Computer Vision

Course webpage URL: http://luthuli.cs.uiuc.edu/~daf

And follow links

Vision group at Illinois

- David Forsyth
  - Fulton Watson Copp chair; Marr prize, 1993; 2 ex students with Marr prizes; IEEE Tech. Achievement, Fellow; ACM Fellow; EIC IEEE TPAMI; 4 patents

- Jim Rehg
  - HCESC director; multiple famous ex-students, best paper awards; 26 patents

- Derek Hoiem
  - best paper, CVPR 2006; ACM Doctoral Dissertation honorable mention; Sloan Fellow; PAMI-TC Young Researcher; major startup

- Lana Lazebnik
  - Microsoft Faculty Fellow; Sloan Fellow; Koenderink Prize (2016); EIC IJCV

- Alex Schwing
  - Visual learning, segmentation and GAN models

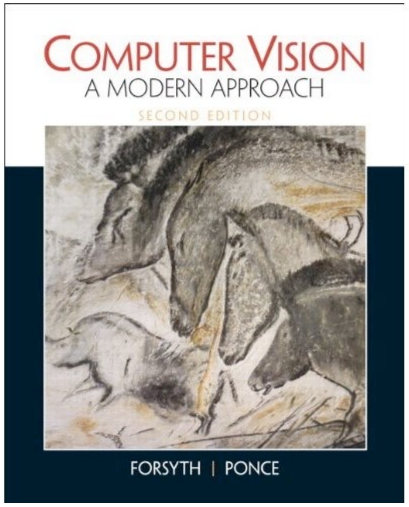
Saurabh Gupta
- Linking visual sensing to motion

Liangyan Gui
- Understanding human movement

Shenlong Wang
- Simulation and sensing for autonomous vehicles

Yuxiong Wang
- Learning to detect and classify with very little data

Vision group



Well-known ex-students:

Lana Lazebnik (UIUC)

Tamara Berg (UNC)

Pinar Duygulu (Hacettepe U.)

Ian Endres

Ali Farhadi (UW)

Varsha Hedau

Nazli Ikizler (Hacettepe U.)

Brett Jones

Kevin Karsch

Zicheng Liao

Deva Ramanan (CMU)

Raj Sodhi

Gang Wang (now Alibaba)

Amin Sadeghi

Zicheng Liao (Zhejiang U.)

The New Computer Vision

D.A. Forsyth

Likely about ~~2024~~ 2026

Cover design opportunity!

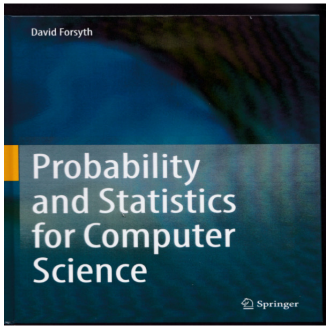
Startups:

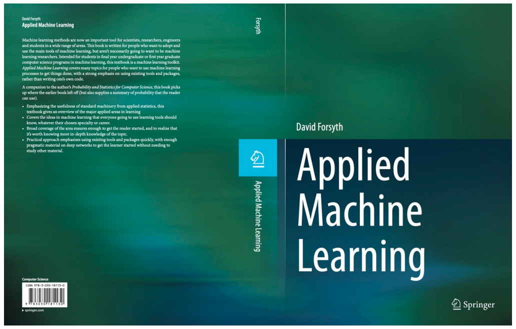
Lightform

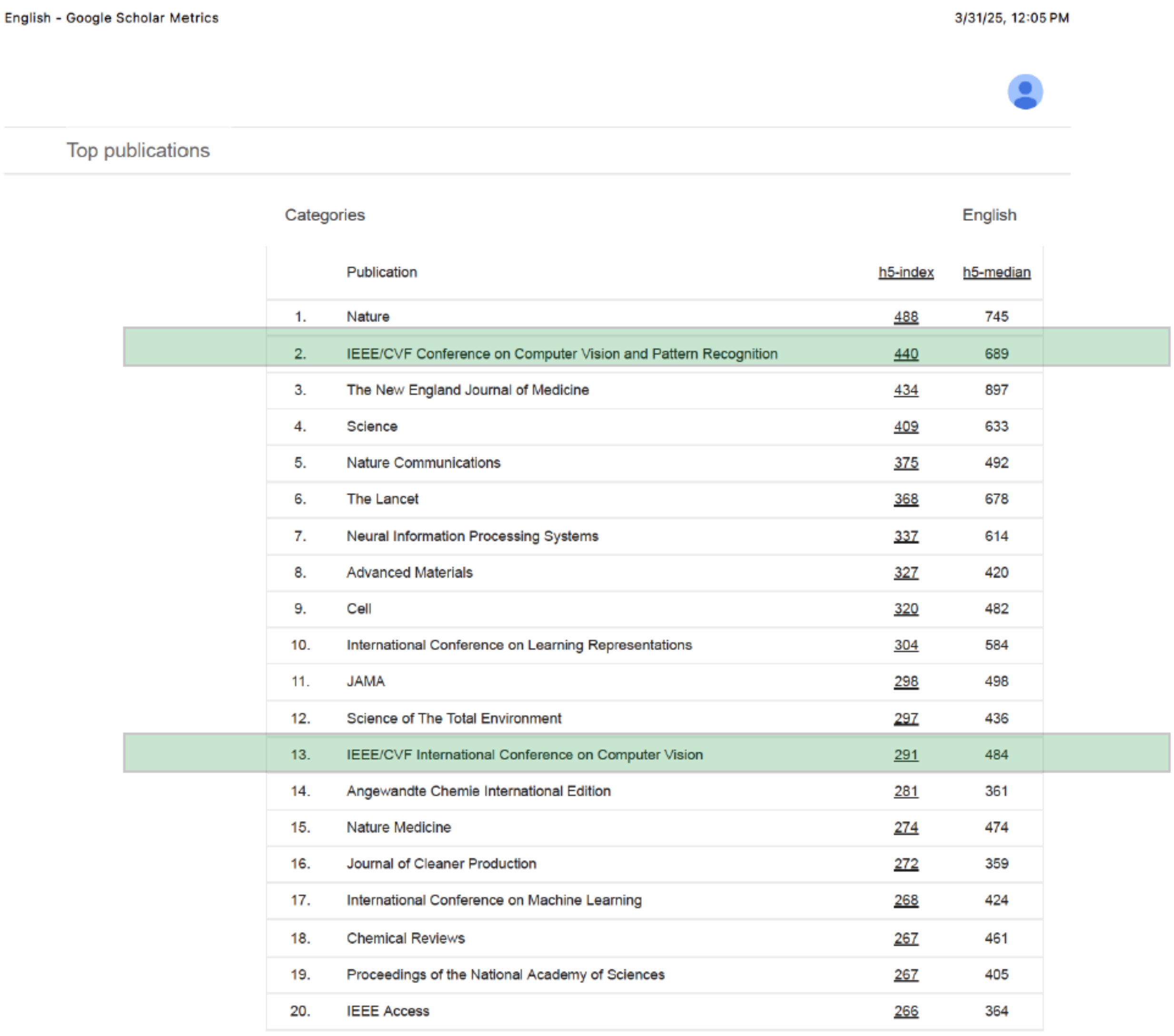
Revery.ai

Reconstruct

Depix





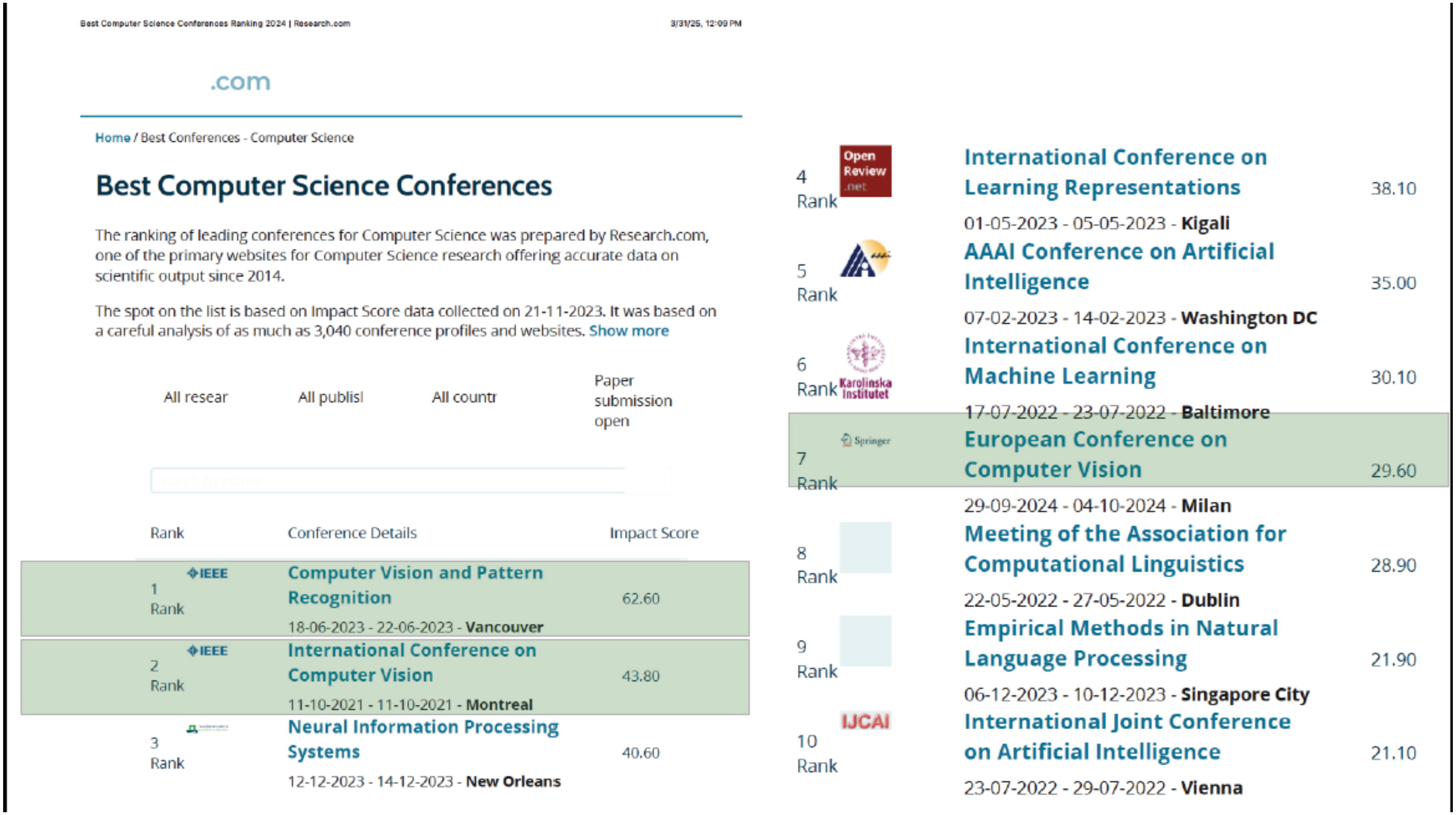


English - Google Scholar Metrics 3/31/25, 12:05 PM

Top publications

Categories English

	Publication	h5-index	h5-median
1.	Nature	488	745
2.	IEEE/CVF Conference on Computer Vision and Pattern Recognition	440	689
3.	The New England Journal of Medicine	434	897
4.	Science	409	633
5.	Nature Communications	375	492
6.	The Lancet	368	678
7.	Neural Information Processing Systems	337	614
8.	Advanced Materials	327	420
9.	Cell	320	482
10.	International Conference on Learning Representations	304	584
11.	JAMA	298	498
12.	Science of The Total Environment	297	436
13.	IEEE/CVF International Conference on Computer Vision	291	484
14.	Angewandte Chemie International Edition	281	361
15.	Nature Medicine	274	474
16.	Journal of Cleaner Production	272	359
17.	International Conference on Machine Learning	268	424
18.	Chemical Reviews	267	461
19.	Proceedings of the National Academy of Sciences	267	405
20.	IEEE Access	266	364



.com

Home / Best Conferences - Computer Science

Best Computer Science Conferences

The ranking of leading conferences for Computer Science was prepared by Research.com, one of the primary websites for Computer Science research offering accurate data on scientific output since 2014.

The spot on the list is based on Impact Score data collected on 21-11-2023. It was based on a careful analysis of as much as 3,040 conference profiles and websites. **Show more**

Rank	Conference Details	Impact Score
IEEE 1 Rank	**Computer Vision and Pattern Recognition** 18-06-2023 - 22-06-2023 - **Vancouver**	62.60
IEEE 2 Rank	**International Conference on Computer Vision** 11-10-2021 - 11-10-2021 - **Montreal**	43.80
3 Rank	**Neural Information Processing Systems** 12-12-2023 - 14-12-2023 - **New Orleans**	40.60
Open Review .net 4 Rank	**International Conference on Learning Representations** 01-05-2023 - 05-05-2023 - **Kigali**	38.10
5 Rank	**AAAI Conference on Artificial Intelligence** 07-02-2023 - 14-02-2023 - **Washington DC**	35.00
Karolinska Institutet 6 Rank	**International Conference on Machine Learning** 17-07-2022 - 23-07-2022 - **Baltimore**	30.10
Springer 7 Rank	**European Conference on Computer Vision** 29-09-2024 - 04-10-2024 - **Milan**	29.60
8 Rank	**Meeting of the Association for Computational Linguistics** 22-05-2022 - 27-05-2022 - **Dublin**	28.90
9 Rank	**Empirical Methods in Natural Language Processing** 06-12-2023 - 10-12-2023 - **Singapore City**	21.90
IJCAI 10 Rank	**International Joint Conference on Artificial Intelligence** 23-07-2022 - 29-07-2022 - **Vienna**	21.10

Outline

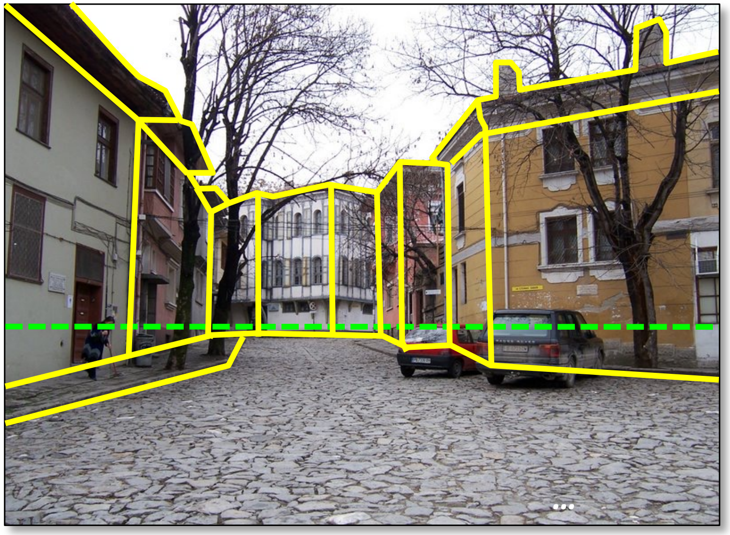
- Key tasks
- Why it is hard
- History of computer vision
- Current state of the art
- Topics covered in class

What does vision do?

- *Classification: What is it?*
- *Localization: Where is it?*
- *Detection: Where and what?*
- *Tracking: Where is it going?*
- *Odometry: How have I moved?*
- *Navigation: Where am I?*
- *Modelling: What is the world like?*
- *Control: What should I do?*
- *Speculation: What will it be like if?*

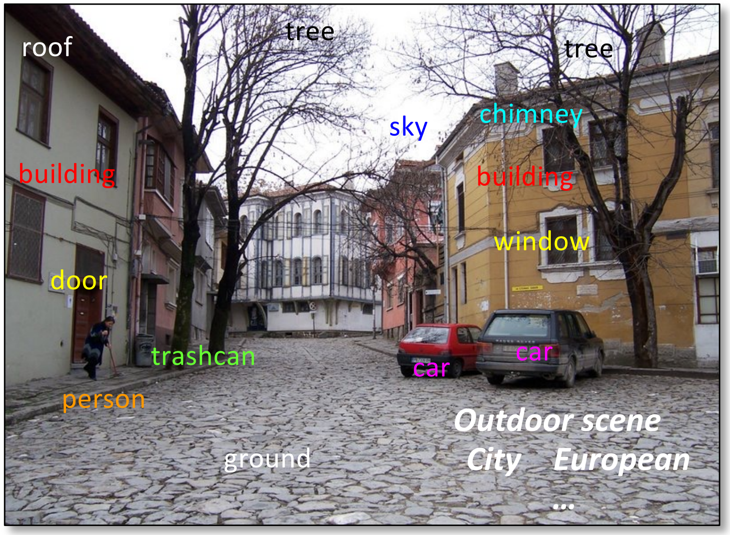
What kind of information can be extracted from an image?

What kind of information can be extracted from an image?



Geometric information

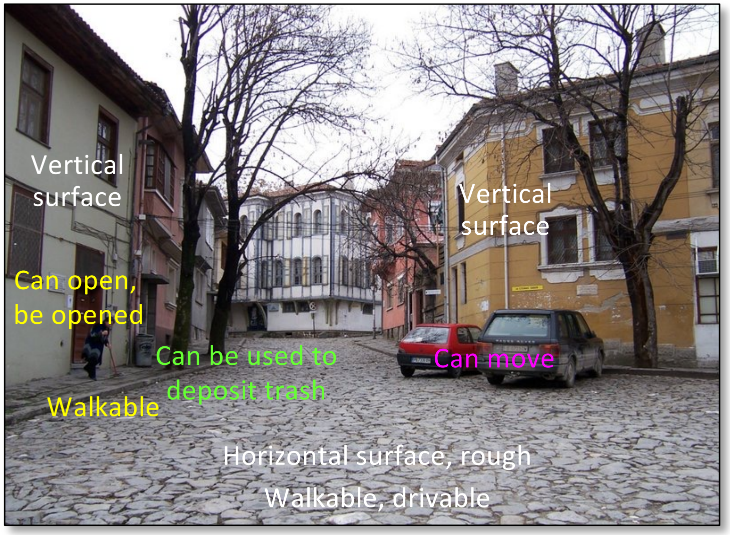
What kind of information can be extracted from an image?



Geometric information

Semantic information

What kind of information can be extracted from an image?



Geometric information

Semantic (?) information – *affordances*

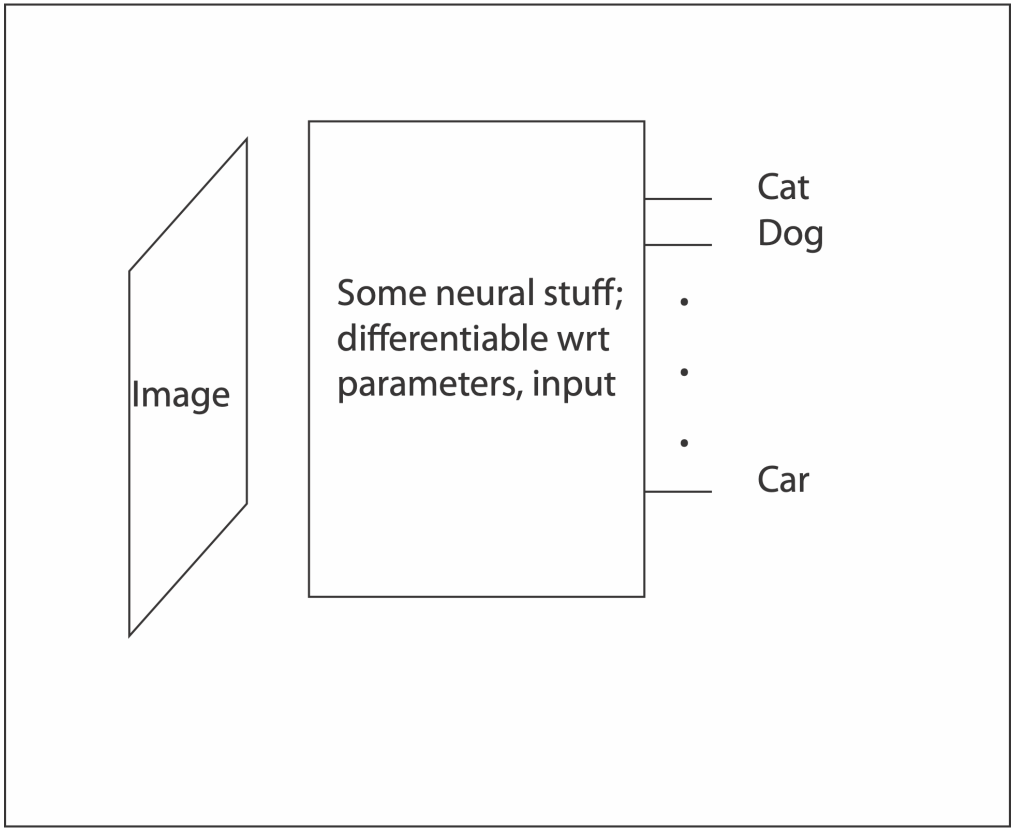
What kind of information can be extracted from an image?

Geometric information

Semantic information

Vision for action

Classification



Detection

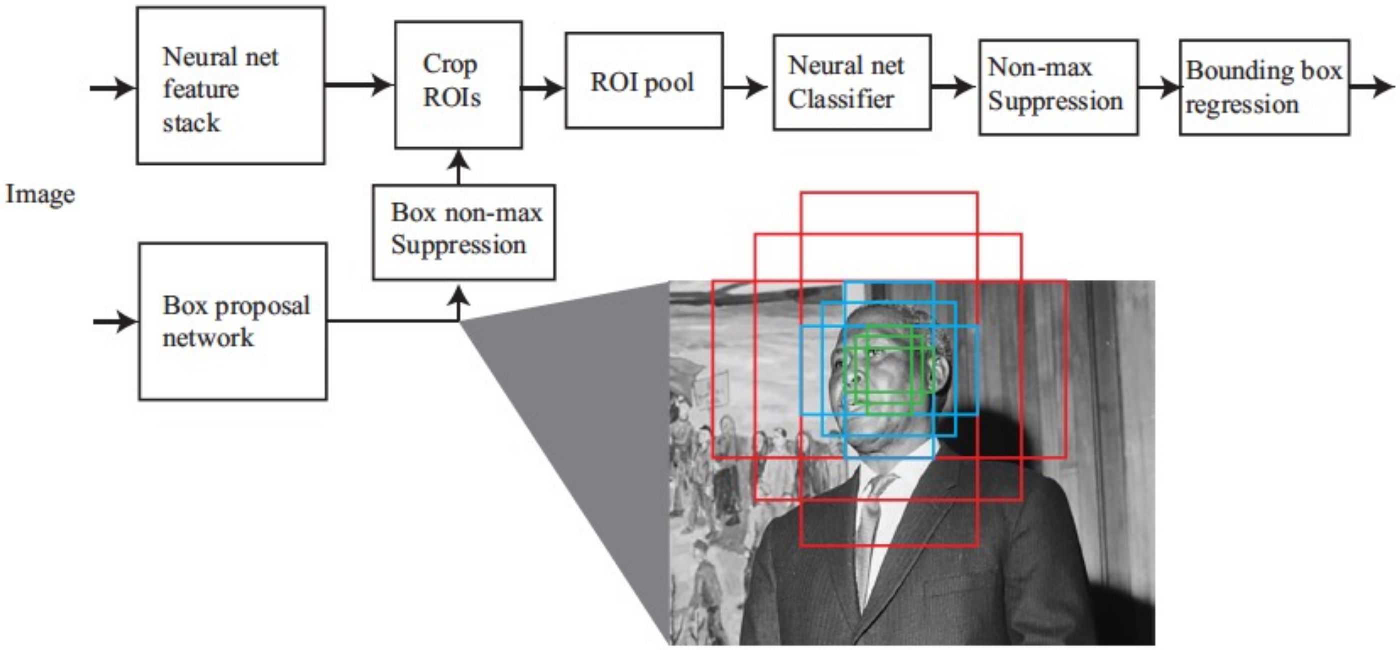
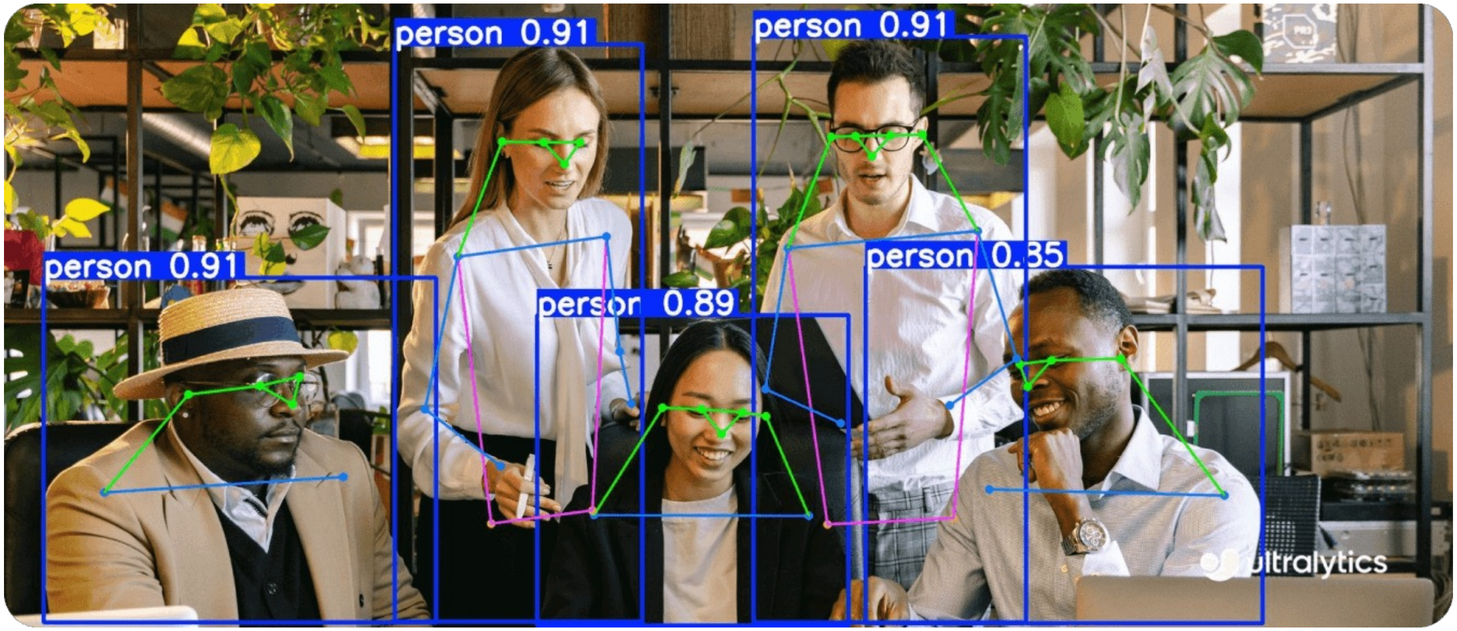


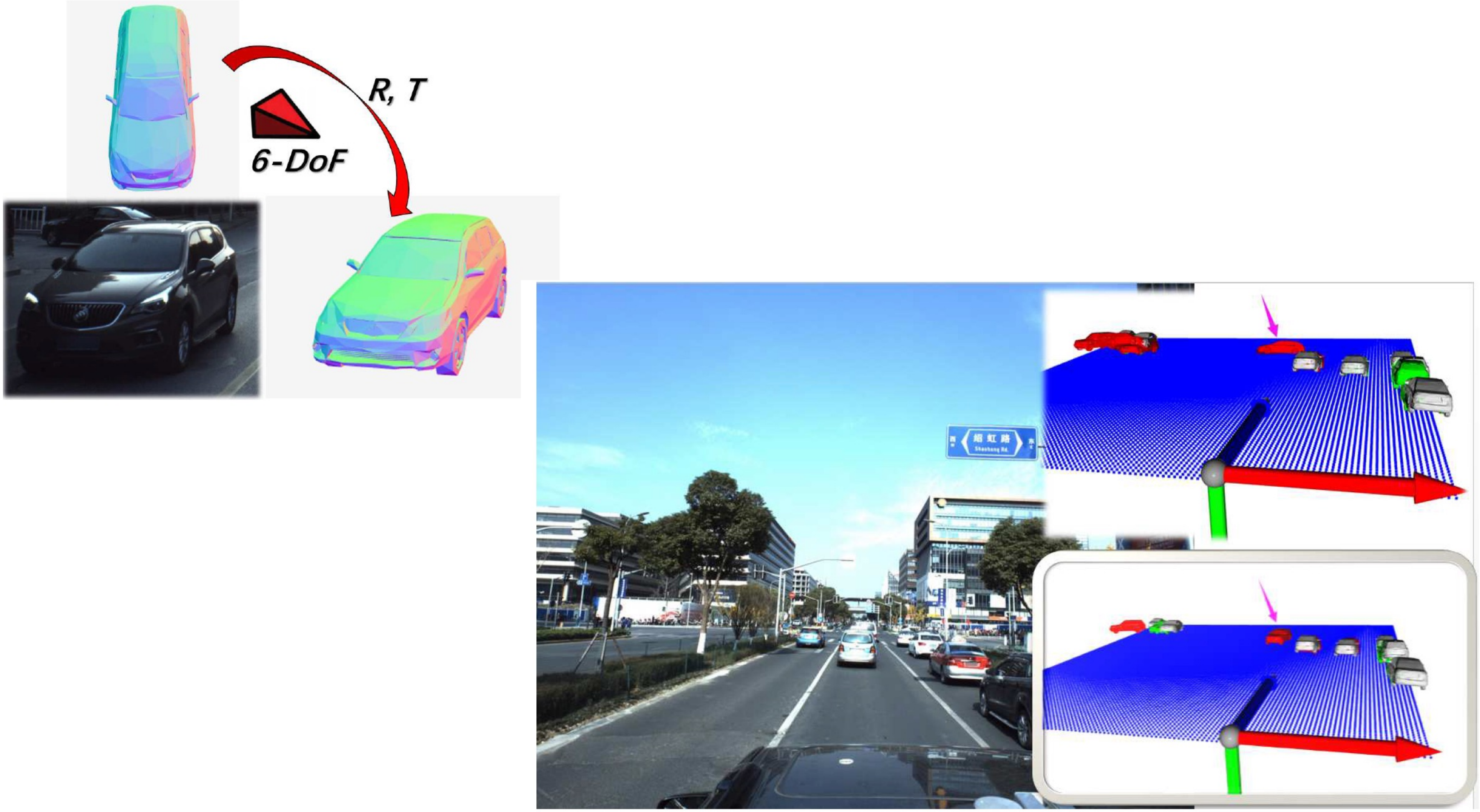
FIGURE 18.8: *Faster RCNN uses two networks. One uses the image to compute "objectness" scores for a sampling of possible image boxes. The samples (called "anchor boxes") are each centered at a grid point. At each grid point, there are nine boxes (three scales, three aspect ratios). The second is a feature stack that computes a representation of the image suitable for classification. The boxes with highest objectness score are then cut from the feature map, standardized with ROI pooling, then passed to a classifier. Bounding box regression means that the relatively coarse sampling of locations, scales and aspect ratios does not weaken accuracy.*

Detection and localization in 2D



YOLOv11 documentation by Ultralytics

Localization in 3D from detection



Wu et al, *6D-VNet: End-to-end 6DoF Vehicle Pose Estimation from Monocular RGB Images*

Lane detection

US 9081385

Waymo and Google 2012

Strategy: detect markers (reflective paint), join up

exercise in robust fitting of curves

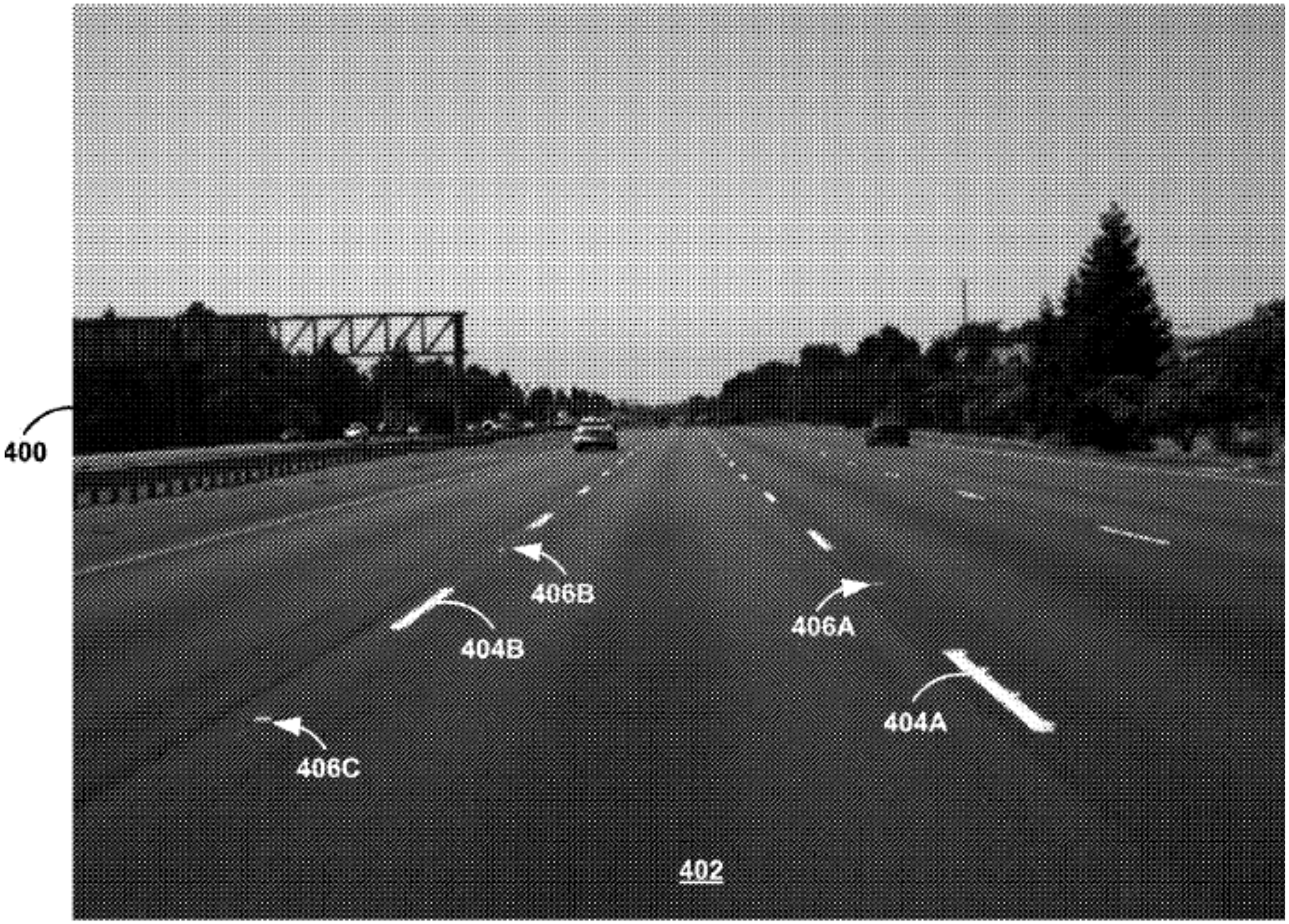
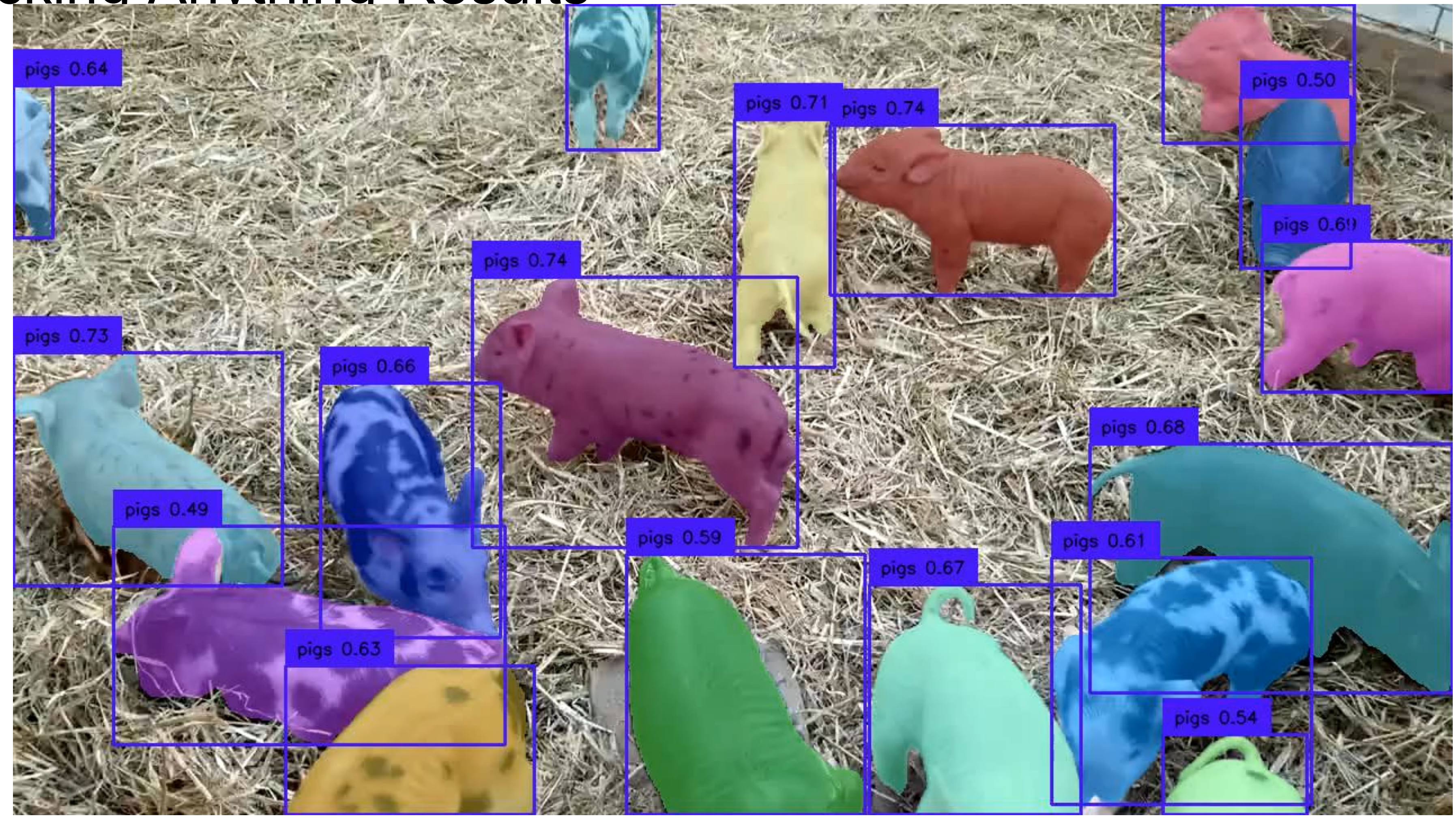


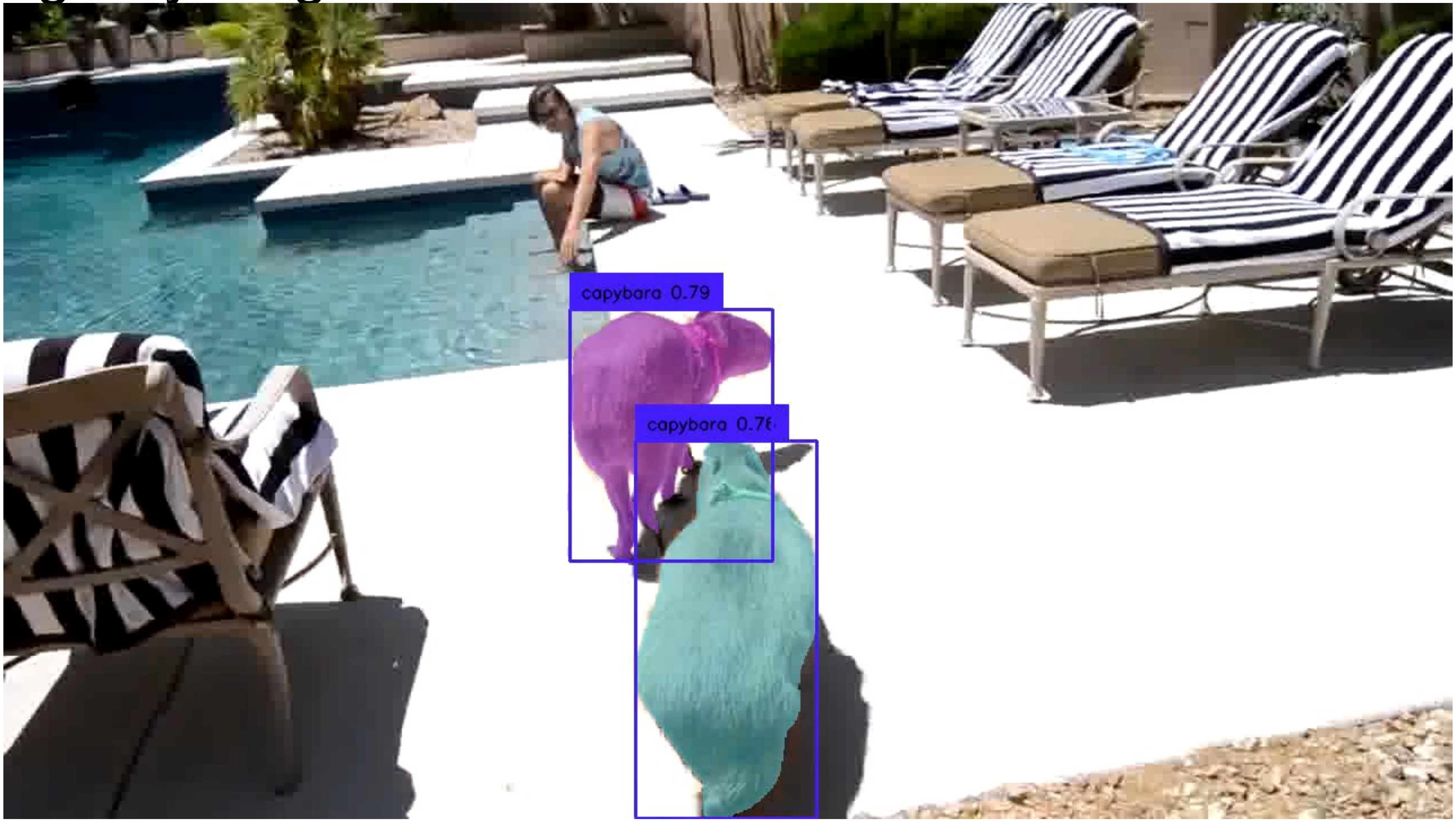
FIGURE 4A

Tracking Anything Results



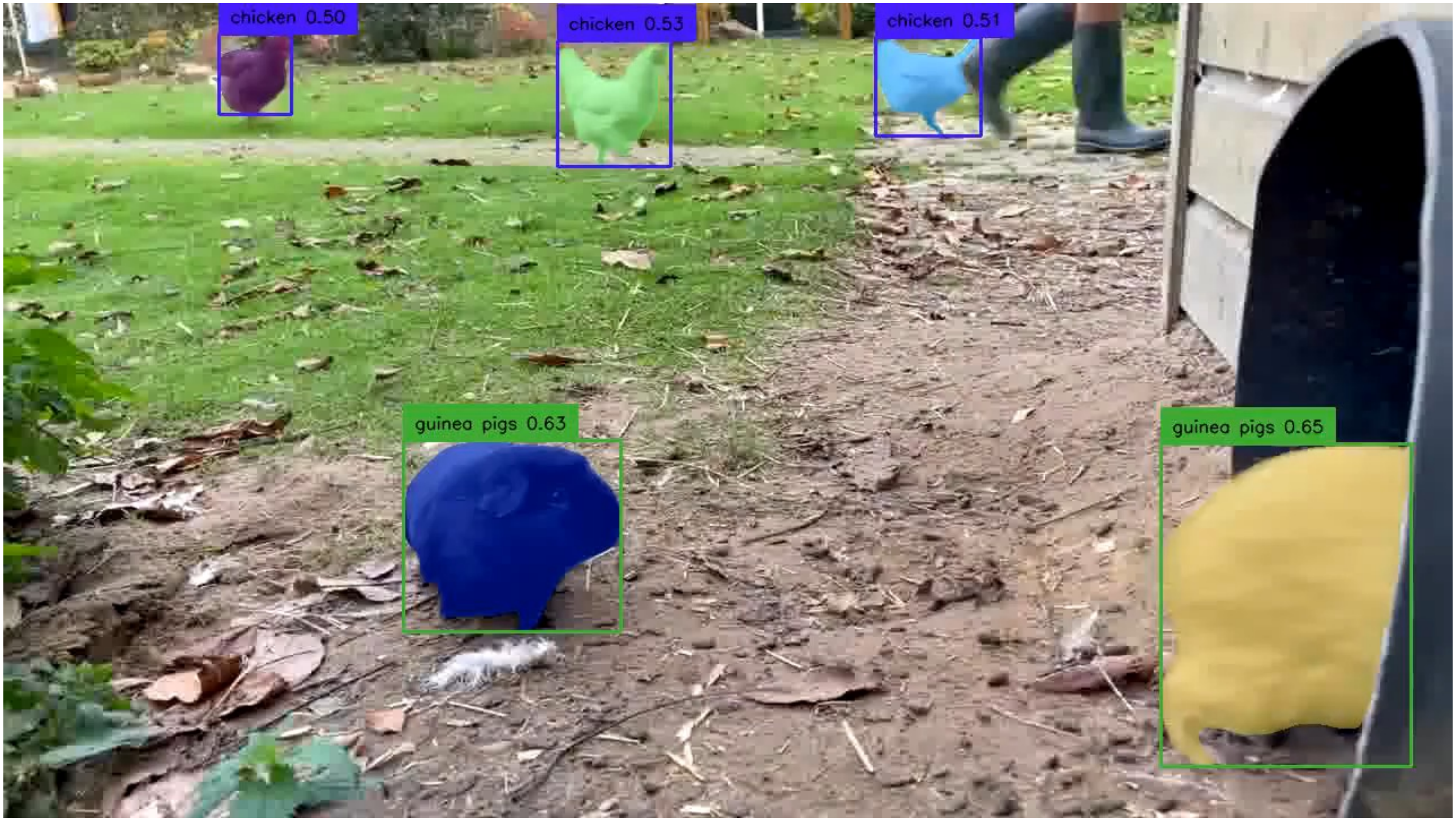
Cheng et al.; DEVA: Tracking anything with decoupled video segmentation; 2023

Tracking Anything Results



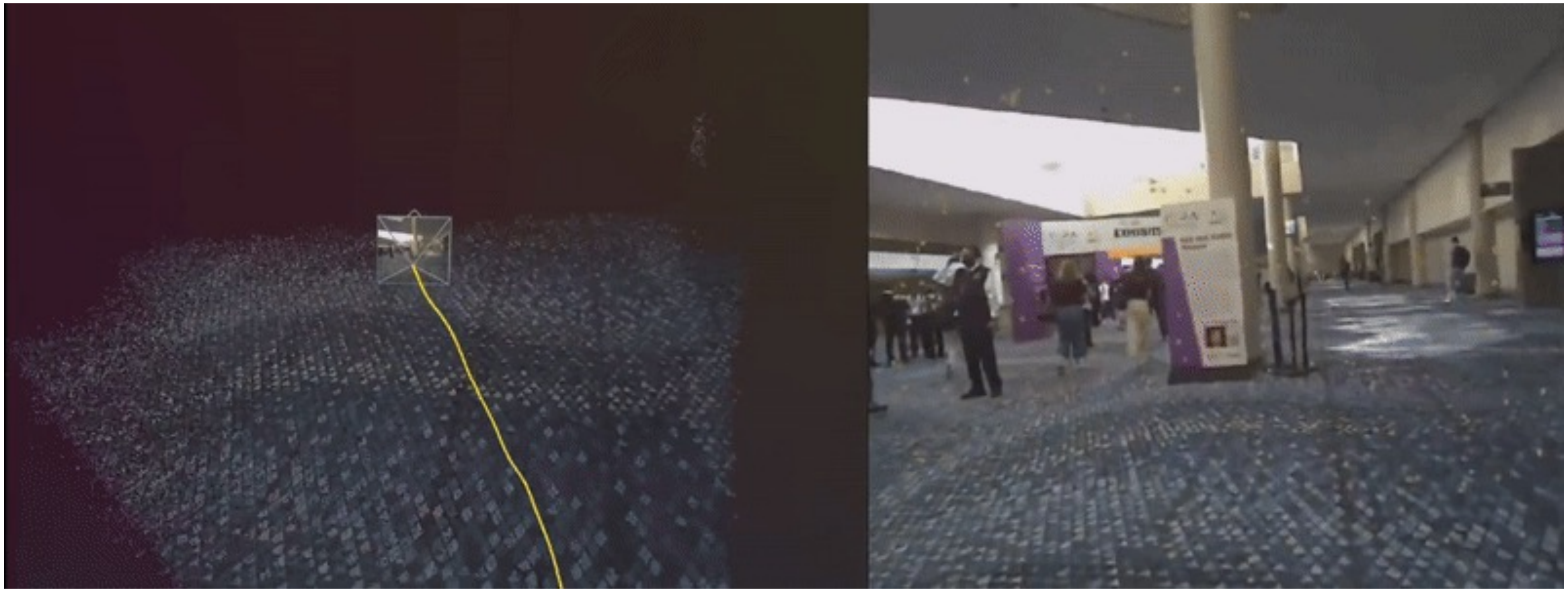
Cheng et al.; DEVA: Tracking anything with decoupled video segmentation; 2023

Tracking Anything Results



Cheng et al.; DEVA: Tracking anything with decoupled video segmentation; 2023

Visual odometry



https://github.com/MAC-VO/MAC-VO/blob/main/asset/ICRAvideo.gif

Extreme odometry

https://www.youtube.com/watch?v=fBiataDpGIo

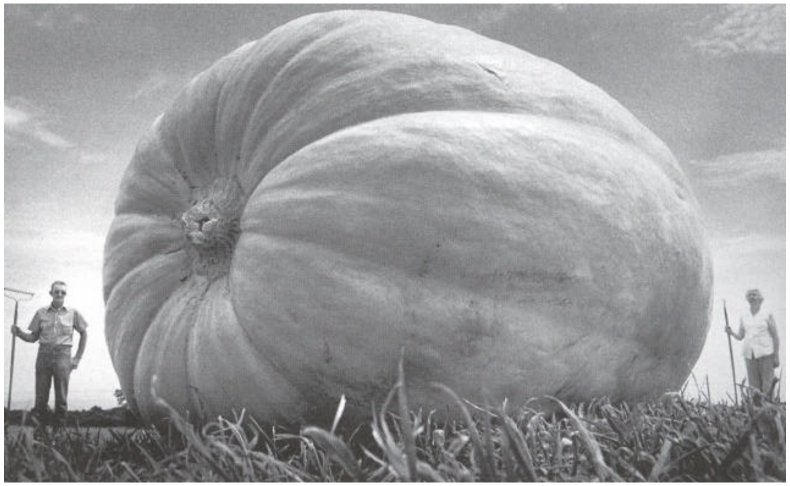
Goal: To extract useful information from pixels

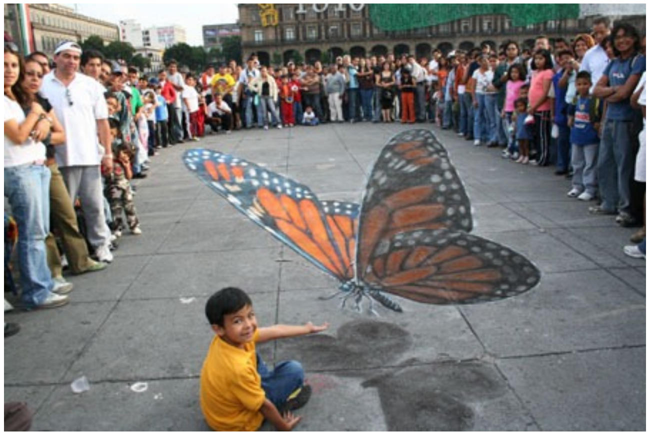
What we see

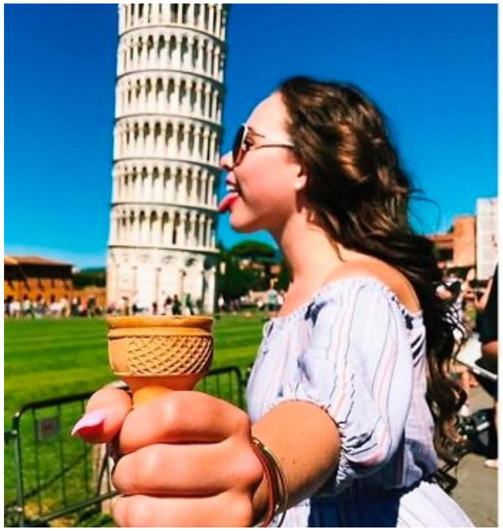
0	3	2	5	4	7	6	9	8
3	0	1	2	3	4	5	6	7
2	1	0	3	2	5	4	7	6
5	2	3	0	1	2	3	4	5
4	3	2	1	0	3	2	5	4
7	4	5	2	3	0	1	2	3
6	5	4	3	2	1	0	3	2
9	6	7	4	5	2	3	0	1
8	7	6	5	4	3	2	1	0

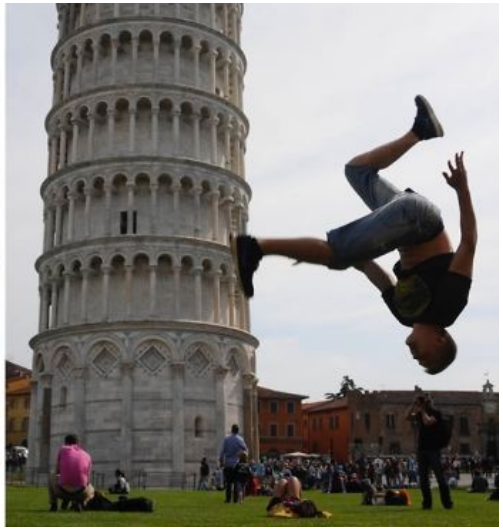
What a computer sees

Trad. View: Images are fundamentally ambiguous!

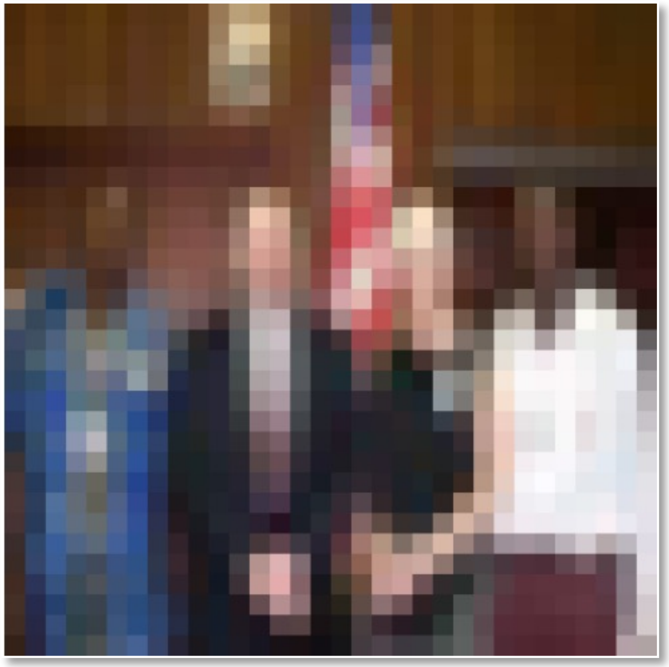








Humans are remarkably good at vision…



Source: “80 million tiny images” by Torralba et al.

…still, vision is hard even for humans

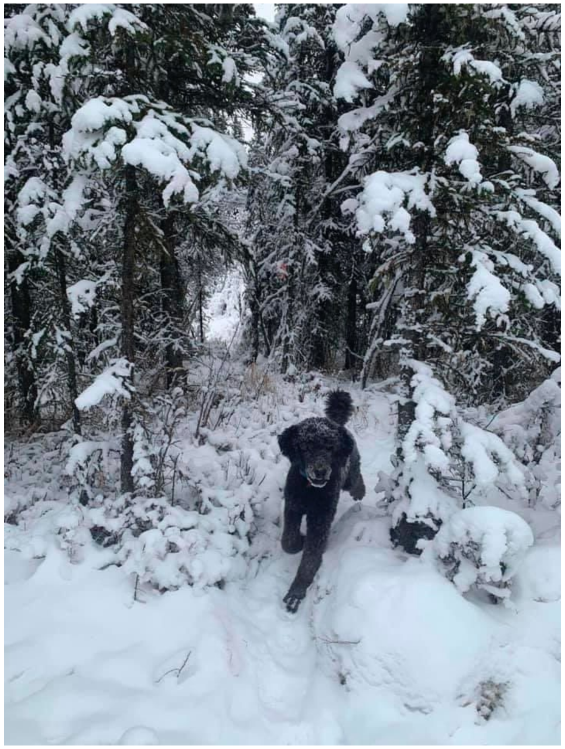


Image source

Image source

…still, vision is hard even for humans

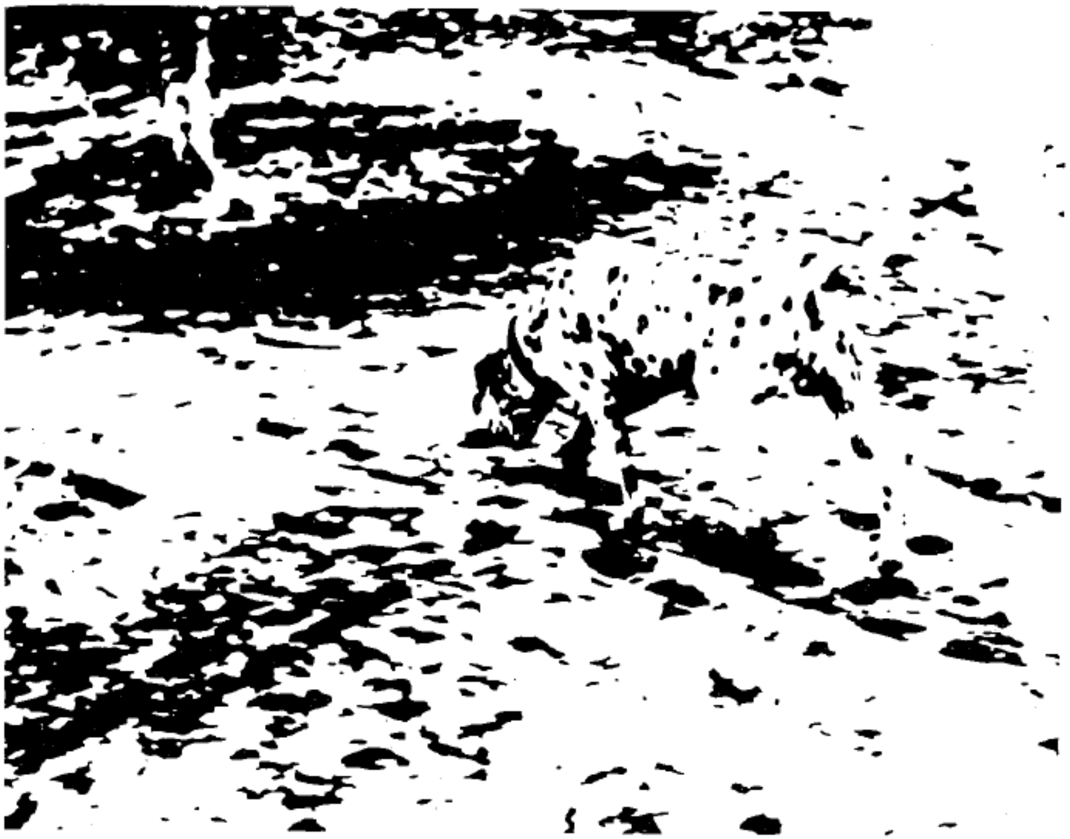
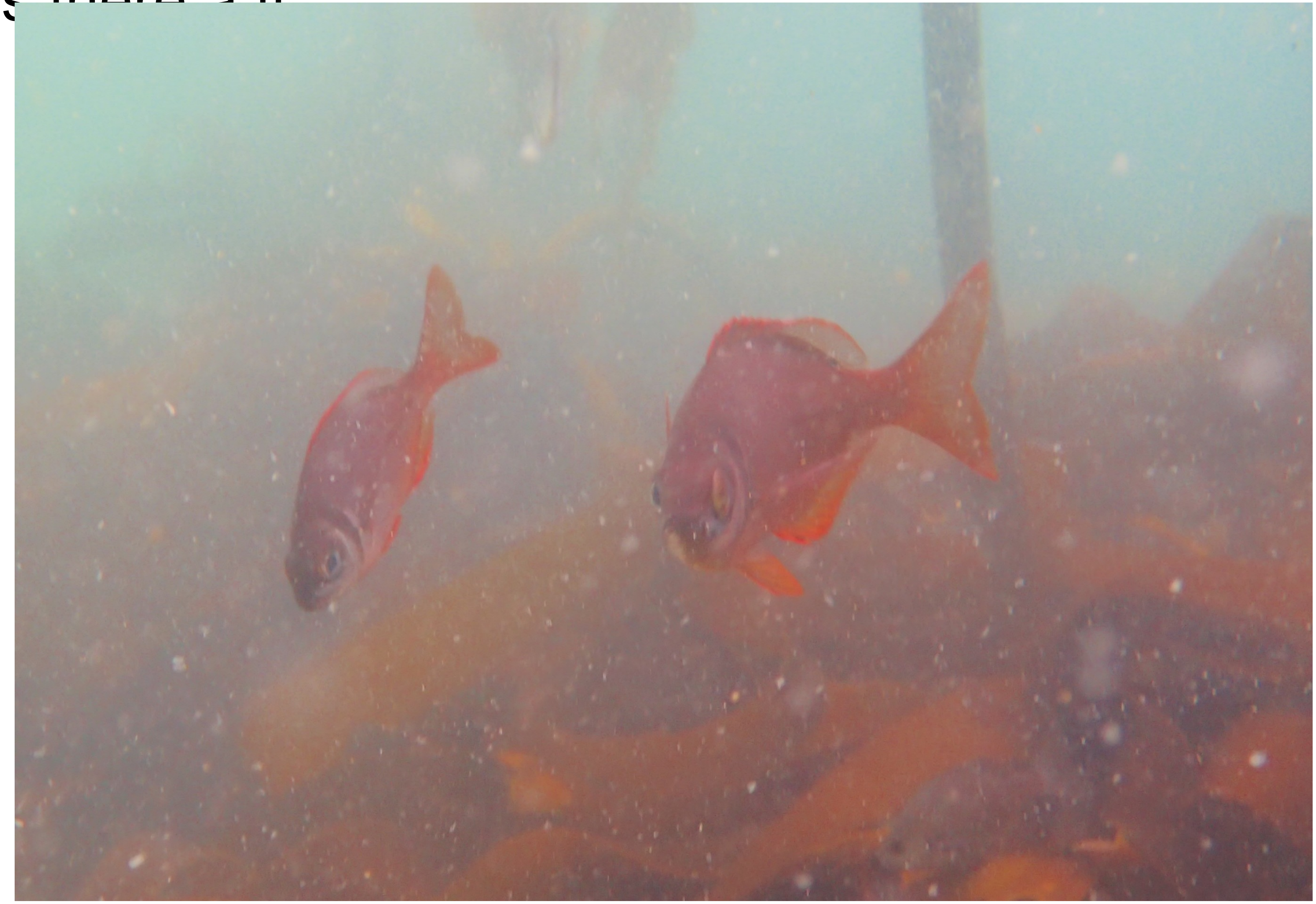
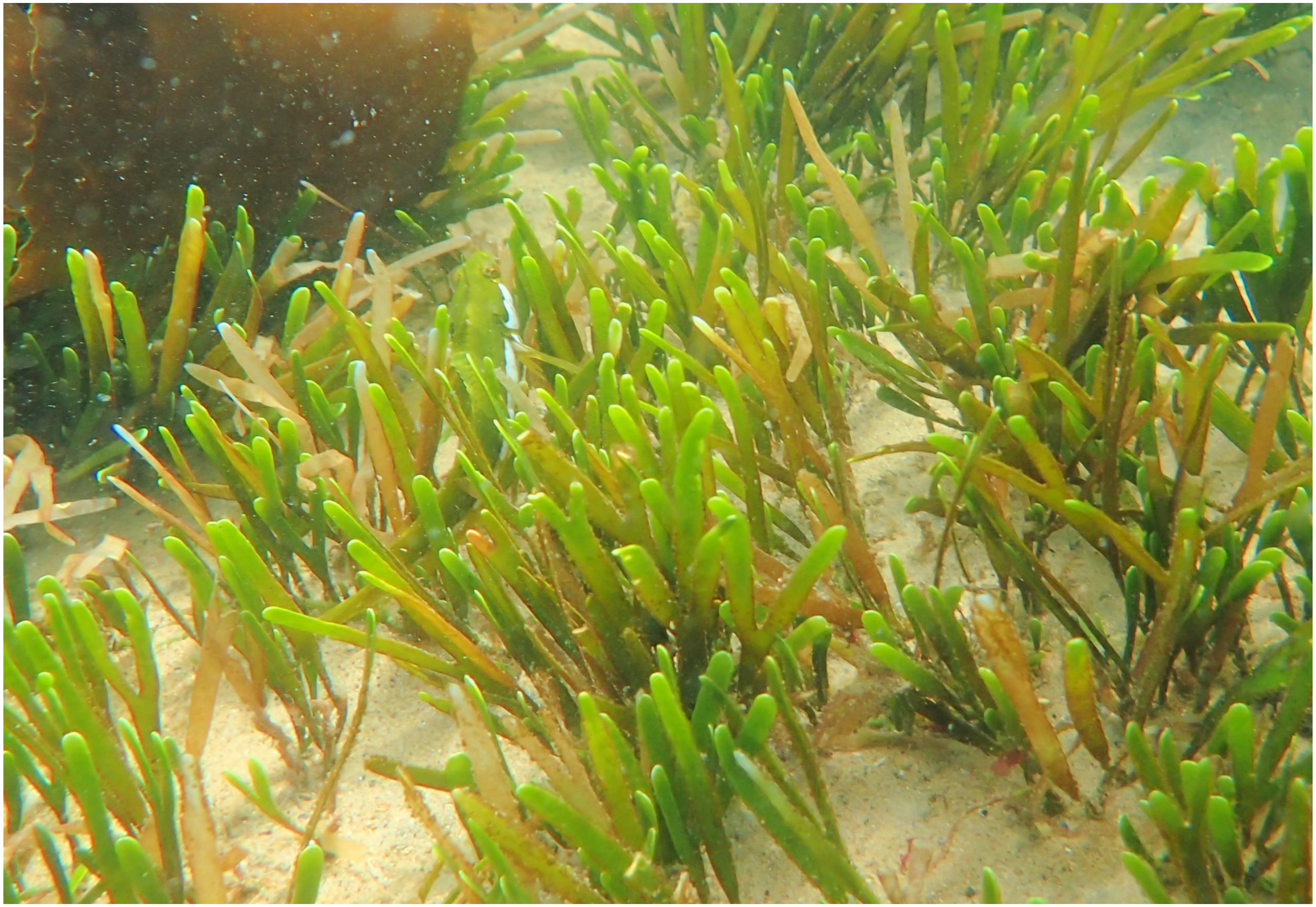
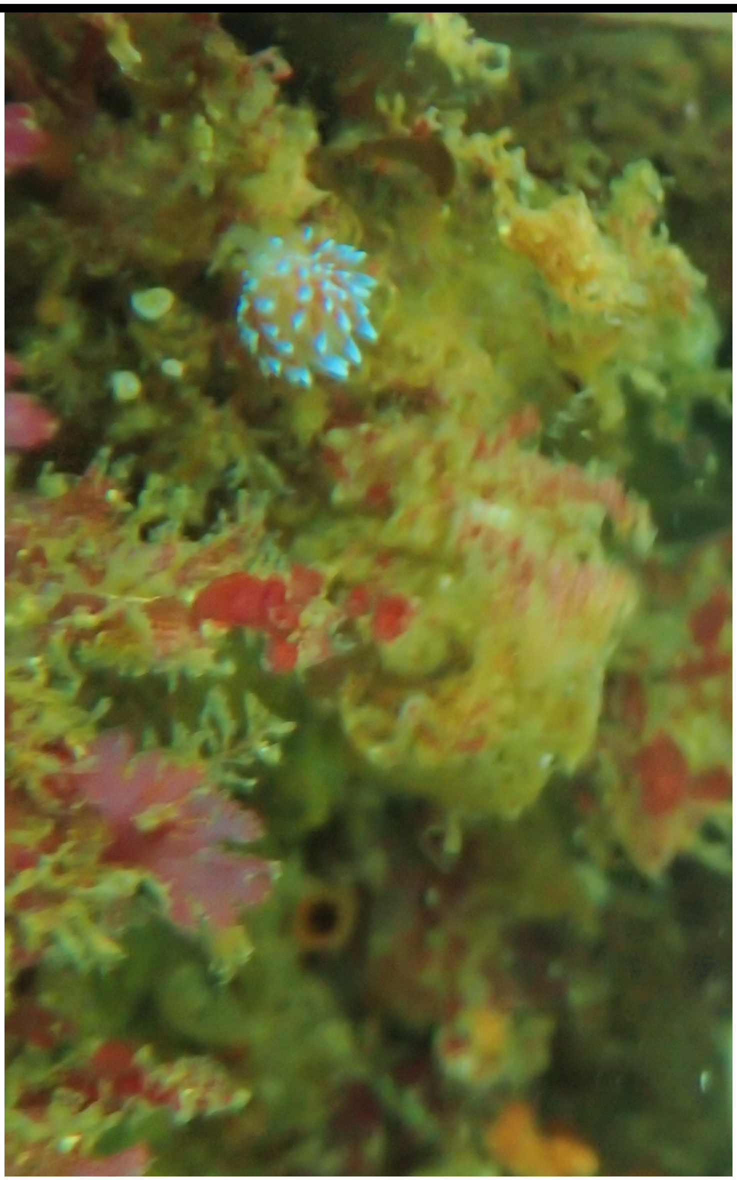


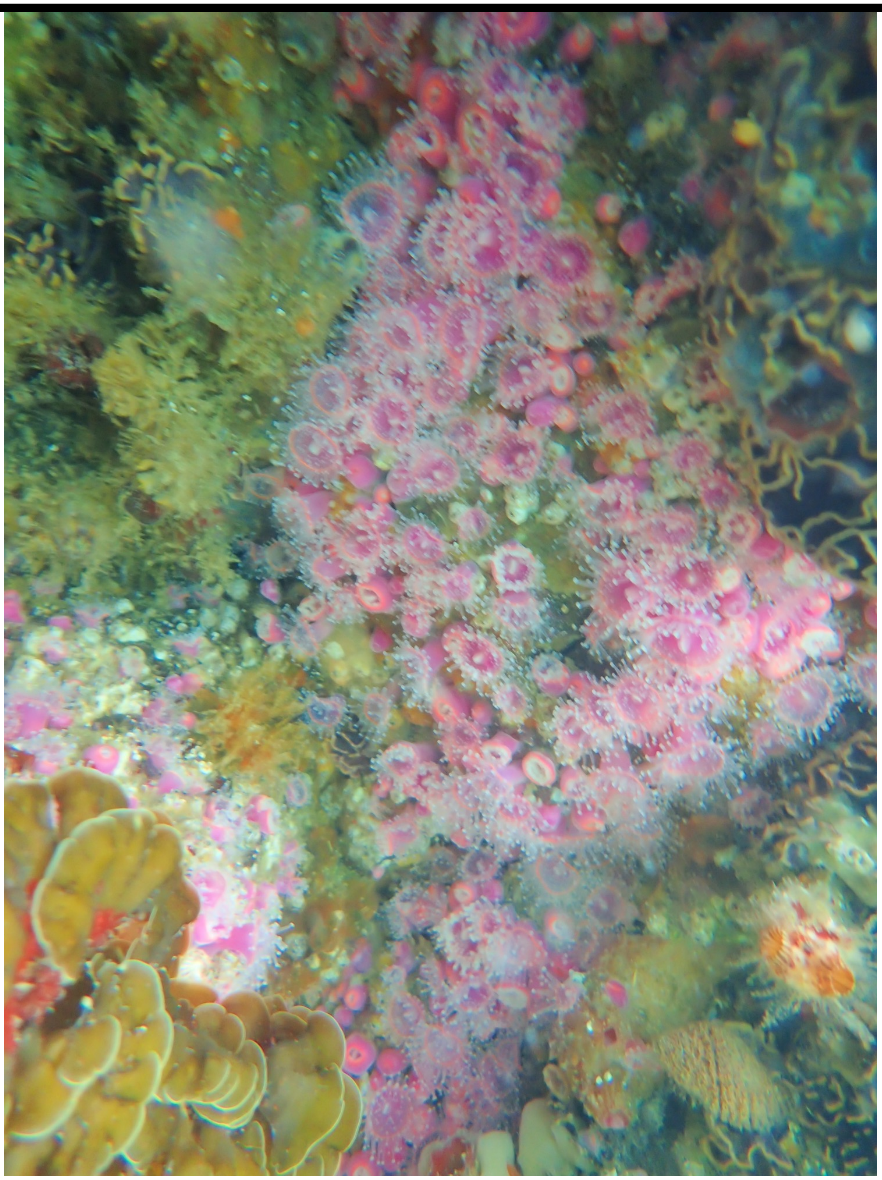
Figure from Marr (1982), attributed to R. C. James

Is there a fi





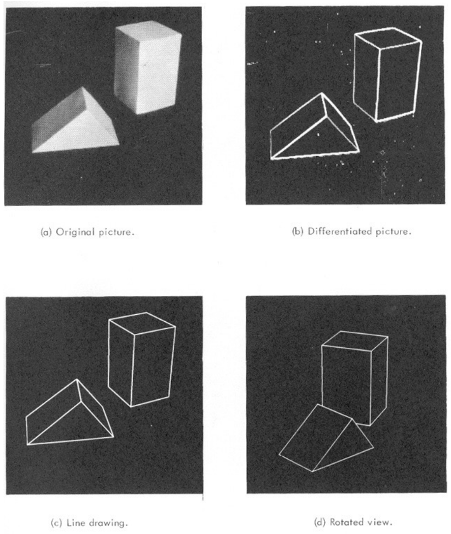




Outline

- Logistics, requirements
- Goal of computer vision and why it is hard
- History of computer vision

How it started



(a) Original picture.

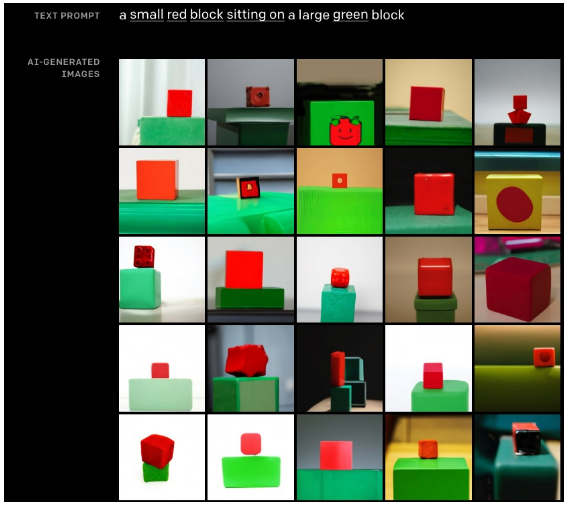
(b) Differentiated picture.

(c) Line drawing.

(d) Rotated view.

L. G. Roberts, 1963

How it's going

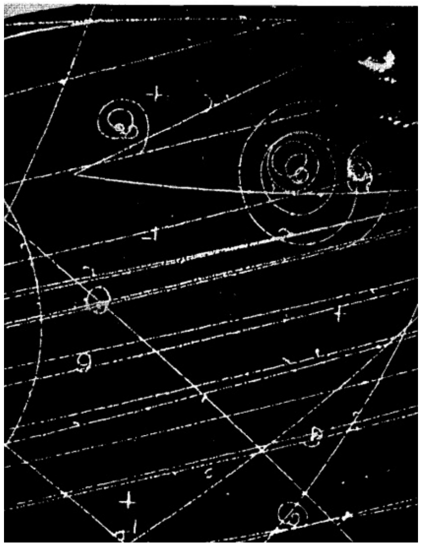


TEXT PROMPT a small red block sitting on a large green block

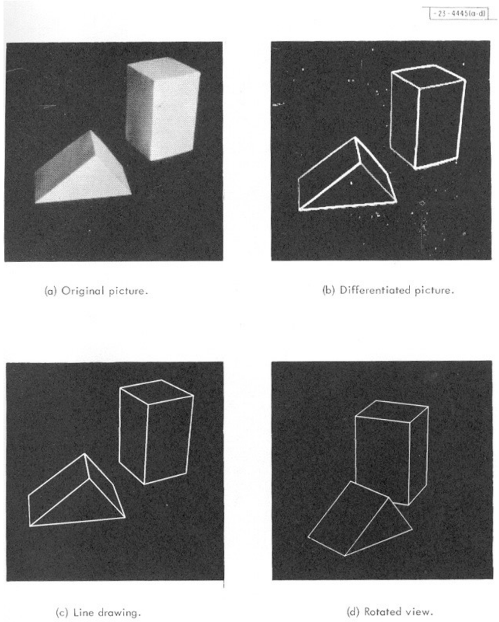
AI-GENERATED IMAGES

OpenAI DALL-E, 2020

Origins



Hough, 1959



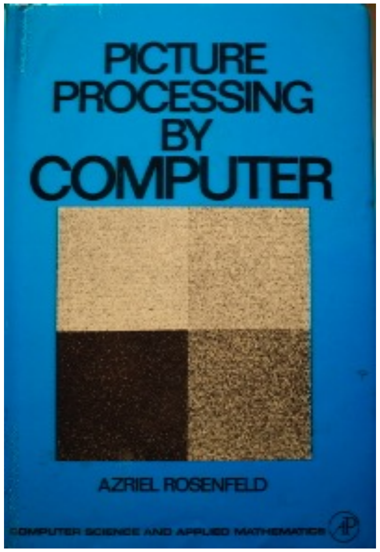
(a) Original picture.

(b) Differentiated picture.

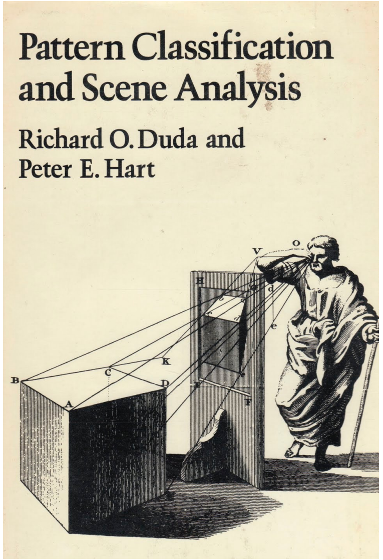
(c) Line drawing.

(d) Rotated view.

Roberts, 1963



Rosenfeld, 1969



Duda & Hart, 1972

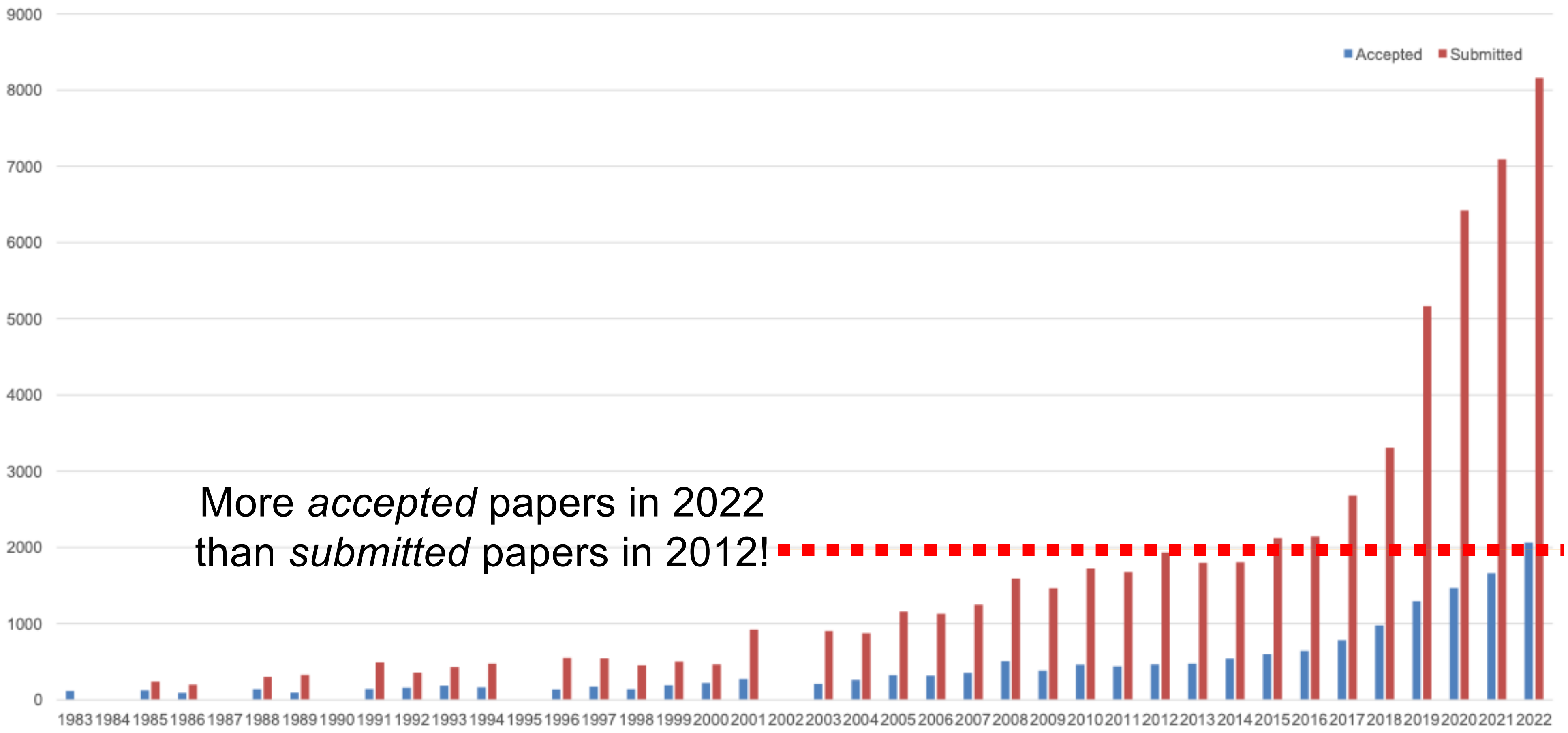
Decade by decade

- **1960s**: Blocks world, image processing and pattern recognition
- **1970s**: Key recovery problems defined: structure from motion, stereo, shape from shading, color constancy. Attempts at knowledge-based recognition
- **1980s**: Fundamental and essential matrix, multi-scale analysis, corner and edge detection, optical flow, geometric recognition as alignment
- **1990s**: Multi-view geometry, statistical and appearance-based models for recognition, first approaches for (class-specific) object detection
- **2000s**: Local features, generic object recognition and detection
- **2010s**: Deep learning, big data

- For much more detail: see Prof Lazebnik's historical overview

Adapted from J. Malik

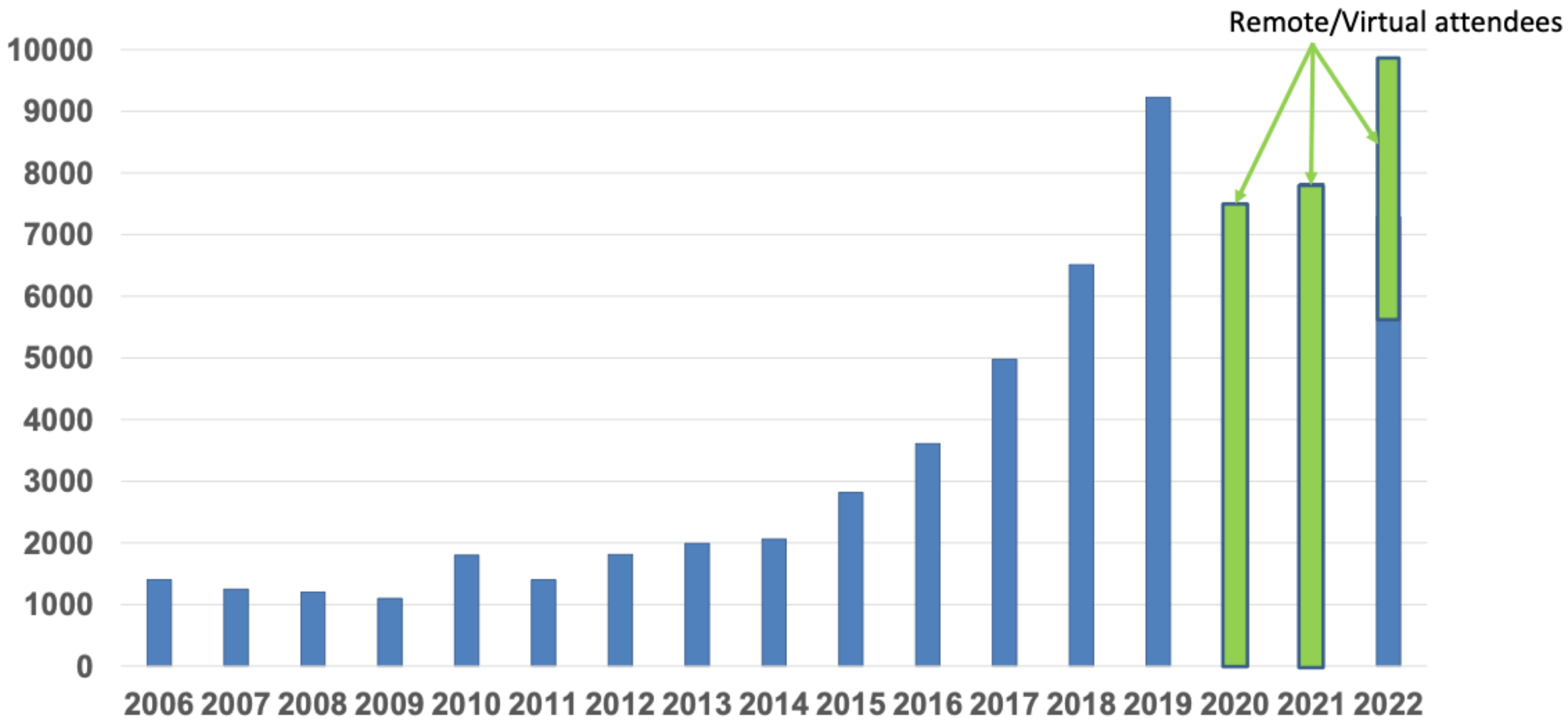
Growth of the field: CVPR papers



More *accepted* papers in 2022 than *submitted* papers in 2012!

Source: CVPR 2022 opening sides

Growth of the field: CVPR attendance

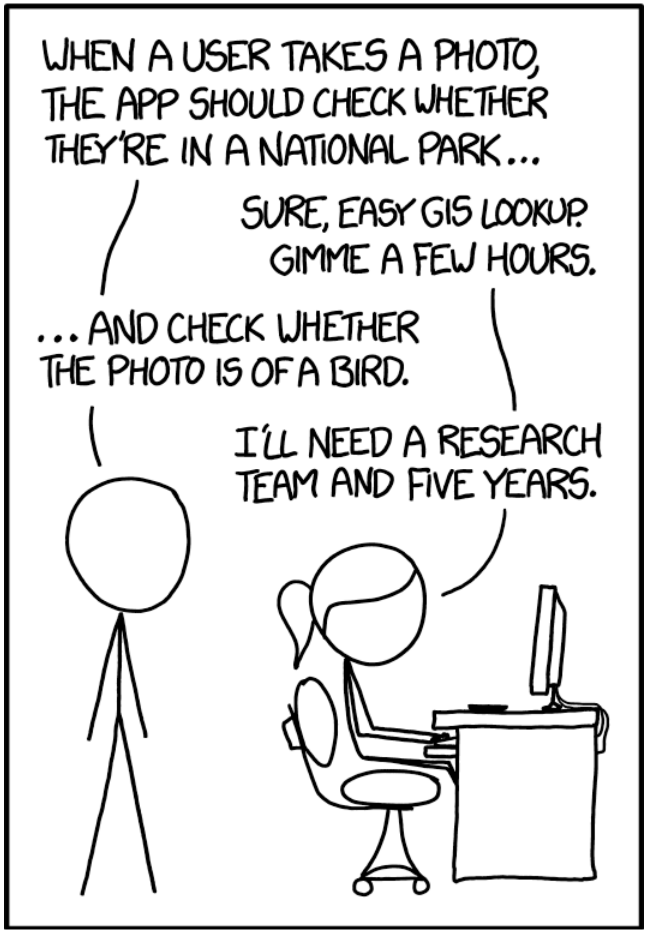


Source: CVPR 2022 opening sides

Introduction: Outline

- Logistics, requirements
- Goal of computer vision and why it is hard
- History of computer vision
- Current(ish) state of the art

What can computer vision do today?


WHEN A USER TAKES A PHOTO, THE APP SHOULD CHECK WHETHER THEY'RE IN A NATIONAL PARK...
SURE, EASY GIS LOOKUP. GIMME A FEW HOURS.
...AND CHECK WHETHER THE PHOTO IS OF A BIRD.
I'LL NEED A RESEARCH TEAM AND FIVE YEARS.

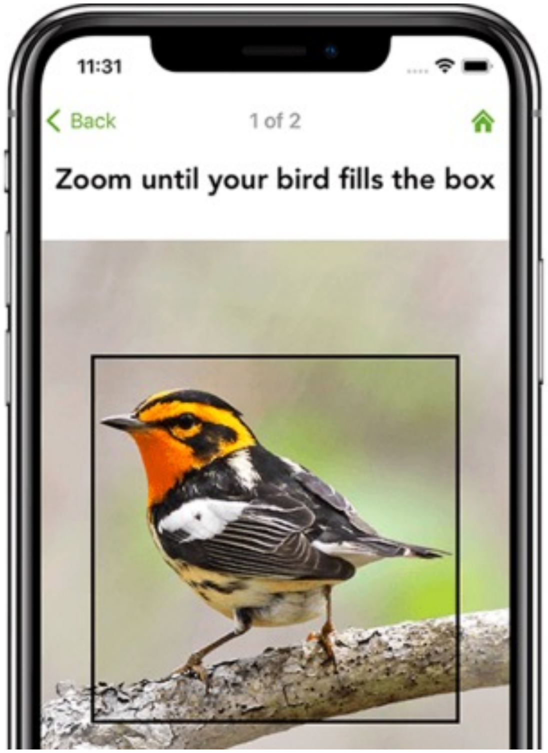
In the 60s, Marvin Minsky assigned a couple of undergrads to spend the summer programming a computer to use a camera to identify objects in a scene. He figured they'd have the problem solved by the end of the summer. Half a century later, we're still working on it.

https://xkcd.com/1425/

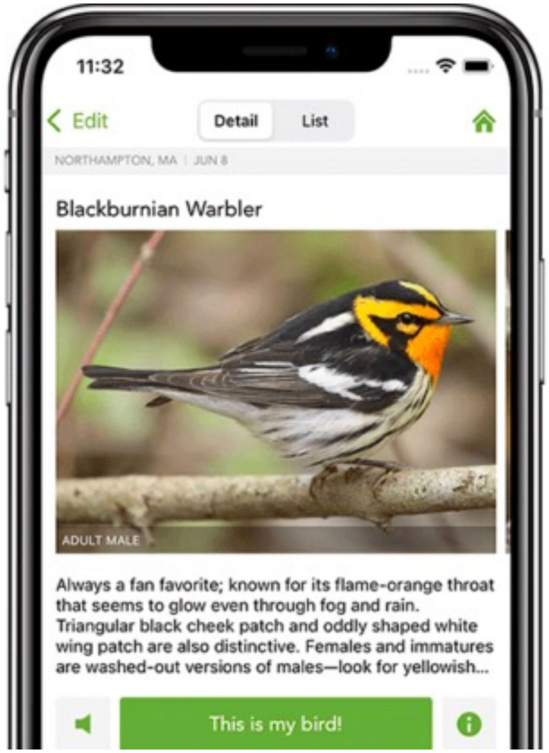
(September 24, 2014)

What can computer vision do today?

- It’s 2025 now…



Zoom until your bird fills the box



Blackburnian Warbler

Always a fan favorite; known for its flame-orange throat that seems to glow even through fog and rain. Triangular black cheek patch and oddly shaped white wing patch are also distinctive. Females and immatures are washed-out versions of males—look for yellowish...

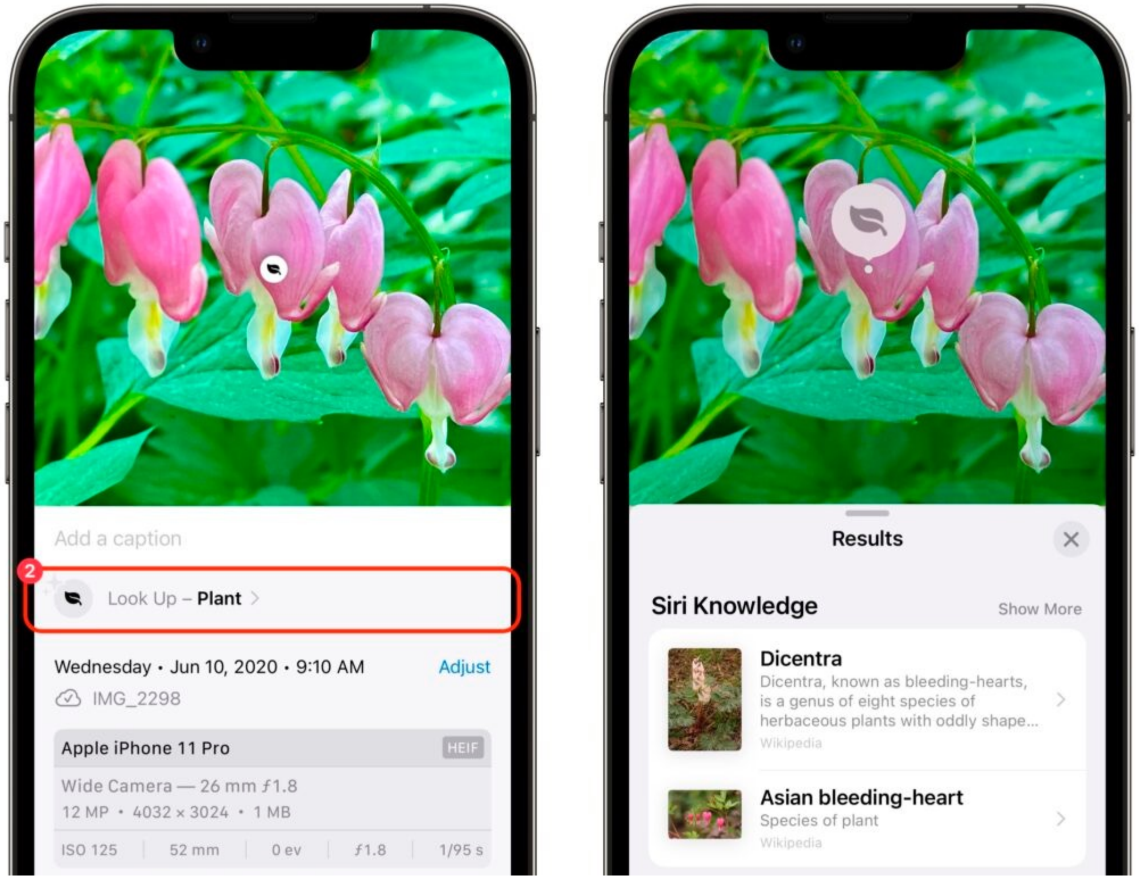
TheCornellLab

Merlin®

https://merlin.allaboutbirds.org/

What can computer vision do today?

- It’s 2025 now…



Wednesday • Jun 10, 2020 • 9:10 AM

IMG_2298

Apple iPhone 11 Pro

Wide Camera — 26 mm ƒ1.8

12 MP • 4032 × 3024 • 1 MB

ISO 125 | 52 mm | 0 ev | ƒ1.8 | 1/95 s

Dicentra

Dicentra, known as bleeding-hearts, is a genus of eight species of herbaceous plants with oddly shape...

Wikipedia

Asian bleeding-heart

Species of plant

Wikipedia

Image source

What can computer vision do today?

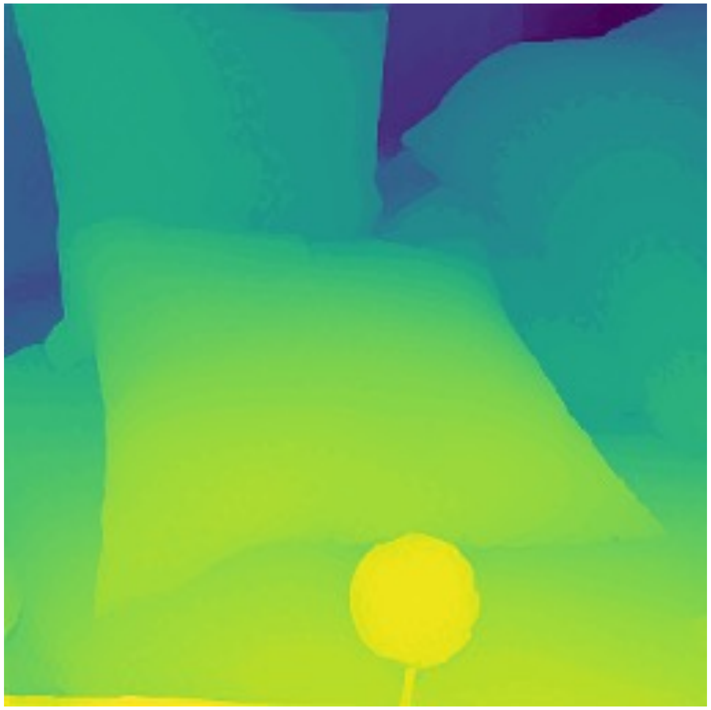
- Reconstruction
- Recognition
- *Reconstruction meets recognition, or 3D scene understanding*
- *Image generation*
- *Vision for action*

Regression

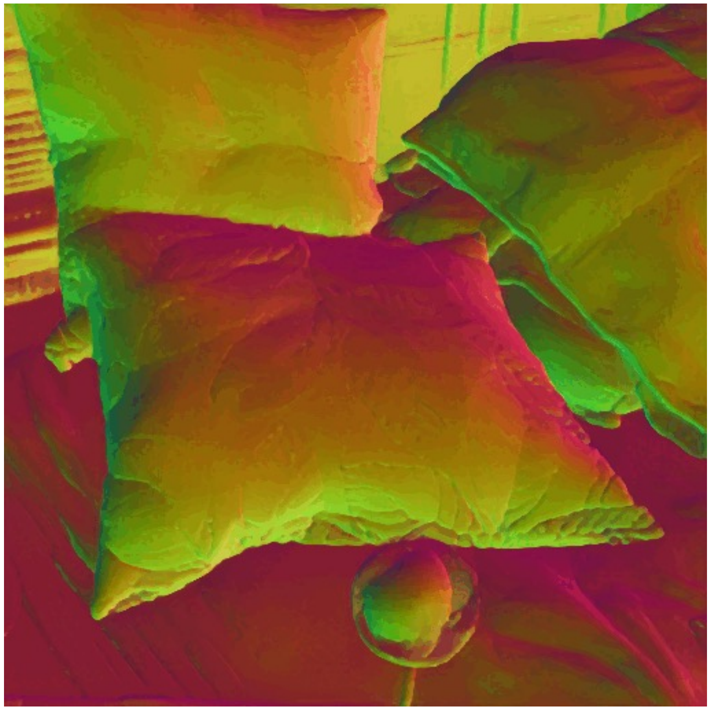
- We must make image-like things from images
- Examples:
  - depth map from image
  - normal map from image
  - derained image from rainy image
  - defogged image from foggy image
- Train with pairs (image, depth)
  - or (image, normal), etc
  - Loss
    - Squared error +abs value of error+other terms as required

E

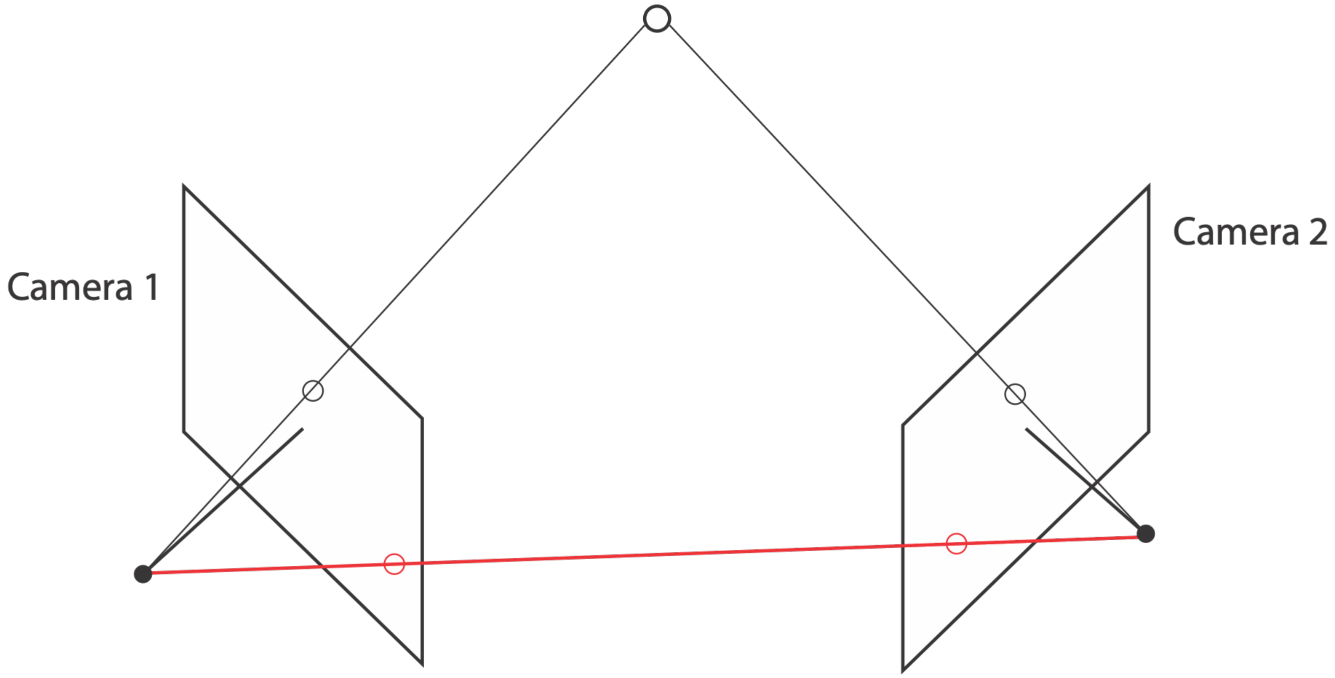
Depth (omnimap, current best depth est)



Normal (omnimap, current best normal est)

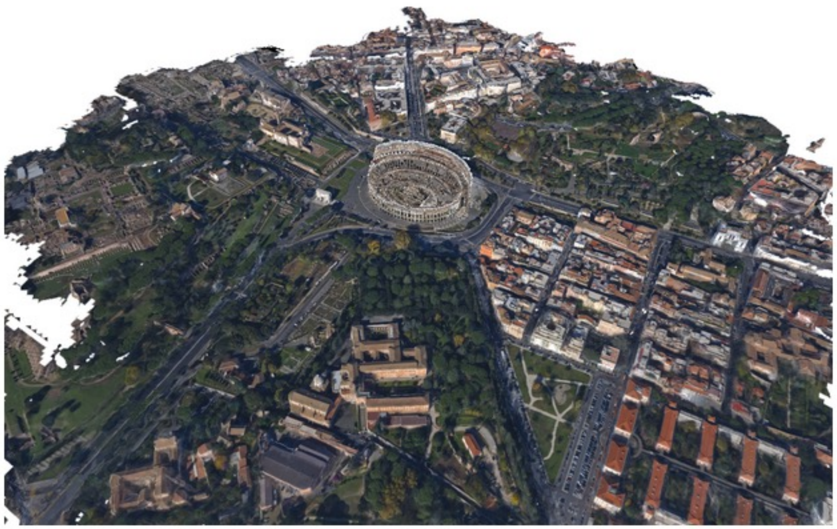


Correspondence yields 3D configuration



Reconstruction: 3D from photo collections

Colosseum, Rome, Italy



San Marco Square, Venice, Italy

Q. Shan, R. Adams, B. Curless, Y. Furukawa, and S. Seitz, The Visual Turing Test for Scene Reconstruction, 3DV 2013

YouTube Video

Reconstruction: 4D from photo collections

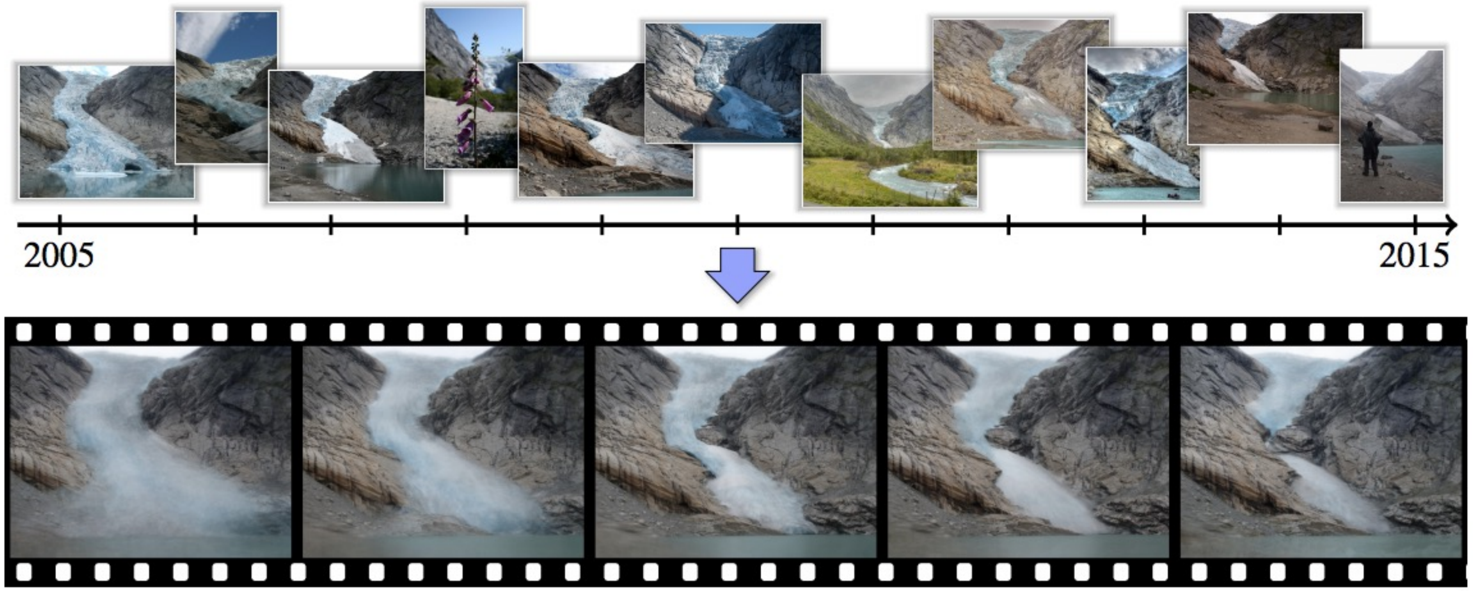


Figure 1: *We mine Internet photo collections to generate time-lapse videos of locations all over the world. Our time-lapses visualize a multitude of changes, like the retreat of the Briksdalsbreen Glacier in Norway shown above. The continuous time-lapse (bottom) is computed from hundreds of Internet photos (samples on top).* *Photo credits:* `Aliento Más Allá`, `jirihnidek`, `mcxurxo`, `elka_cz`, *Juan Jesús Orío, Klaus Wißkirchen,* `Daikrieg`, `Free the image`, `dration` *and Nadav Tobias.*

R. Martin-Brualla, D. Gallup, and S. Seitz, Time-Lapse Mining from Internet Photos, SIGGRAPH 2015

YouTube Video

Reconstruction: 4D from depth cameras

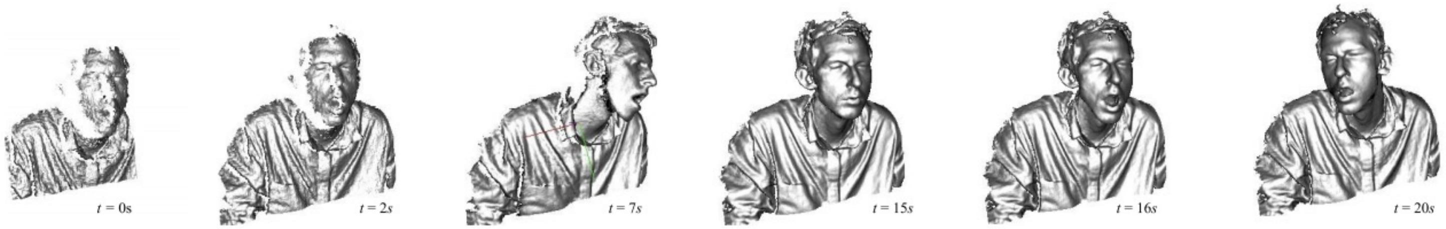
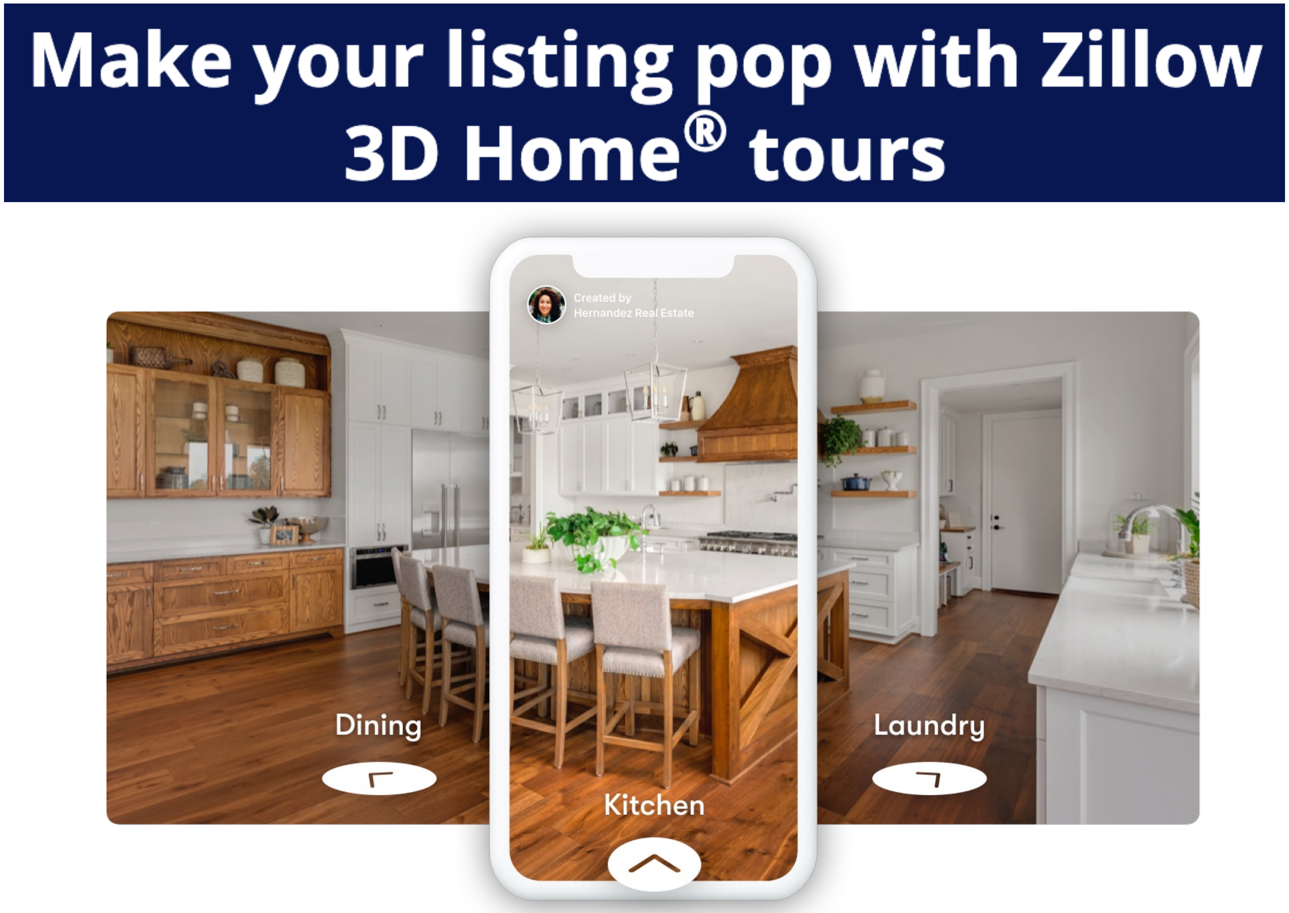


Figure 1: Real-time reconstructions of a moving scene with DynamicFusion; both the person and the camera are moving. The initially noisy and incomplete model is progressively denoised and completed over time (left to right).

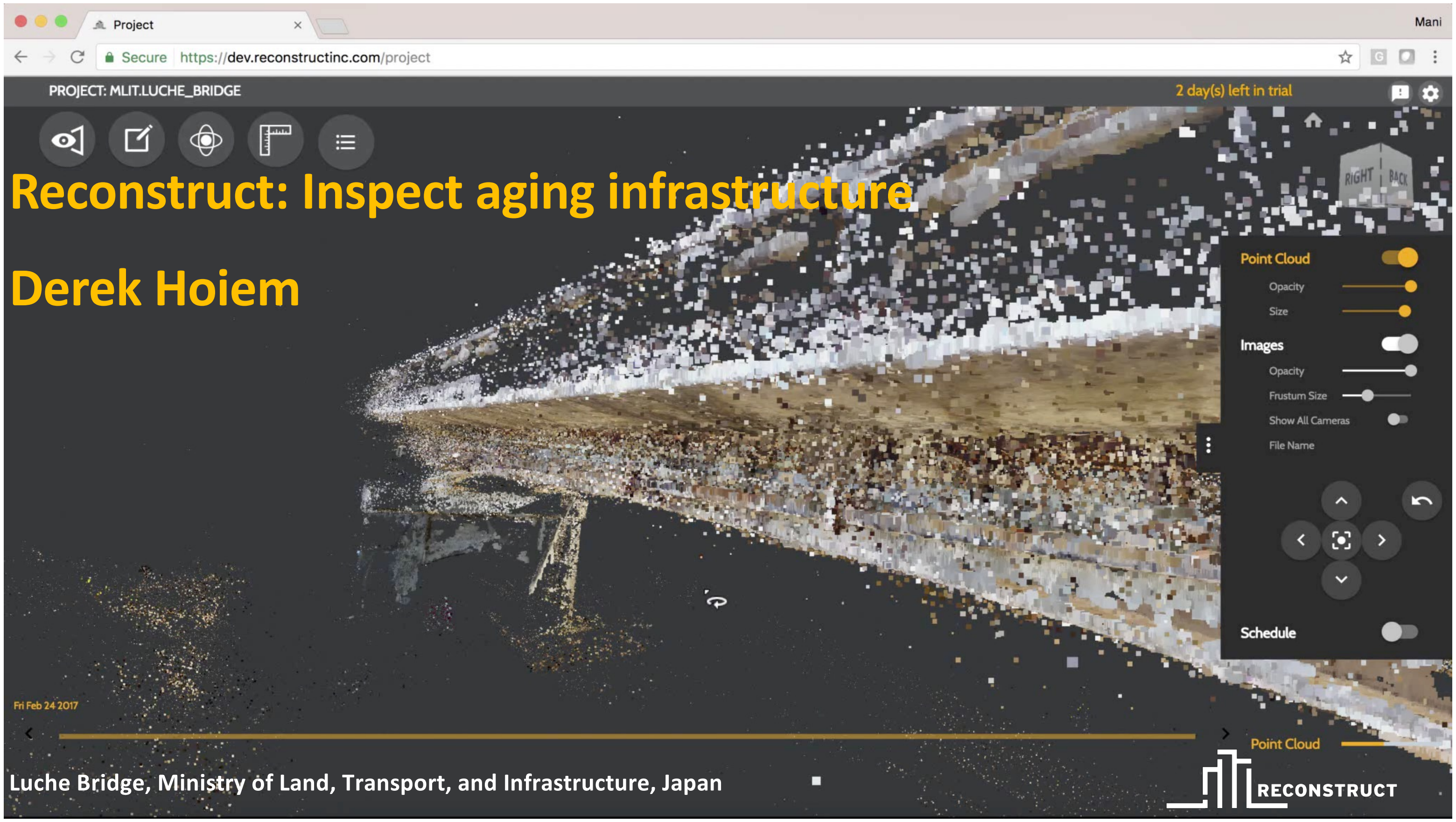
R. Newcombe, D. Fox, and S. Seitz, DynamicFusion: Reconstruction and Tracking of Non-rigid Scenes in Real-Time, CVPR 2015

YouTube Video

Reconstruction: Commercial applications


Make your listing pop with Zillow 3D Home® tours
Created by Hernandez Real Estate
Dining
Kitchen
Laundry

https://www.zillow.com/z/3d-home/



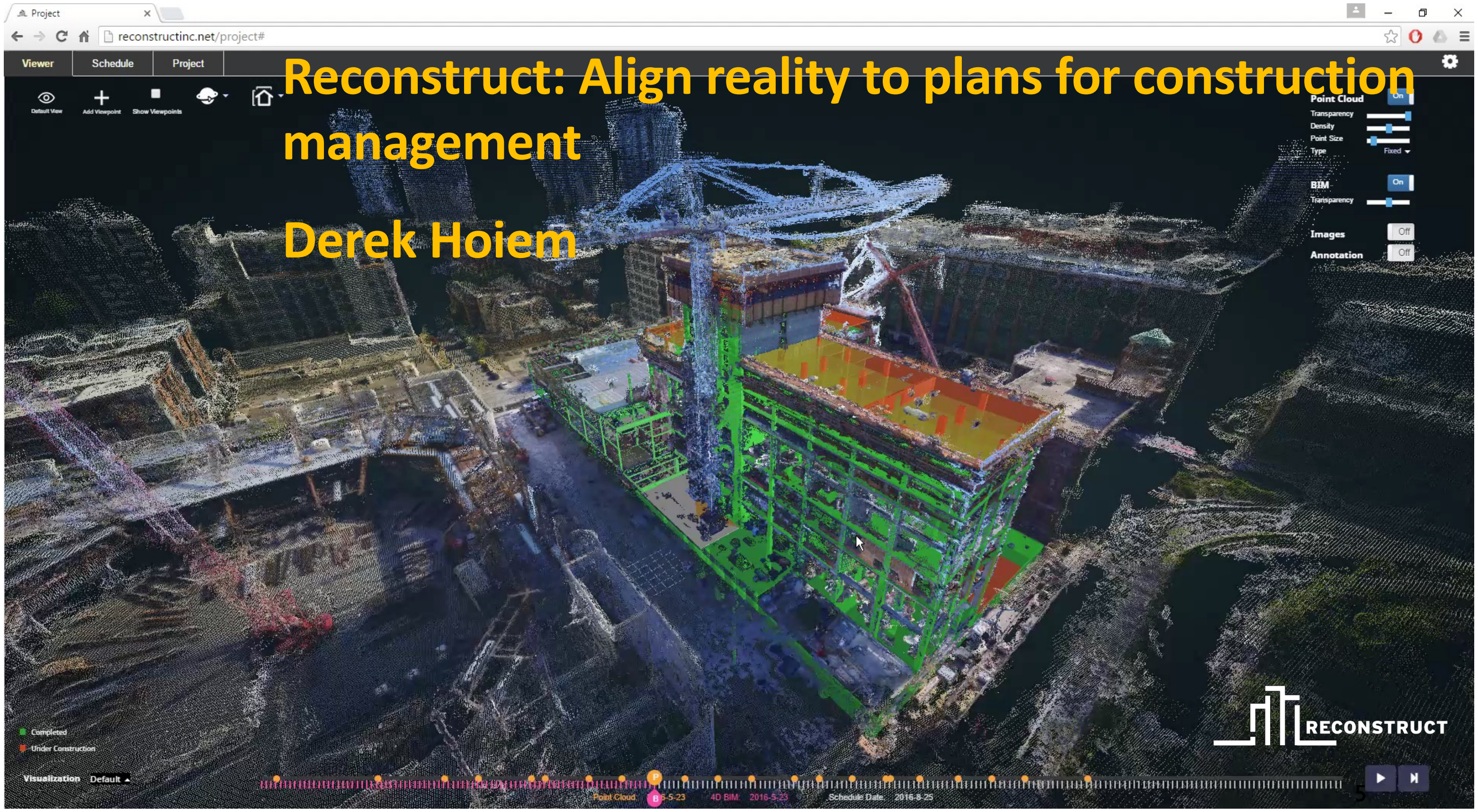
Reconstruct: Inspect aging infrastructure

Derek Hoiem

Luche Bridge, Ministry of Land, Transport, and Infrastructure, Japan

Reconstruct: Align reality to plans for construction management

Derek Hoiem



Point Cloud: On
Transparency
Density
Point Size
Type: Fixed

BIM: On
Transparency

Images: Off
Annotation: Off

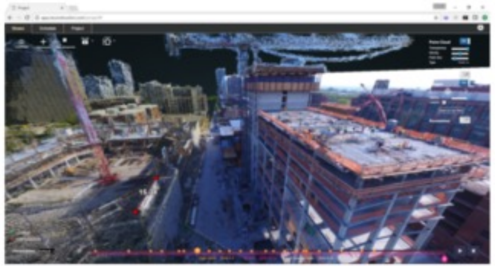
🟩 Completed
🟥 Under Construction

Visualization: Default

Point Cloud 2016-5-23 4D BIM 2016-5-23 Schedule Date 2016-8-25

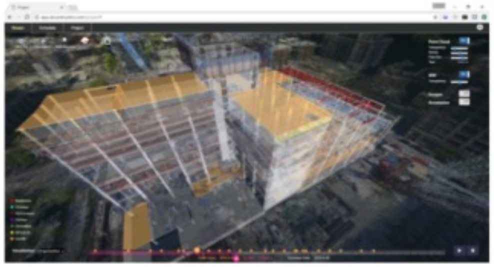
Reconstruction: Commercial applications

RECONSTRUCT INTEGRATES REALITY AND PLAN



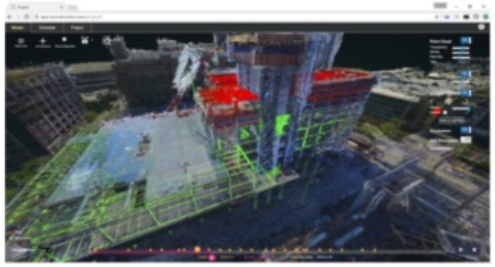
Visual Asset Management

Reconstruct 4D point clouds and organize images and videos from smartphones, time-lapse cameras, and drones around the project schedule. View, annotate, and share anywhere with a web interface.



4D Visual Production Models

Integrate 4D point clouds with 4D BIM, review "who does what work at what location" on a daily basis and improve coordination and communication among project teams.



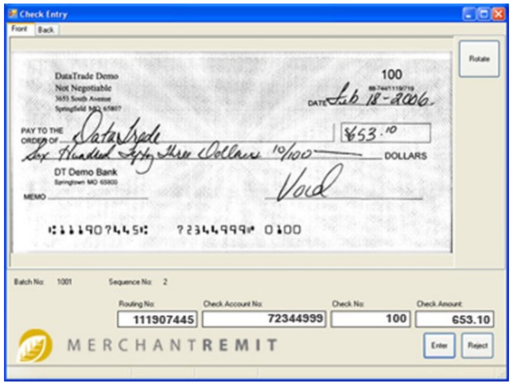
Predictive Visual Data Analytics

Analyze actual progress deviations by comparing Reality and Plan and predict risk with respect to the execution of the look-ahead schedule for each project location, to offer your project team with an opportunity to tap off potential delays before they surface on your jobsite.

reconstructinc.com

Source: D. Hoiem

Recognition: “Simple” patterns



Check Entry

DataTrade Demo
Not Negotiable
3653 South Avenue
Springfield MO 65807

100
88-7441119/719

DATE Feb 18-2006

PAY TO THE ORDER OF DataTrade

$653.10

Six Hundred Fifty Three Dollars 10/100 DOLLARS

DT Demo Bank
Springtown MO 65800

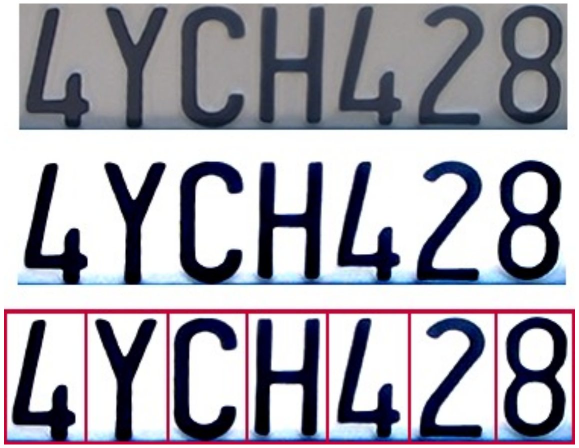
MEMO

Void

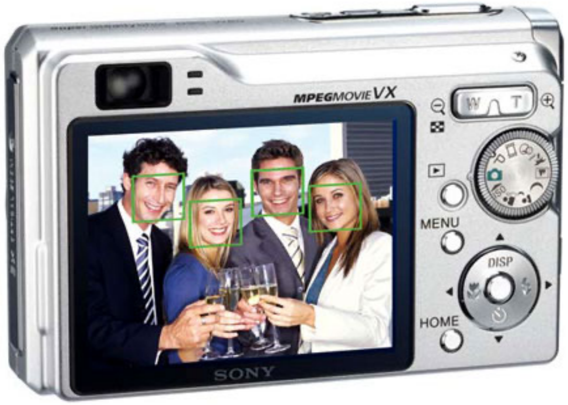
⑆111907445⑆ 72344999⑈ 0100

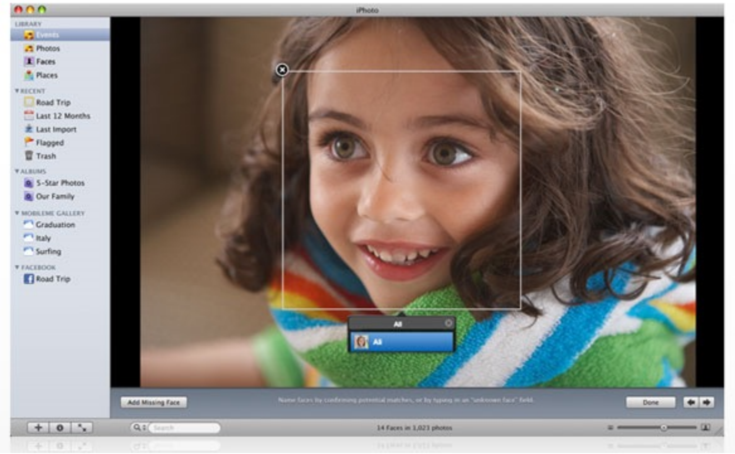
Batch No: 1001 Sequence No: 2

Routing No:	Check Account No:	Check No:	Check Amount:
111907445	72344999	100	653.10



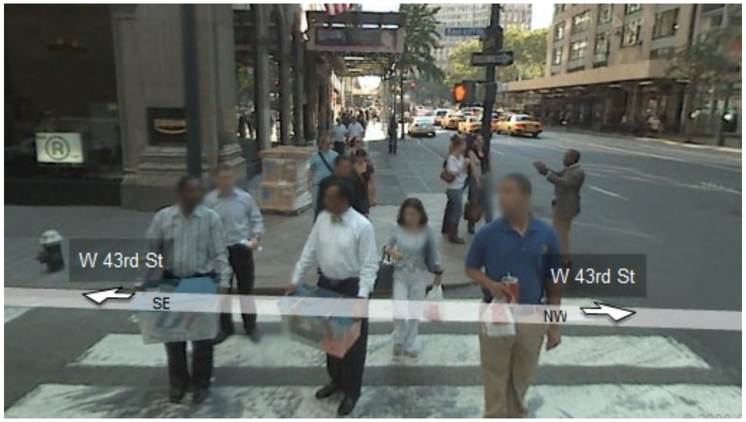
Recognition: Faces





Name faces by confirming potential matches, or by typing in an "unknown face" field.

14 Faces in 1,023 photos



Recognition: Faces

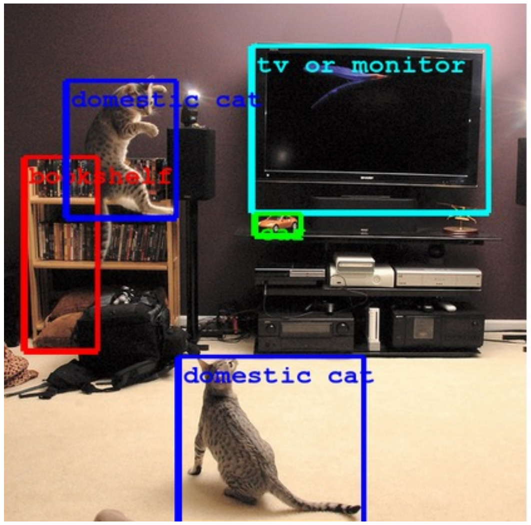
How China Uses High-Tech Surveillance to Subdue Minorities – New York Times, 5/22/2019

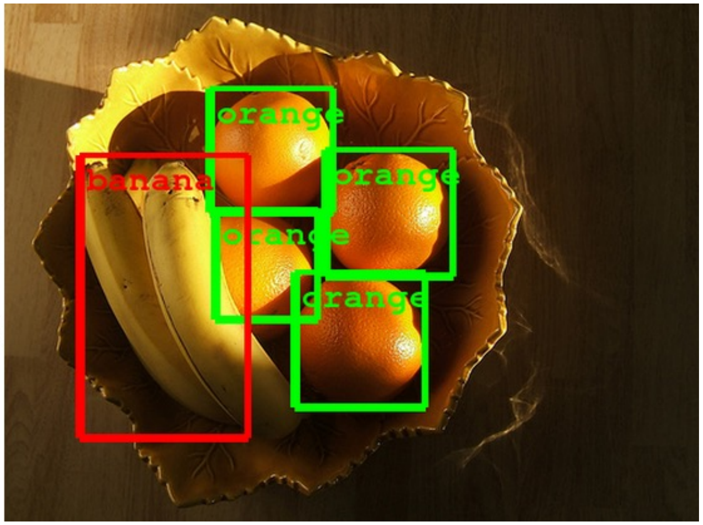
The Secretive Company That Might End Privacy As We Know It – New York Times, 1/18/2020

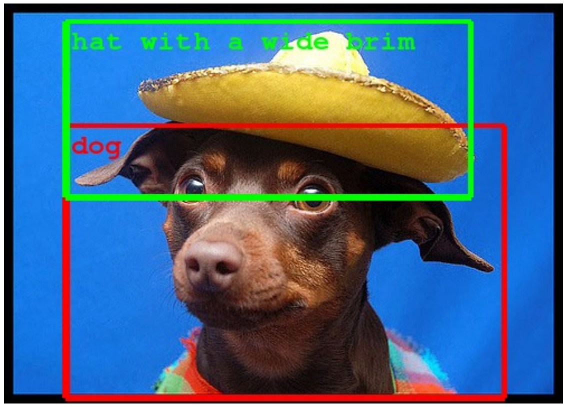
Wrongfully Accused by an Algorithm – New York Times, 6/24/2020

Facial Recognition Goes to War – New York Times, 4/7/2022

Recognition: General categories



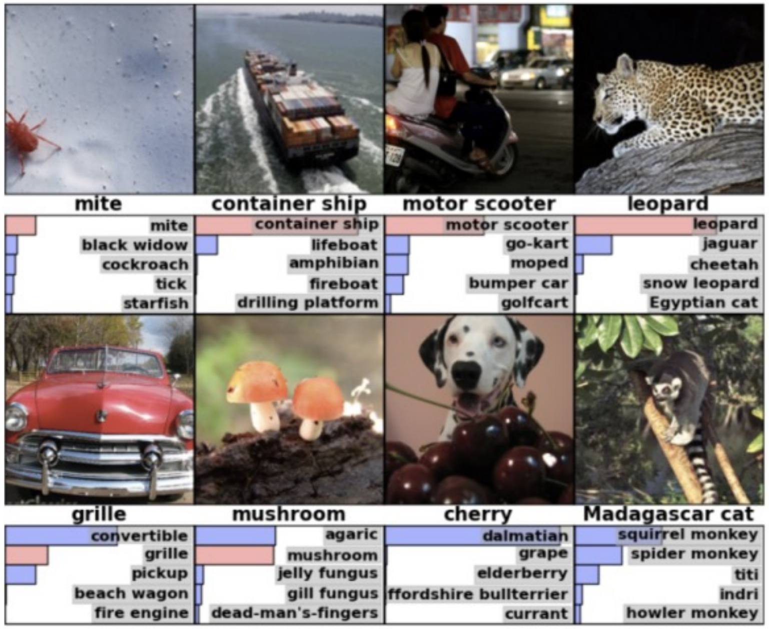




- Computer Eyesight Gets a Lot More Accurate, NY Times Bits blog, August 18, 2014
- Building A Deeper Understanding of Images, Google Research Blog, September 5, 2014

Recognition: General categories

ILSVRC



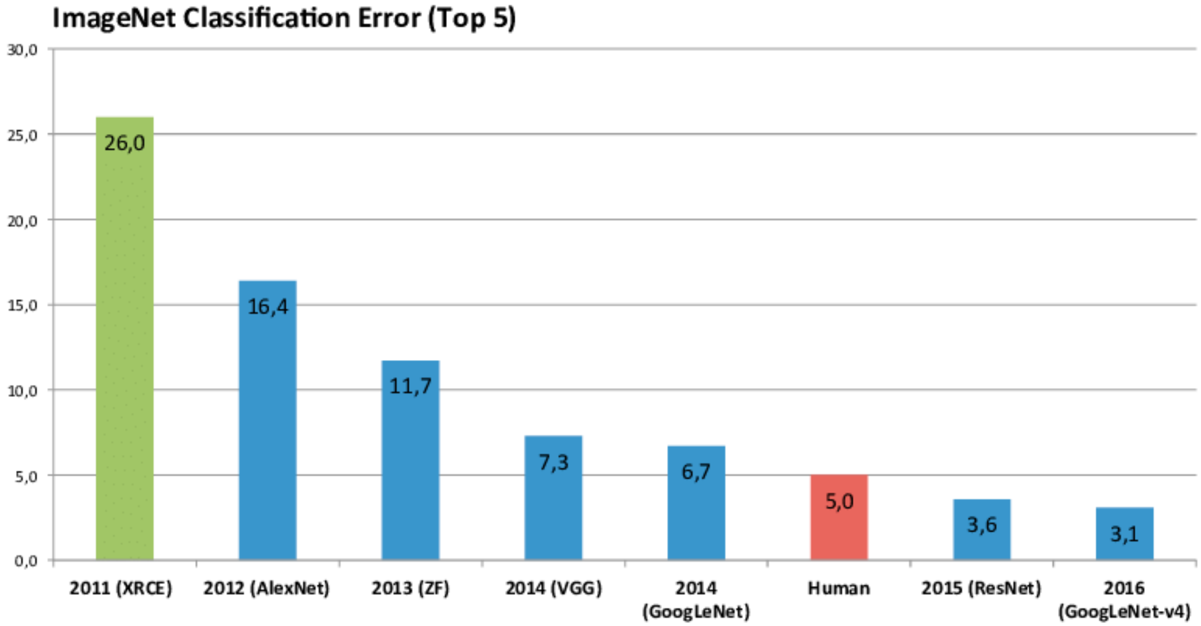
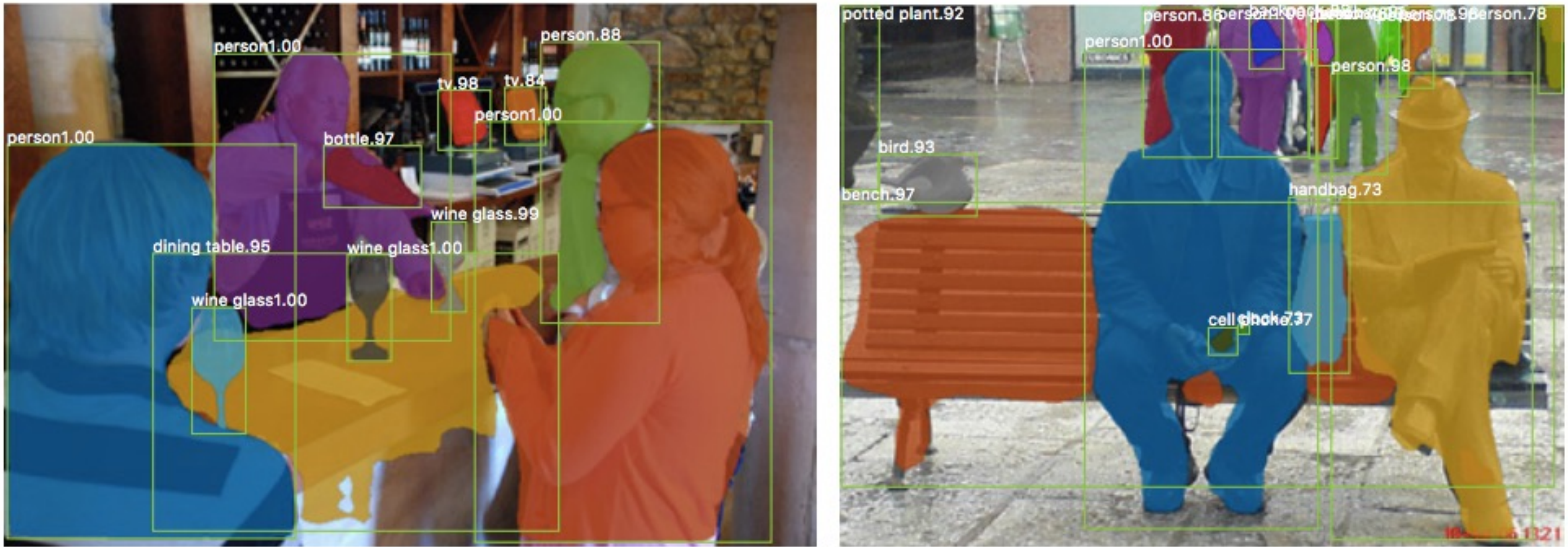


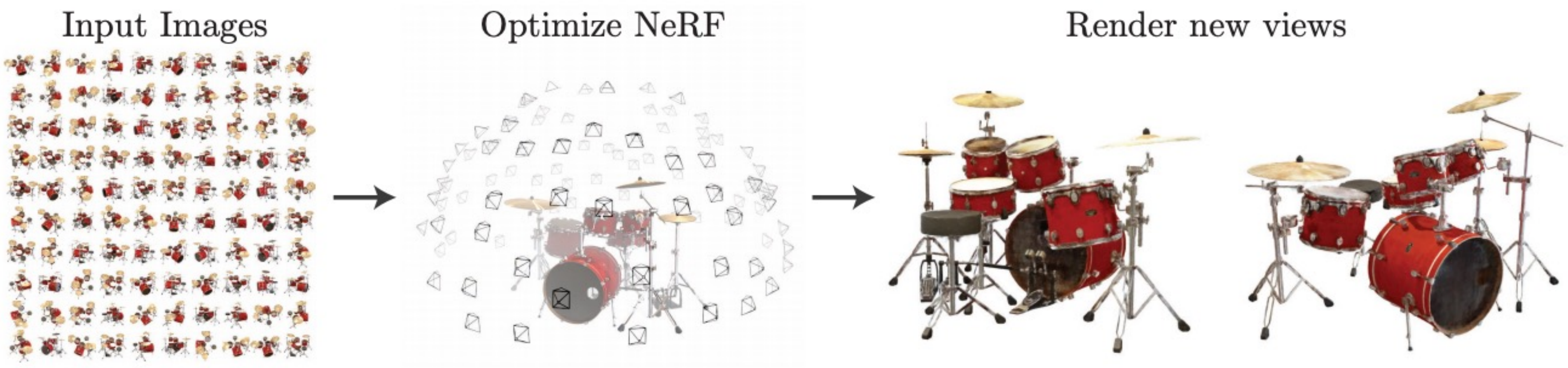
Figure source

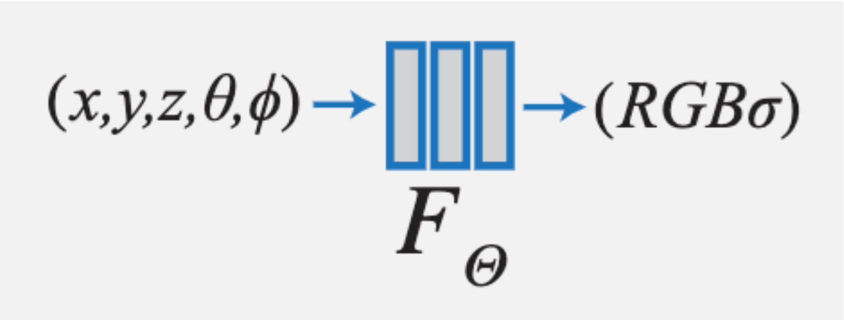
Object detection, instance segmentation



K. He, G. Gkioxari, P. Dollar, and R. Girshick, Mask R-CNN, ICCV 2017 (Best Paper Award)

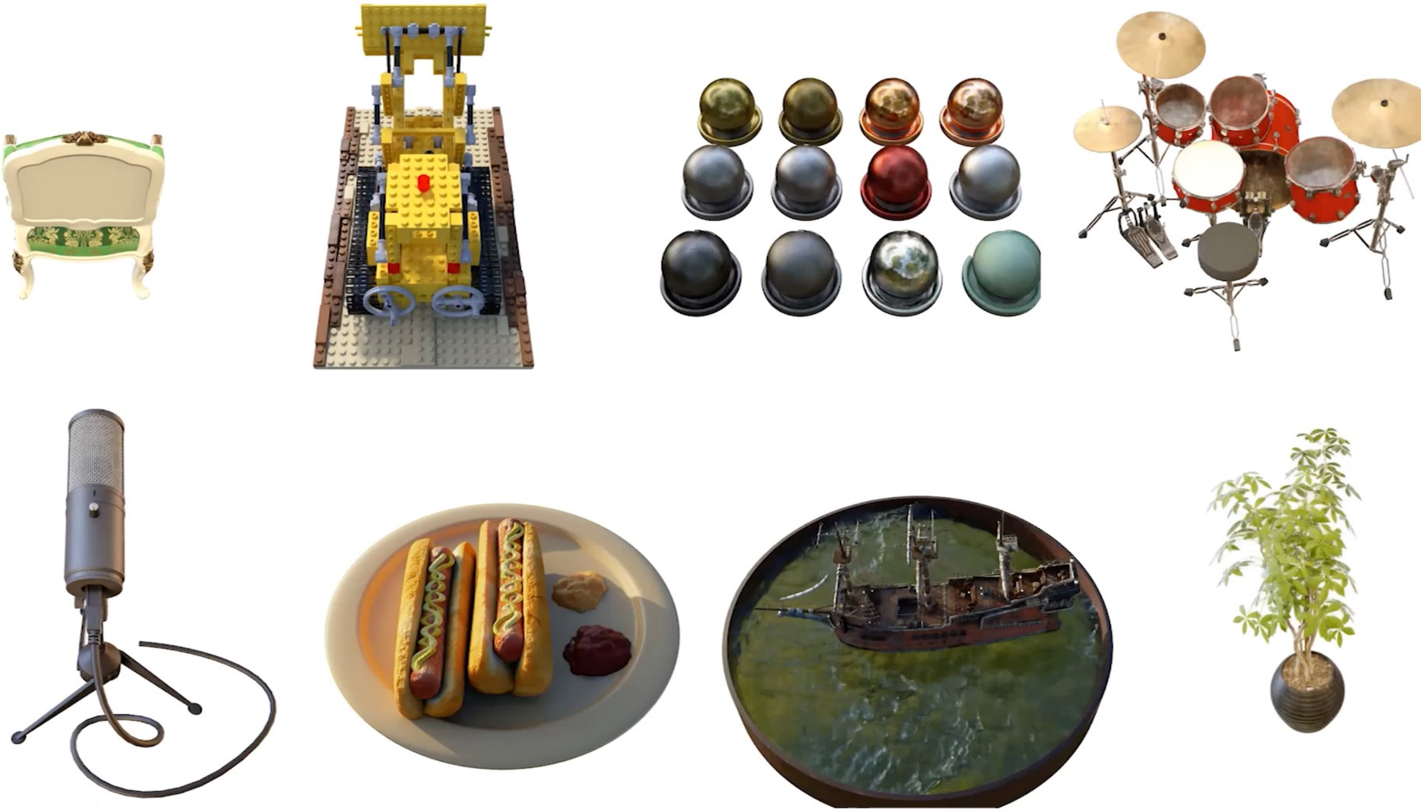
3D scene understanding: NERFs




$(x,y,z,\theta,\phi) \rightarrow F_{\Theta} \rightarrow (RGB\sigma)$

B. Mildenhall et al., Representing Scenes as Neural Radiance Fields for View Synthesis, ECCV 2020

3D scene understanding: NERFs



B. Mildenhall et al., Representing Scenes as Neural Radiance Fields for View Synthesis, ECCV 2020

3D scene understanding: Single-view reconstruction

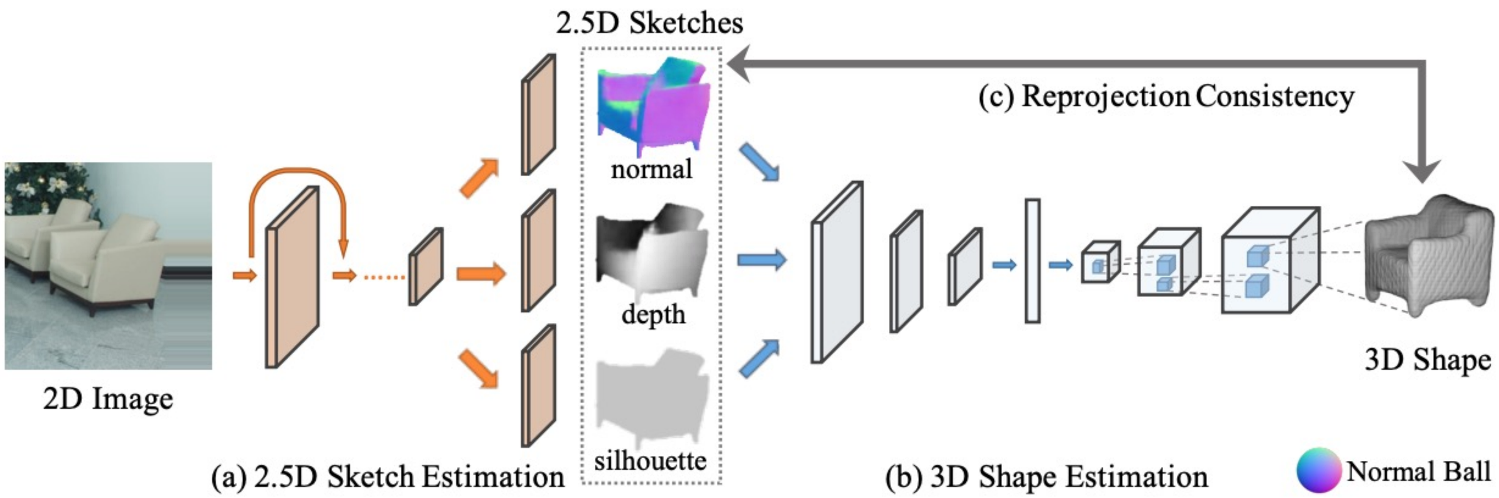
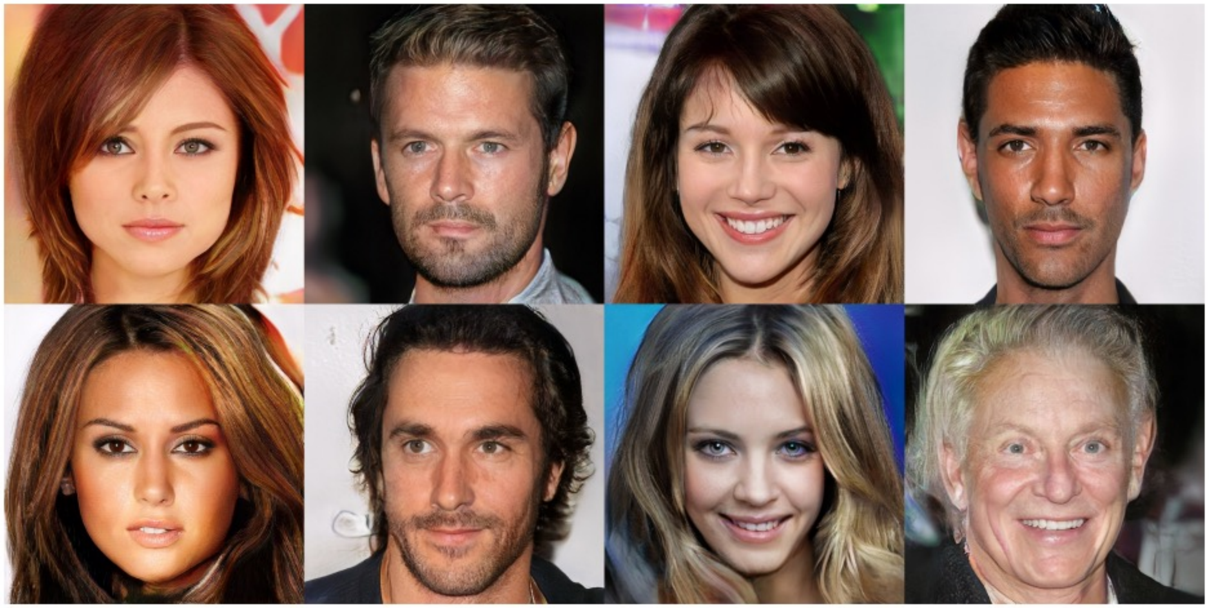


Figure 2: Our model (MarrNet) has three major components: (a) 2.5D sketch estimation, (b) 3D shape estimation, and (c) a loss function for reprojection consistency. MarrNet first recovers object normal, depth, and silhouette images from an RGB image. It then regresses the 3D shape from the 2.5D sketches. In both steps, it uses an encoding-decoding network. It finally employs a reprojection consistency loss to ensure the estimated 3D shape aligns with the 2.5D sketches. The entire framework can be trained end-to-end.

J. Wu, Y. Wang, T. Xue, X. Sun, W. Freeman, J. Tenenbaum, MarrNet: 3D Shape Reconstruction via 2.5D Sketches, NeurIPS 2017

Image generation: Faces

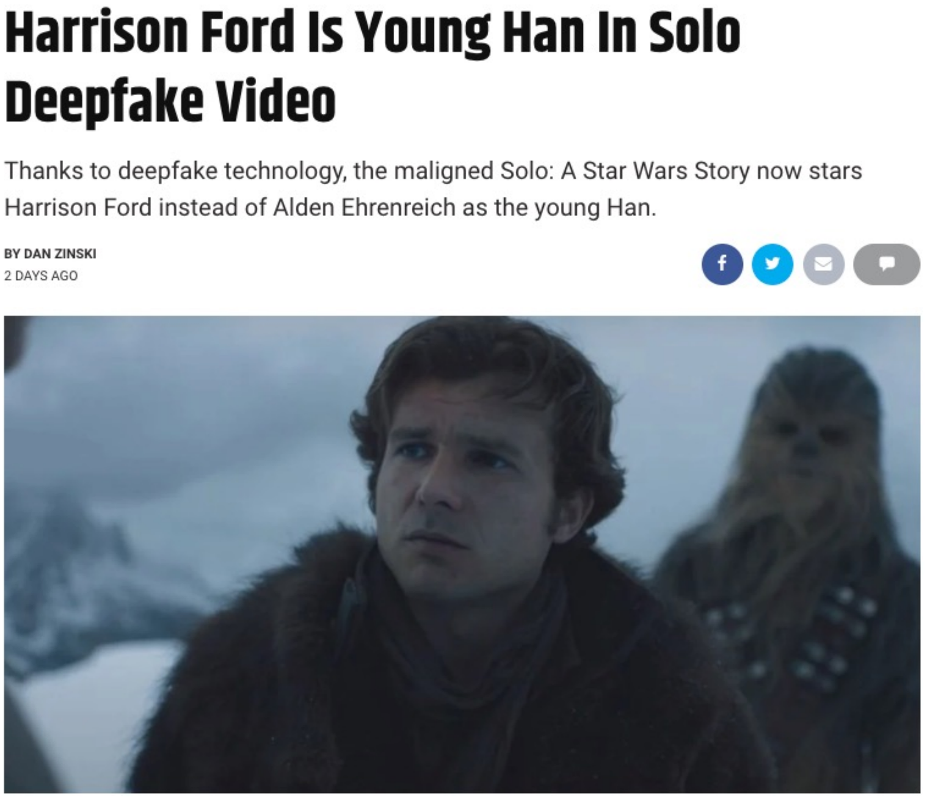
- 1024x1024 resolution, CelebA-HQ dataset



T. Karras, T. Aila, S. Laine, and J. Lehtinen, Progressive Growing of GANs for Improved Quality, Stability, and Variation, ICLR 2018

Follow-up work

Image generation: DeepFakes



Harrison Ford Is Young Han In Solo Deepfake Video

Thanks to deepfake technology, the maligned Solo: A Star Wars Story now stars Harrison Ford instead of Alden Ehrenreich as the young Han.

BY DAN ZINSKI
2 DAYS AGO

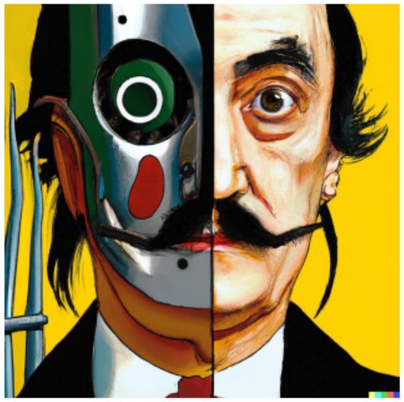
https://screenrant.com/star-wars-han-solo-movie-harrison-ford-video-deepfake/

https://www.youtube.com/watch?v=bC3uH4Xw4Xo

Just a random recent example…

https://en.wikipedia.org/wiki/Deepfake

Image generation: OpenAI DALL-E, DALL-E 2



vibrant portrait painting of Salvador Dalí with a robotic half face

a shiba inu wearing a beret and black turtleneck

a close up of a handpalm with leaves growing from it

an espresso machine that makes coffee from human souls, artstation

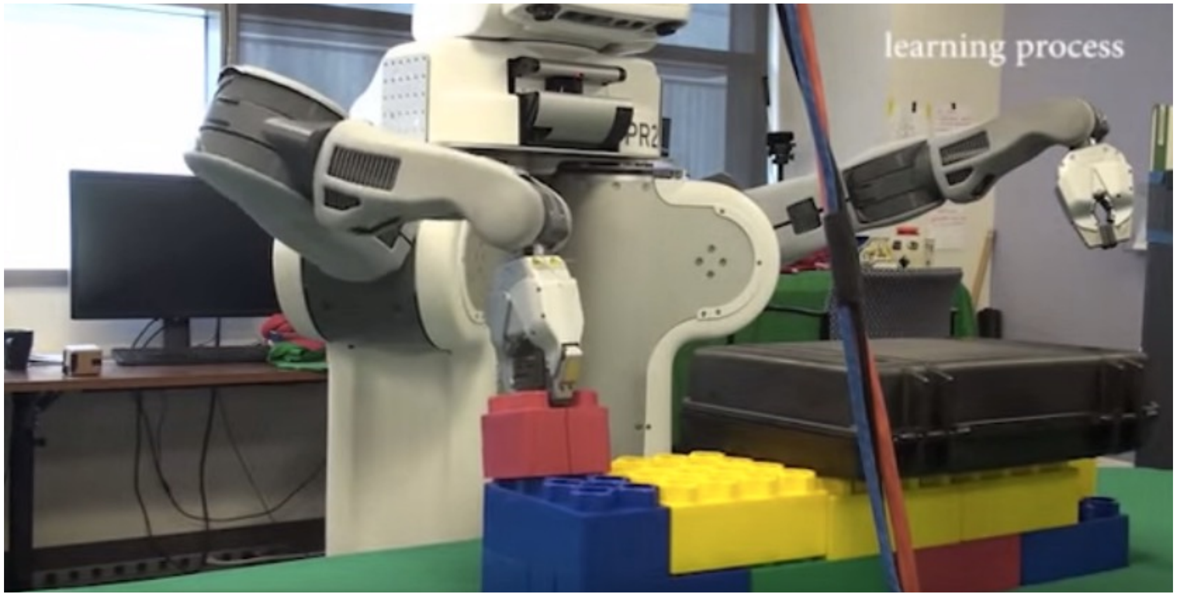
panda mad scientist mixing sparkling chemicals, artstation

a corgi's head depicted as an explosion of a nebula

A. Ramesh et al., Zero-Shot Text-to-Image Generation, ICML 2021. https://openai.com/blog/dall-e/

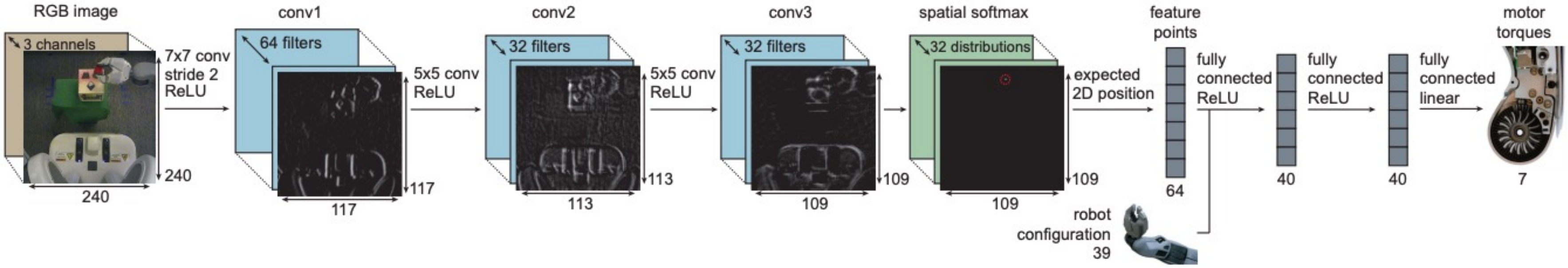
A. Ramesh et al., Hierarchical Text-Conditional Image Generation with CLIP Latents, arXiv 2022. https://openai.com/dall-e-2/

Vision for action: Visuomotor learning



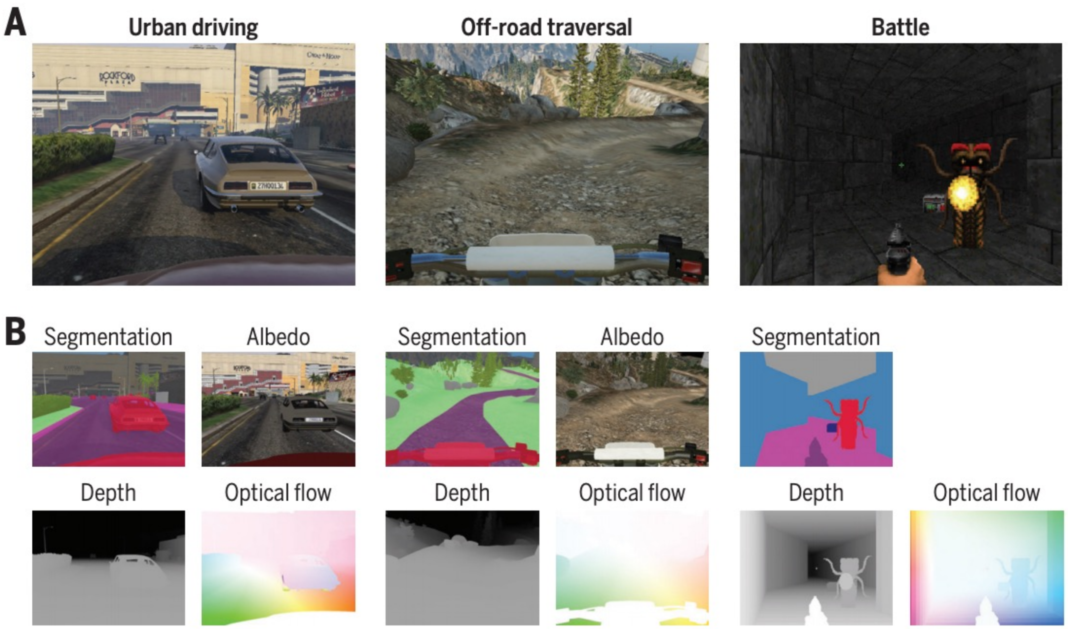
Overview video,

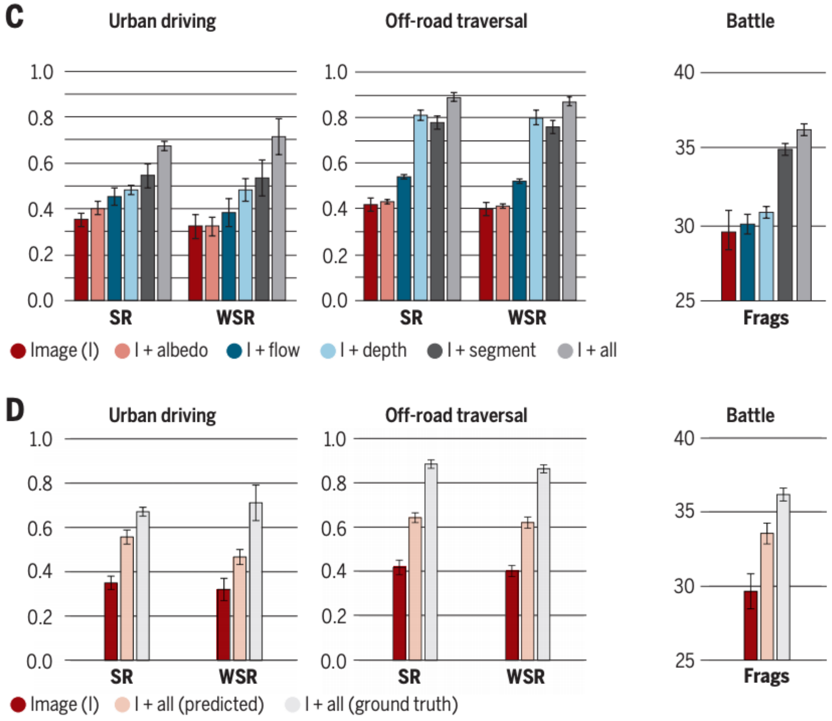
training video



S. Levine, C. Finn, T. Darrell, P. Abbeel, End-to-end training of deep visuomotor policies, JMLR 2016

Does computer vision matter for action?





> “Our main finding is that computer vision does matter. Models equipped with intermediate representations train faster, achieve higher task performance, and generalize better to previously unseen environments.”

B. Zhou, P. Krähenbühl, and V. Koltun, Does Computer Vision Matter for Action? Science Robotics, 4(30), 2019 (video)

Vision for action: Learning skills from video

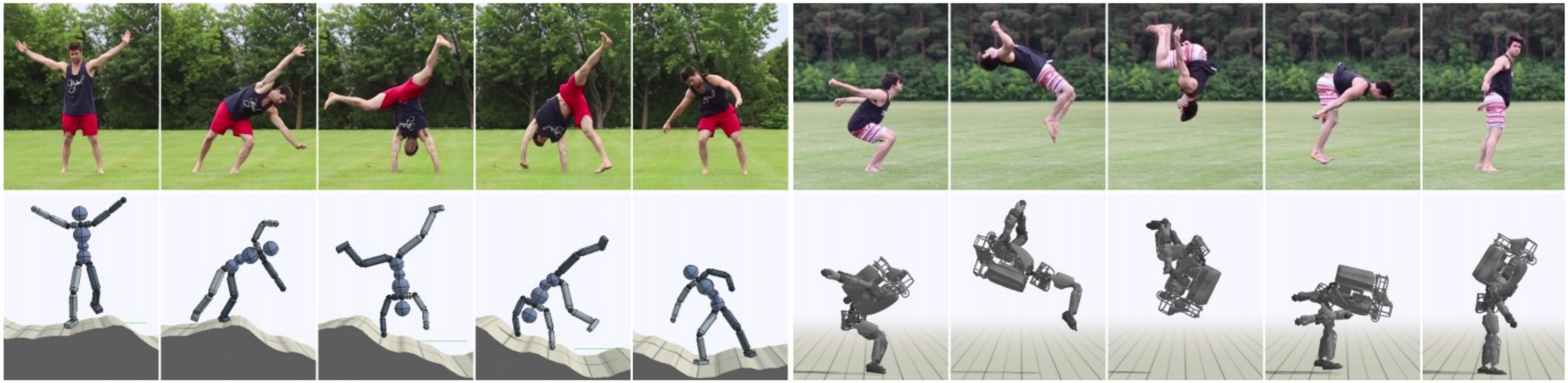


Fig. 1. Simulated characters performing highly dynamic skills learned by imitating video clips of human demonstrations. **Left:** Humanoid performing cartwheel B on irregular terrain. **Right:** Backflip A retargeted to a simulated Atlas robot.

Video

X. B. Peng, A. Kanazawa, J. Malik, P. Abbeel, S. Levine, SFV: Reinforcement Learning of Physical Skills from Videos,
SIGGRAPH Asia 2018

Outline

- Logistics, requirements
- Goal of computer vision and why it is hard
- History of computer vision
- Current state of the art
- Topics covered in class

Topics covered in class

I. Elementary Image Representations:

Point transformations, geometric transformations, filters, denoising, edges, interest points

II. Mid-level vision:

Voting, Fitting, Registration

III. Learned Image Representations:

Learned denoising, Mapping images to images, Classification, Detection

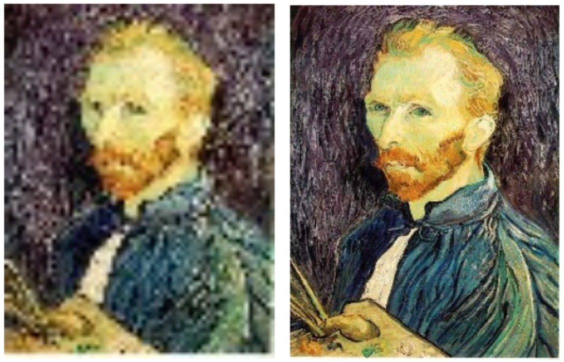
IV. Image formation and geometric vision

Cameras, Light, Color, Calibration

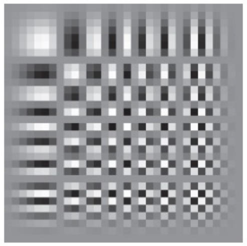
V. Pairs of Cameras and more:

Geometry, Odometry, Optic Flow, Stereopsis, Structure from Motion, Tracking

Elementary image representations

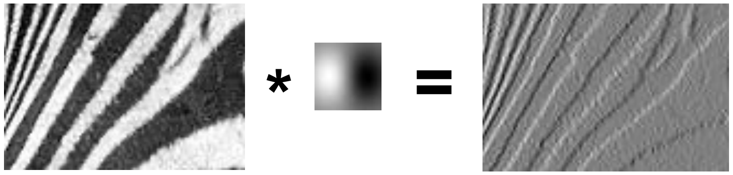


Basic image processing

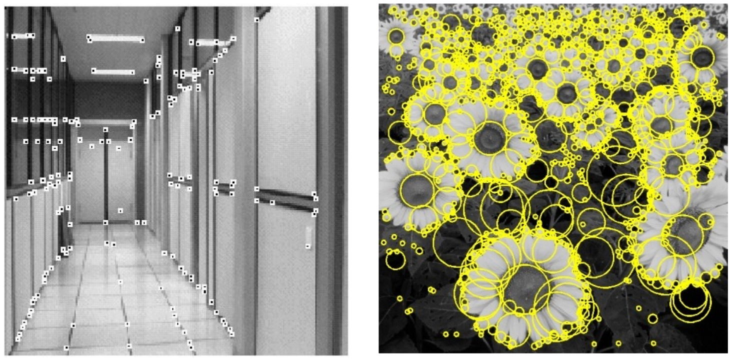


Upsampling and downsampling

downsampled by 8

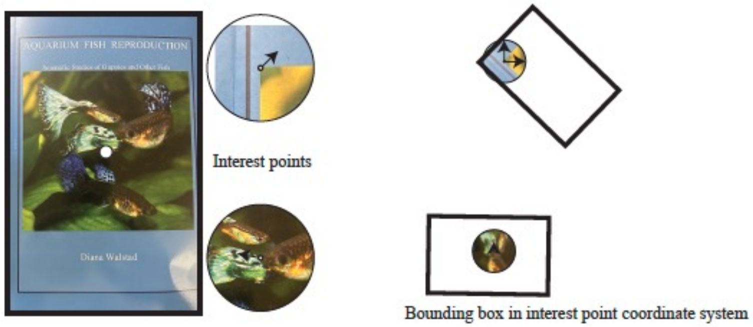


Linear filtering
Edge detection

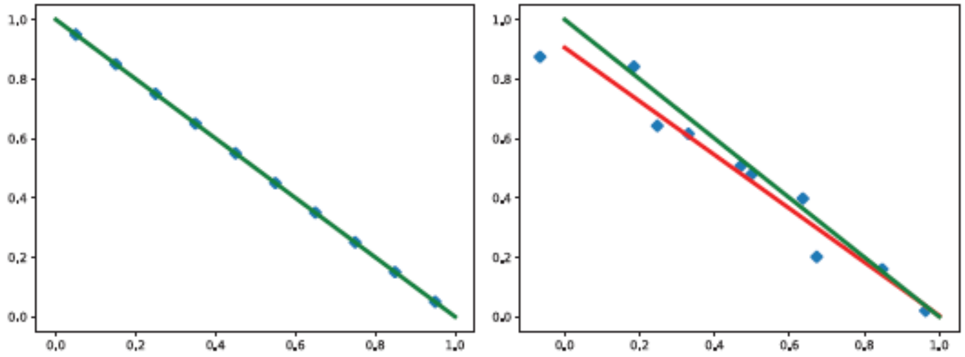


Feature extraction

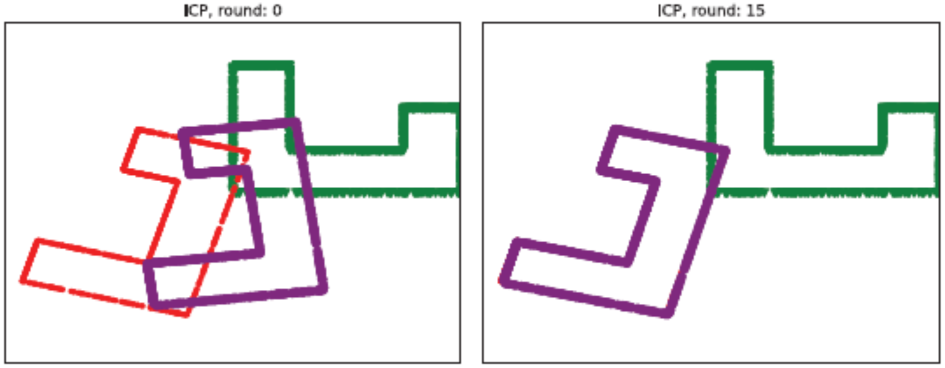
Mid-level Vision


AQUARIUM FISH REPRODUCTION
Diana Walstad
Interest points
Bounding box in interest point coordinate system

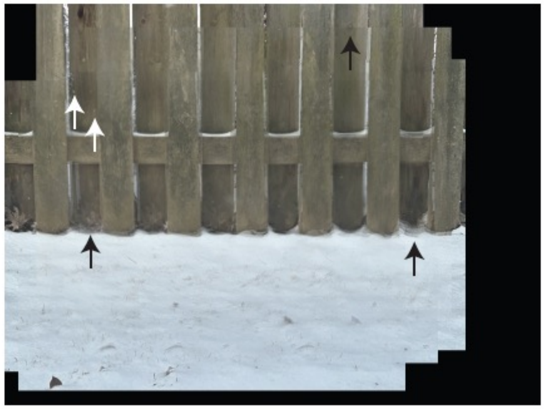
Voting



Fitting

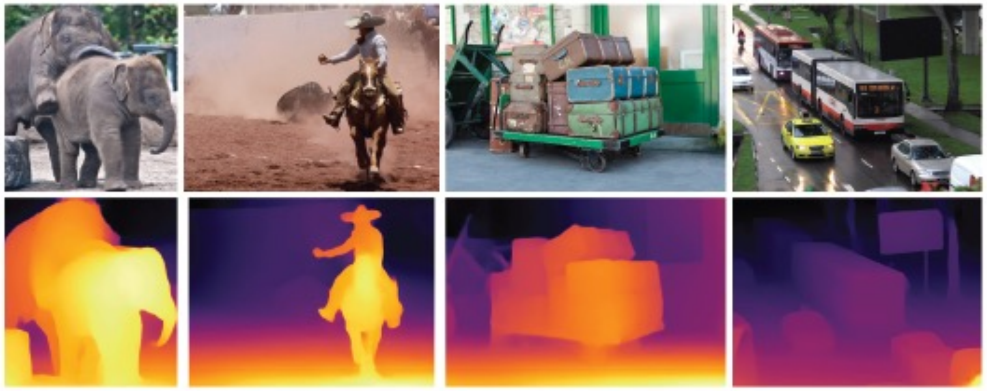


Registration



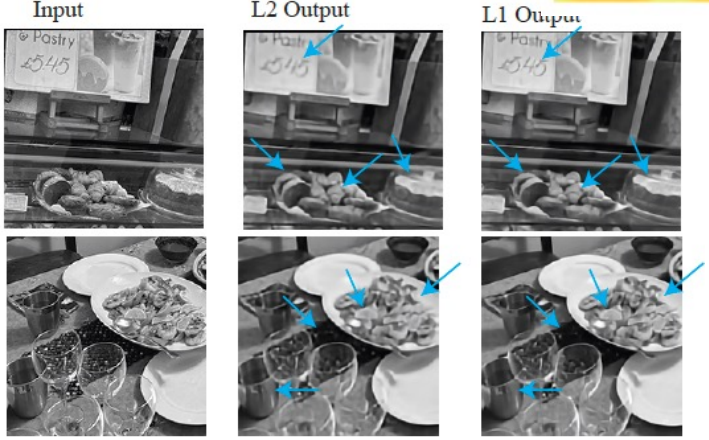
Mosaics

Learned Image Representations

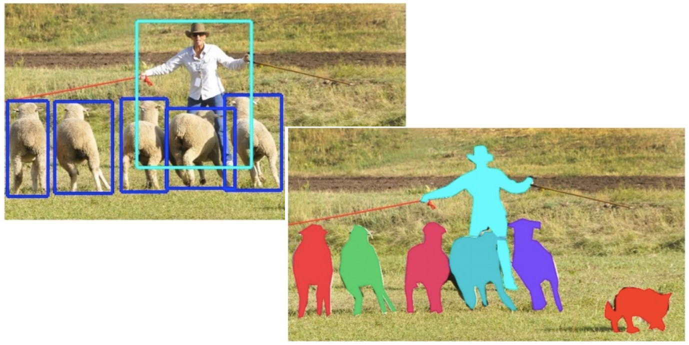


Depth, normal, etc

From images

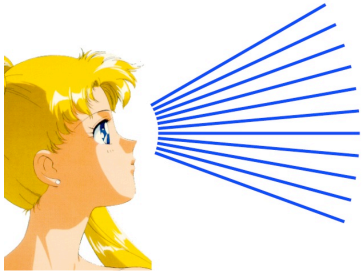


Learned denoising

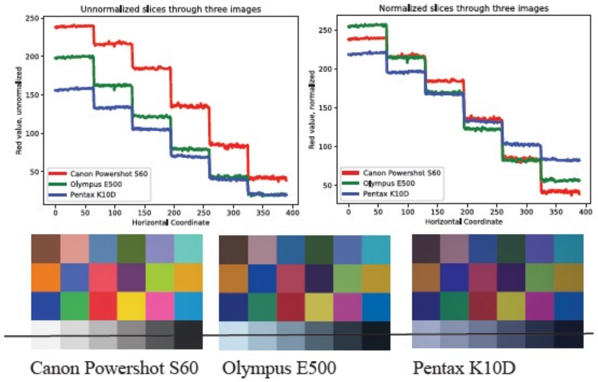


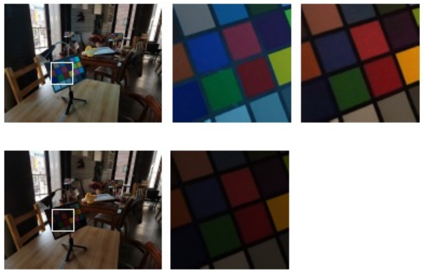
Object detection and segmentation

IV. Image formation and geometric vision

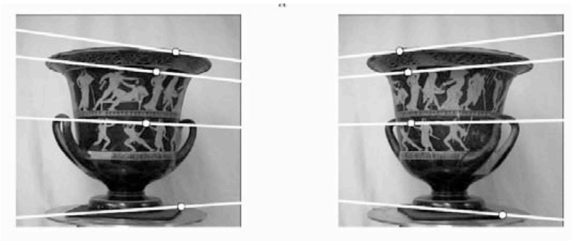


Cameras and sensors

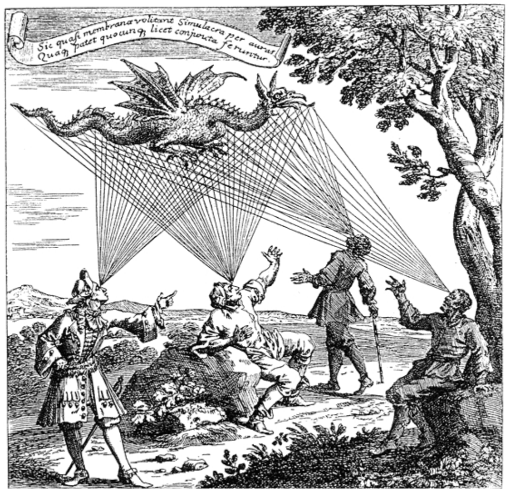




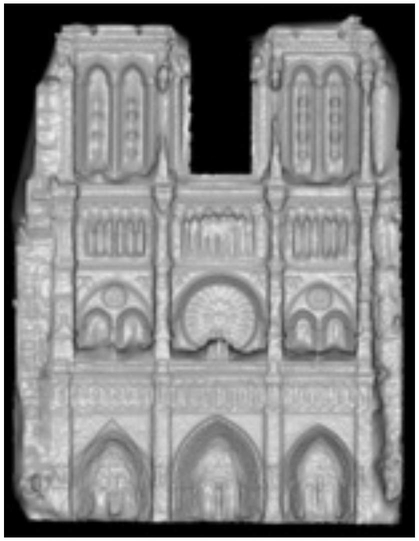
V. Pairs of cameras and more



Two-view geometry, stereo


Sic quaſi membrana volitant Simulacra per auras
Quaq patet quocunq licet conjuncta feruntur.

Structure from motion



Multi-view stereo