Deep Learning for Computer Vision

Course Introduction

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Outline

What is Computer Vision?

Where is the gluestick? Find the book - what's its full title?

Credit: Bharath Kishore, Flickr CC License

What is wrong with this image?

Credit: Erik Johansson

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Can a machine answer the above questions?

What is Computer Vision?

Computer Vision

- A field that seeks to automate and endow a computing framework with the ability to interpret images the way humans do.
- A sub-topic of Artificial Intelligence.

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Other Definitions

- "the construction of explicit, meaningful descriptions of physical objects from images" (Ballard & Brown, 1982)
- "computing properties of the 3D world from one or more digital images" (Trucco & Verri, 1998)
- "to make useful decisions about real physical objects and scenes based on sensed images" (Sockman & Shapiro, 2001)

Why? Applications of Computer Vision

Autonomous Vehicles

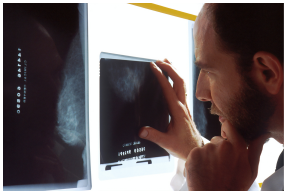
Credit: smoothgrover22, Flickr CC License

Surveillance

Credit: Yeong Nam, Flickr CC License

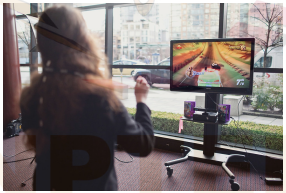
Factory Automation

Credit: KUKA Roboter GmbH, Bachmann



Medical Imaging

Credit: National Cancer Institute



Human-Computer Interaction

Credit: Vancouver Film School

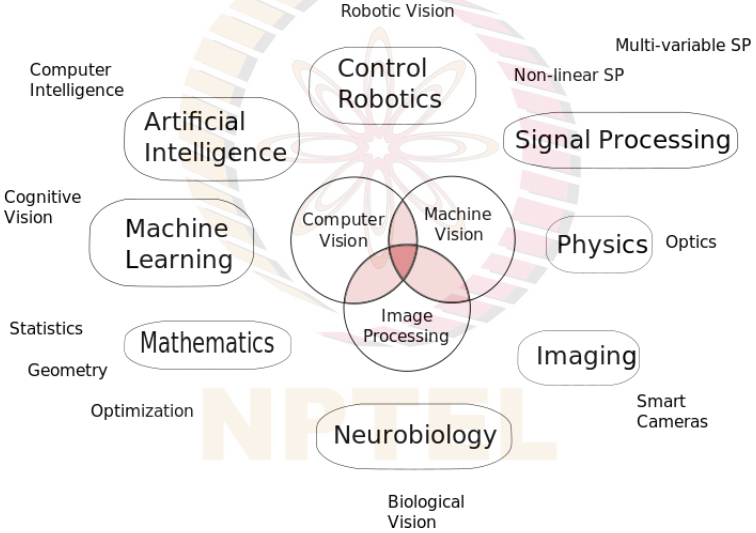
Visual Effects

Credit: AntMan3001, Flickr CC License

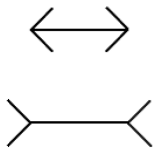
Applications of Computer Vision: More...

- **Retail and Retail Security** (Amazon Go, Virtual Try-on, StopLift)
- **Healthcare** (Blood Loss Detector, DermLens)
- **Agriculture** (SlantRange, Cainthus - Livestock facial recognition)
- **Banking and Finance** (Mobile Deposit, Insurance Risk Profiling)
- **Remote Sensing** (Land Use Understanding, Forestry Modeling)
- **Structural Health Monitoring** (Oilwell Inspection, Drone-based Bridge Inspection and 3D Reconstruction)
- **Document Understanding** (Optical Character Recognition, Robotic Process Automation)
- **Tele- and Social Media** (Image Understanding, Brand Exposure Analytics)
- **Augmented Reality** (TechSee Visual Support, Warehouse and Enterprise Management)

Perspectives of Study



Why is it hard?[1]



Müller-Lyer illusion: Which line is longer?

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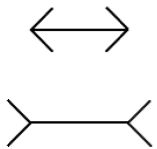

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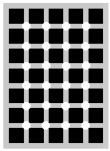

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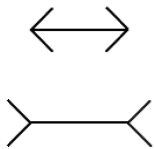

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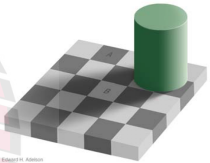
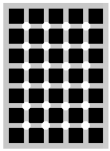


Adelson's brightness constancy illusion: Which is brighter, A or B?



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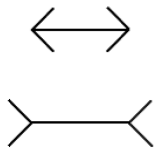

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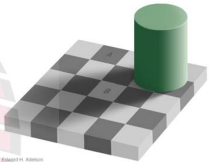

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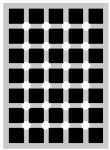

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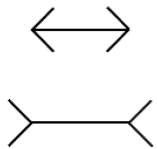

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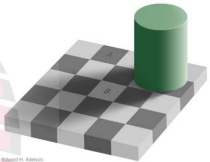

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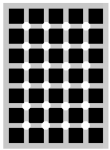

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- Many practical use cases are **inverse model** applications
  - No knowledge of how an image was taken or camera parameters - but need to model the real world in which picture/video was taken (shape, lighting, color, objects, interactions). $\Longrightarrow$ Need to almost always model from incomplete/partial noisy information
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- High-dimensional data $\Longrightarrow$ heavy computational requirements
- Computer vision is AI-complete

Credit: Anish Chopra, Medium.com

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- No complete models of the human visual system exist
  - Existing models largely related to subsystems, not holistic
  - What is perceived, and what is cognized? When is an object important for a task, and when is the context important?

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- No complete models of the human visual system exist
  - Existing models largely related to subsystems, not holistic
  - What is perceived, and what is cognized? When is an object important for a task, and when is the context important?
- Verifiability of mathematical/physical models non-trivial
  - How should similarity/dissimilarity between representations be defined? Is this a distance metric? Do all images follow such a distance metric?
  - How would a manipulation (counterfactual) in a given (potentially noisy) environment behave, w.r.t. the captured image/video? Can a physical model capture this?

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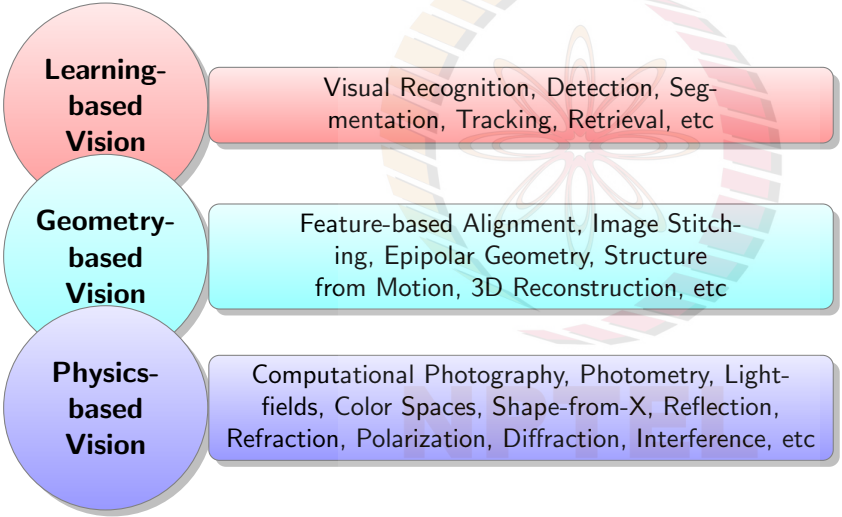
Outline

Computer Vision: Topics



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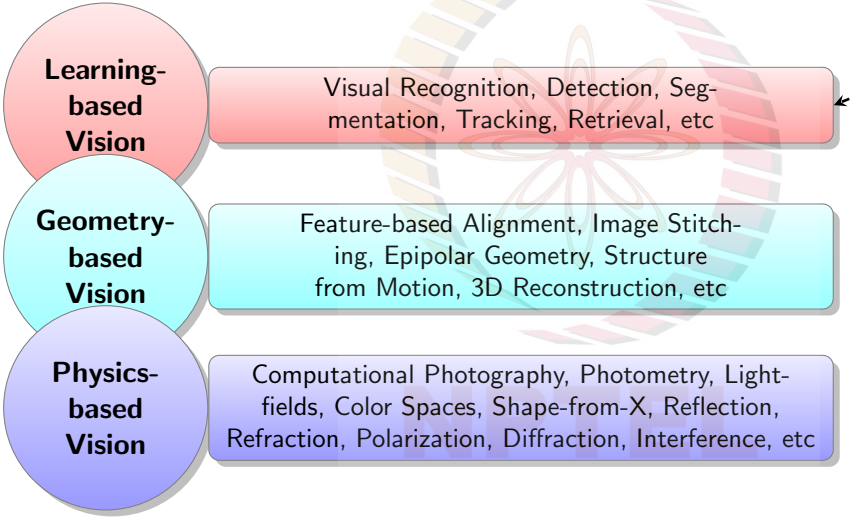

Course Topics

Segment 1: The Journey So Far

- Image Formation, Linear Filtering
- Edges, Blobs, Features
- Visual Descriptors, Matching

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Segment 5: Staying Contemporary

- Deep Generative Models
- Learning with Limited Supervision
- Recent Trends

Course Eligibility

Theory

- Completion of a basic course in Machine Learning
- Completion of a basic course in Deep Learning highly recommended
- Knowledge of basics in probability, linear algebra, and calculus

Programming

- Comfort with programming in Python
- Knowledge of a deep learning framework (PyTorch or TensorFlow) highly recommended

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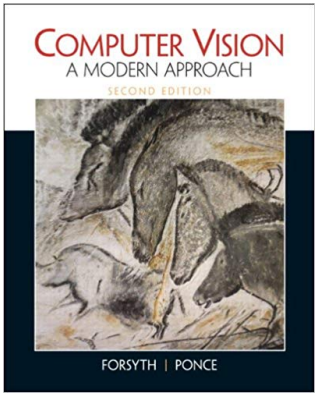
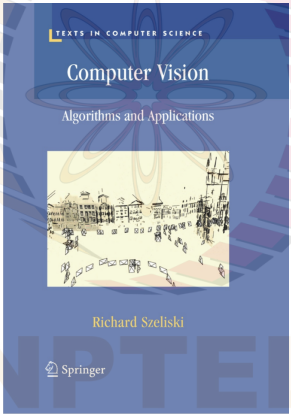
Traditional Computer Vision: References



Book website



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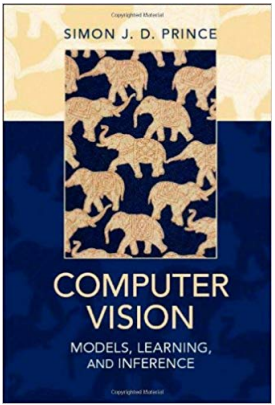

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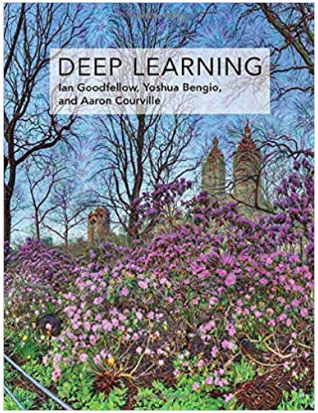

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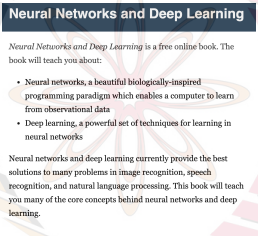
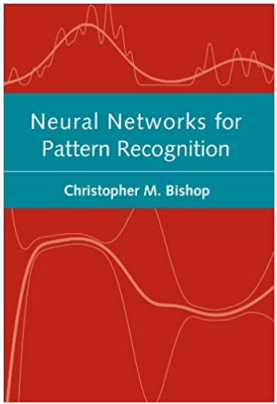


A nice, short online book by Michael Nielsen



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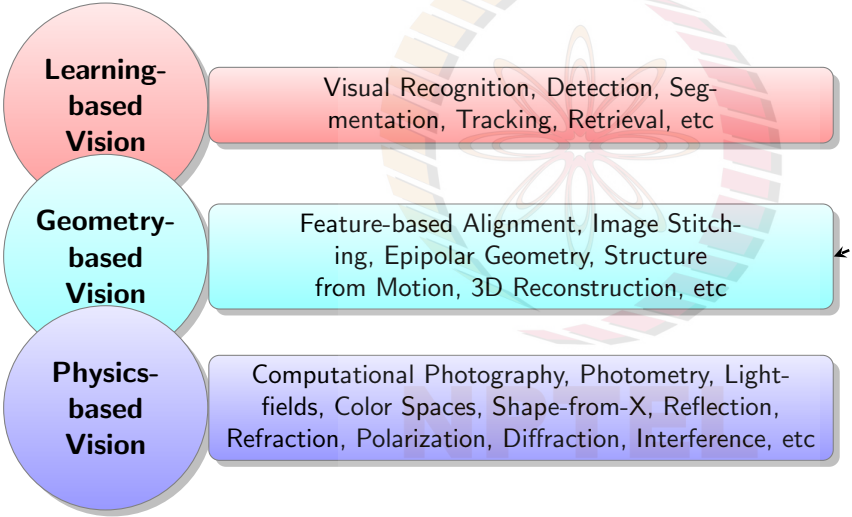
Want to Learn Other Topics?



Book Link: Multiple View Geometry in Computer Vision

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Relevant Course Links: Link 1, NPTEL Course, See Weeks 2-5

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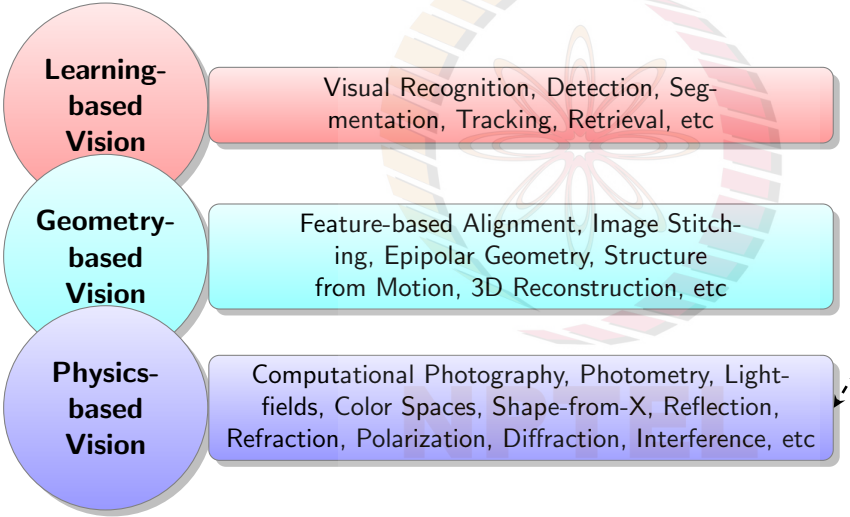

Book Link: Physics-Based Vision: Principles and Practice
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Relevant Course Links: Link 1

Homework!

- Go through all links on the Applications of Computer Vision slide (Slide 6) - they are interesting views/reads!

Acknowledgements and Disclaimers

- We are grateful to the deep learning/computer vision courses and their contents that are publicly available online. Wherever possible and relevant, these sources have been cited. If you notice an oversight, please let us know, and we will be glad to acknowledge.
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