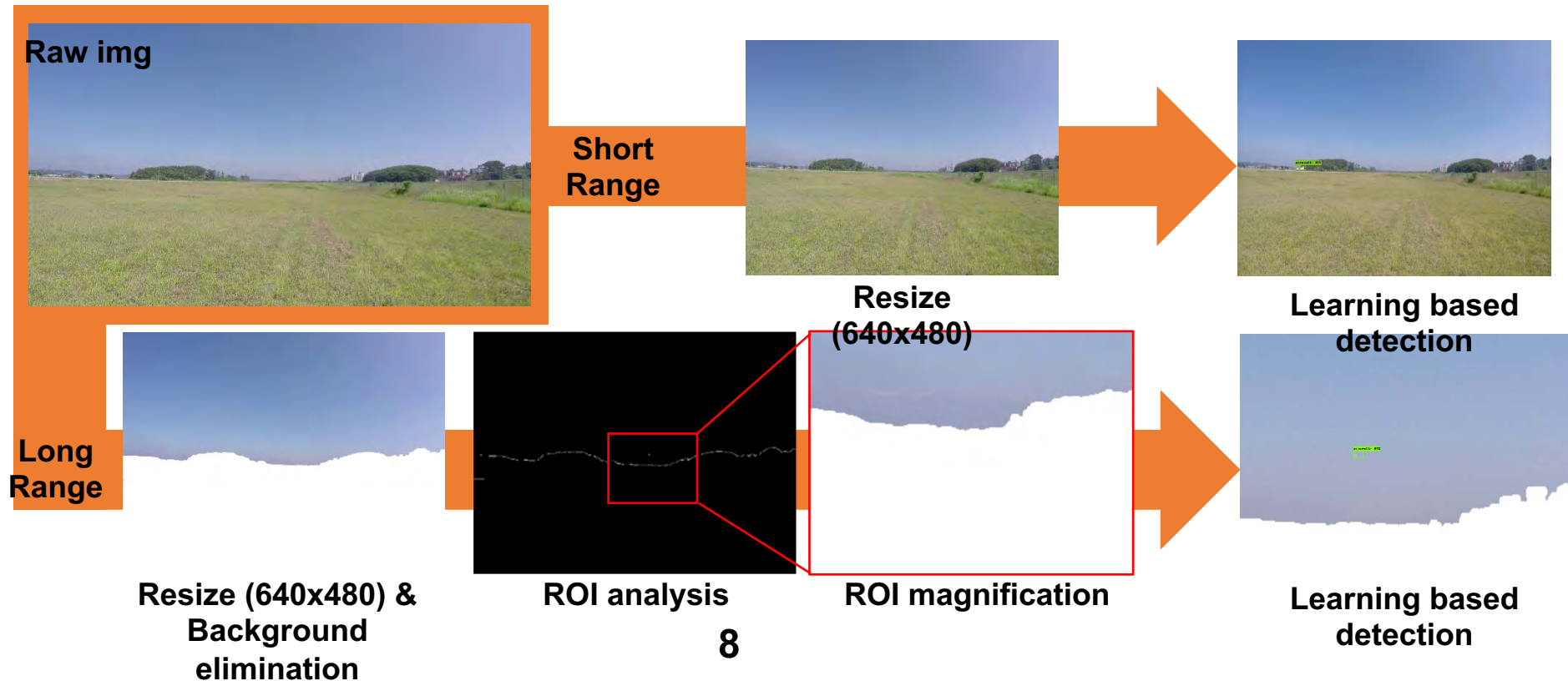
II. Advent of AI and Robotics

Further Improvement of learning based image detection for DAA

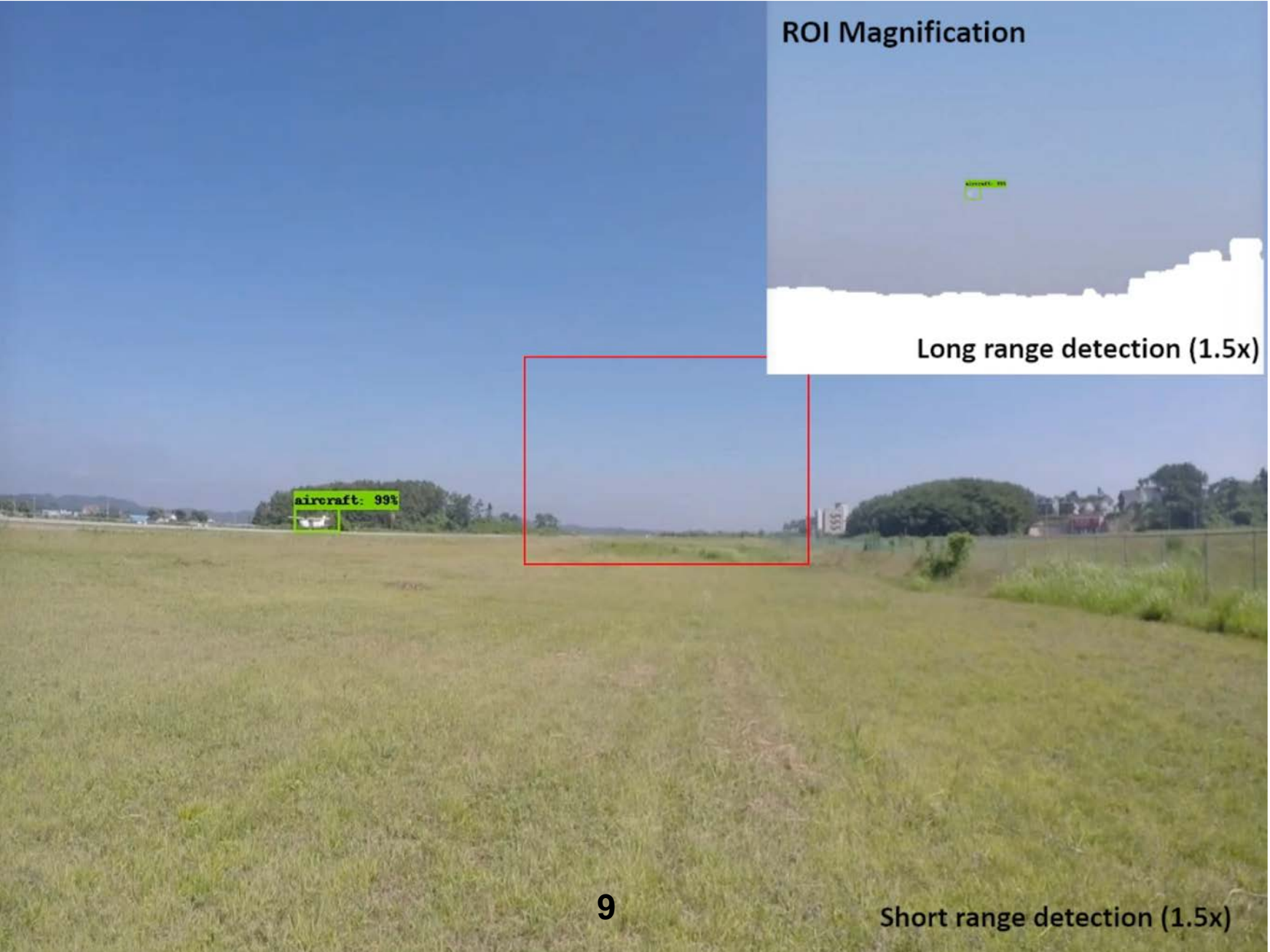
- Learning based detection is highly depending on the shape of aircraft
- The shape should be clear enough : close and danger enough to see the shape
- Dot-like aircraft is difficult to be detected by learning based detector
- Distorted or blurred image is not suitable for learning based detector



Detect dot-like aircraft using ROI magnification and SSD using dot-like aircraft learning data



II. Advent of AI and Robotics



II. Advent of AI and Robotics

- Future of AI application to civil aviation
 - A highly automating autopilot can be developed
 - There are ongoing efforts. (DARPA ALIAS)



Aviation and robots

Flight fantastic

Instead of rewiring planes to fly themselves, why not give them android pilots?

Aug 20th 2016 | From the print edition



The screenshot shows the SBIR-STTR America's Seed Fund website. The header includes the logo and navigation links for Home Links, About, Funding, Awards, News, Tutorials, and Resources. The main content area is titled 'Autonomous Robot for Unmanned Air Vehicle Operations'. A note states that the solicitations and topics listed are copies from various SBIR agency solicitations and are not necessarily the latest and most up-to-date. The official link for this solicitation is provided. Below the note is a table with the following information:

Agency:	Department of Defense	Release Date:	April 22, 2016
Branch:	n/a	Open Date:	April 22, 2016
Program / Phase / Year:	SBIR / Phase 1 / 2016	Application Due Date:	June 22, 2016
Solicitation:	DoD SBIR 2016.2	Close Date:	June 22, 2016
Topic Number:	AF162-D003		

II. Advent of AI and Robotics

Human Pilot

Flexible, Adaptive

Hard to retrain

Existing rules and systems are made for humans

Can make mistakes (physical and mental causes)

Job issues

Very long time to train. Hard to "transfer" knowledge and experiences



Robot Pilot

Not flexible nor adaptive (for now)

Easy type conversion

Hard to integrate

Follows programs without error

Have extremely large memory, easy to update

Can directly talk to avionics

Can compute very complex equations

Not tiring (no loss of vigilance)

Easily manufactured and duplicated

II. Advent of AI and Robotics

- Future of AI application to civil aviation
 - It need a long time before the adoption, but it is certainly an intriguing direction.
 - A robot pilot will be a great help.
 - Using its large memory, it can memorize entire Jeppesen chart.
 - Using data communication, it can directly “talk” to avionics.
 - Using voice communication, it can converse with pilot
(hopefully better than today’s AI speakers)
 - Using hands and feet, it can manipulate all the levers, switches, yokes, pedals and so on without any modification.
 - Using its vision, it can recognize the cockpit and outside of the window.
 - Using its own sensors, it can estimate the motion.
 - **It is not wise to to replace human pilots, but to complement.**

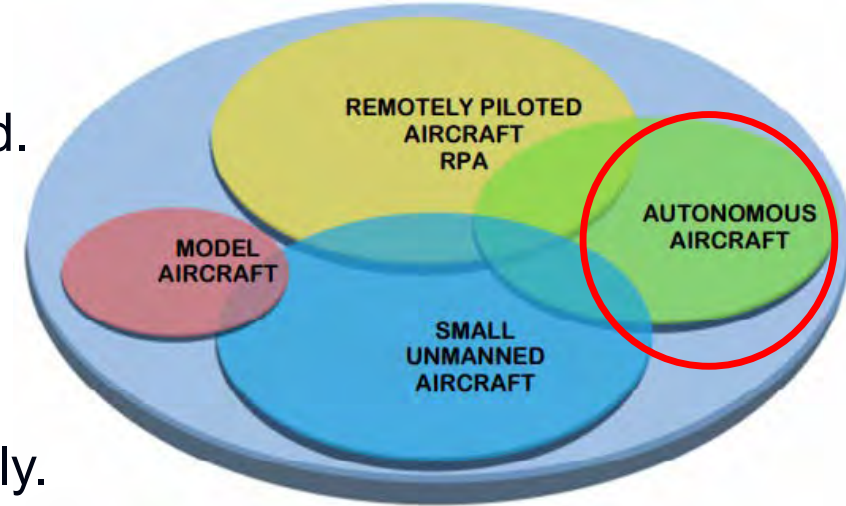
III. Beyond of UAVs

- “Manned Drone”

- Combining RPAS and UAS, “manned drone” can be developed.
 - There always have been demands for ultimate air mobility
- Just like self-driving cars, “manned drone” will be operated without passenger’s help

→ Currently, RPAS is not allowed to operate autonomously.

- Many “silicon-valley” style companies are suggesting Urban Aerial Mobility (UAM)
 - Google, Uber, Ehang, Airbus, and more.
- While safety is the utmost concern of civil aviation, legislation is not a simple task.



III. Beyond of UAVs

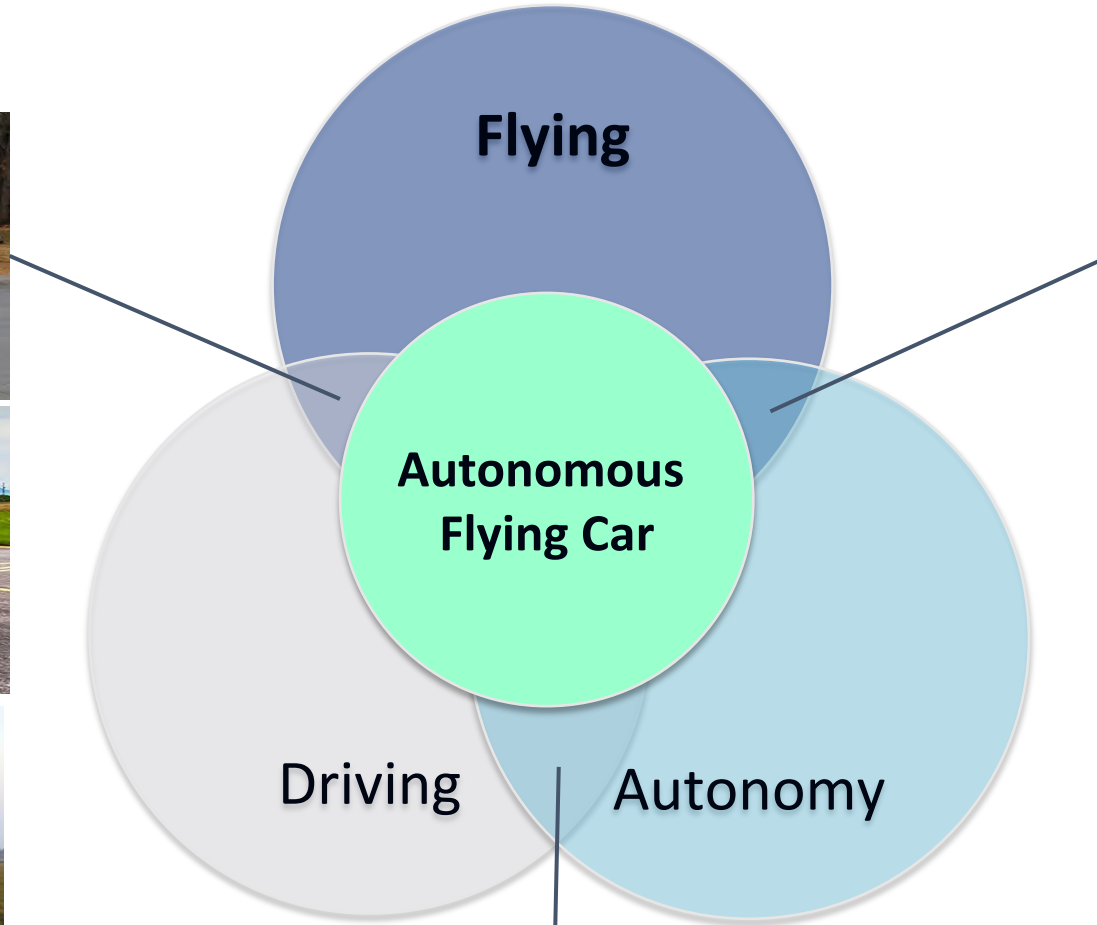
- Comparison of UAV and Self-Driving cars

		
Technological Status	Almost fully developed (except C2 and DAA)	Not yet ready
Risk level	Catastrophic to passengers if onboard and any people and property on ground	Can be fatal (but mitigated) to passengers and along the path. No indiscriminate.
Contributors	Aircraft Companies	Automotive Companies and IT Companies
Regulations	Driven by ICAO, JARUS, and states	Not yet much discussed
Target Date	RPAS: 2024	2020+ (step by step)
Major Challenge	Safety, global harmonization	Technology itself.

III. Beyond of UAVs



Flying Cars
(by human pilot/drivers)



Autonomous Car
(human passengers, driving autonomously)



Drone Taxi
(human passengers,
flying autonomously)

IV. Closing remarks

- Recently, UAS are prepared for integration into civil airspace.
- RPAS is almost ready (2014), UTM is being studied, UAM is being “invented”.
- Recent advent of machine learning-based AI is making huge impacts everywhere.
- Machine learning can be used for many applications in civil aviation, most notably vision-based detection of other aircraft in VFR condition.
- A robot powered by latest AI can be developed to aid human pilot
- Machine learning-based system requires different way of certification.
- It takes a VERY LONG time to prepare regulation for any new technologies, not fast enough to meet the expectation of “silicon-valley minds”.
- Aviation authorities should find some ways to become faster to keep up with technology advances *without compromising safety in civil aviation.*