

Data-driven & Model-driven Methods and their use in computer vision

Xiaohao Cai

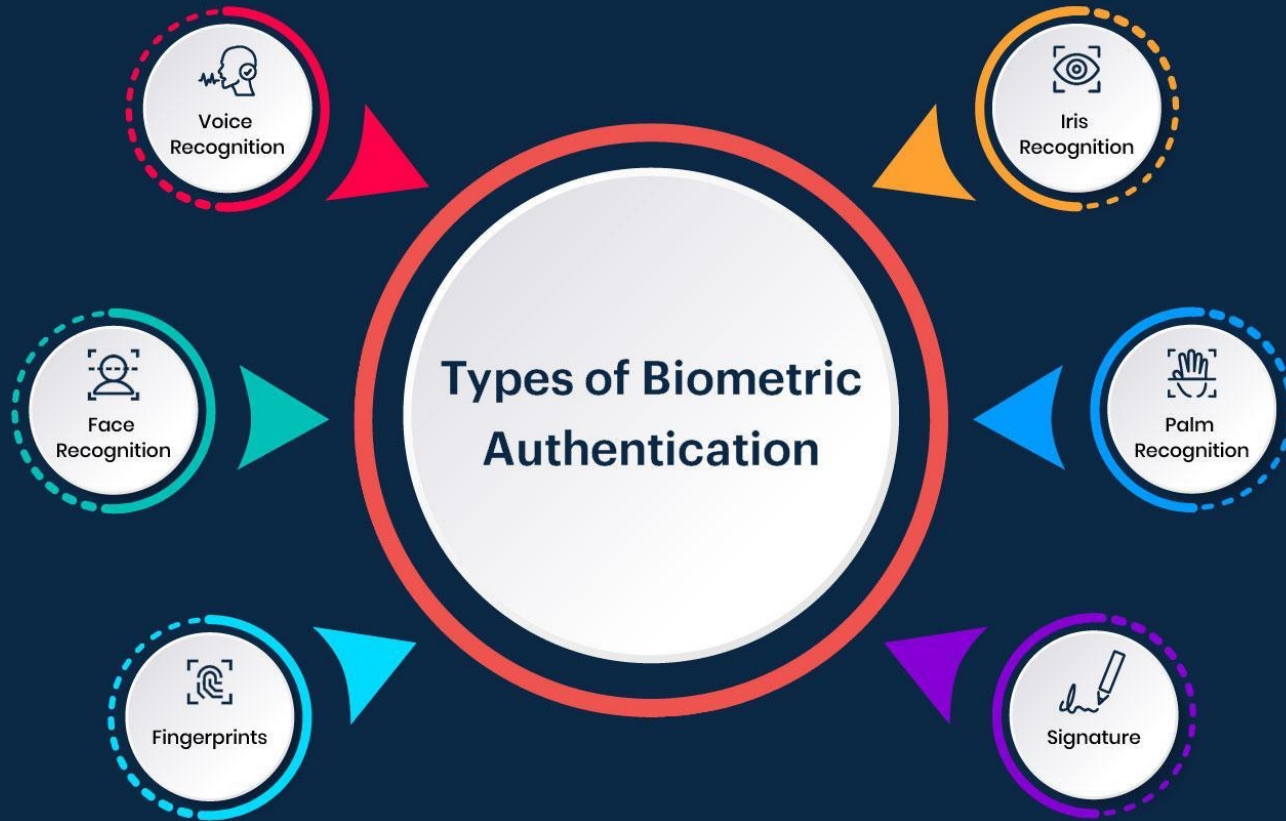
University of Southampton UK

COMP3204 Computer Vision

What are their pros and cons?

Content

1. Biometrics account for a large portion
in computer vision
2. Some data-driven and model-driven methods
in computer vision



Different Types of Biometrics



Typing Style



Navigation Style

Behavioral Biometric Identifiers



Interaction Style



Physical Style



Signature



Face Recognition

Physical Biometric Identifiers



Fingerprints



Voice
Recognition



Eye
Scanners



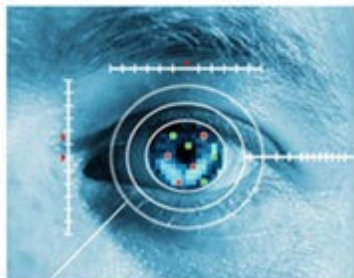
DNA

Chemical & Vein Biometric Identifiers



Vein
Recognition

Physiological



Iris



Fingerprint



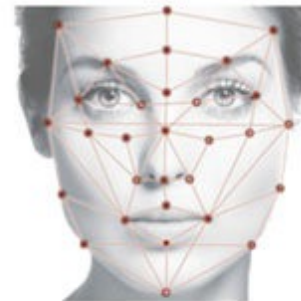
Ear



DNA



Vein print



Face

Behavioral



Voice

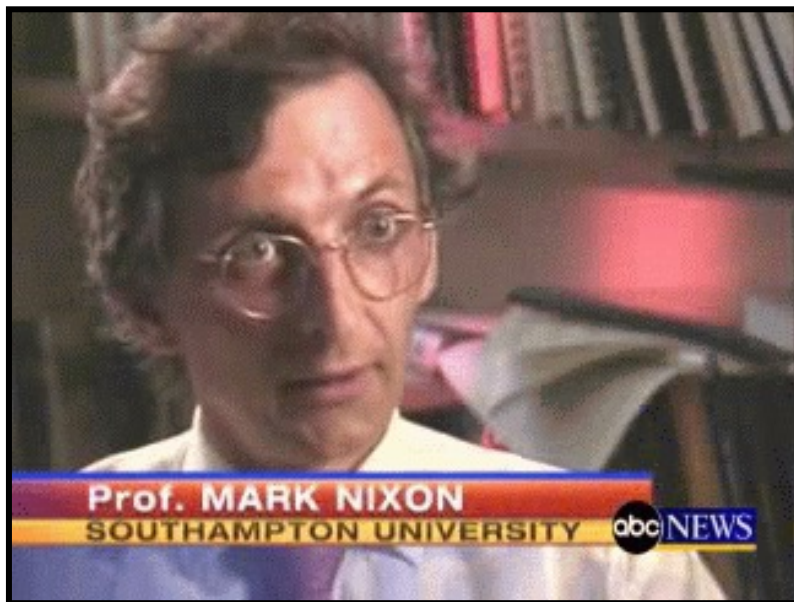


Gait



Signature

Gait biometrics

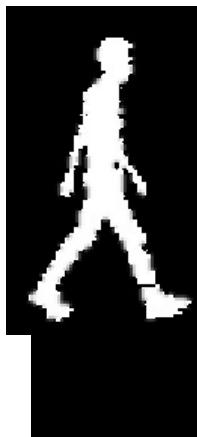


Identifying people
by their gait

As a biometric, **gait** is available at a **distance** when other biometrics are obscured or at too **low resolution**

Many gait representations possible

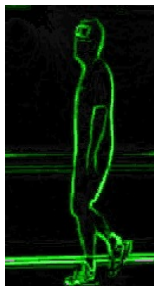
Recognising people from the motion of the **whole** body



silhouette



flow



edges

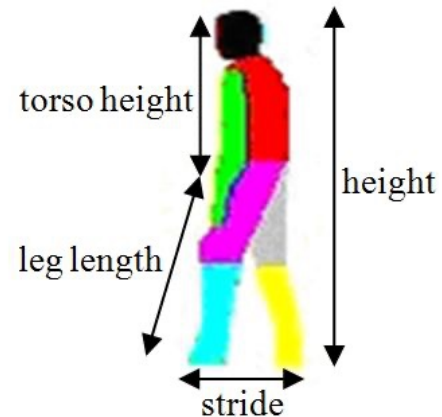
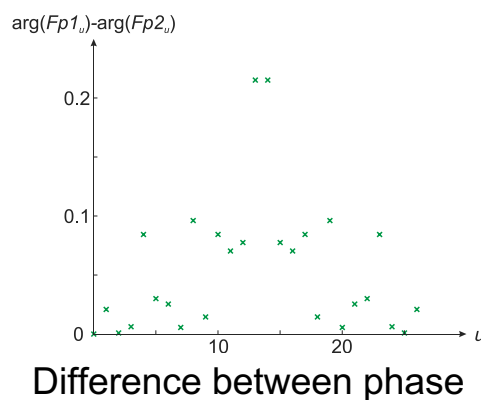
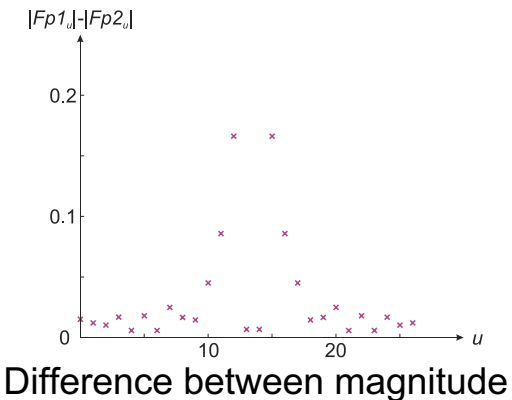
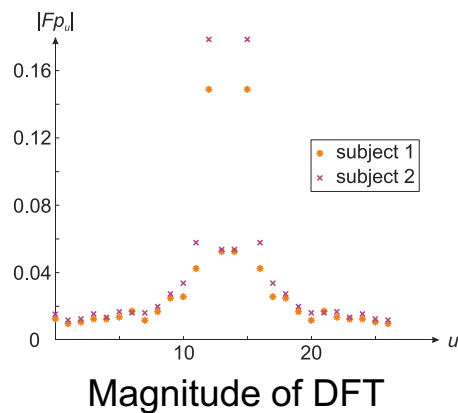
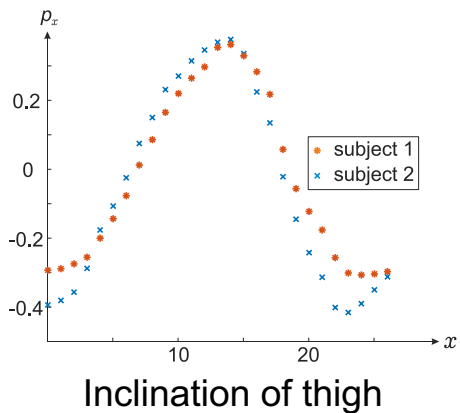


symmetry



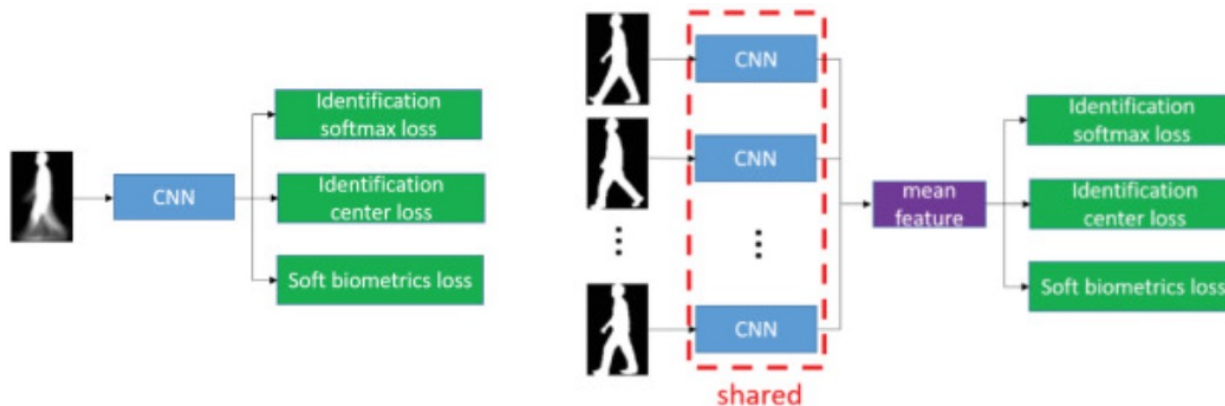
acceleration

Model-based recognition



Other models are possible

Hand crafted then; deep learning now



(a) Image level fusion

(b) Feature level fusion

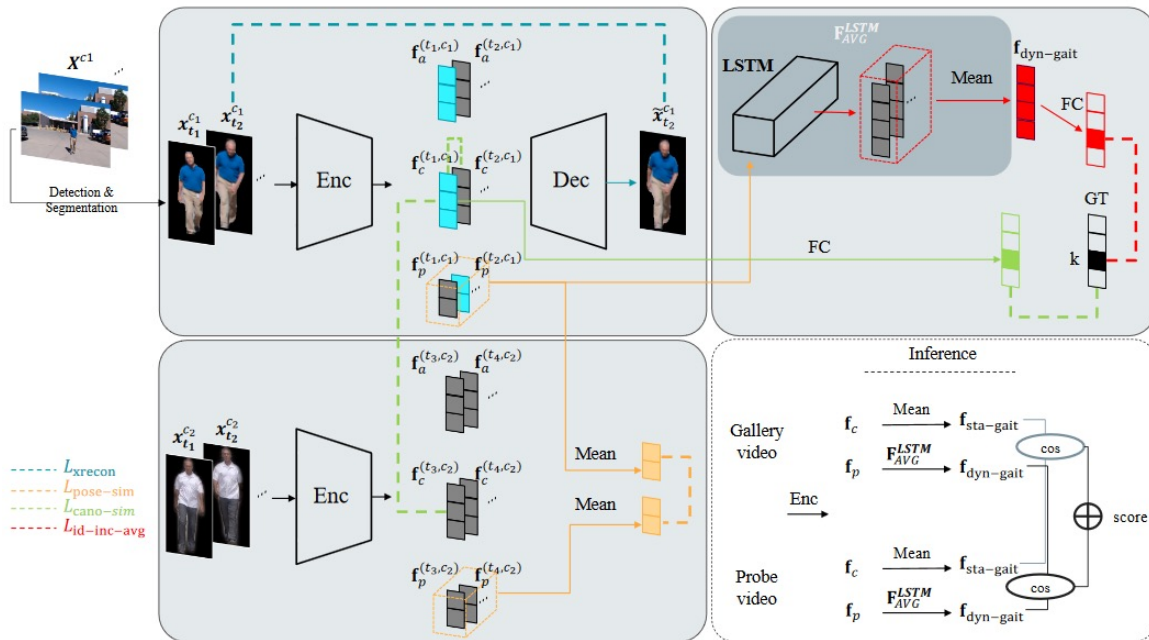


(c) Network architecture

Recent works - Gait



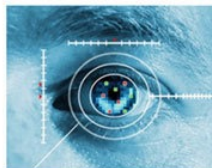
Fig. 1. Samples from the KinGaitWild dataset



SE Bekhouche, A Chergui, A Hadid...,
 ICIP 2020

Z Zhang, L Tran, F Liu, X Liu,
 IEEE TPAMI 2019

Physiological



Iris



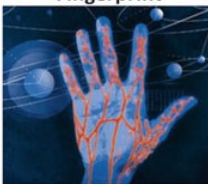
Fingerprint



Ear



DNA



Vein print



Face

Behavioral



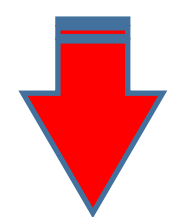
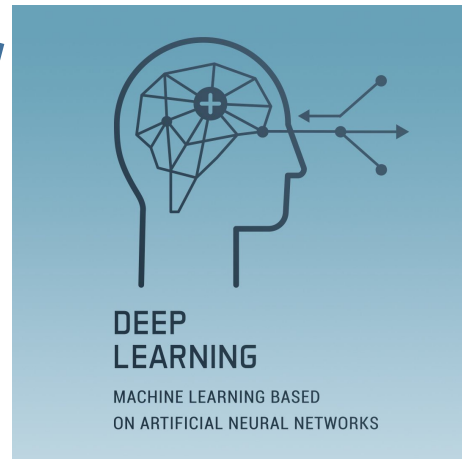
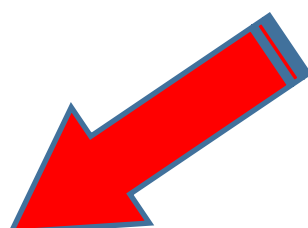
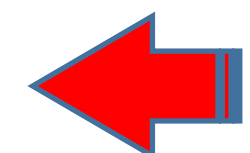
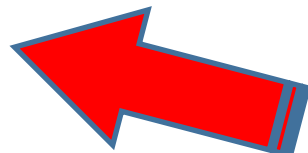
Voice



Gait



Signature



**and many
more ...**

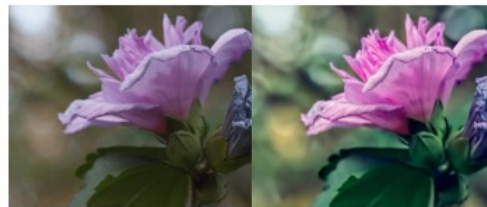
IMAGE COLORING

IMAGE NOISE REDUCTION



Before

After



Before

After



“DATA IS THE NEW GOLD”

Gait biometrics databases

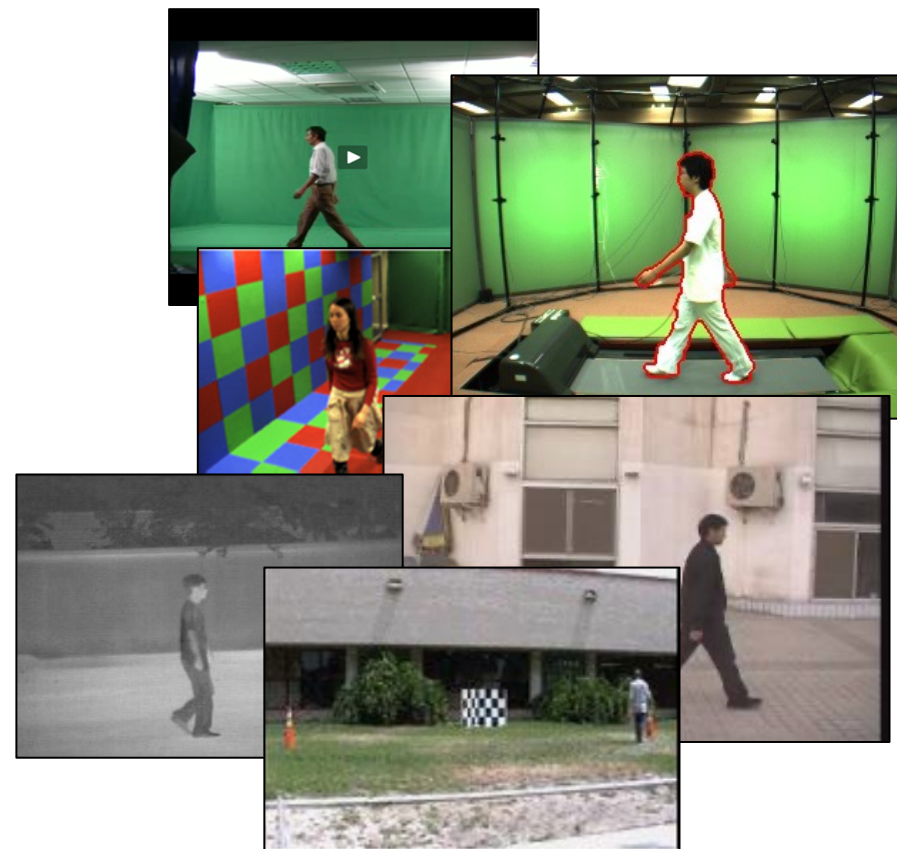
Laboratory

- Southampton 3D and 2D
- CASIA (+ multiview, thermal)
- Osaka OU-ISIR (+ multiview)

'Real' World

- HumanID
- Southampton
- CASIA

+ accelerometer, footfall, medical



What changes regarding datasets?

Many covariates can affect walking style

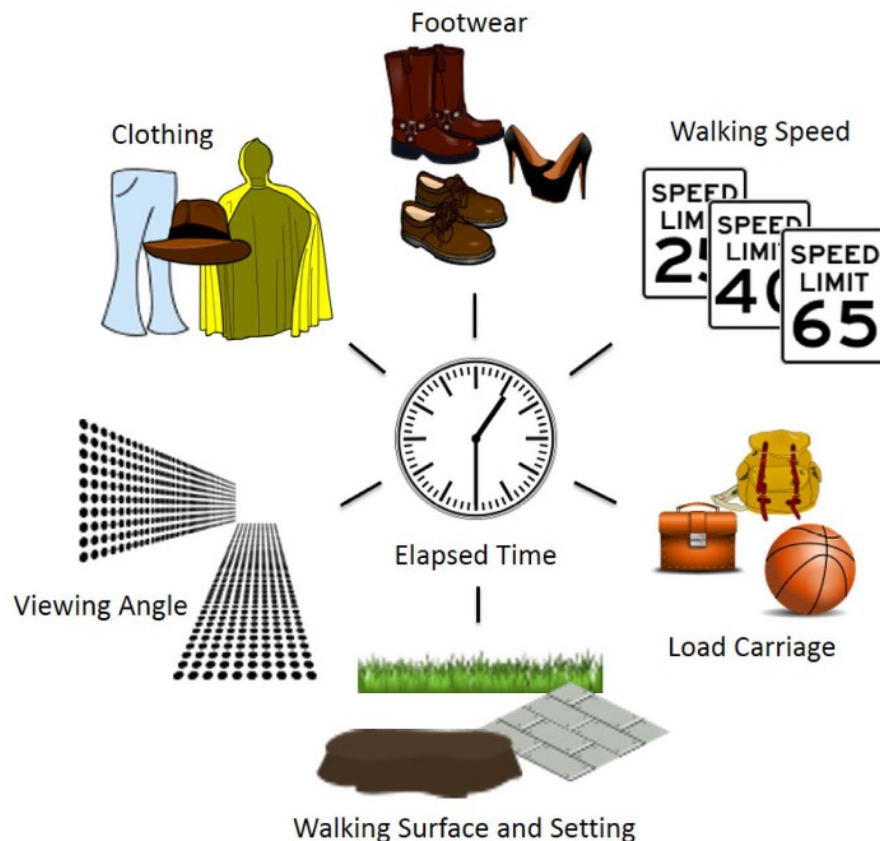
.... + health, drugs, mood ...

Domain shift

Class imbalance

Noisy annotation

and more ...





**KEEP
CALM
AND
USE DATA
WISELY**

A Microsoft AI tool is helping to speed up cancer treatment – and Addenbrooke’s will be the first hospital in the world to use it

December 9, 2020 | Microsoft reporter

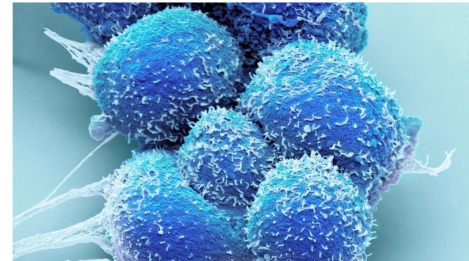


Medical imaging with AI

Inner Eye AI identifies tumours to speed up treatment of cancer

Katie Gibbons

Monday January 11 2021, 12:01am, The Times



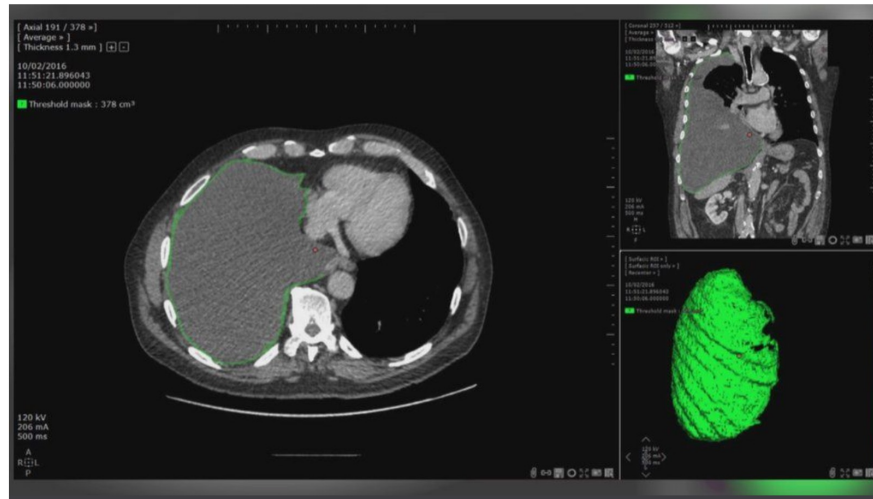
The Inner Eye software is the result of an eight-year project with Microsoft and Addenbrooke's hospital ALAMY

A hospital in Cambridge is the first to use artificial intelligence technology developed by Microsoft to treat cancer patients faster, helping to cut the treatment backlog and save lives.

AI technology used to track asbestos cancer tumours

By [Laura Goodwin](#)
BBC Scotland Innovations Correspondent

🕒 2 days ago



Medical imaging with AI

<https://www.bbc.co.uk/news/uk-scotland-56734407>

Research

Use of artificial
programmes:

BMJ 2021 ;374 d
Cite this as: BMJ 20

Article

Rela

Karoline Freeman Daniel Todkill , cl

Aileen Clarke, profess

Author affiliation

Correspondence to

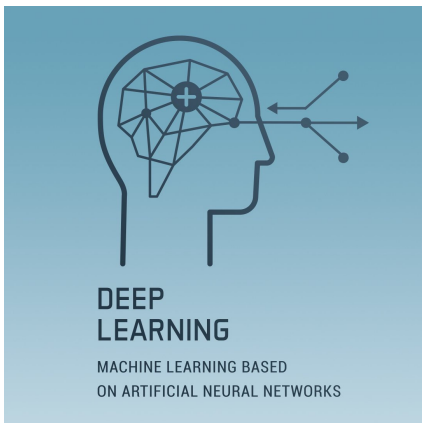
Accepted 21 July 2

Abstract

Conclusions

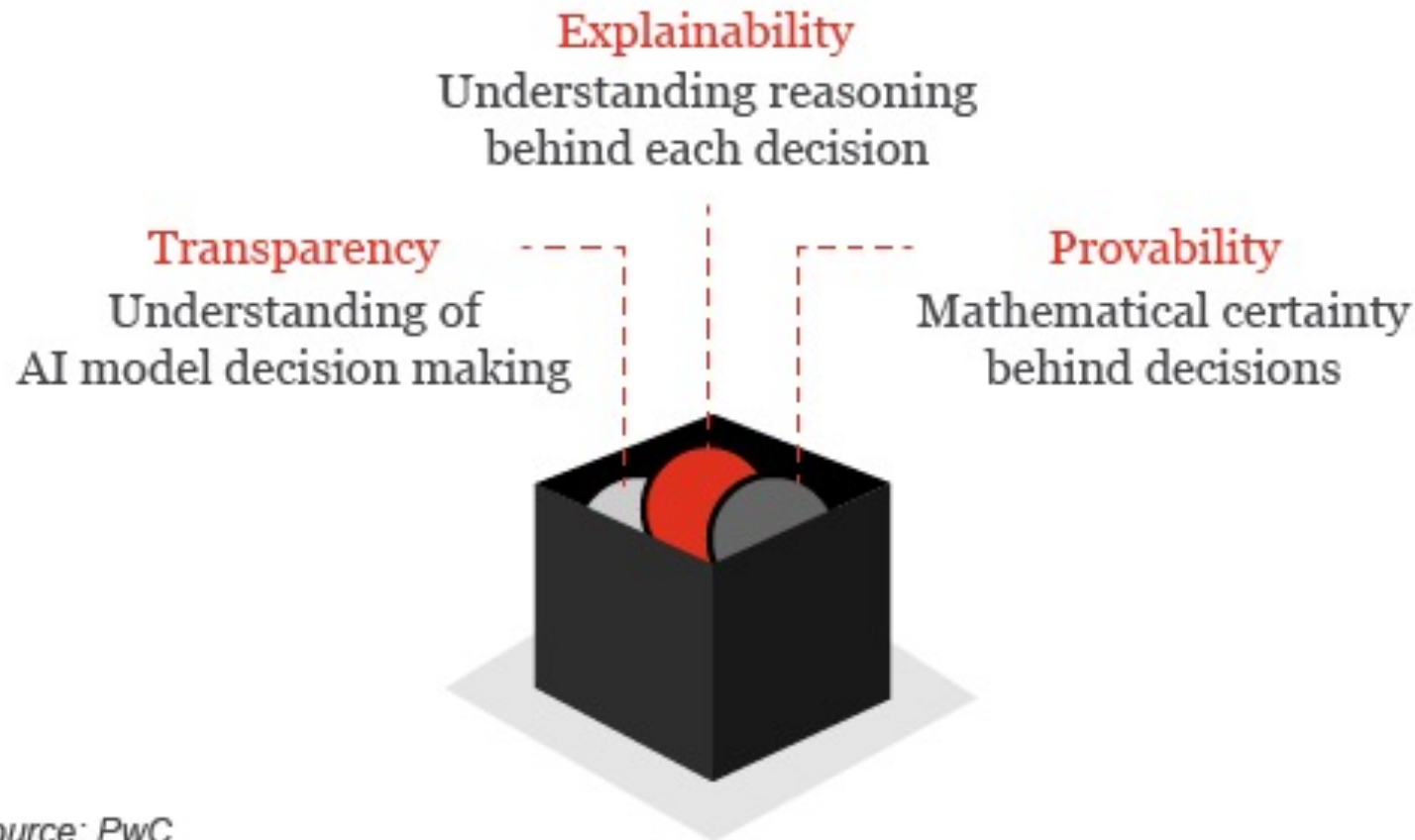
Current evidence on the use of AI systems in breast cancer screening is a long way from having the quality and quantity required for its implementation into clinical practice. Well designed comparative test accuracy studies, randomised controlled trials, and cohort studies in large screening populations are needed which evaluate commercially available AI systems in combination with radiologists. Such studies will enable an

flow¹,



Internal behavior of the code is unknown

What it means to look inside the black box



POST

[UK Parliament](#) > [POST](#) > [Interpretable machine learning](#)

Research Briefing

Interpretable machine learning

Published Tuesday, 06 October, 2020

POSTnote


Crime and justice

Digital tech

Health and social care


Transport and infrastructure

Research

 [Lorna Christie](#)

Machine learning (ML, a type of artificial intelligence) is increasingly being used to support decision making in a variety of applications including recruitment and clinical diagnoses. While ML has many advantages, there are concerns that in some cases it may not be possible to explain

This POSTnote gives an overview of ML and its role in decision-making. It also explains how a complex ML system has reached its output and how to make ML easier to interpret. It also gives a brief overview of how to make ML systems more accountable.



In 2018, the Lords Committee on AI called for the development of AI systems that are “intelligible to developers, users and regulators”. It recommended that an AI system that could have a substantial impact on an individual’s life should not be used unless it can produce an explanation of its decisions.⁴ In a



**KEEP
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AND
USE DATA
WISELY**

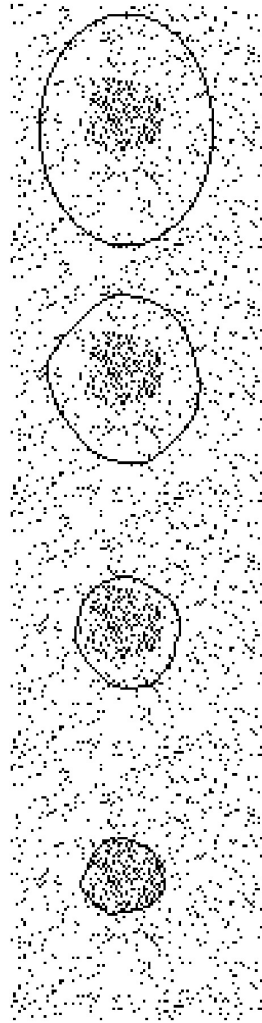
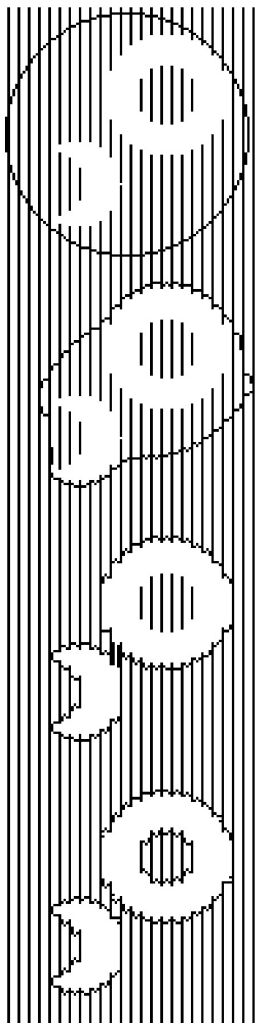


International Journal of Computer Vision, 321-331 (1988)
© 1987 Kluwer Academic Publishers, Boston, Manufactured in The Netherlands

Snakes: Active Contour Models

MICHAEL KASS, ANDREW WITKIN, and DEMETRI TERZOPOULOS
Schlumberger Palo Alto Research, 3340 Hillyview Ave., Palo Alto, CA 94304

[credit: wikipedia]



Active Contours Without Edges

Tony F. Chan, *Member, IEEE*, and Luminita A. Vese

Abstract—In this paper, we propose a new model for active contours to detect objects in a given image, based on techniques of curve evolution, Mumford–Shah functional for segmentation and level sets. Our model can detect objects whose boundaries are not necessarily defined by gradient. We minimize an energy which can be seen as a particular case of the minimal partition problem. In the level set formulation, the problem becomes a “mean-curvature flow”-like evolving the active contour, which will stop on the desired boundary. However, the stopping term does not depend on the gradient of the image, as in the classical active contour models, but is instead related to a particular segmentation of the image. We will give a numerical algorithm using finite differences. Finally, we will present various experimental results and in particular some

the image (the external energy). Observe that, by minimizing the energy (1), we are trying to locate the curve at the points of maxima $|\nabla u_0|$, acting as an edge-detector, while keeping a smoothness in the curve (object boundary).

A general edge-detector can be defined by a positive and decreasing function g , depending on the gradient of the image u_0 , such that

$$\lim_{z \rightarrow \infty} g(z) = 0.$$

For instance

Models

Models proposed in our work, e.g.:

- ▶ $\min_x \left\{ \frac{\lambda}{2} \|y - \mathcal{A}x\|_2^2 + \|\mathcal{W}x\|_1 \right\}$
- ▶ $\min_g \left\{ \frac{\lambda}{2} \|f - \mathcal{A}g\|_2^2 + \frac{\mu}{2} \|\nabla g\|_2^2 + \|\nabla g\|_1 \right\}$
- ▶ $\mu\Phi(f, \mathcal{A}g) + \lambda\Psi(g, u_i, c_i) + \sum_{i=1}^K \int_{\Omega} |\nabla u_i|$
 s.t. $\sum_{i=1}^K u_i(x) = 1, u_i(x) \in \{0, 1\}$
- ▶ $\min_{u \in S} \left\{ \frac{1}{2} \|f - \mathcal{B}u\|_2^2 + \lambda \|\nabla u\|_0 \right\}$
- ▶ $\min_{\psi} \left\{ D[T(\psi), R] + \alpha \|\Delta\psi\|_2^2 \right\}$

Convex optimisation
 algorithms

- ▶ ADMM
- ▶ Primal-dual
- ▶ Split-Bregman
- ▶ Augmented
Lagrangian

Sparse regularizations

- ▶ $\|\cdot\|_0, \|\cdot\|_1, \|\cdot\|_2$
- ▶ with $\nabla, \Delta, \mathcal{W}$
- ▶ \mathcal{W} : Wavelet transform

T-ROF (*Thresholded-ROF*)

[SISC, '19; EMMCVPR, '13]

X. Cai, R. Chan, C.-B. Schönlieb

G. Steidl, T. Zeng

Image Restoration

ROF model

(1992, citation > 15,700)

thresholding

Image Segmentation

Chan-Vese model

(2001, citation > 12,600)

$$\min_{u \in BV(\Omega)} \left\{ TV(u) + \frac{\mu}{2} \int_{\Omega} (f - u)^2 dx \right\},$$

$TV(u)$: total variation of u

$$\min_{\Omega_i; m_i} \left\{ \text{Per}(\Omega_1; \Omega) + \lambda \sum_{i=0}^1 \int_{\Omega_i} (m_i - f)^2 dx \right\},$$

$$\Omega := \Omega_0 + \Omega_1$$

$\text{Per}(\Omega_1; \Omega)$: perimeter of set Ω_1

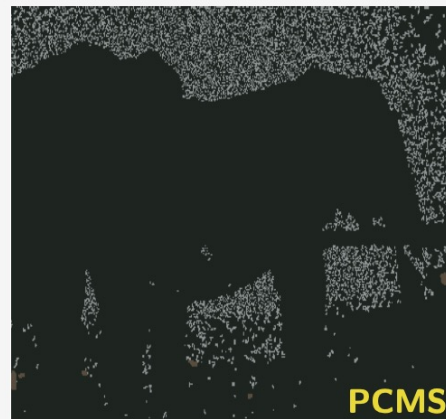
Theorem

(Relation between ROF and Chan-Vese model) *Let $u^* \in BV(\Omega)$ solve the ROF model. For given $0 < m_0 < m_1 \leq 1$, let $\tilde{\Sigma} := \{x \in \Omega : u^*(x) > \frac{m_1 + m_0}{2}\}$ fulfill $0 < |\tilde{\Sigma}| < |\Omega|$. Then $\tilde{\Sigma}$ is a minimizer of the Chan-Vese model for $\lambda := \frac{\mu}{2(m_1 - m_0)}$ and fixed m_0, m_1 . In particular, $(\tilde{\Sigma}, m_0, m_1)$ is a partial minimizer of the Chan-Vese model if $m_0 = \text{mean}_f(\Omega \setminus \tilde{\Sigma})$ and $m_1 = \text{mean}_f(\tilde{\Sigma})$.*

Colour image

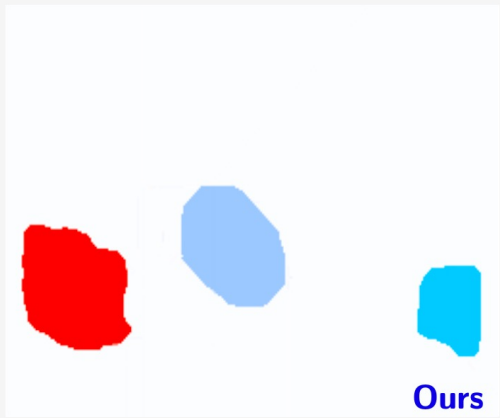
Research Grants Council
of Hong Kong
香港 研究資助局

Method: SLaT



Disparity and optical flow

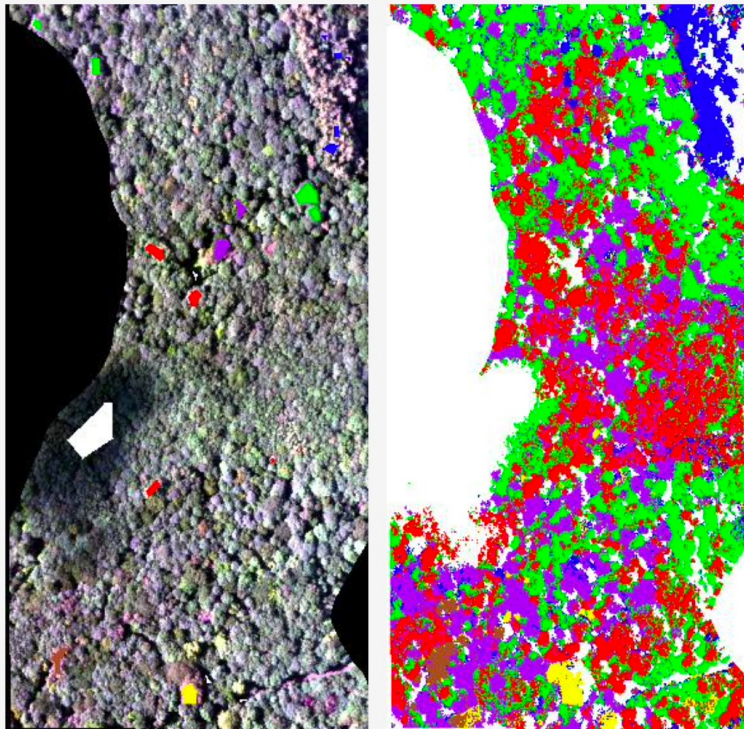
Algorithm for
NP-hard problem
 $\|\nabla \cdot\|_0$



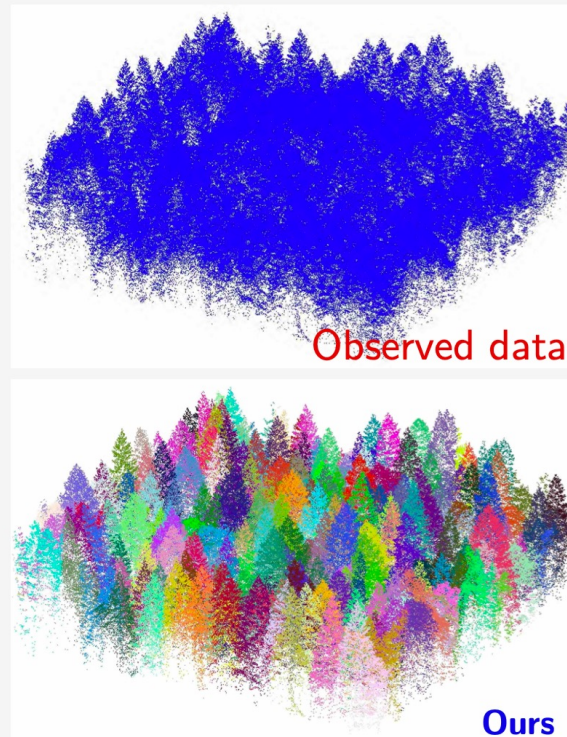
Computer
vision

IEEE Tr., '15, '16, '19
J. Lee, X. Cai, D. Coomes
C.-B. Schönlieb, et al.

Hyperspectral



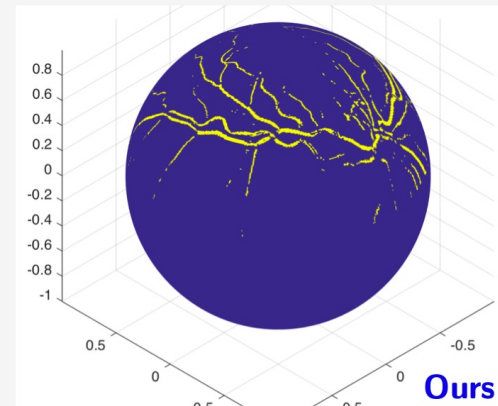
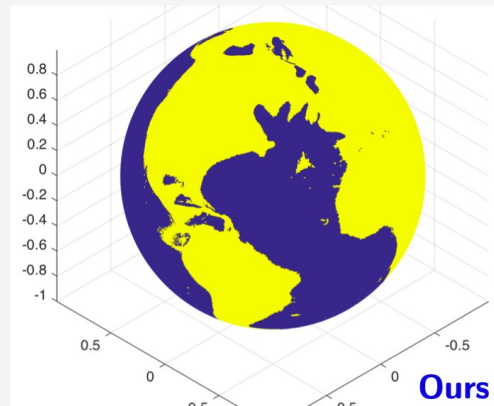
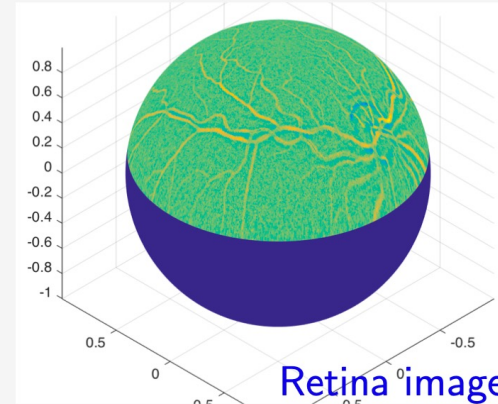
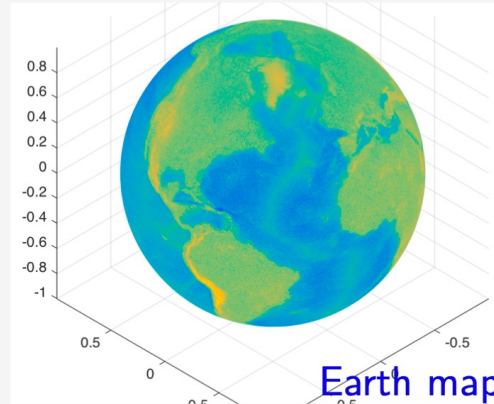
LiDAR



Spherical image

Wavelet-based
algorithm

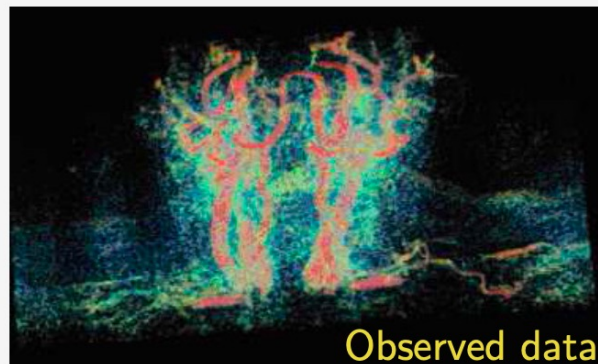
First
segmentation paper
on the sphere



SIIMS, '13
SSVM, '12
X. Cai, et al.

3D image – tubular

Wavelet-based
algorithm



Data provided:

Prof. S. Morigi
Prof. F. Sgallari
Uni. of Bologna
Italy



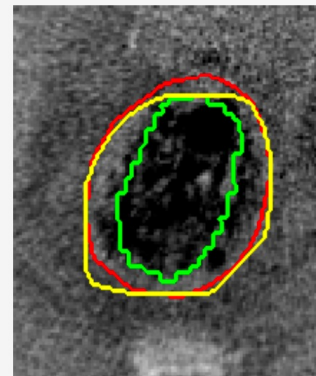
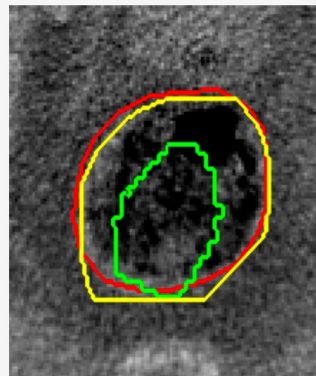
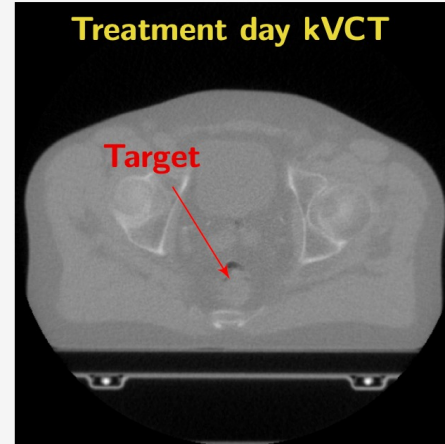
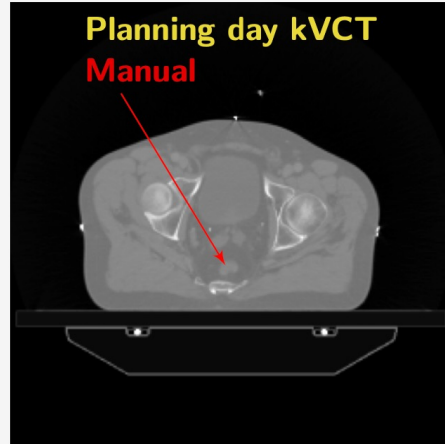
Anisotropic PDE



Ours

Image-guided radiotherapy

CIJ, '17
EUSIPCO, '21



Manual
ours
Initial.

<http://www.componc.org/research/voxtox>

Recent: models leveraging deep learning

Models proposed in our work, e.g.:

$$\blacktriangleright \min_x \left\{ \frac{\lambda}{2} \|y - \mathcal{A}x\|_2^2 + \|\mathcal{W}x\|_1 \right\}$$

$$\blacktriangleright \min_g \left\{ \frac{\lambda}{2} \|f - \mathcal{A}g\|_2^2 + \frac{\mu}{2} \|\nabla g\|_2^2 + \|\nabla g\|_1 \right\}$$

$$\blacktriangleright \mu\Phi(f, \mathcal{A}g) + \lambda\Psi(g, u_i, c_i) + \sum_{i=1}^K \int_{\Omega} |\nabla u_i|$$

s.t. $\sum_{i=1}^K u_i(x) = 1, u_i(x) \in \{0, 1\}$

$$\blacktriangleright \min_{u \in \mathcal{S}} \left\{ \frac{1}{2} \|f - \mathcal{B}u\|_2^2 + \lambda \|\nabla u\|_0 \right\}$$

$$\blacktriangleright \min_{\psi} \left\{ D[T(\psi), R] + \alpha \|\Delta\psi\|_2^2 \right\}$$

Convex optimisation
algorithms

- \blacktriangleright ADMM
- \blacktriangleright Primal-dual
- \blacktriangleright Split-Bregman
- \blacktriangleright Augmented Lagrangian

Sparse regularizations

- \blacktriangleright $\|\cdot\|_0, \|\cdot\|_1, \|\cdot\|_2$
- \blacktriangleright with $\nabla, \Delta, \mathcal{W}$
- \blacktriangleright \mathcal{W} : Wavelet transform

Conclusions

1. Computer vision works and has a great future
2. Big difference between data-driven and model-driven
3. Gap is becoming smaller
4. What will happen in the future?

We have more to learn ...