BLG453E COMPUTER VISION

Fall 2021

Istanbul Technical University
Computer Engineering Department

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Computer vision: a scientific discipline that studies how computers can efficiently perceive, process, and understand visual data such as images and video

or Building artificial systems that process, perceive and reason about visual data

1

Implications on Industry

John Deere is buying an AI startup to help teach its tractors how to farm

Blue River Technology builds tools to help crop sprayers identify weeds and blast them with pesticide

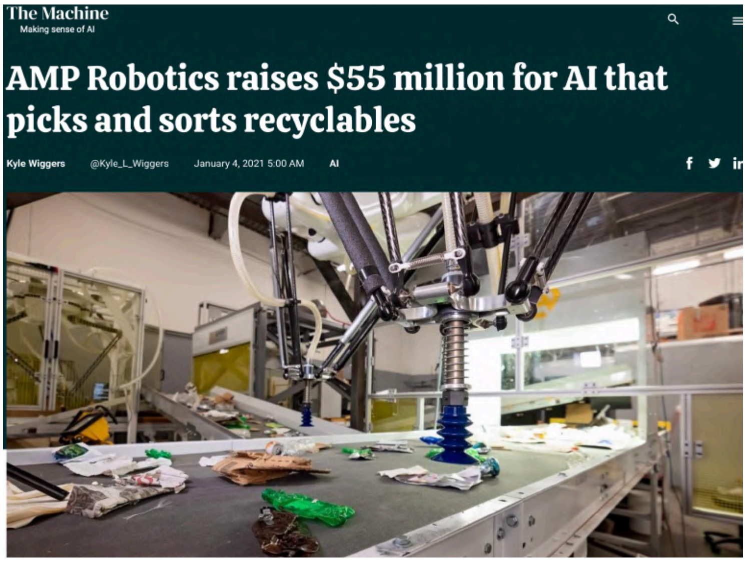
By James Vincent | Sep 7, 2017, 12:52pm EDT

Blue River Technology's "see and spray" tech at work on a crop sprayer. | Image: Blue River Technology

2

Implications on Industry

https://venturebeat.com/wp-content/uploads/2019/11/ezgif-6-bd22dd7a6723.gif?resize=600%2C338&strip=all



https://venturebeat.com/2021/01/04/amp-robotics-raises-55-million-for-ai-that-picks-and-sorts-recyclables/

3

Implications on Industry

TECH

Snap looks to enhance augmented reality features with acquisition of British research lab Ariel AI

PUBLISHED TUE, JAN 26 2021-12:39 PM EST | UPDATED TUE, JAN 26 2021-12:48 PM EST

Sam Shead
@SAM_L_SHEAD

SHARE

KEY POINTS
- Snap, the parent company of social media app Snapchat, has acquired a British artificial intelligence start-up called Ariel AI which focuses on augmented reality.

3D human perception" in real time

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

Dense Pose: dense correspondences from a 2D image to a 3D, surface-based representation of the human body.

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Computer Vision is everywhere !

http://www.bostondynamics.com/atlas
Min: 1:10

The amount of visual data online is way above our human capacity to be able to process them in a reasonable amount of time. These numbers are from last year : 2019-20: There are about about a million photos uploaded to Instagram and Facebook every minutes. Similarly 300 hours of video are uploaded to YouTube every minute!

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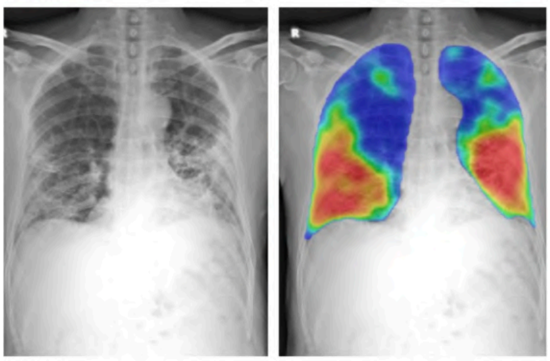
Machine Vision

Free AI-software for Covid-19 triage on chest x-rays

30 March 2020

ARNOUD CORNELISSEN



© Delft Imaging

https://innovationorigins.com/en/free-ai-software-for-covid-19-triage-on-chest-x-rays/

Self-driving cars:

https://www.tesla.com/en_EU/videos/autopilot-self-driving-hardware-neighborhood-long?redirect=no

https://www.google.com/selfdrivingcar/how/

https://www.youtube.com/watch?v=BNHJRRUKMa4&t=257s

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A few more examples…

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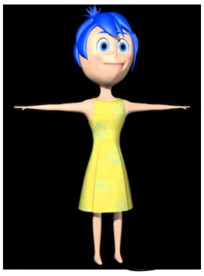

Image Formation: how objects give rise to images

Computer Graphics

Image Processing

Image

Object, Scene Model and Description

Computer Vision, Image Analysis, Pattern Recognition, Machine Learning

Computer Vision: Inverse problem of image formation; uses images to recover a description of objects in space

Ill-posed since we lose 1 dim from 3D world to 2D images

Joy:
- has blue hair
- wears a yellow dress
- has her arms up in a T shape
- is smiling
- is happy,.....

Designing vision algorithms: requires appropriate modeling of relevant information in images

Appropriate models: manageable; trade-off between physical complexity - constraints and mathematical simplicity while keeping fidelity to the existing visual information

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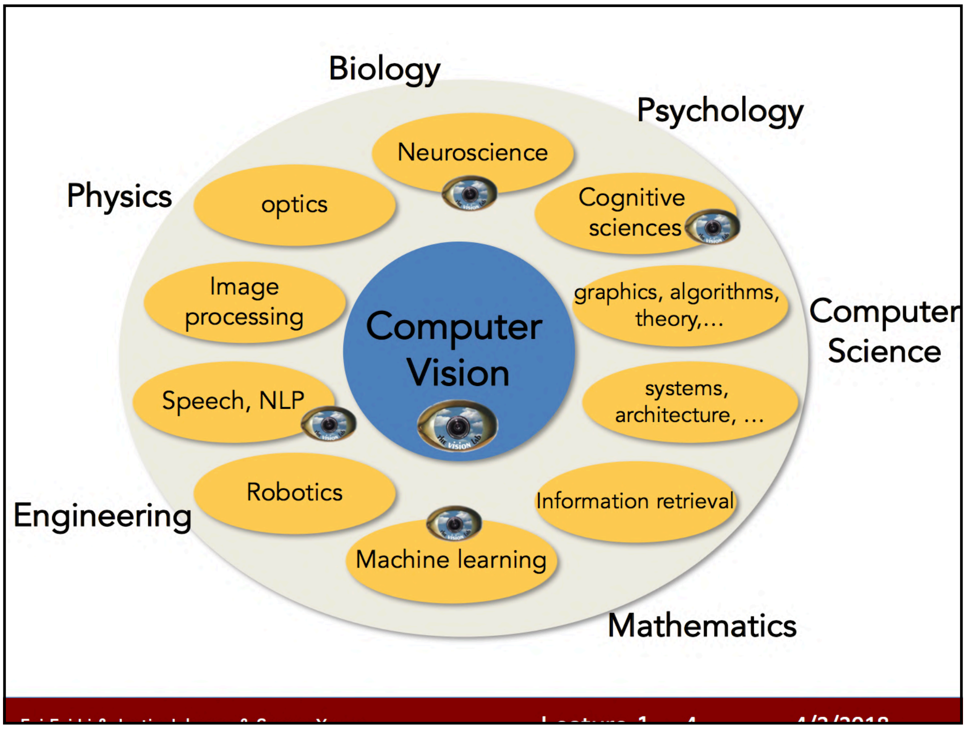

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AI, Machine Vision and Machine Learning

- Machine learning: current core technology of artificial intelligence (AI) that provides computer systems with the ability to learn from data and experience, adapt themselves to the data/ new conditions
- Recently: Machine Learning has become a crucial component of Computer (Machine) Vision algorithms
- Particularly learning is important to build generalizable systems
- Supervised
- Unsupervised
- Reinforcement learning

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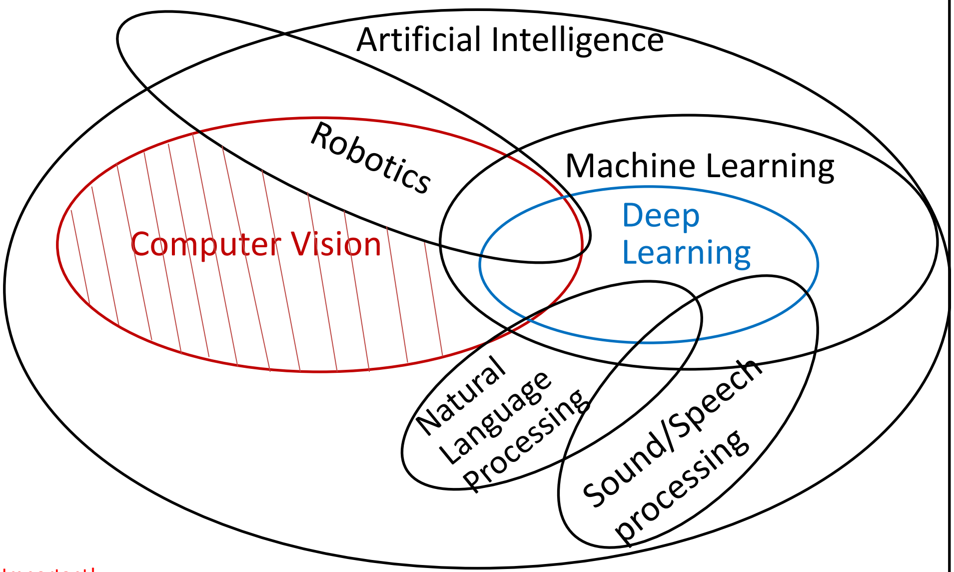

Important!
We focus on the shaded area in this course

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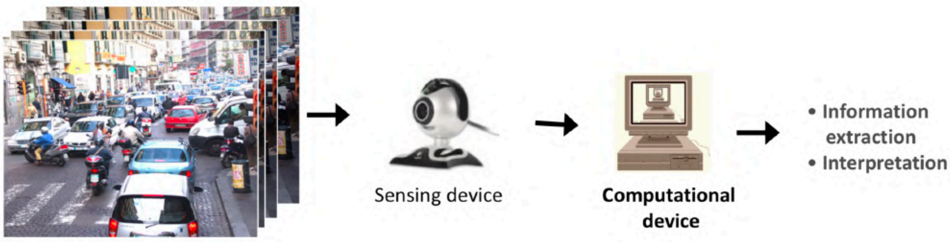
Computer Vision



1. **Information extraction:** features, 3D structure, motion flows, etc…
2. **Interpretation:** recognize objects, scenes, actions, events

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How difficult is it?

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What do you see?

Visual Perception: the whole differs from the sum of its parts

- Perception is not only built up from sensations but is a result of perceptual organization

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Visual perception refers to the way in which the brain interprets and processes visual information

How do our brains do it?

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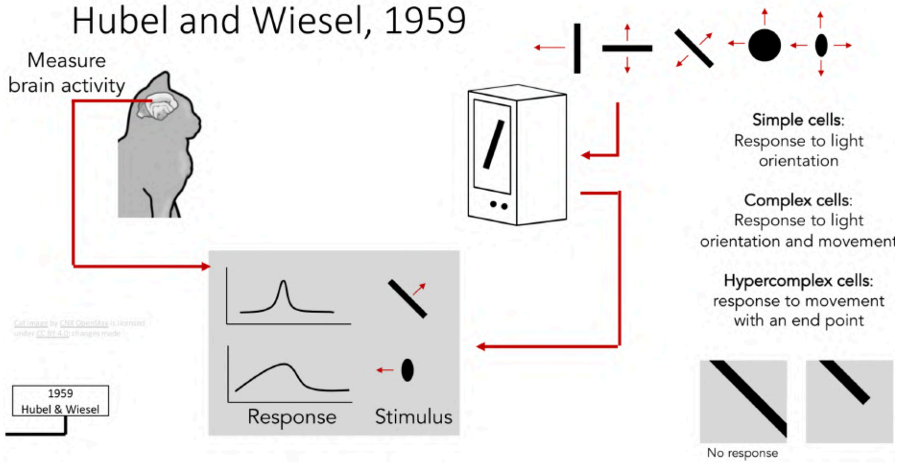
Hubel and Wiesel, 1959



Low-level processing in the visual cortex starts with sensitivity to EDGES

Vision starts with simple structure processing, such as edges, lines etc/low level. It does not start with holistic object like flower, fish, etc.

Hubel and Wiesel (1959): The Nobel Prize in Physiology or Medicine 1981 *for their discoveries concerning information processing in the visual system”*

J. Johnson, Umich

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Vision ... with holistic object like flower, fish, etc.

cortex

Hubel and Wiesel (1959): The Nobel Prize in Physiology or Medicine 1981 *for their discoveries concerning information processing in the visual system"*

J. Johnson, Umich

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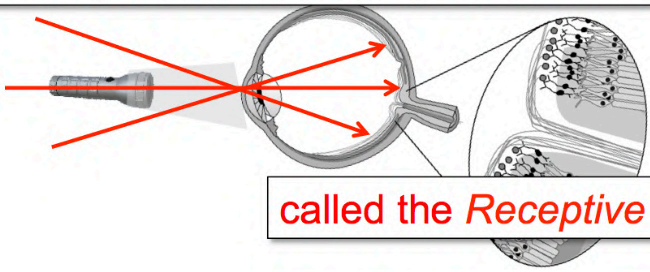
Vision: Image Formation in your Brain

Each photoreceptor only "sees" one place



called the *Receptive Field*

The receptive field of a photoreceptor is a region of the visual field to which the photoreceptor is sensitive.

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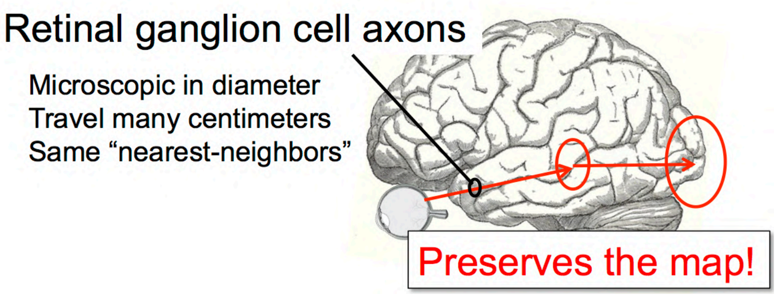
Vision: Image Formation in your Brain



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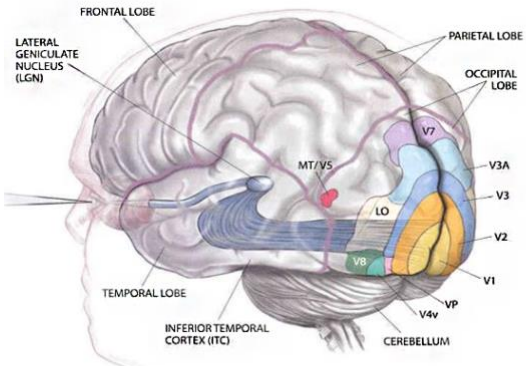
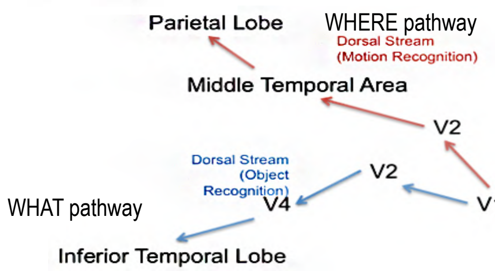
Human visual cortex



Hierarchical processing in the brain

VI	Edges
V2	Surfaces
V4	Color
MT	Motion
IT	Object Recognition



X

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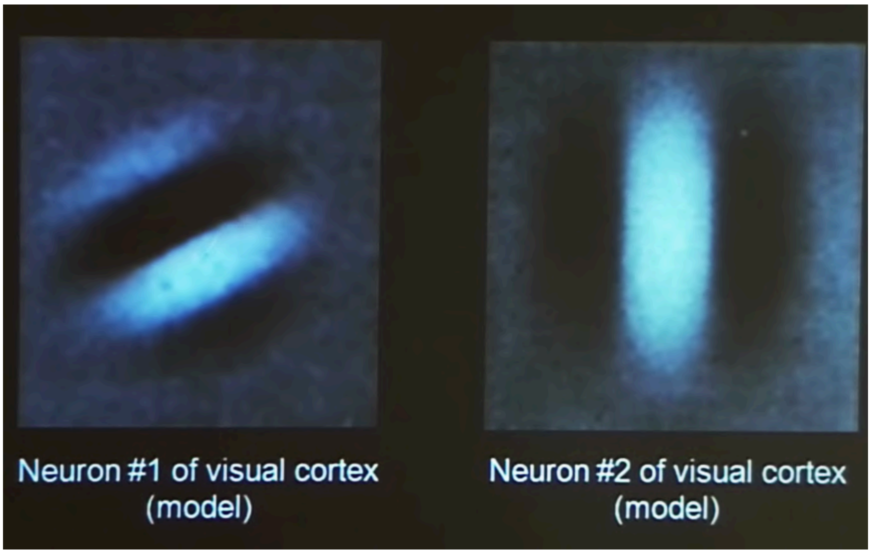
V1 Neurons



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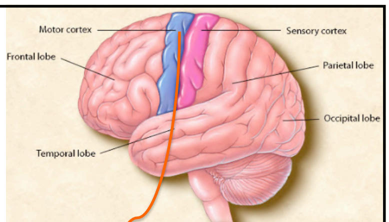
Visual Circuits in our brain? Mapping Brain Circuits

The details of our body map were studied in detail by a Canadian neurosurgeon Wilder Penfield in 1930-40s (Nobel prize recipient)

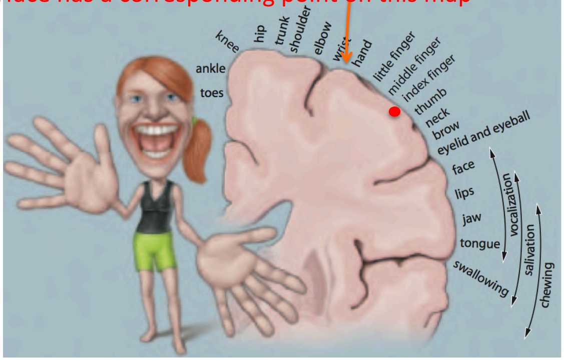
Below is a drawing of the body part and the corresponding location in the brain cortex: e.g. if you stimulate the red point, the patient feels a sensation in the index finger



About half of the entire cerebral cortex in primates is devoted to processing of visual information!

Every point on your body surface has a corresponding point on this map

e.g. professional guitar players or violinists ?



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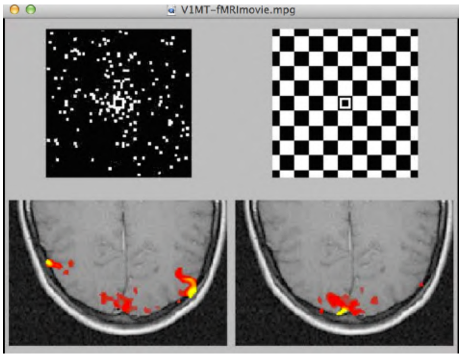
Mapping the Brain: Imaging Studies

About half of the entire cerebral cortex in primates is devoted to processing of visual information!

Vision is hiearchical

Magnetic Resonance Imaging (MRI)

Functional MRI



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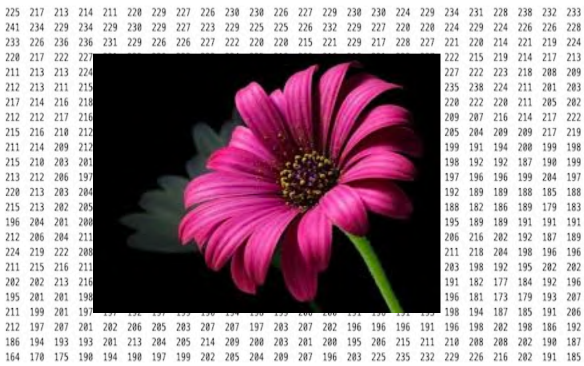
How can we interpret these pixel values?



to tell whether we are looking at

- an apple
- or an house
- or a flower ?

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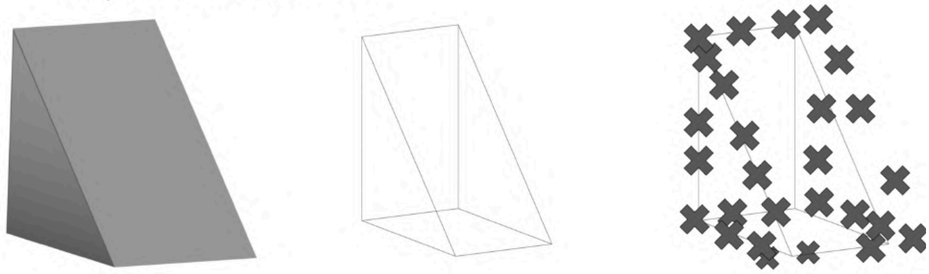
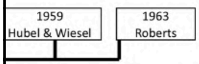
Larry Roberts, 1963



(a) Original picture (b) Differentiated picture (c) Feature points selected



MACHINE PERCEPTION OF THREE-DIMENSIONAL SOLIDS

by

LAWRENCE GILMAN ROBERTS

SUBMITTED IN PARTIAL FULFILLMENT OF THE
REQUIREMENTS FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY
June, 1963

J. Johnson, Umich

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The Summer Vision Project

Download

Author: Papert, Seymour A.

Citable URI: http://hdl.handle.net/1721.1/6125
Date Issued: 1966-07-01
Abstract:
The summer vision project is an attempt to use our summer workers effectively in the construction of a significant part of a visual system. The particular task was chosen partly because it can be segmented into sub-problems which allow individuals to work independently and yet participate in the construction of a system complex enough to be real landmark in the development of "pattern recognition". The basic structure is fixed for the first phase of work extending to some point in July. Everyone is invited to contribute to the discussion of the second phase. Sussman is coordinator of "Vision Project" meetings and should be consulted by anyone who wishes to participate. The primary goal of the project is to construct a system of programs which will divide a vidisector picture into regions such as likely objects, likely background areas and chaos. We shall call this part of its operation FIGURE-GROUND analysis. It will be impossible to do this without considerable analysis of shape and surface properties, so FIGURE-GROUND analysis is really inseparable in practice from the second goal which is REGION DESCRIPTION. The final goal is OBJECT IDENTIFICATION which will actually name objects by matching them with a vocabulary of known objects.
URI: http://hdl.handle.net/1721.1/6125

Summer Vision Project at MIT (1966)
https://dspace.mit.edu/handle/1721.1/6125

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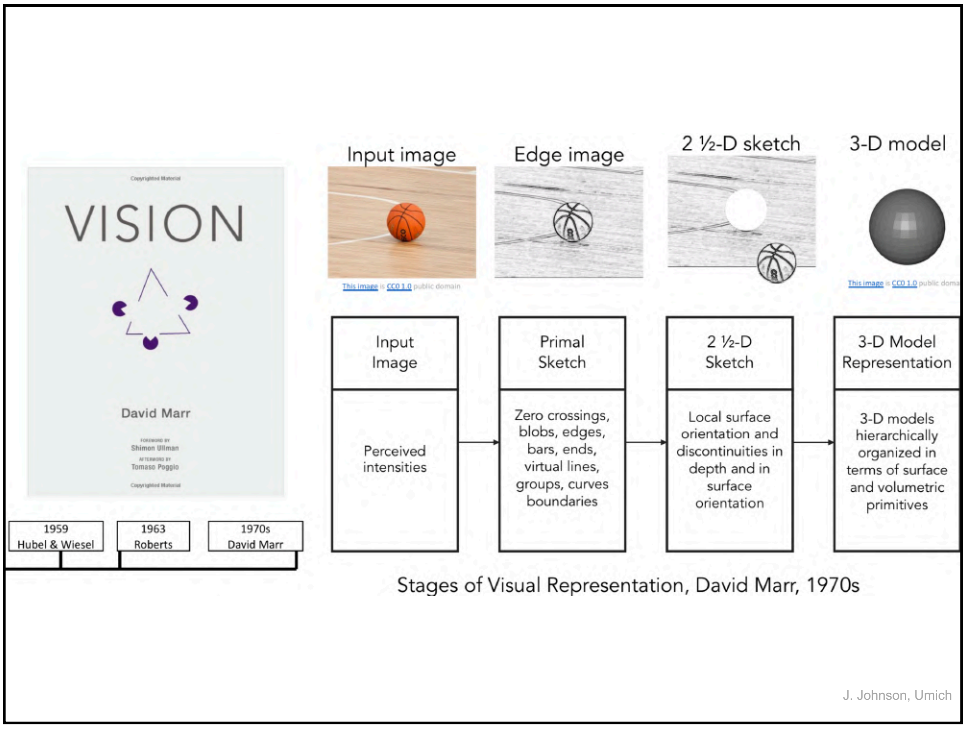
VISION
David Marr
1959
Hubel & Wiesel
1963
Roberts
1970s
David Marr
Input image
Edge image
2 ½-D sketch
3-D model
Input Image
Perceived intensities
Primal Sketch
Zero crossings, blobs, edges, bars, ends, virtual lines, groups, curves boundaries
2 ½-D Sketch
Local surface orientation and discontinuities in depth and in surface orientation
3-D Model Representation
3-D models hierarchically organized in terms of surface and volumetric primitives
Stages of Visual Representation, David Marr, 1970s
J. Johnson, Umich

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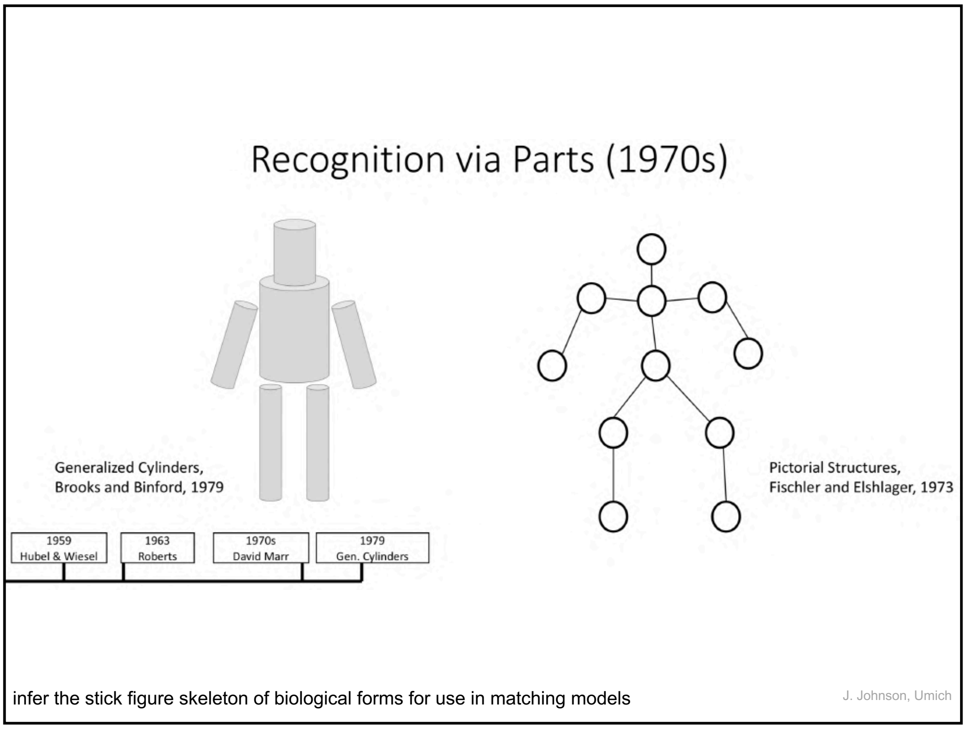
Recognition via Parts (1970s)
Generalized Cylinders, Brooks and Binford, 1979
Pictorial Structures, Fischler and Elshlager, 1973
1959
Hubel & Wiesel
1963
Roberts
1970s
David Marr
1979
Gen. Cylinders
infer the stick figure skeleton of biological forms for use in matching models
J. Johnson, Umich

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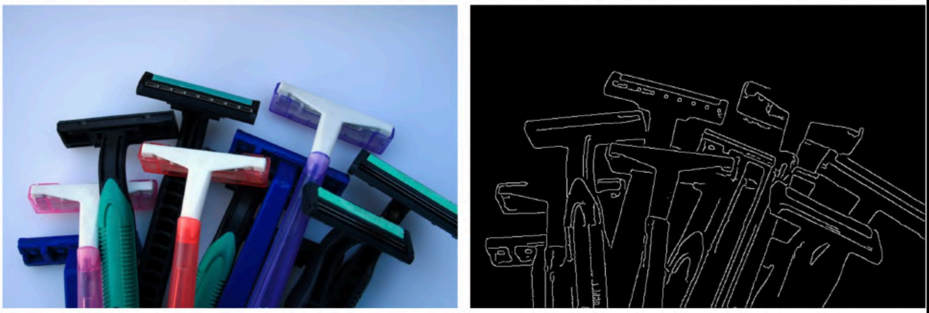
Recognition via Edge Detection (1980s)



1959 Hubel & Wiesel | 1963 Roberts | 1970s David Marr | 1979 Gen. Cylinders | 1986 Canny

John Canny, 1986
David Lowe, 1987

Three-Dimensional Object Recognition from Single Two-Dimensional Images, David Lowe 1987

Sobel Edge Detector:
Irwin Sobel, 1968

J. Johnson, Umich

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Recognition via Grouping (1990s)

1959 Hubel & Wiesel | 1963 Roberts | 1970s David Marr | 1979 Gen. Cylinders | 1986 Canny | 1997 Norm. Cuts

AI Winter

Normalized Cuts, Shi and Malik, 1997

J. Johnson, Umich

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Recognition via Matching (2000s)

Distinctive invariant feature keypoints

Image is public domain

Image is public domain

1959 Hubel & Wiesel | 1963 Roberts | 1970s David Marr | 1979 Gen. Cylinders | 1986 Canny | 1997 Norm. Cuts | 1999 SIFT

AI Winter

SIFT, David Lowe, 1999

J. Johnson, Umich

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Face Detection

Viola and Jones, 2001

One of the first successful applications of machine learning to vision

1959 Hubel & Wiesel | 1963 Roberts | 1970s David Marr | 1979 Gen. Cylinders | 1986 Canny | 1997 Norm. Cuts | 1999 SIFT | 2001 V&J

AI Winter

J. Johnson, Umich

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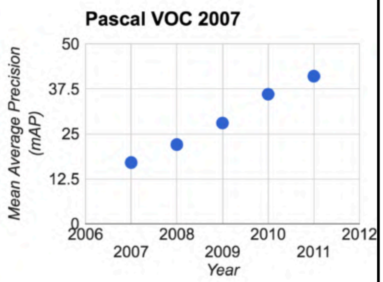
PASCAL Visual Object Challenge

Image is CC0 1.0 public domain

Image is CC0 1.0 public domain



1959 Hubel & Wiesel | 1963 Roberts | 1970s David Marr | 1979 Gen. Cylinders | 1986 Canny | AI Winter | 1997 Norm. Cuts | 1999 SIFT | 2001 V&J | 2001 PASCAL

In early 2000's, over the internet (internet was invented :)) one can download images from the internet, label those images, and use machine learning algorithms to learn those labels.

J. Johnson, Umich

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IMAGENET Large Scale Visual Recognition Challenge

The Image Classification Challenge:
1,000 object classes
1,431,167 images

Output:
Scale
T-shirt
Steel drum
Drumstick
Mud turtle

Deng et al, 2009
Russakovsky et al. IJCV 2015

1959 Hubel & Wiesel | 1963 Roberts | 1970s David Marr | 1979 Gen. Cylinders | 1986 Canny | AI Winter | 1997 Norm. Cuts | 1999 SIFT | 2001 V&J | 2001 PASCAL | 2009 ImageNet

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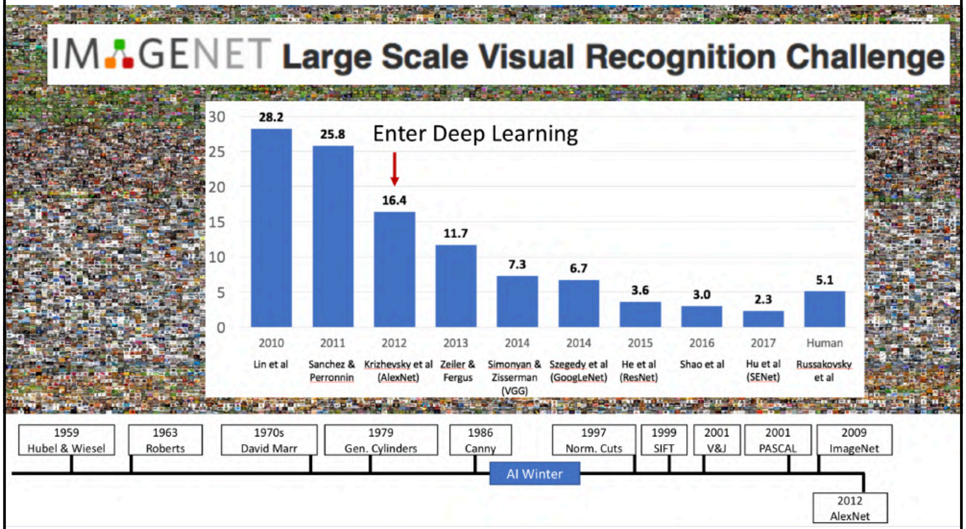

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Image Classification

Task: Given an image of a digit (e.g. 28x28 grayscale) write a program that outputs the number of the digit

Approach 1: try to write a program by hand that uses your a priori knowledge about what images look like to determine what number they are

 → 8  → 5

Approach 2: (the machine learning approach) collect a large volume of images and their corresponding numbers, let the "write its own program" to map from these images to their corresponding number
This is supervised learning

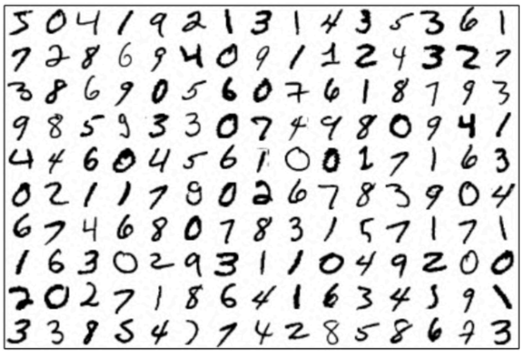

Image: digits from the MNIST data set: (http://yann.lecun.com/exdb/mnist/)

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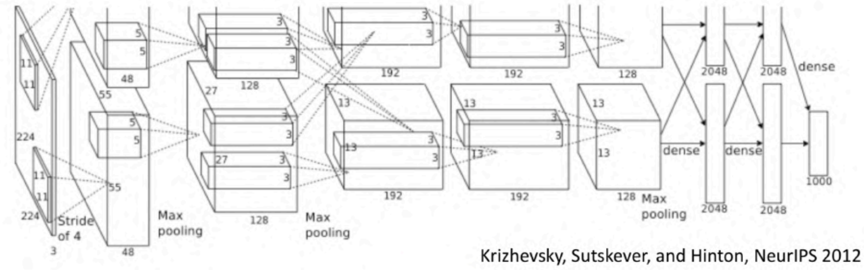
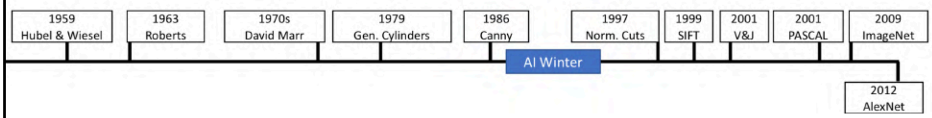
AlexNet: Deep Learning Goes Mainstream



Krizhevsky, Sutskever, and Hinton, NeurIPS 2012



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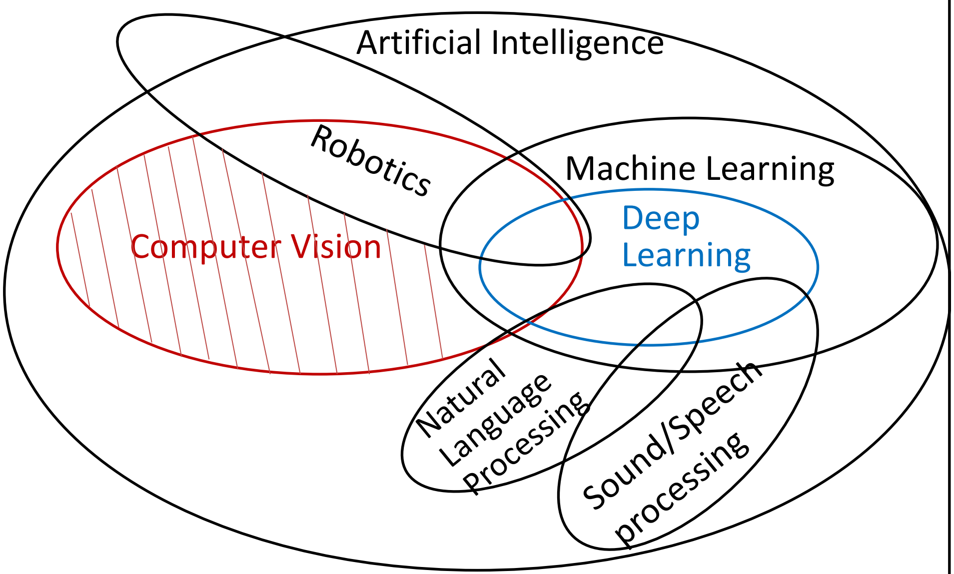

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What you will learn in this course

Fundamentals of computer vision

- Vision applications
- Digital images, Pointwise Image Processing
- Spatial Transforms = Filtering
- Geometric Transforms (=Coordinate Transformations)
- Feature extraction, including edges, corners, keypoints
- Segmentation: Clustering
- Video analysis, Motion Detection and Estimation
- Object Recognition: Dimensionality Reduction with Principal Component Analysis
- **BONUS:** Deep Learning in Vision

⇨ **Assignments with Coding in Python**

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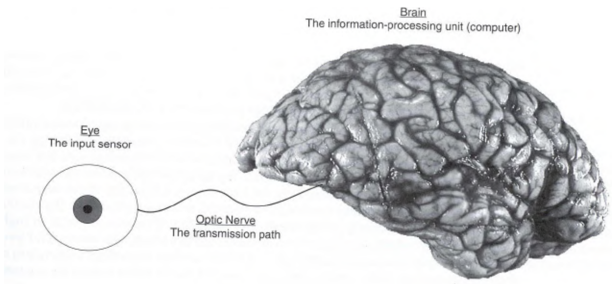
Computer Vision

- Visual System: a collection of devices that transform measurements of light into information about spatial and material properties of a scene
- Among the devices:
  - Photosensitive sensors (camera or retina)
  - Computational mechanisms (computer or brain) to extract information from raw sensory readings



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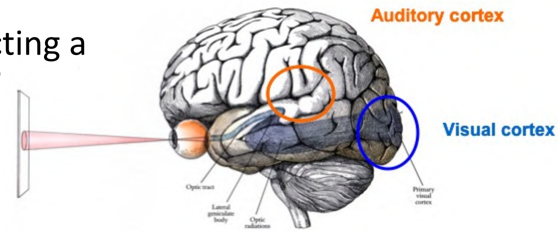
Computer Vision

Is it as simple as connecting a camera to a computer ?



- ❑ Camera → Computer
- ❑ Retina → Brain

- Nowadays, a digital camera can deliver many many “frames” per second to a computer

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How can we interpret these pixel values?

to tell whether we are looking at an apple or an eye or a face or a tree?

* Each image frame is just a collection of positive numbers that measure the amount of light incident on a particular location (or pixel) on a photosensitive surface

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Viewpoint and Illumination Changes

We have no difficulty in interpreting the scene having the same objects!

Frog pictures from Osadchy-Keren CVIU-04

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Complexity of Computer Vision

Where are these objects in this complicated scene: bird, helmet, lamp, plate, map ….

https://www.clarifai.com/demo

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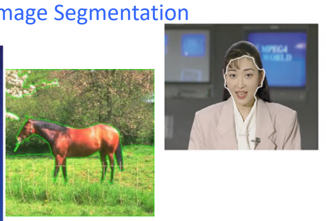
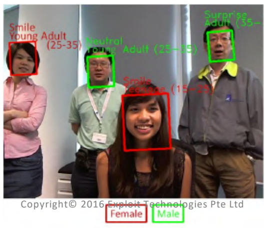
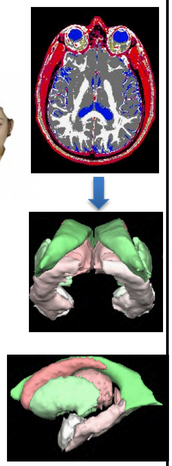
Computer Vision: numerous areas

Image / Object Recognition

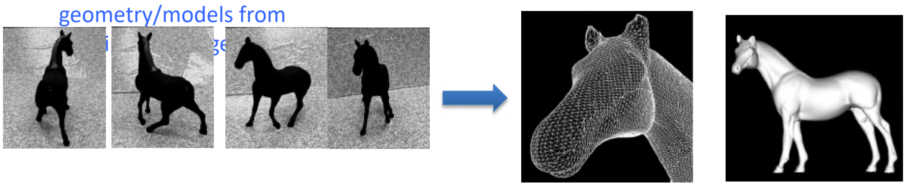
Image Segmentation







Constructing 3D geometry/models from



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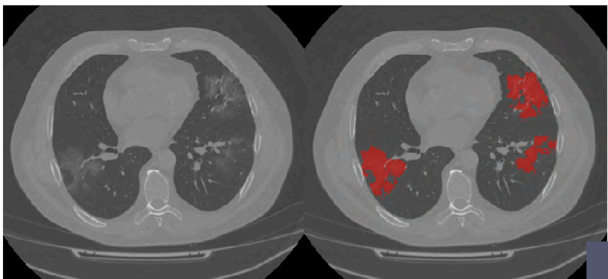
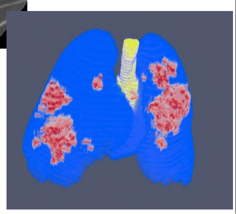
AI – based COVID-19





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Computer / Machine Vision in Medical Diagnosis Intervention and Monitoring

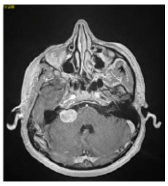
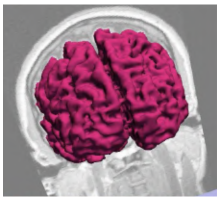


Image Guided Intervention and Surgery

Image Analysis

Segmentation, Registration, Diagnostic, Prognostic disease specific analysis, markers, measures, ...



3D Slicer: MGH

http://www.highpointregional.com/sites/www/Uploads/images/CancerCenter/interradiology_004.jpg

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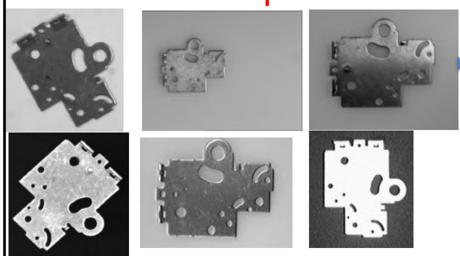
Industrial Computer Vision



Pose estimation of parts for industrial robots

Have to be Robust to: Position; Orientation; Lighting

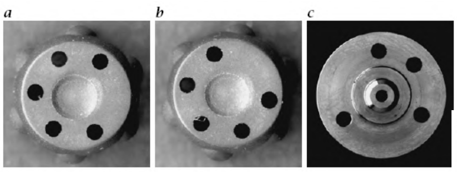


Figure 1.2: Industrial parts that are checked by a visual inspection system for the correct position and diameter of holes (courtesy of Martin von Brocke, Robert Bosch GmbH).

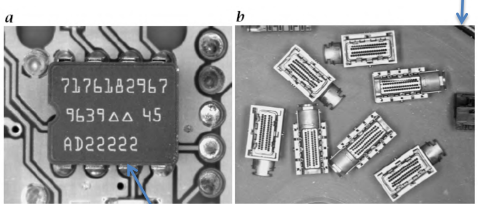
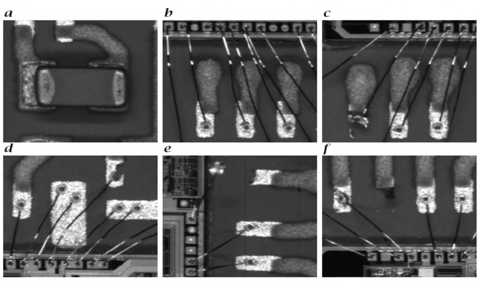


Figure 1.10: Industrial inspection tasks: a Optical character recognition. b Connectors (courtesy of Martin von Brocke, Robert Bosch GmbH).

Classification: label recognition on a chip



Circuit board inspection

Figure 1.11: Errors in soldering and bonding of integrated circuits. Courtesy of Florian Raisch, Robert Bosch GmbH).

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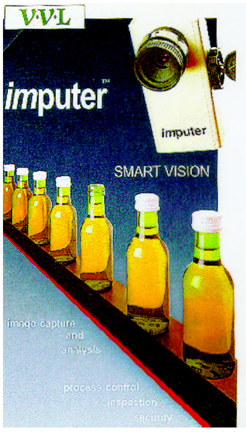
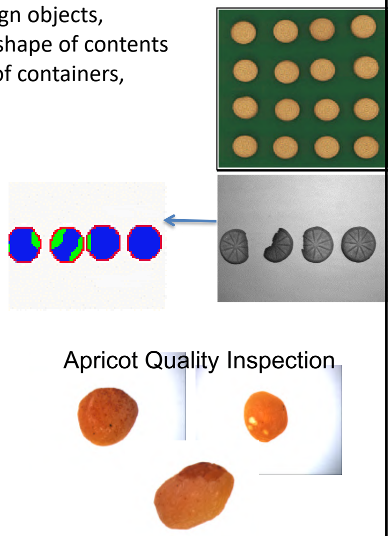
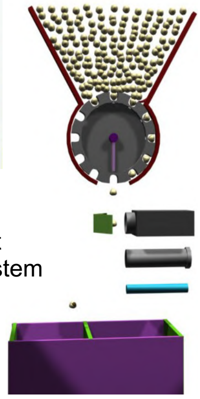
Food Industry



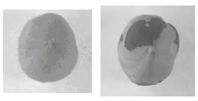
- fruit and vegetable sorting and grading
- automatic portioning,
- inspection for foreign objects,
- verify the size and shape of contents
- quality inspection of containers,
- fill level inspection,
- closure inspection



Apricot Quality Inspection



Automatic Nut Inspection system



Slide: Prof. Aytul Erçil

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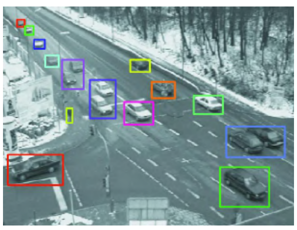
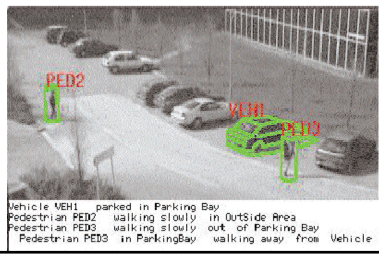
Surveillance Applications

London Residents: the most watched people on Earth
About 5 million cameras placed on corners around the city
People are caught on camera roughly 300 times a day!

Traffic control





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Robot Guidance, Navigation

Unmanned Air
Vehicles (UAVs)

Honda, Asimo Robot

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Satellite Imaging: Remote Sensing

e.g. Land Classification

Recognize:
- Forests
- Buildings
- Agricultural land
- Roads
- Industrial regions
- etc

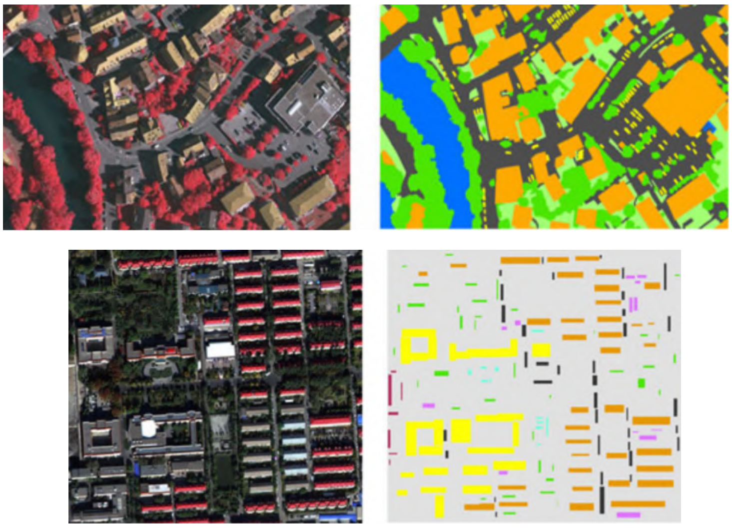

Figure: Zhao et al, "Object-Based Convolutional Neural Network for High-Resolution Imagery Classification", IEEE Journal Selected Topics in Applied Earth Observations and Remote Sensing

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Space Imaging

Images from the Hubble Telescope
Ability to image distant galaxies:
Task: Separate galaxies into different classes (shape, color, ...)
Distinguish stars, planets etc from other objects

Figure 1.12: Hubble deep space image: classification of distant galaxies (http://hubblesite.org/).

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@ITU Vision Lab / ITU AI

Samples from our academic projects

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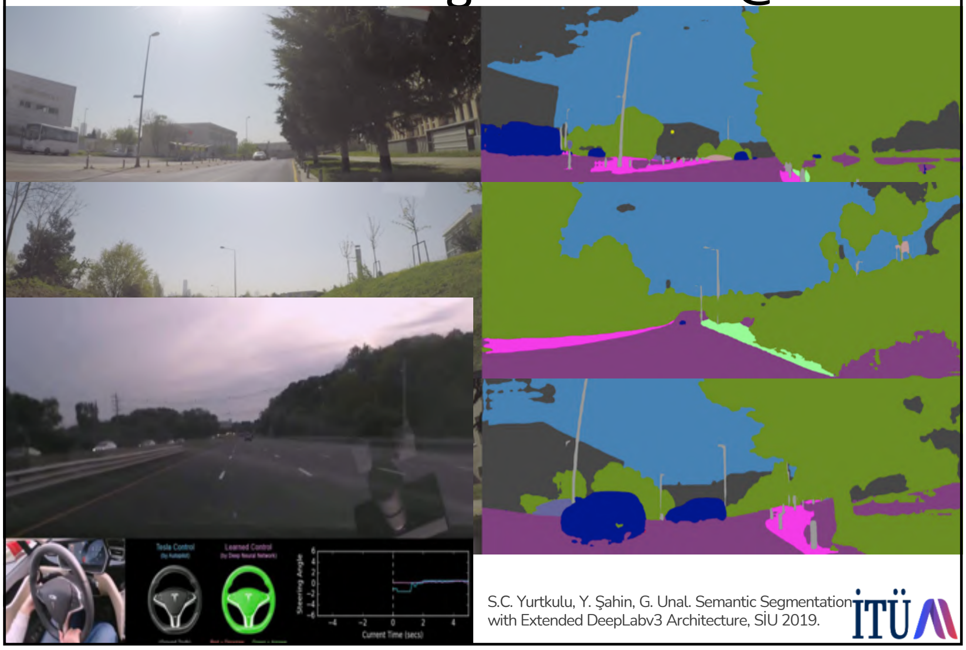
Semantic Segmentation @İTÜ



S.C. Yurtkulu, Y. Şahin, G. Unal. Semantic Segmentation with Extended DeepLabv3 Architecture, SİU 2019.

58

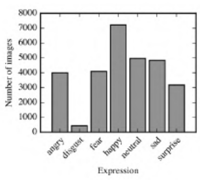
Facial Emotion Recognition

- Goal: Classify among 7 emotion classes from face images
- Datasets: highly imbalanced
- Human precision estimated around 65-68% due to noisy data
- FER2013 Dataset from Kaggle competition, contains nearly 35K grayscale face images collected from web. https://www.kaggle.com/c/challenges-in-representation-learning-facial-expression-recognition-challenge/overview

Testing model using some images from AffectNet* dataset.

(Blue: Correct Red: Wrong)

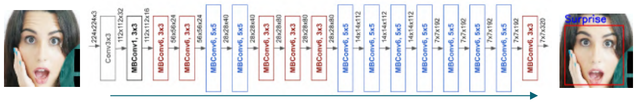
*AffectNet: http://mohammadmahoor.com/affectnet/



FER2013 data distribution

Results on FER2013:
Overall: 70%

```
Test Accuracy of Angry: 59% (290/491)
Test Accuracy of Disgust: 70% (39/55)
Test Accuracy of  Fear: 50% (267/528)
Test Accuracy of Happy: 89% (788/879)
Test Accuracy of   Sad: 55% (331/594)
Test Accuracy of Surprise: 79% (329/416)
Test Accuracy of Neutral: 68% (431/626)
```



CNN-based Encoder

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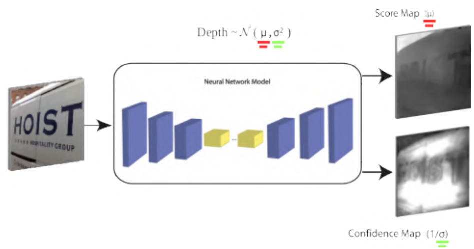
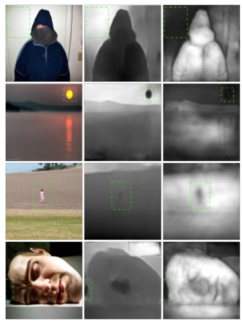
Depth Estimation from 2D Images





We treat depth as it is **normally distributed** and propose a **novel ranking loss function**, distributional loss, to learn from ordinal relations of pixel pairs. Our approach allows models to **output confidence information** and **facilitates better learning**.

* A. Mertan, Y. H. Sahin, D. J. Duff, and G. Unal. 2020. "A New Distributional Ranking Loss with Uncertainty: Illustrated in Relative Depth Estimation", International Conference on 3D Vision (3DV) IEEE, 2020

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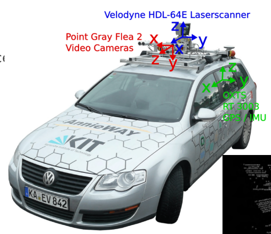
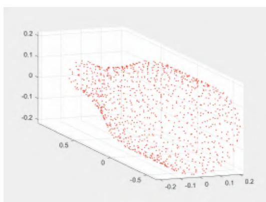
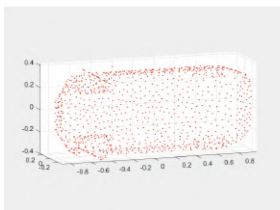
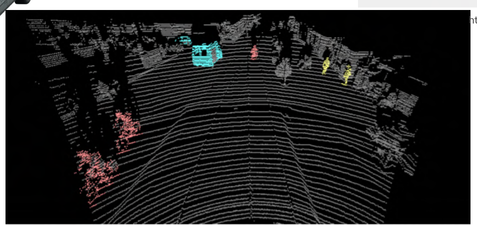
Learning on Non-Euclidean Spaces

Inference on LIDAR data









http://modelnet.cs.princeton.edu/

Picture Credits: Liu, Yanqing, et al. "Robust stereo visual odometry using improved RANSAC-based methods for mobile robot localization." Sensors 17.10 (2017): 2339.
Biasutti, P., et al. "LU-Net: An Efficient Network for 3D LiDAR Point Cloud Semantic Segmentation Based on End-to-End-Learned 3D Features and U-Net" CVPR Workshops. 2019.

62

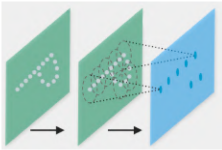
How to operate on point clouds?

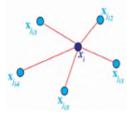
Point Cloud: Nx3 data: N points

Permutation invariance of points should be regarded!

Design novel models for unstructured data?

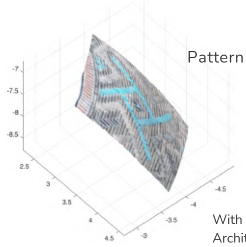
Learn a representation for point clouds?





Classification & Segmentation

Pattern Analysis



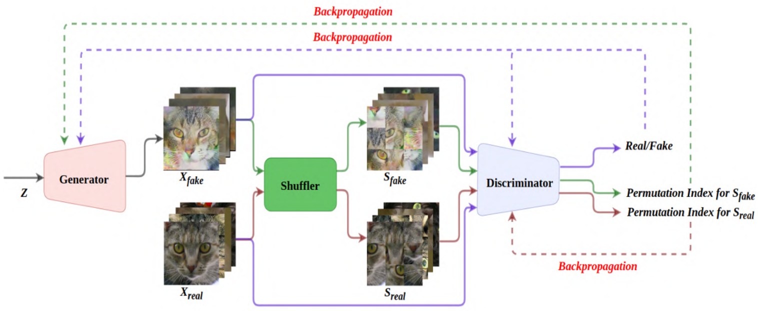
With İTÜ Faculty of Architecture, M. Ozkar

Y. Sahin, G. Unal. "ODFNet: Using Orientation Distribution Functions to Characterize 3D Point Clouds. 2020. Under Review.

63

Image Generation with GANs-Generative Adversarial Networks

DeShuffleGAN



With this new model, we teach the model to learn to deshuffle the images, which helps to learn the underlying structural properties of the images better

* **Gülçin Baykal**, **Gözde Ünal**. "DeShuffleGAN: A Self-Supervised GAN to Improve Structure Learning". IEEE Conference on Image Processing (ICIP) 2020.

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DeshuffleGAN

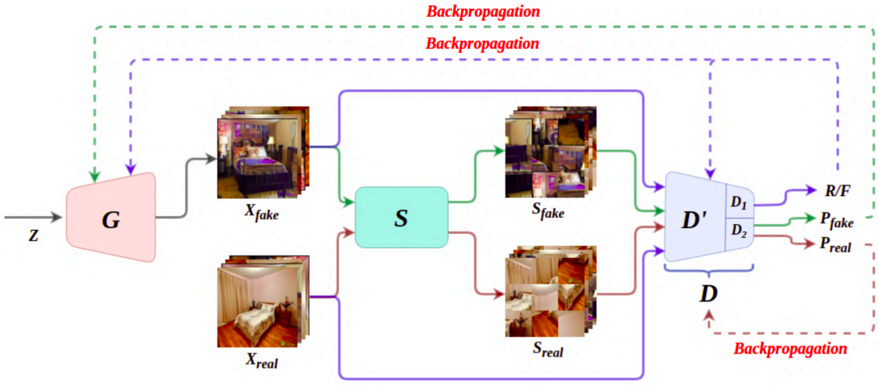

Fig. 1. Proposed training mechanism for DeshuffleGAN. X_{fake} represents a batch of generated images while X_{real} represents the real images. S is the Shuffler and it shuffles X_{fake} and X_{real} as S_{fake} and S_{real} respectively. P_{fake} and P_{real} are the permutation predictions for S_{real} and S_{fake}. Green and Red lines indicate the shuffling and deshuffling operations, including their backpropagation paths. Purple lines refer to the standard adversarial training of the GAN.

* Gulcin Baykal, Gozde Unal, Deshuffle GAN, Int Conf. Image Processing, and extended manuscript under Review, 2020

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DeshuffleGAN

(a) LSUN-Bedroom (b) LSUN-Church

Fig. 3. Randomly generated samples for (a) LSUN-Bedroom and (b) LSUN-Church by the best-performing DeshuffleGANs.

* Gulcin Baykal, Gozde Unal, Deshuffle GAN, Int Conf. Image Processing, and extended manuscript under Review, 2020

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SuperResolution & Colorization with Deep NNs

Pansharpening: Construct a Highres Multispectral Image from Lowres Multispectral Image and Highres Panchromatic Image

Collaboration with İTÜ UHUZAM:

ITÜ

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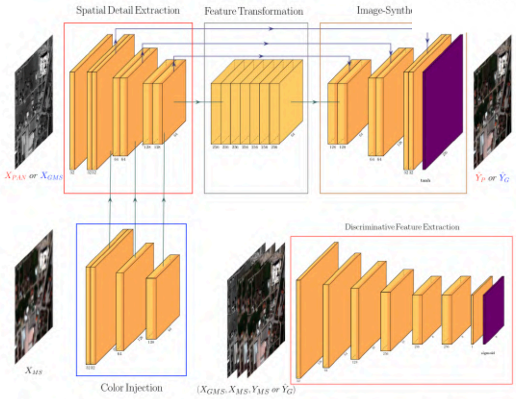
TO APPEAR IN IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING, 2020

Rethinking CNN-Based Pansharpening: Guided Colorization of Panchromatic Images via GANs

Furkan Ozcelik, Ugur Alganci, Elif Sertel, and Gozde Unal



ig. 4. PanColorGAN model: Architecture details for its Generator and Discriminator Networks are depicted. Two modes exist for Generator network: In he training phase, X_{GMS} is provided along with X_{MS} to generate $\hat{Y}_G$. In the testing phase, X_{PAN} is provided along with X_{MS} to generate $\hat{Y}_P$. Also uring the training phase, Discriminator network gets two different types of batches. A real batch consists a concatenated set of X_{GMS}, X_{MS} and Y_{MS}. fake batch consists a concatenated set of X_{GMS}, X_{MS} and $\hat{Y}_G$, as shown on the bottom right.

ITÜ

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PanColorGAN

Original Panchromatic Image

Traditional SR / CNNs

PanColorGAN *

Full Resolution

* F. Ozcelik, U. Algan, E. Sertel, G. Unal. "Rethinking CNN-Based Pansharpening: Guided Colorization of Panchromatic Images via GANs". IEEE Trans. Geoscience & Remote Sensing. 2020.

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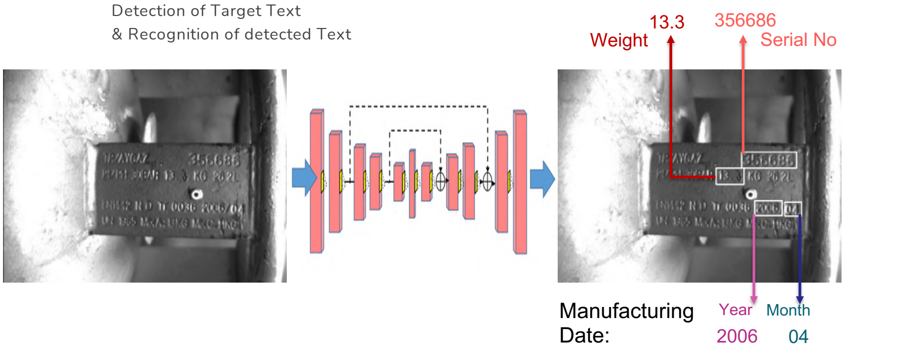
AYGAZ

AI-based Text Reading from Images

Detection of Target Text
& Recognition of detected Text



LPG gas cylinder label detection and recognition

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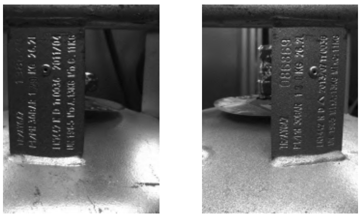
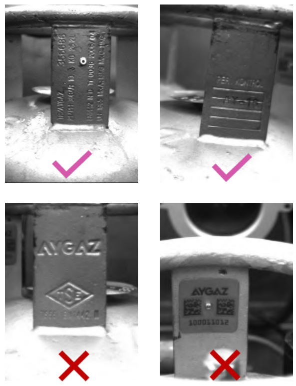
AI-based Text Reading from Images

- Challenges: Position, Brightness, Clarity/Blur, Missing letters, Format changes





LPG gas cylinder label detection and recognition

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Wrap-up Introduction to Computer Vision

- We understand the fact that Computer Vision is not an easy task, in fact a quite involved perception problem.
- The field together with machine learning is currently at the intelligence level of a 3 year old human ! (Opinion from 2018)
- There are a HUGE range of applications that require intelligent processing of visual data

In this course: we will start with the basics: Need to learn LOW-LEVEL PROCESSING first in order to go to image understanding / higher level processing and cognition!

- Next: Pointwise Image Operations
  - Image Intensity Transformations
- Image Coordinate Transformations
- Neighborhood Image Operations (filtering etc)
- Extracting Edges, Corners, other features in images
- Segmentation
- Continue with other more advanced topics

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Learning Outcomes of the Course

Students will be able to:

1. Discuss the main problems of computer (artificial) vision, its uses and applications
2. Design and implement various image transforms: point-wise transforms, neighborhood operation-based spatial filters, and geometric transforms over images
3. Define and construct segmentation, feature extraction, and visual motion estimation algorithms to extract relevant information from images
4. Construct least squares solutions to problems in computer vision
5. Describe the idea behind dimensionality reduction and how it is used in data processing
6. Apply object recognition approaches to problems in computer vision

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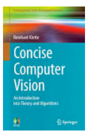
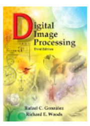
References

Numerous books exist on computer vision. Here are a few recommendations (You can find them online or in the library):



Concise Computer Vision: An Introduction into Theory and Algorithms, Springer. R. Klette



Digital Image Processing, R.C. Gonzalez, R.E. Woods, Pearson Prentice Hall 2008

Image Processing, Analysis, and Machine Vision , Hlavac et al.

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What we expect from you for this course
Spend TOTAL of 3 to 7 hours each week

- **2 hours:** Attend Lectures, Respond to Online Quizzes at the lectures
- **1 hour:** Study the related material afterwards
- **4 hours:** Work on your homework assignments: both algorithm development and Python programming

Ex python/numpy tutorial: http://cs231n.github.io/python-numpy-tutorial/

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Week 1 and Week 2 Topics and Learning Objectives:
Introduction to Computer Vision
Pointwise Image Processing
Image Intensity Transformations, Image Histograms,
Image Enhancement

At the end of Week 1&2: Students will be able to:

1. Discuss the main problems of computer (artificial) vision, its uses and applications
2. Design and implement various image transforms: point-wise transforms, neighborhood operation-based spatial filters, and geometric transforms over images

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