UNIVERSITÉ SORBONNE PARIS NORD

L2TI LABORATOIRE DE TRAITEMENT ET TRANSPORT DE L'INFORMATION

MathSTIC – CNRS

Computational Visual Perception and Data-Driven Framework for Medical Imaging

By

Prof. Azeddine Beghdadi
L2TI, MathSTIC, Univ-Sorbonne Paris Nord

My Generation

Major Scientific Waves / “Revolutions”

- ✓ 80’s : Fractal Geometry in Signal and Image Processing (SIP)
- ✓ 1980-90’s : Wavelet Representation and Analysis
- ✓ 1990-2000’s : Compressive Sensing & Sparse Representation
- ✓ 2000’s: Sparse Dictionary Learning for SIP
- ✓ 2010 → <u>Deep Learning-based Computer Vision</u>
- ✓ Next? Unifying Revolution?*

* Simple mathematical statements can elegantly unite and express a multitude of concepts and observations

My main current research areas

Applied research topics

Healthcare

- Video-guided surgery
- Intelligent Wireless Capsule Endoscopy for the Diagnosis of Gastrointestinal Diseases

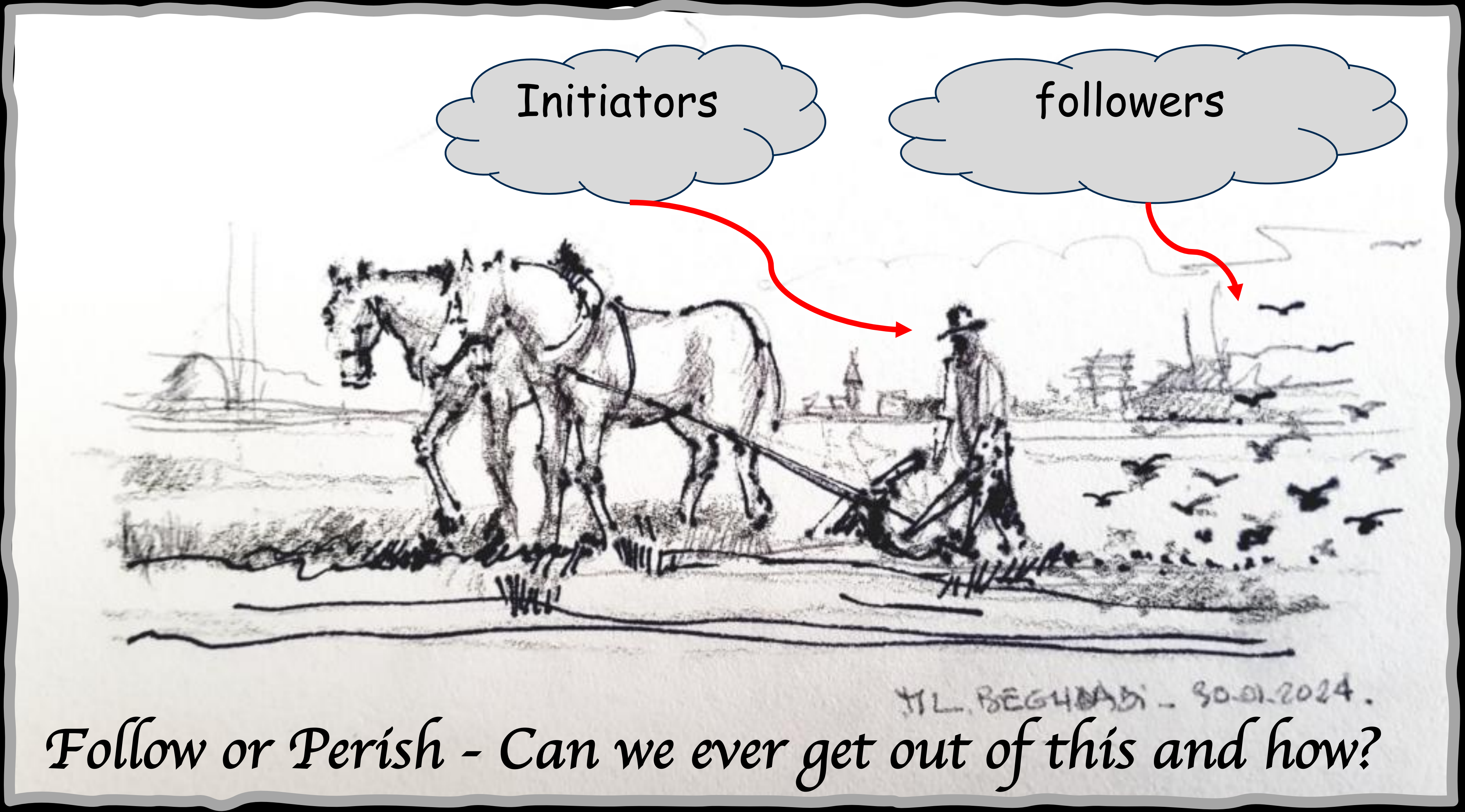
Public Security

- Intelligent Video Surveillance

Theoretical research

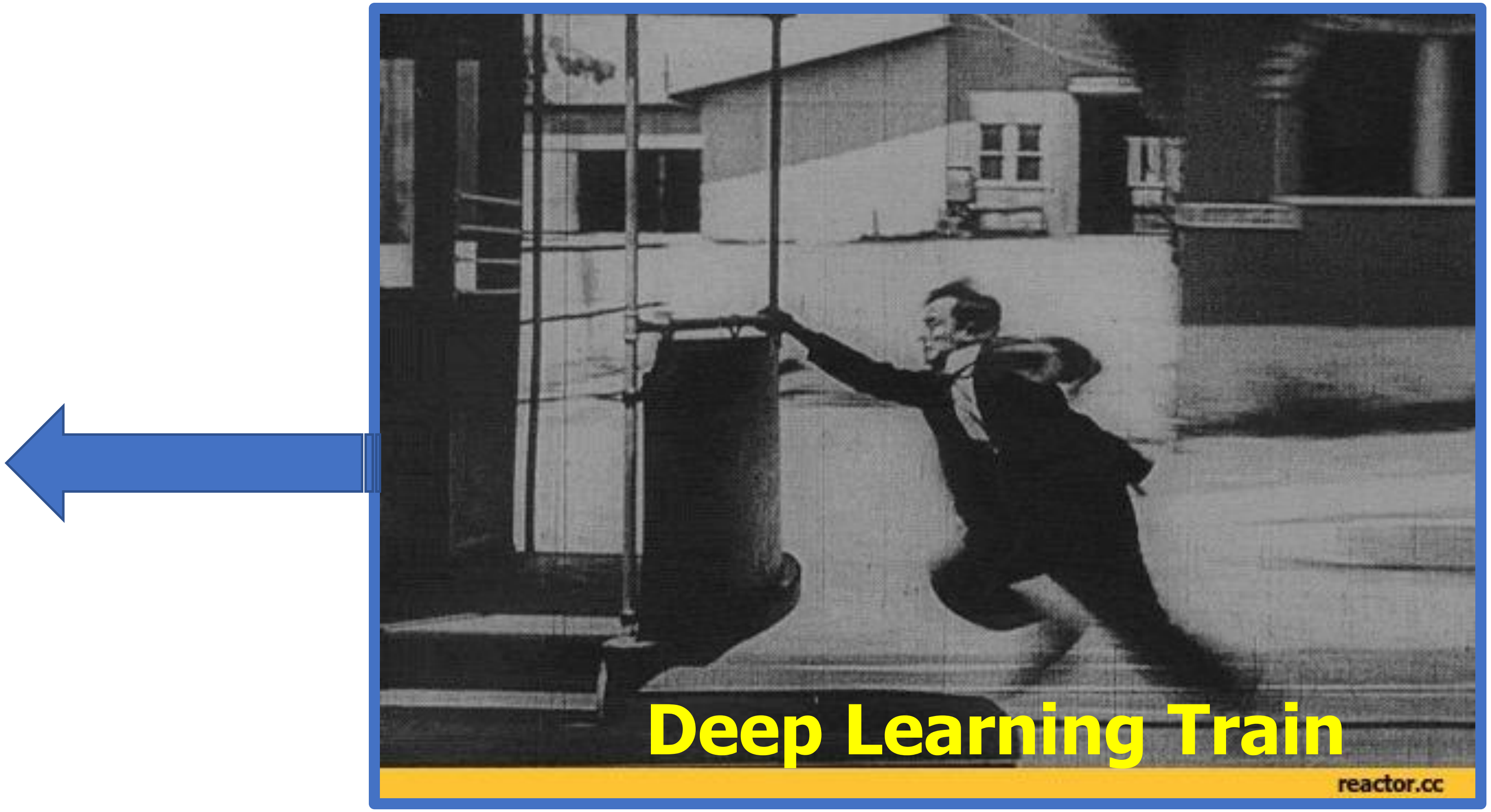
- Perceptual Vision Models for Visual Data Processing and Analysis
- Bio-inspired Machine Learning Architectures

Taking part in Deep Learning Wave



Follow or Perish - Can we ever get out of this and how?

Better inside than outside.



The focus of today's talk

Image Quality Assessment and Enhancement in Medical Imaging

From Perceptual Modeling to Physics-Informed and AI-Based Approaches

Some Key Challenges & Questions

- Traditional Approaches Vs ML-based Approaches
  - What's wrong/good with traditional approaches?
  - Should we abandon traditional approaches?
  - Is it relevant and easy to reconcile the two?
  - Are there any objective criteria for evaluating AI-based technologies ?
- Do we really need to enhance image quality in the era of AI?
- Image Quality Enhancement Evaluation challenges
- Medical Imaging /Diagnosis and surgical workflow context
  - Is measuring and improving quality always relevant/useful?
  - Can we expect progress in terms of systems and image sensors, or should we rely more on software solutions?

Outline

- ❑ Part I
  - ✓ Model-based Approaches vs Data-driven Approaches
  - ✓ Computational Visual Perception & Deep Learning
- ❑ Part II
  - ✓ Image Quality Assessment in the context of medical imaging and diagnosis
    - ▪ Basic Notions on IQA
    - ▪ IQA in Medical Imaging Context
- ❑ Part III
  - ✓ Selected Applications
    - ▪ Video-guided surgery
    - ▪ Low dose CT imaging
- ❑ Concluding Remarks, Challenges and Open Problems

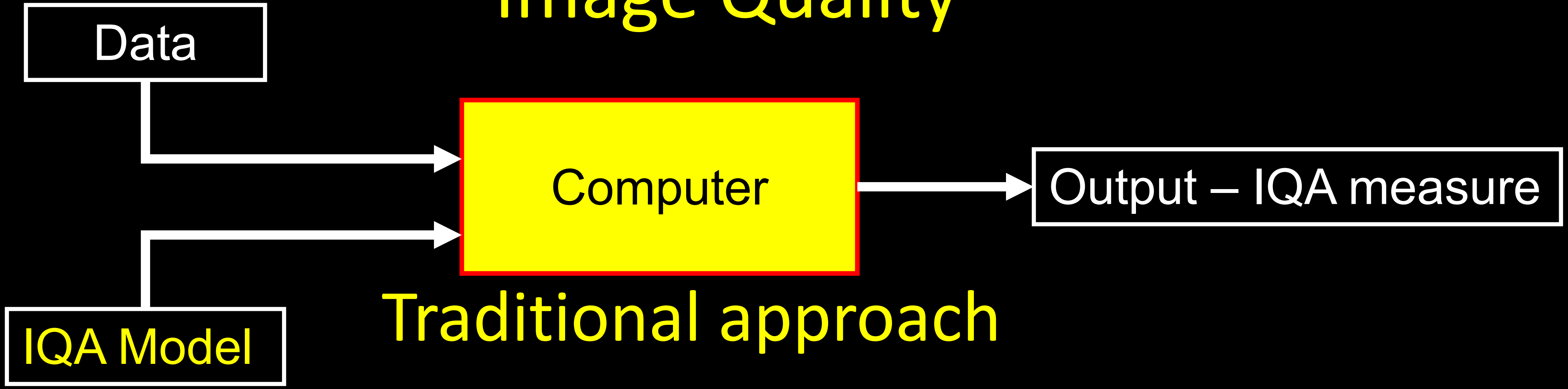
Part I

Model-based Approaches Vs Data-driven Approaches

Towards Hybrid approaches

Computational Visual Perception & Deep Learning

Traditional methods Vs ML-based methods
Image Quality



Data

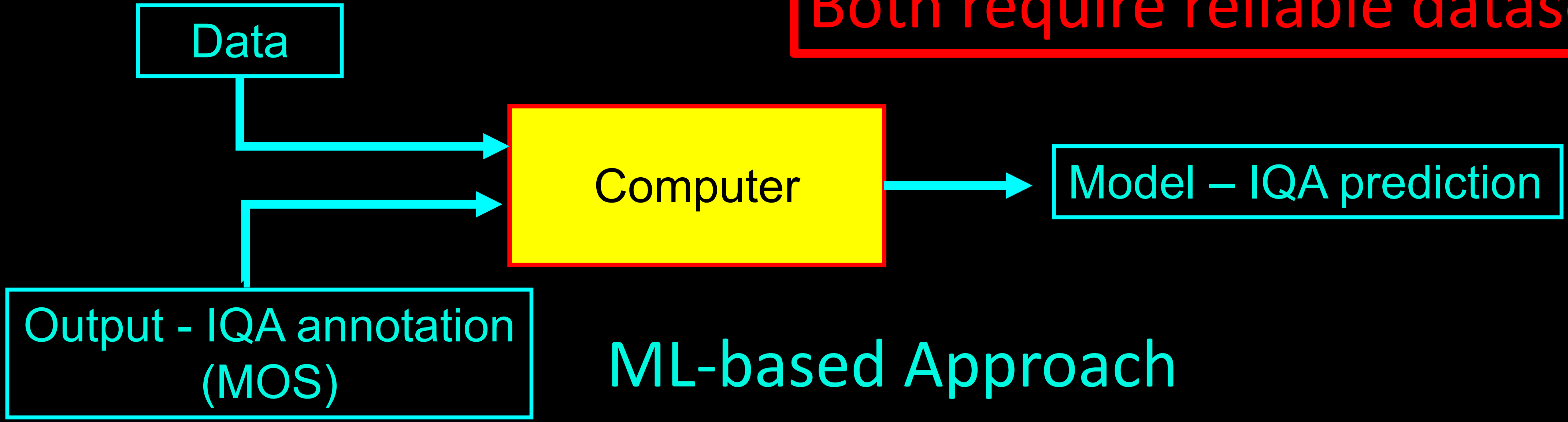
IQA Model

Computer

Output – IQA measure

Traditional approach

Both require reliable dataset



Data

Output - IQA annotation (MOS)

Computer

Model – IQA prediction

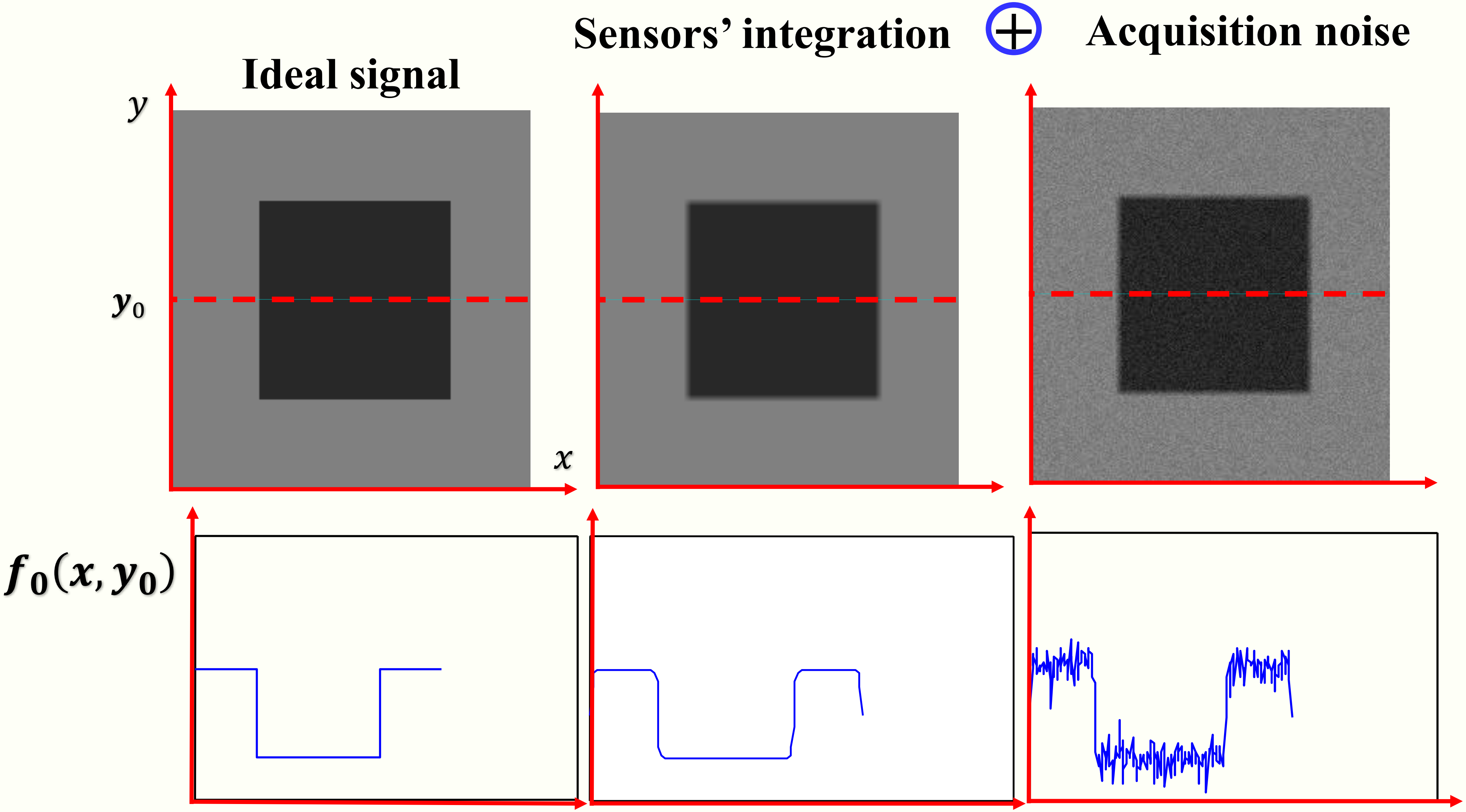
ML-based Approach

What’s wrong with traditional methods ?

Selected Topics

- ✓ Edge detection
- ✓ Image binarization
- ✓ Optical Flow
- ✓ Heisenberg’s Uncertainty Principle in Visual Signals
- ✓ …

Illustration of an image signal as captured by image sensors



Ideal signal

Sensors' integration ⊕ Acquisition noise

Image formation models used in image processing

Simplified optical image acquisition model : linear space-invariant system

$$g(x,y) = (f * h)(x,y) + \eta(x,y)$$

f the free distortion signal to be estimated
g the observed scene intensity
η the additive noise acquisition
h impulse response of the linear system

Smoke video model used in video guided surgery

$$g(x,y) = J(x,y)T(x,y) + A(1 - T(x,y))$$

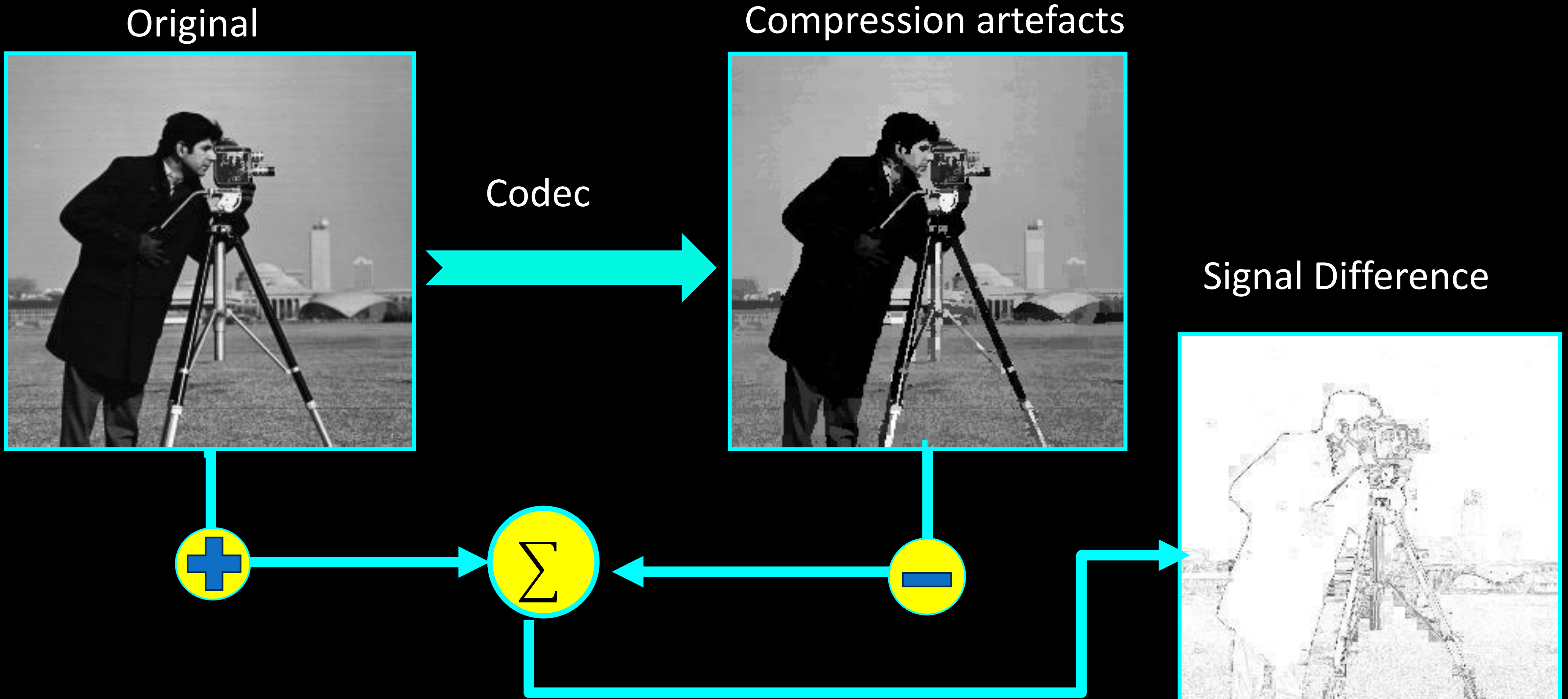
J the scene radiance
g the observed scene intensity
A the global ambiant light
T the transmittance of the medium

Retinex model used in endoscopy IQE

$$g(x,y) = R(x,y).L\,(x,y)$$

g the observed scene intensity
R(x,y) is the reflectance
L(x,y) is the luminance

The importance of edginess information



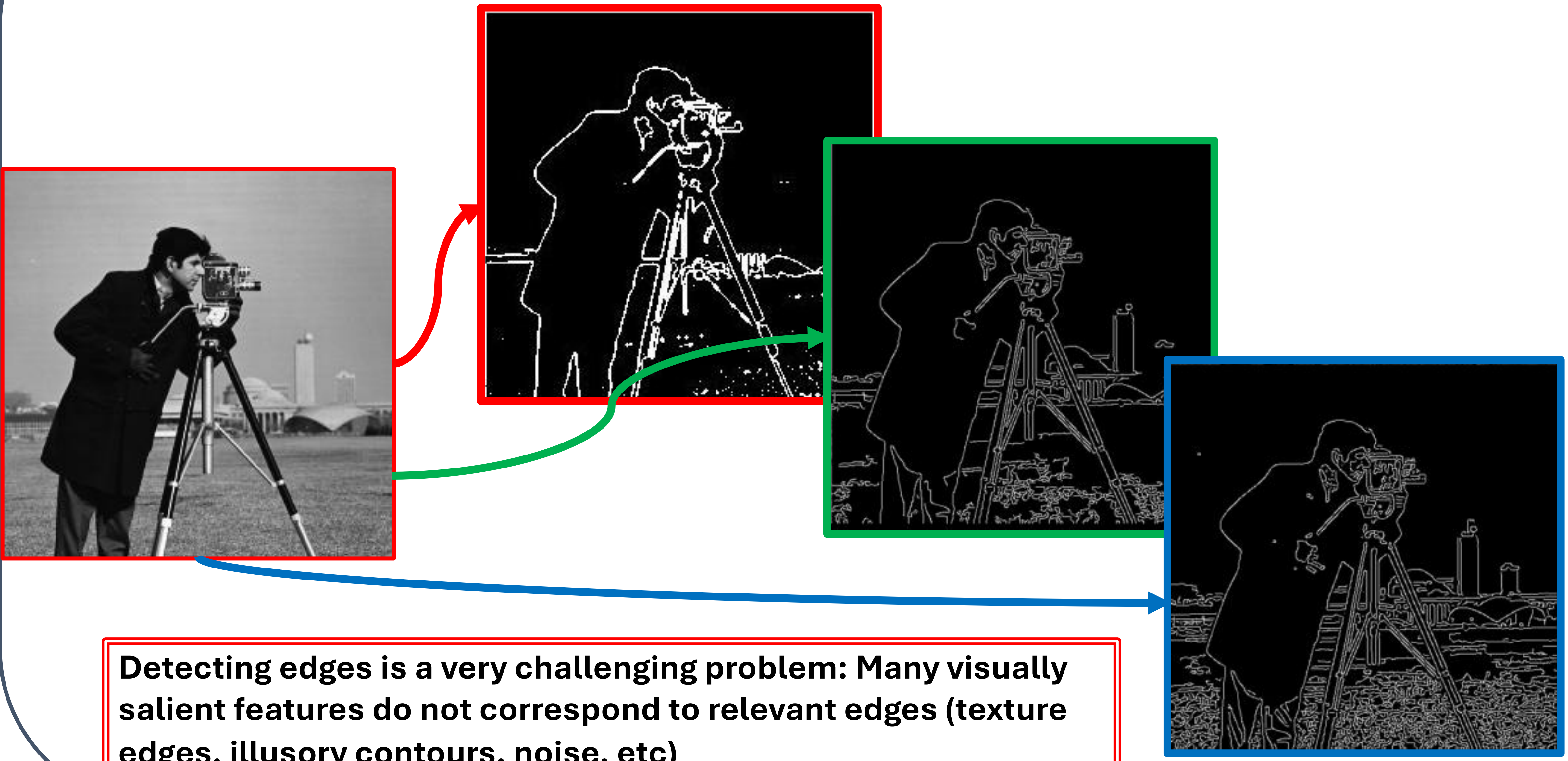
Original

Codec

Compression artefacts

Signal Difference

Edge Detection using traditional IP

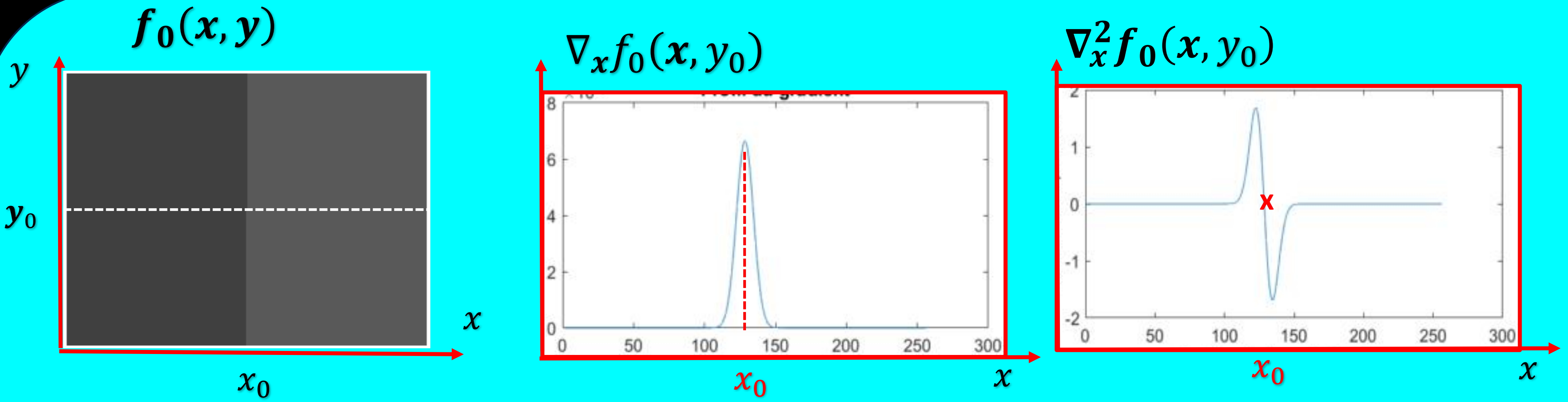


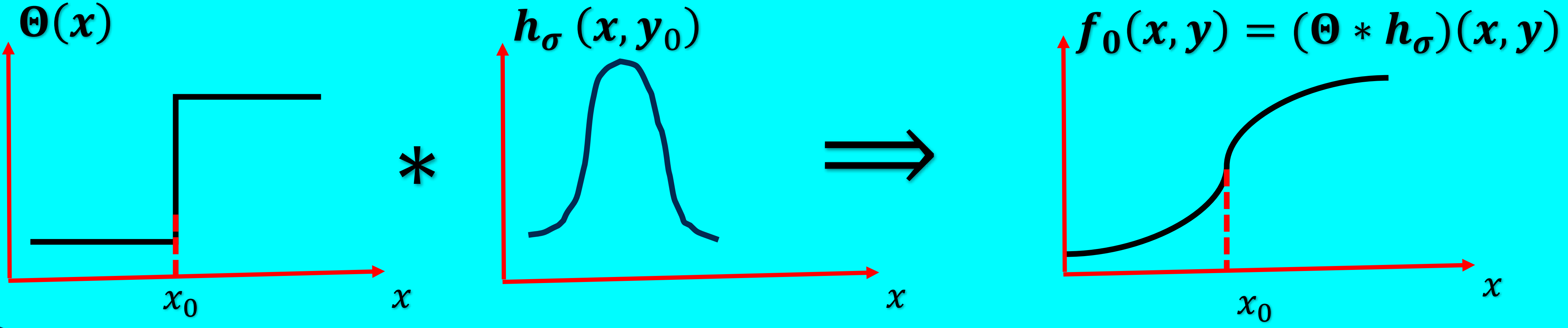
Detecting edges is a very challenging problem: Many visually salient features do not correspond to relevant edges (texture edges, illusory contours, noise, etc)

Traditional approach

Model-based image signal analysis

1- Edge detection

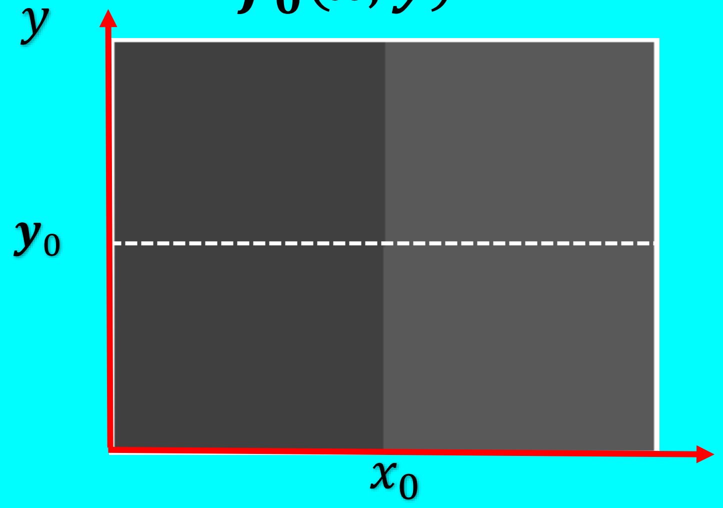




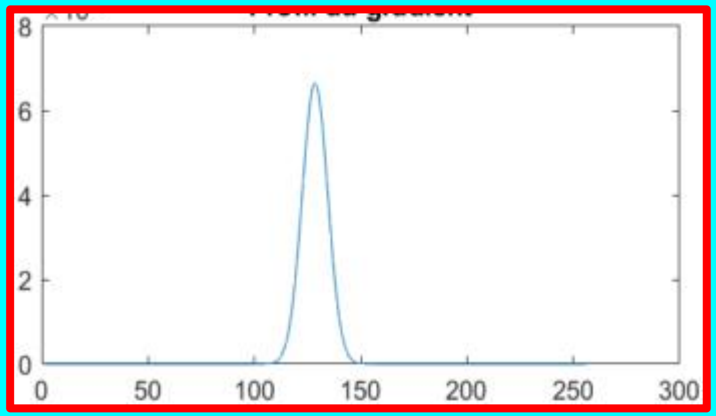
Traditional approach (cont’d)

- Model-based image signal analysis

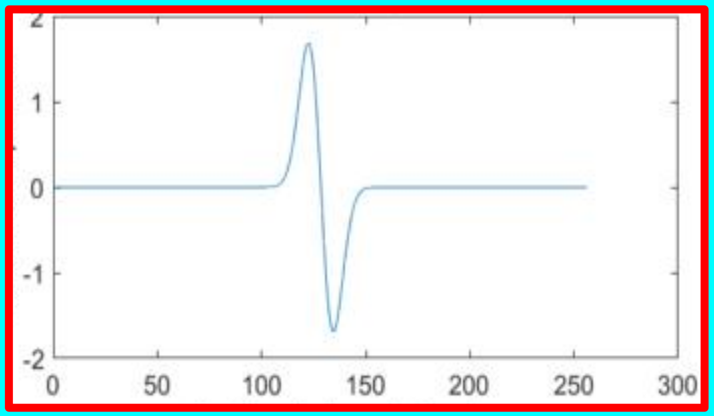
$f_0(x, y)$



$\nabla_x f_0(x, y_0)$

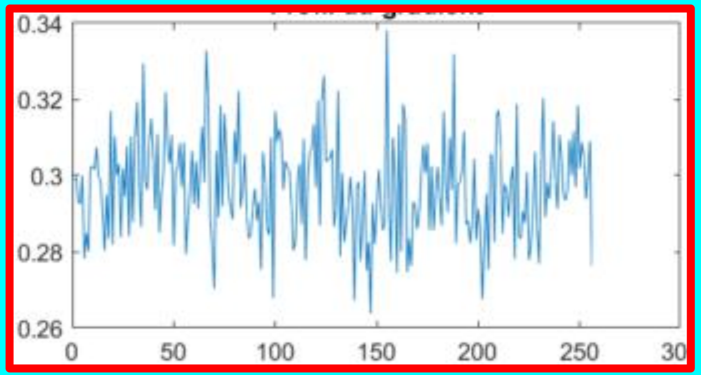


$\nabla_x^2 f_0(x, y_0)$

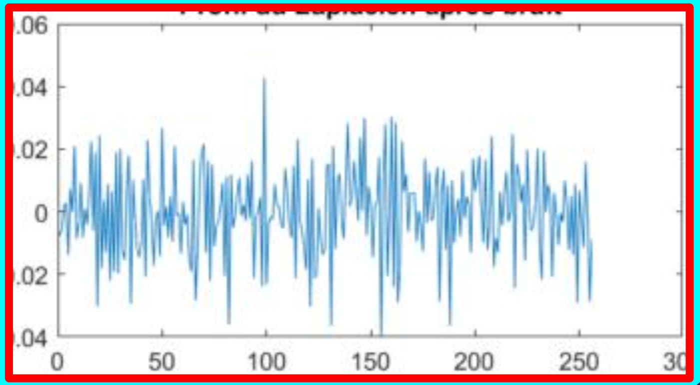


$f(x, y) = f_0(x, y) + \eta(x, y)$

$\nabla_x f(x, y)$

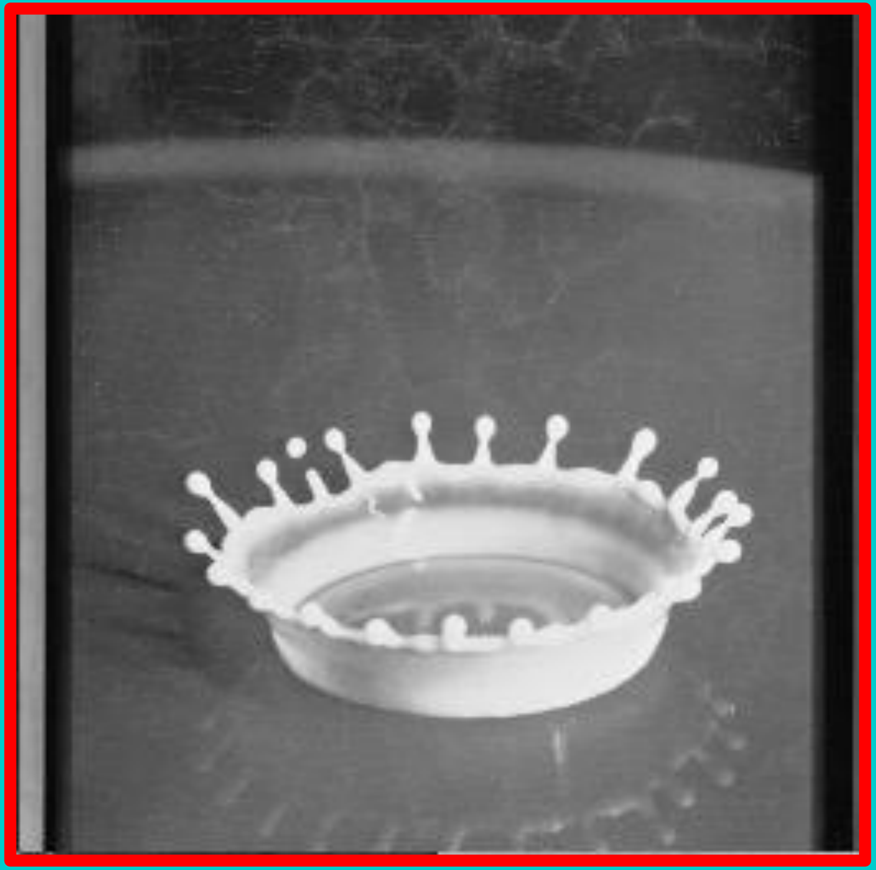


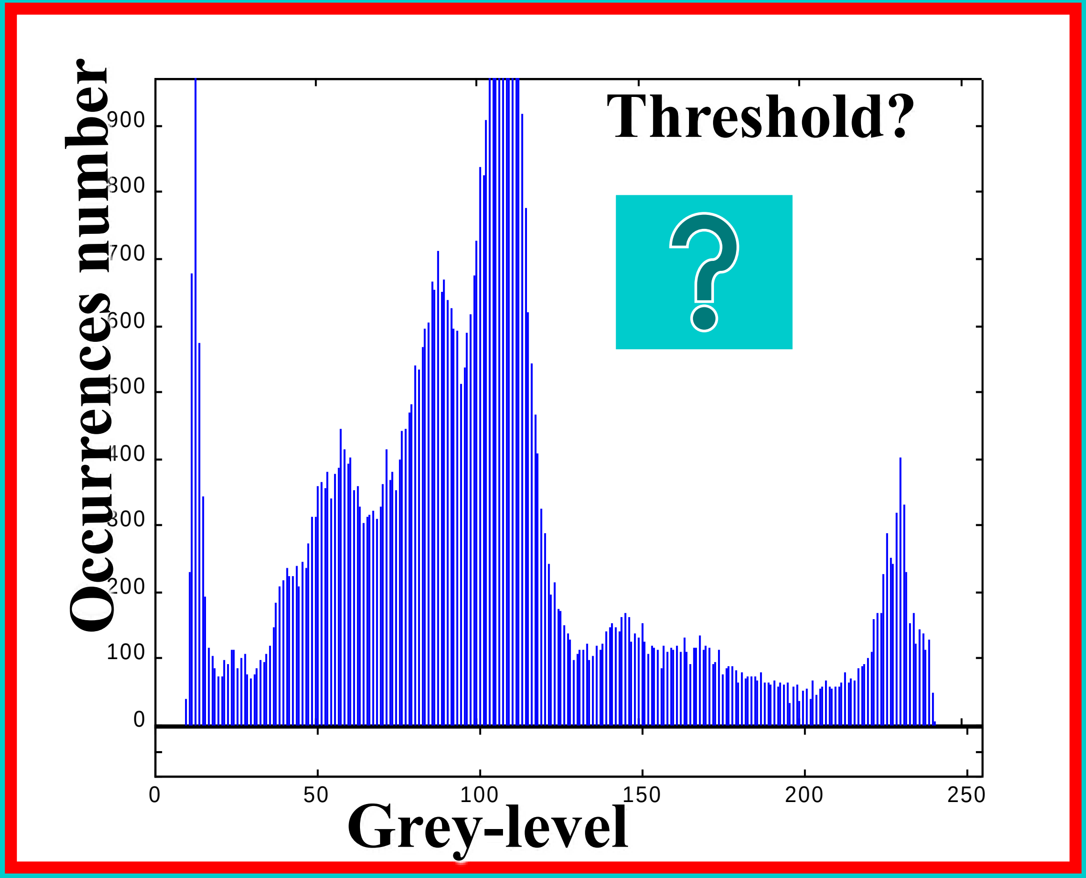
$\nabla_x^2 f(x, y)$



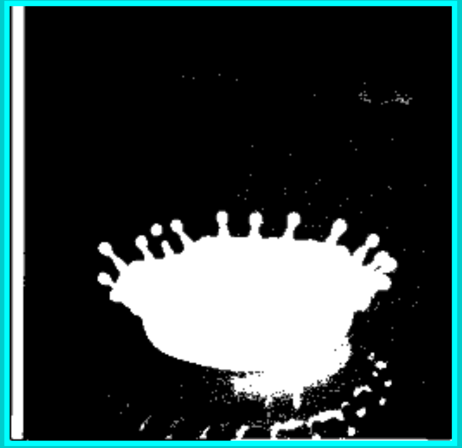
2. Binarization - Bimodality vs Multimodality

How many objects of visual interest ?

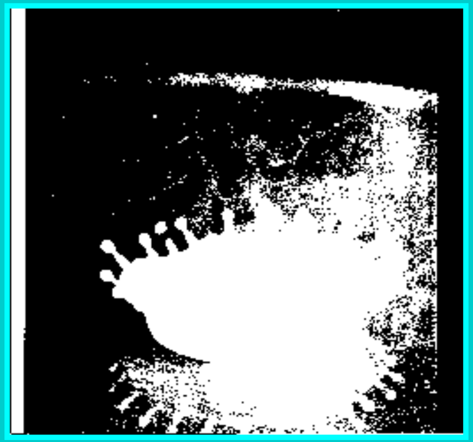




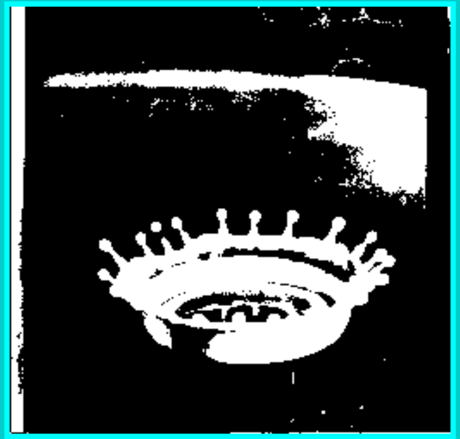
Grey-level thresholding – Visual comparison



A. S. Abutaleb (1989)



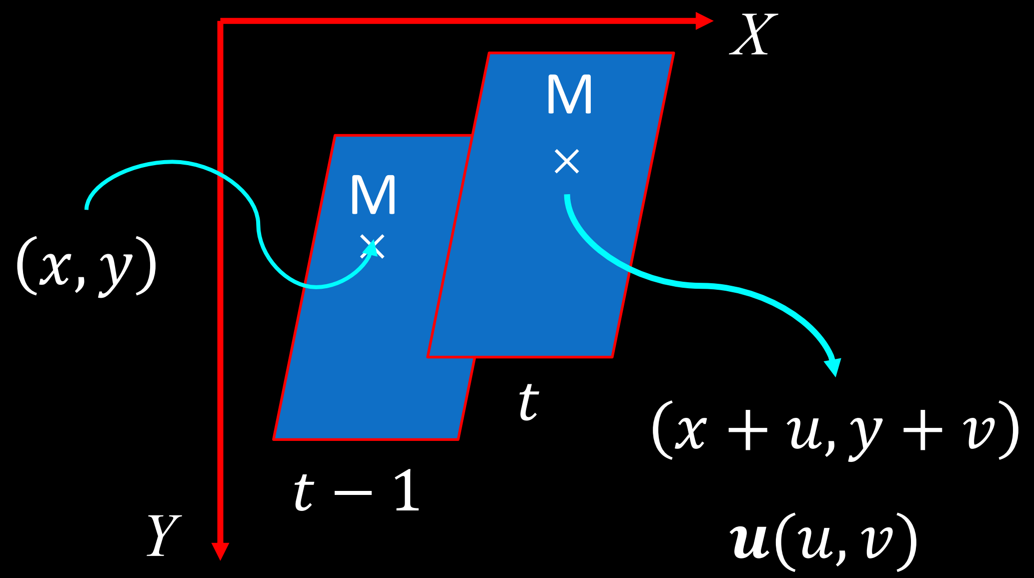
T. Pun (1980)



Beghdadi et al. (1995)

Kapur et al. (1985)

3- A case study: Optical flow estimation



Assumptions:

- Brightness constancy constraint

$$I(x, y, t-1) = I(x+u, y+v, t)$$

- Small inter-frame motion

$$I_t(x, y) + \nabla I^T \boldsymbol{u} = 0$$

Optical flow estimation is an ill-posed problem

Additional assumption:

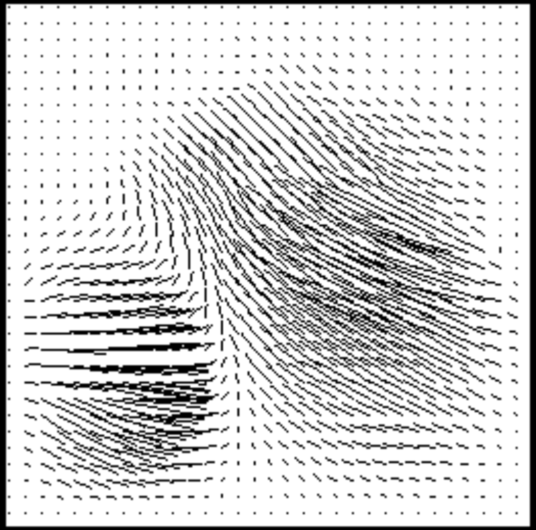
Spatial coherence (smoothness assumption) $\nabla^2 u + \nabla^2 v \approx 0$

$$E = \int\int [(I_x u + I_y v + I_t)^2 + \alpha^2 (||\nabla u||^2 + ||\nabla v||^2)] \mathrm{d}x \mathrm{d}y$$

A case study: Optical flow estimation

Initial Image

Final Image



Estimated Flow Field

OF estimation is formulated as an energy minimization problem

Beghdadi, A., Mesbah, M., & Monteil, J. (2003). A fast incremental approach for accurate measurement of the displacement field. image and vision computing, 21(4), 383-399.

What we perceive does not always correspond to what the machine sees through mathematical models.

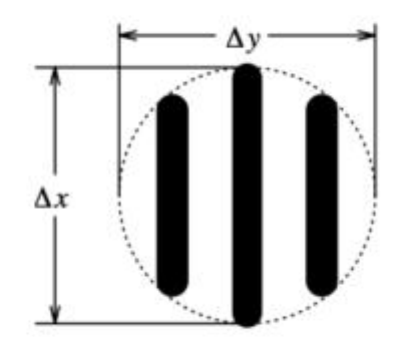
Traditional approach (cont’d)

- Model-based Image Signal Analysis

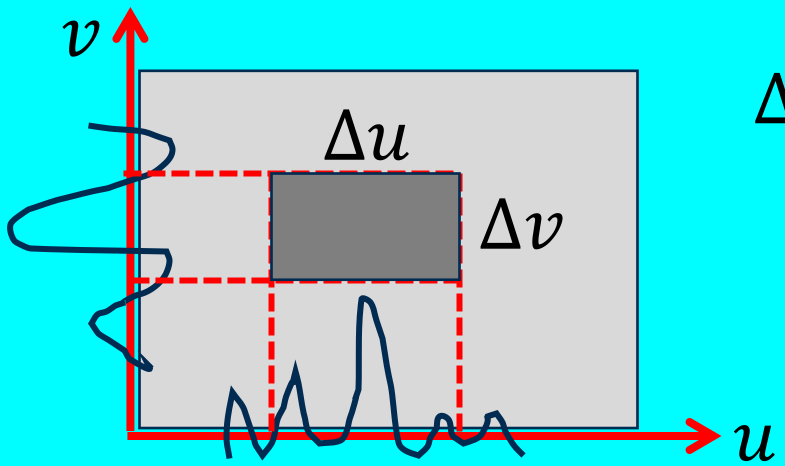
Other theoretical limitations

✓ **2D linear spatial filters are constrained by Heisenberg uncertainty**

  - **Heisenberg uncertainty principle in image processing: Space and spatial-frequency localizations are limited by the Heisenberg uncertainty principle**



Spatial domain



Spatial frequency domain

$$\Delta x \Delta u \geq 1/4\pi$$

$$\boxed{(\Delta x)\,(\Delta y)(\Delta u)\,(\Delta v) \geq 1/16\pi^2}$$

John G. Daugman, JOSA, 1985

What is Wrong/Good with Traditional Methods In Computer Vision?

- ✓ Observations/Experiments → Models
- ✓ Derive equations
- ✓ Define the conditions and hypotheses for solving the problem
- ✓ Adding constraints and conditions in the case of ill-posed problems

Switching to Artificial Intelligence Paradigm

ML-based approach

- ✓ Problem Identification
- ✓ Data collection
- ✓ Choosing an architecture
- ✓ Training/retraining for model estimation
- ✓ Validation & Optimization

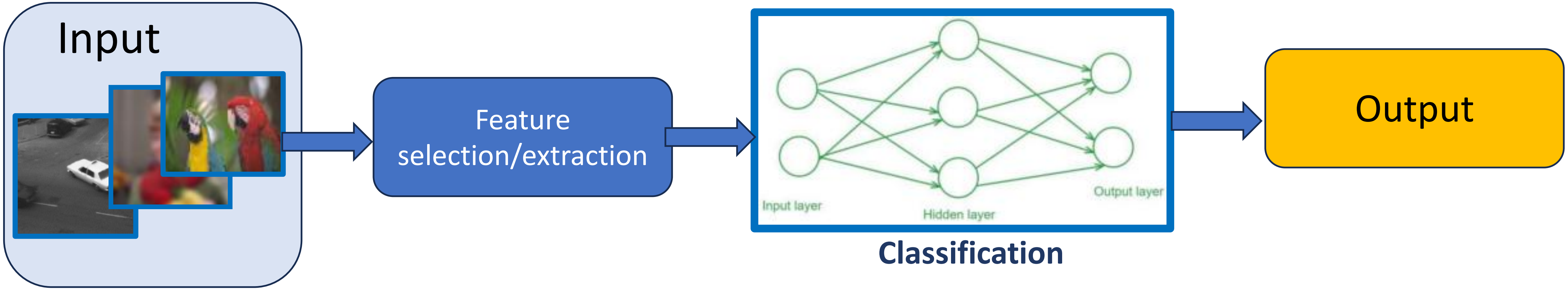
Are we condemned to go towards fully AI-based approaches?
Benefit.vs.Risk Analysis

Traditional approaches vs Artificial Intelligence Paradigm

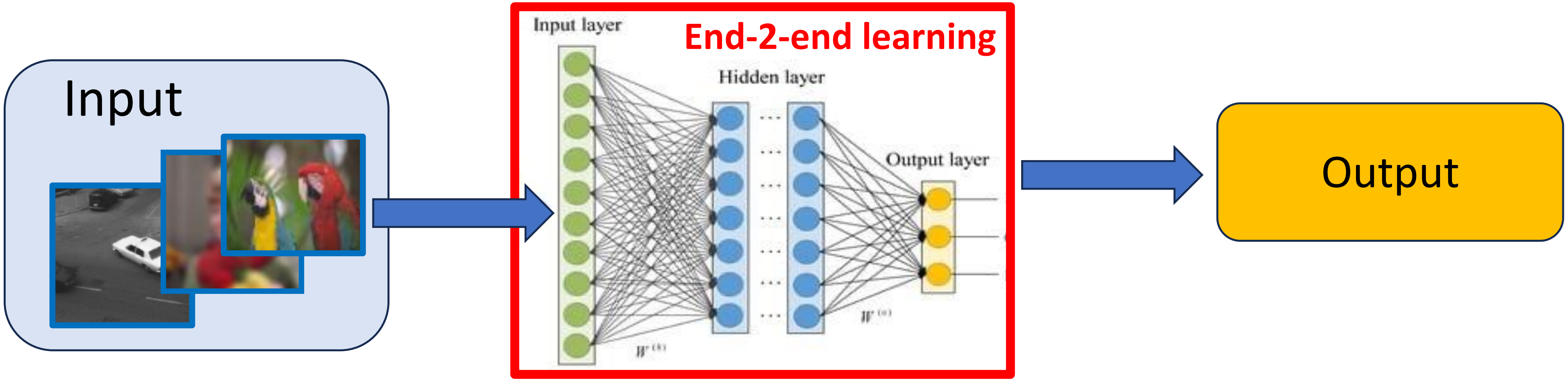
Some key questions

- ✓ Can we make a reasonable distinction between essential and non-essential traditional approaches to be integrated into AI-based technologies?
- ✓ Are traditional approaches all so important for developing efficient solutions for solving medical imaging problems?
- ✓ Is it appropriate to integrate computational models of visual perception and signal processing tools into CNN-based architectures to improve medical imaging technologies?

Traditional ML vs Deep Learning



Classification



Feature extraction &Classification

Traditional ML vs Deep Learning

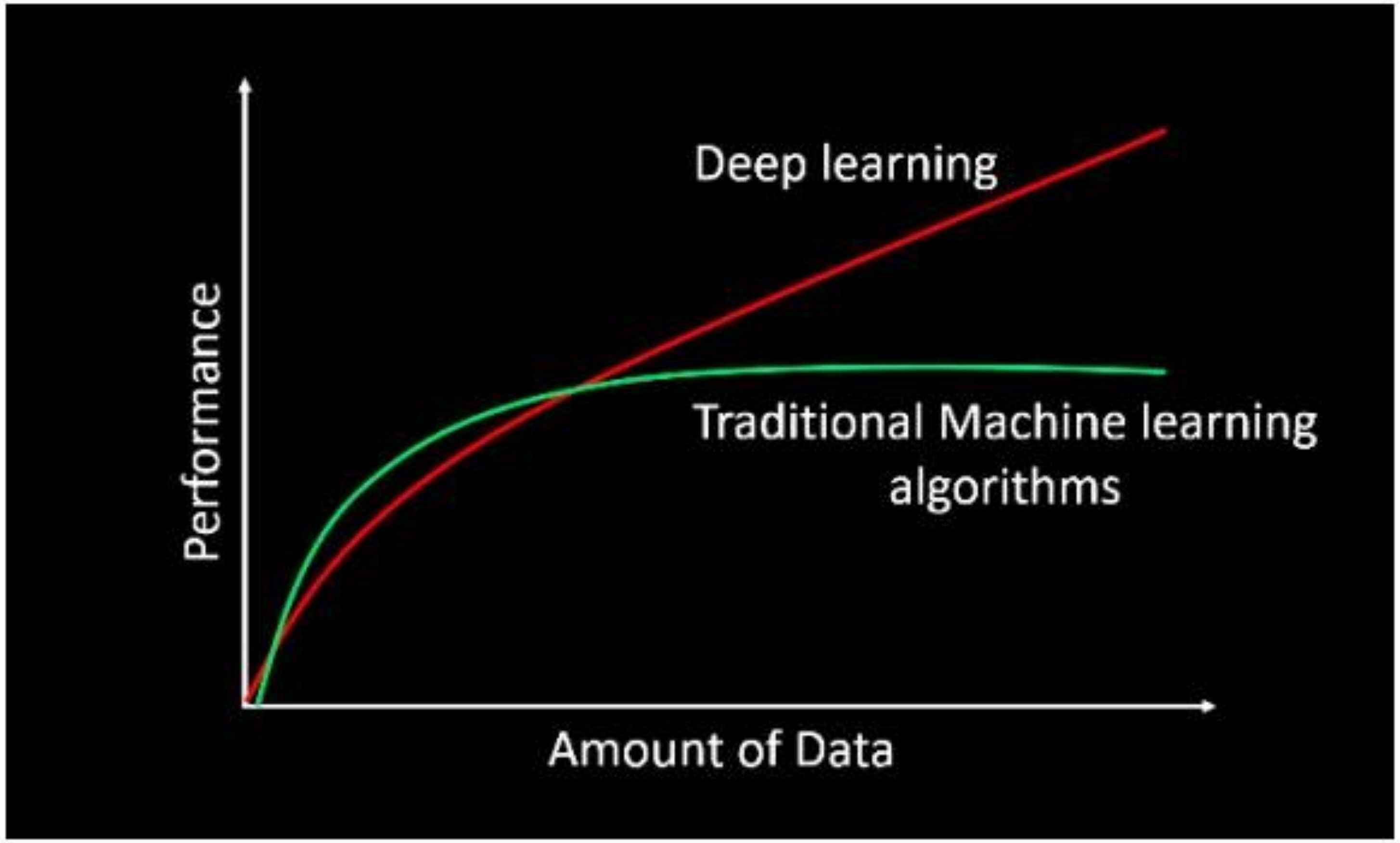


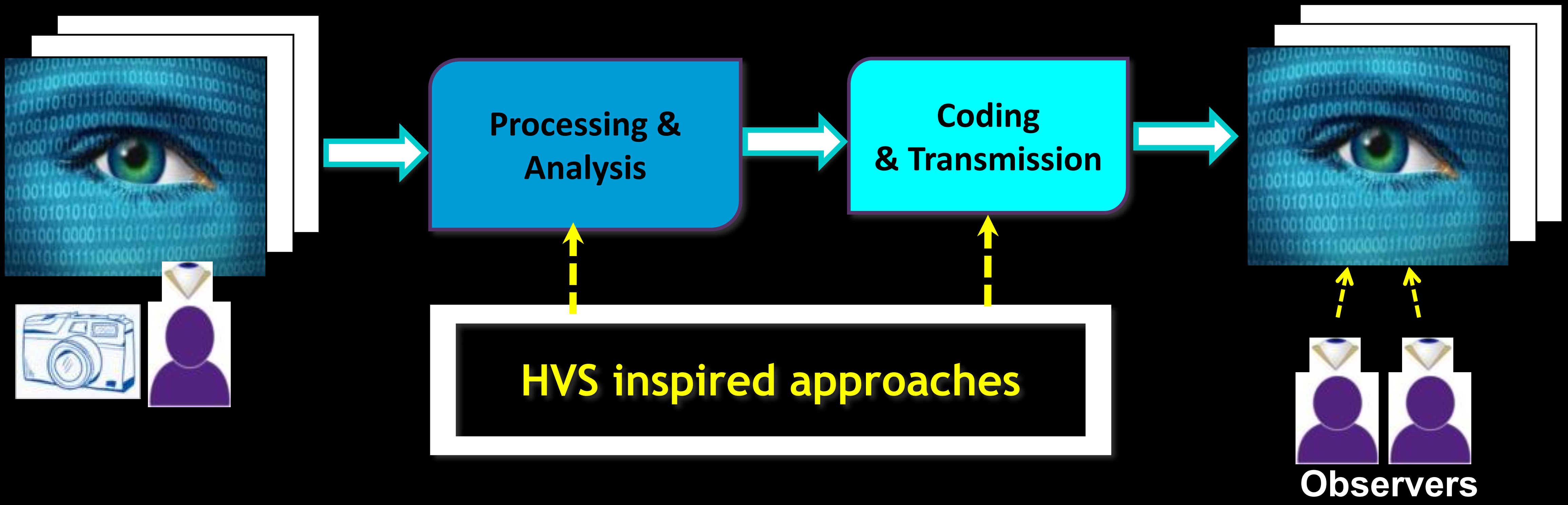
Figure 2: Data vs Performance Comparison

https://www.imveurope.com/sites/default/files/content/white-paper/pdfs/HCL_IMVE_WP-ImageProcessing_vs_DL.pdf

Towards Hybrid Approaches

Computational Visual Perception & Deep Learning

Why Computational Visual Perception ?



Processing & Analysis

Coding & Transmission

HVS inspired approaches

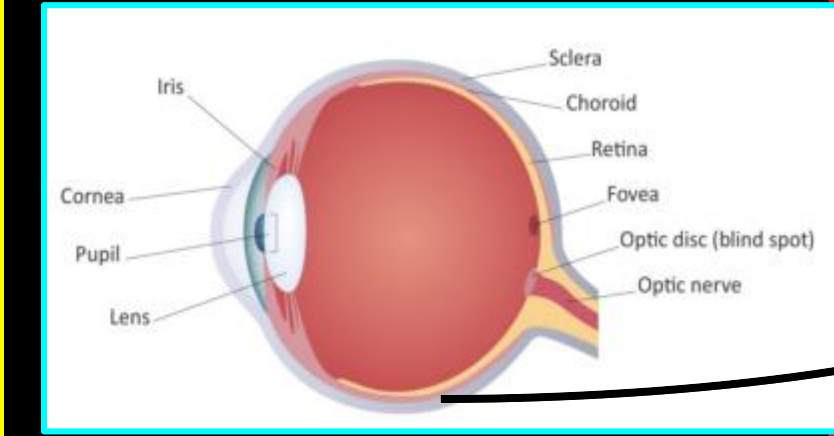
Observers

- ❖ It is estimated that 75% of the information received by a human is visual (Ernest L. Hall 1979)

A. Beghdadi et al., « Biologically inspired approaches for visual information processing and analysis », Signal Processing: Image Communication , 28(8):809 -810, 2013

Basic Notions on **H**uman **V**isual **S**ystem

Acquistion



Processing/analysis/understanding

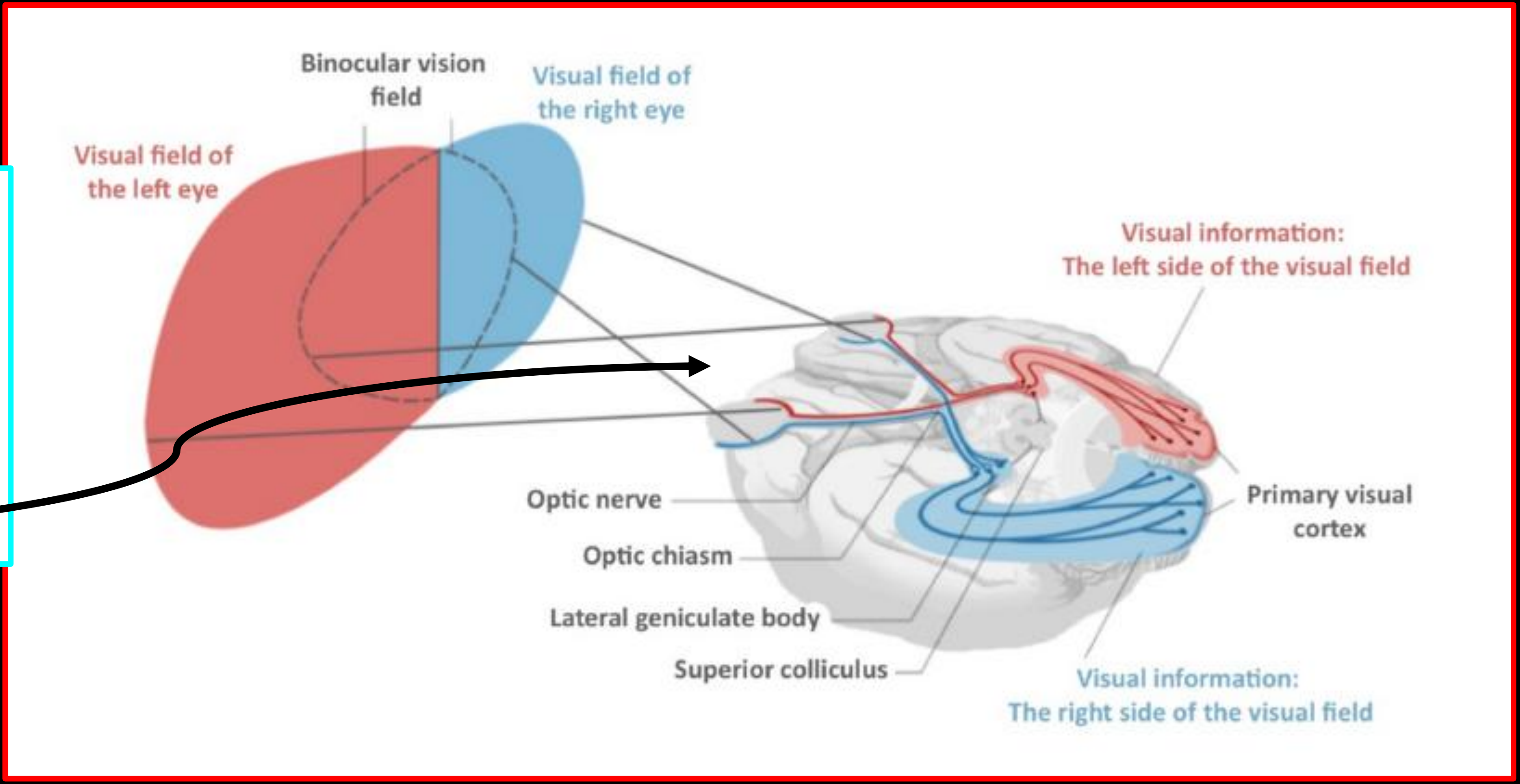
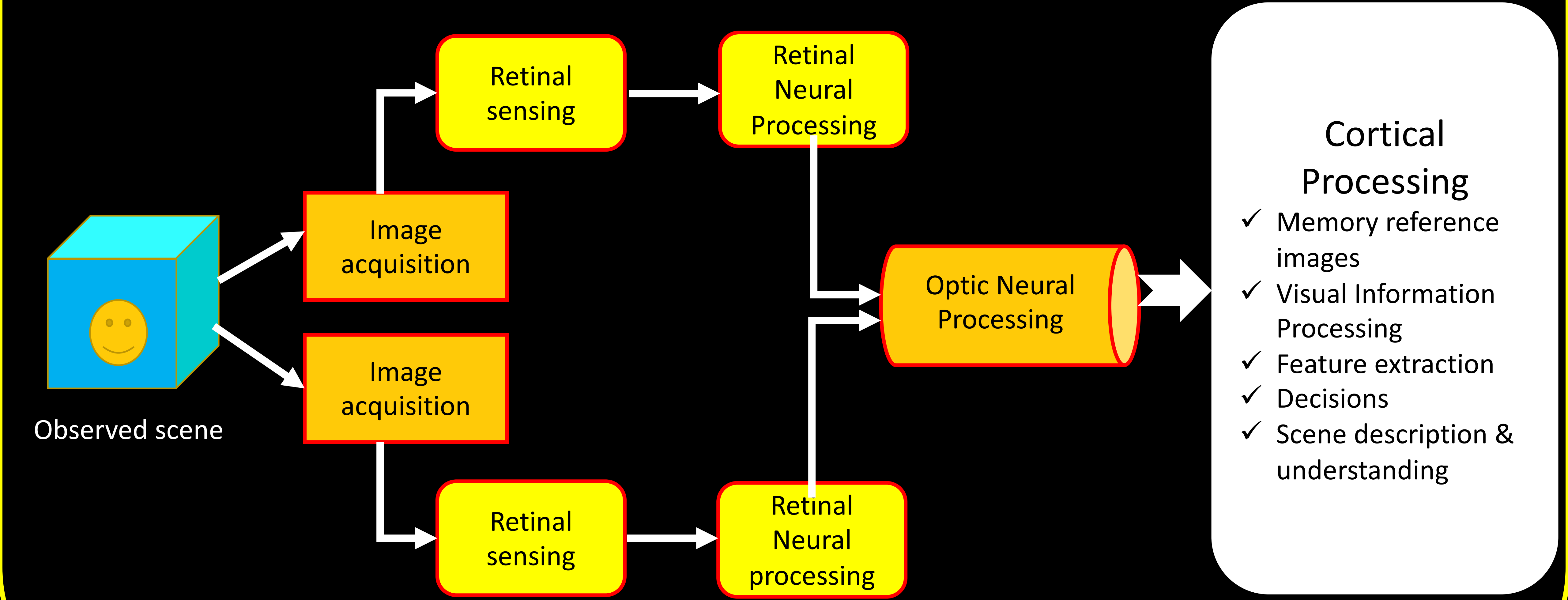


Figure designed by B. Sdiri, PhD thesis Sorbonne Paris Nord 2018

Simplified Model of the Visual Information Processing and Analysis Workflow in the HVS



Observed scene

Image acquisition

Image acquisition

Retinal sensing

Retinal sensing

Retinal Neural Processing

Retinal Neural processing

Optic Neural Processing

Cortical Processing

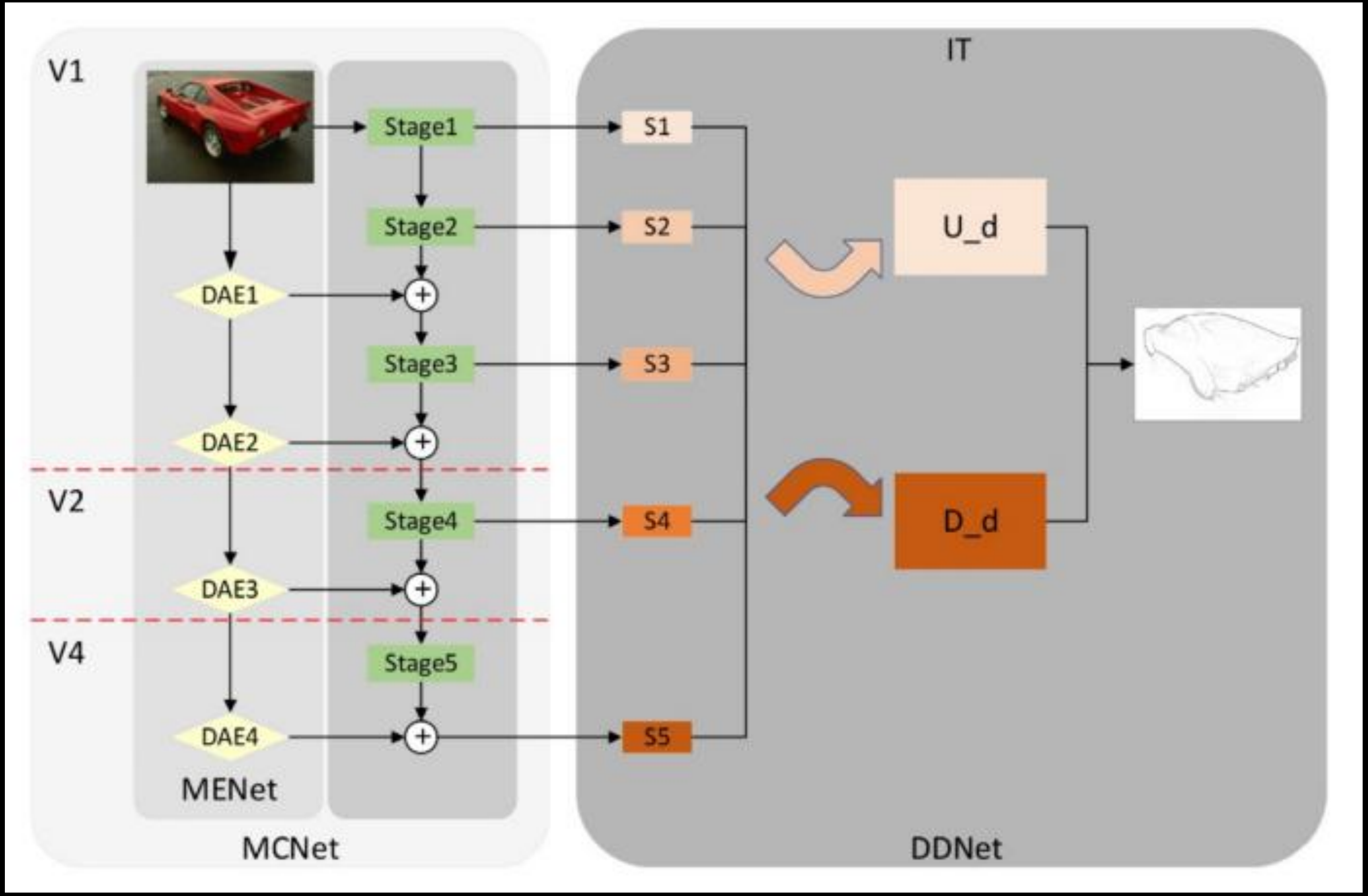
- ✓ Memory reference images
- ✓ Visual Information Processing
- ✓ Feature extraction
- ✓ Decisions
- ✓ Scene description & understanding

Biological Vision Inspired Deep Learning Approach

Ingredients

- ✓ Traditional signal processing tools
- ✓ Neurophysiological findings : Selective mechanisms in biological visual pathways in the visual cortex
- ✓ Plausible Neural Network Architectures
- ✓ Plausible Perceptual Loss Function
- ✓ Large-scale Performance Evaluation

Biological Vision Inspired Deep Learning Approach
Edge detection problem : a case study



Z. Zhang, C. Lin, Y. Qiao and Y. Pan, "Edge detection networks inspired by neural mechanisms of selective attention in biological visual cortex", Frontiers in Neurosciences. 16:1073484, 2022

Biological Vision Inspired Deep Learning Approach

Z. Zhang, C. Lin, Y. Qiao and Y. Pan, "Edge detection networks inspired by neural mechanisms of selective attention in biological visual cortex", Frontiers in Neurosciences. 16:1073484, 2022

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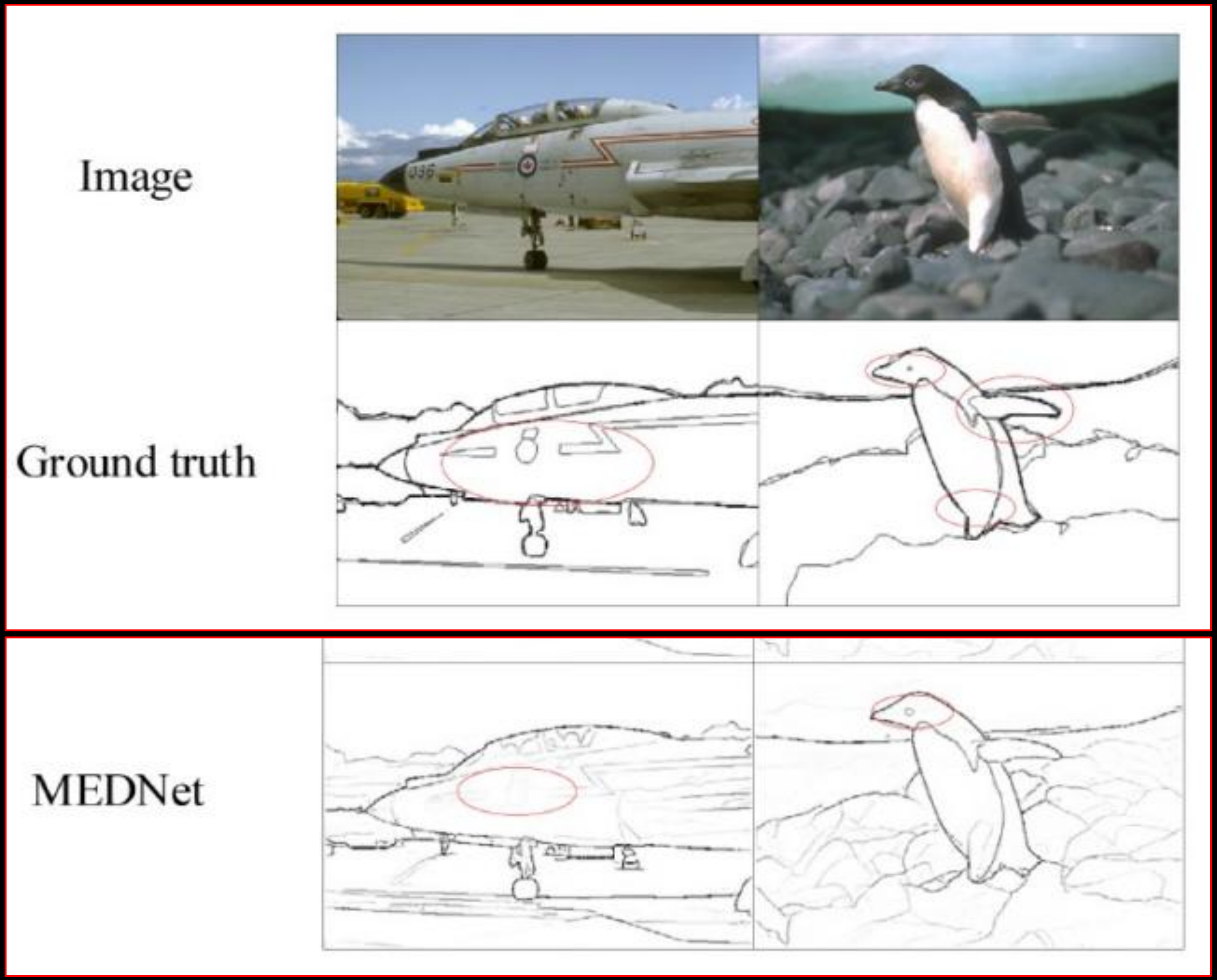

Z. Zhang, C. Lin, Y. Qiao and Y. Pan, "Edge detection networks inspired by neural mechanisms of selective attention in biological visual cortex", Frontiers in Neurosciences. 16:1073484, 2022

Part II

Image Quality in Medical Imaging and Diagnosis Context

Goal Oriented IQA (GO-IQA)

Outline

- The importance of IQA in the medical context
- Challenges in Medical Imaging Quality
- Medical Image Distortions Analysis
- Image quality enhancement for video guided surgery
- Concluding Remarks and Learned Lessons

Perceptual Quality of Images of Natural Scenes

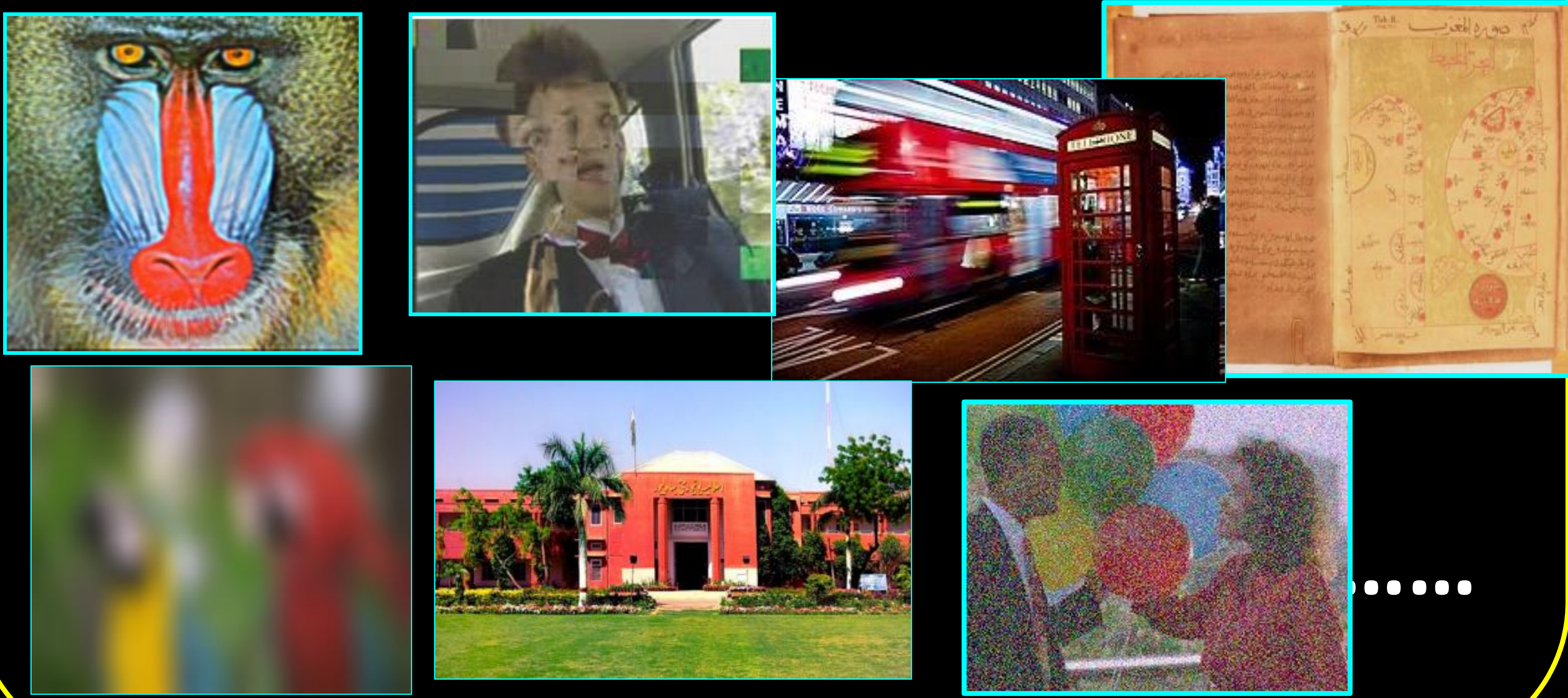

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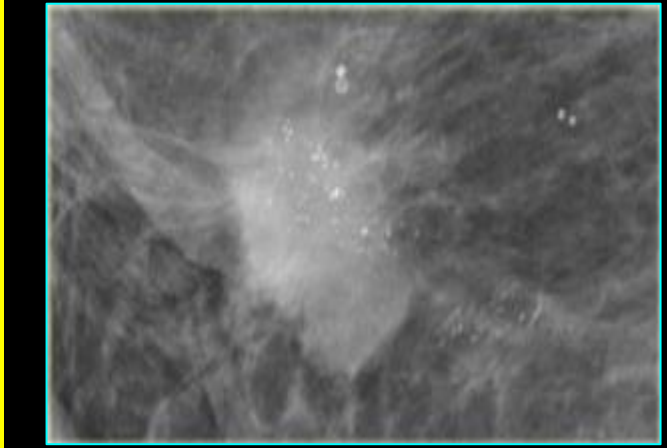
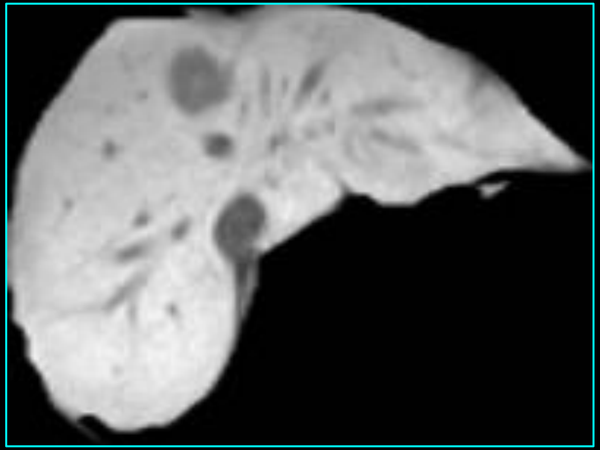
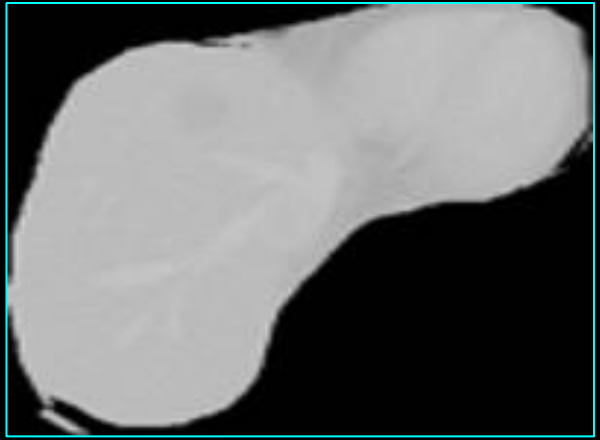
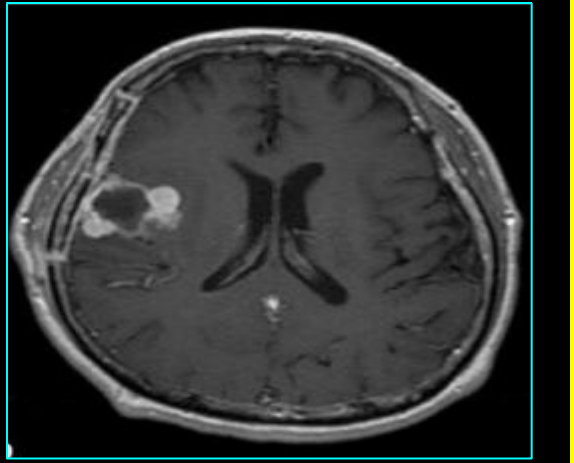
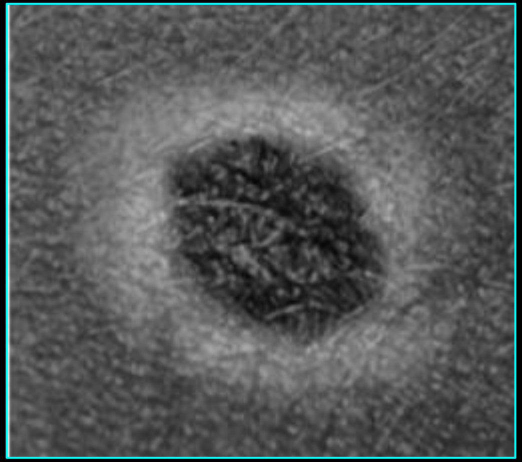
Image Quality in the Context of Medical Imaging and Diagnosis





Objective Image Quality

Can objective metrics replace the HVS

?

Yes/No

How AI Paradigm is Reshaping IQA ?

What does the deep learning paradigm bring ?

Why is IQA so Important in Medical Context ?

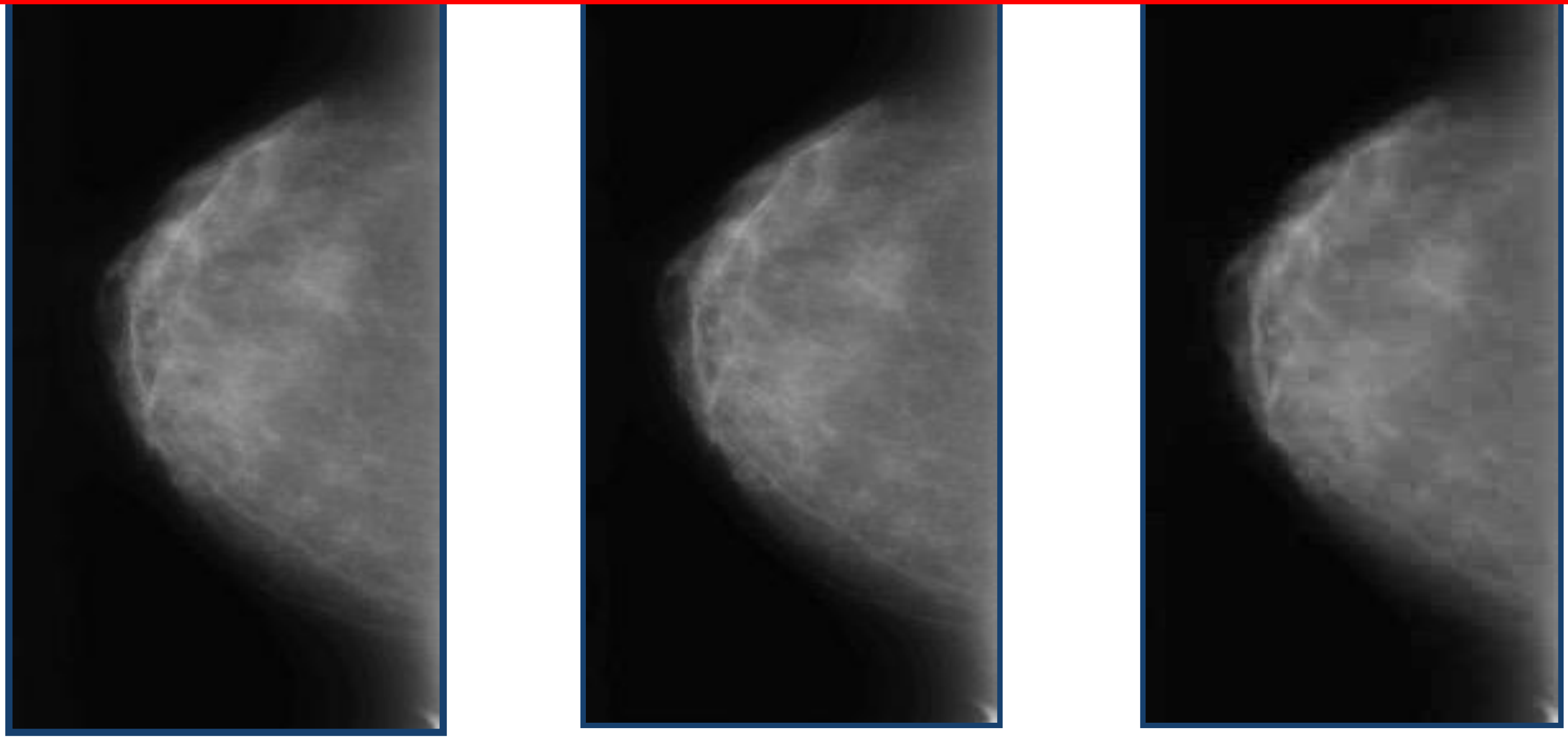
- ✓Medical Imaging
    - Medical Image acquisition quality assessment
    - Image quality reconstruction optimization
- ✓ Image/Video Guided Medical Diagnosis
- ✓ Video Guided Surgery Monitoring
- ✓Image Guided Radiotherapy
- ✓Image Enhancement Evaluation

…..

Digital Mammography Quality

Image quality vs medical diagnosis

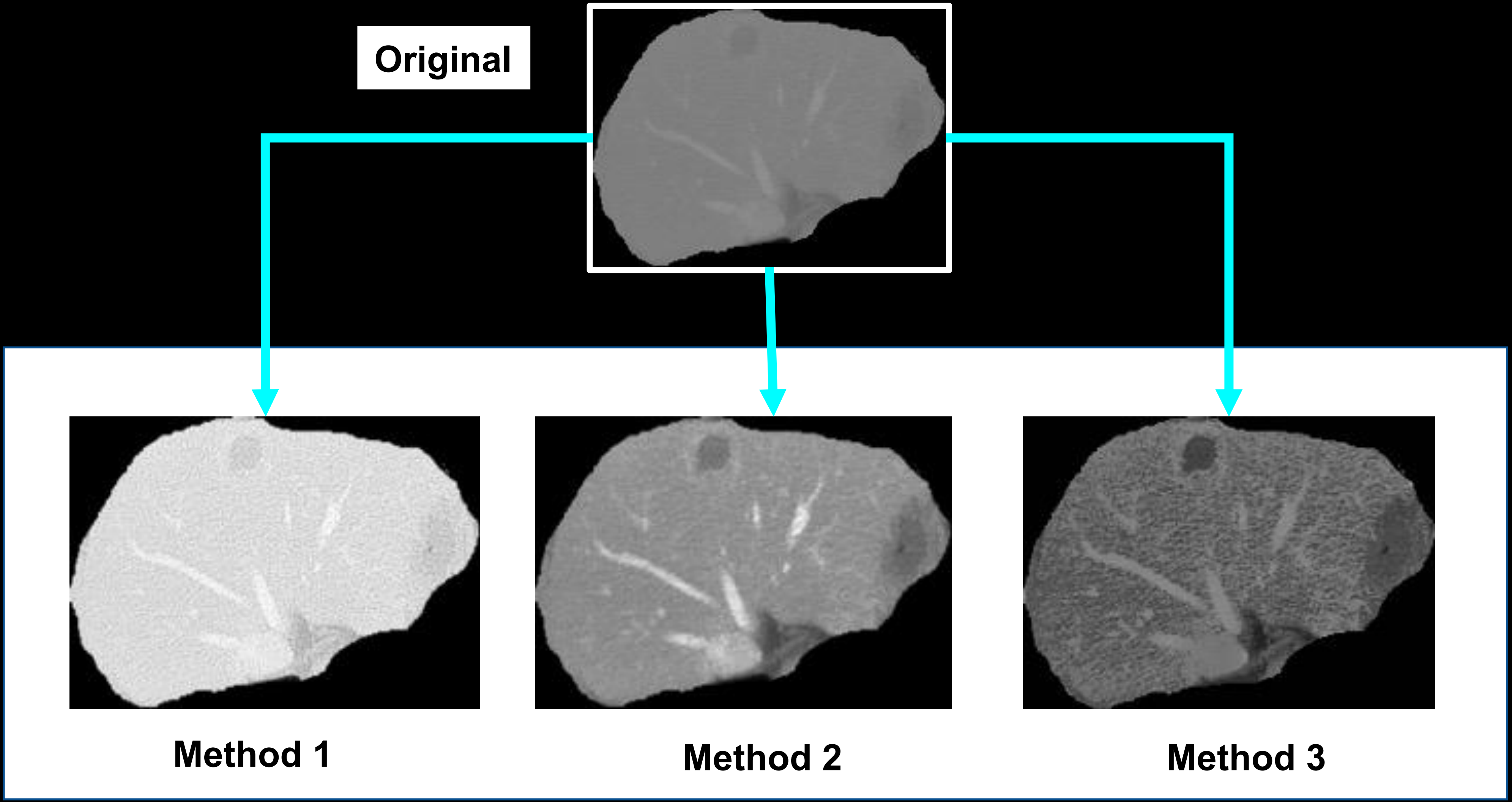
Do radiologists tolerate lossy compression?



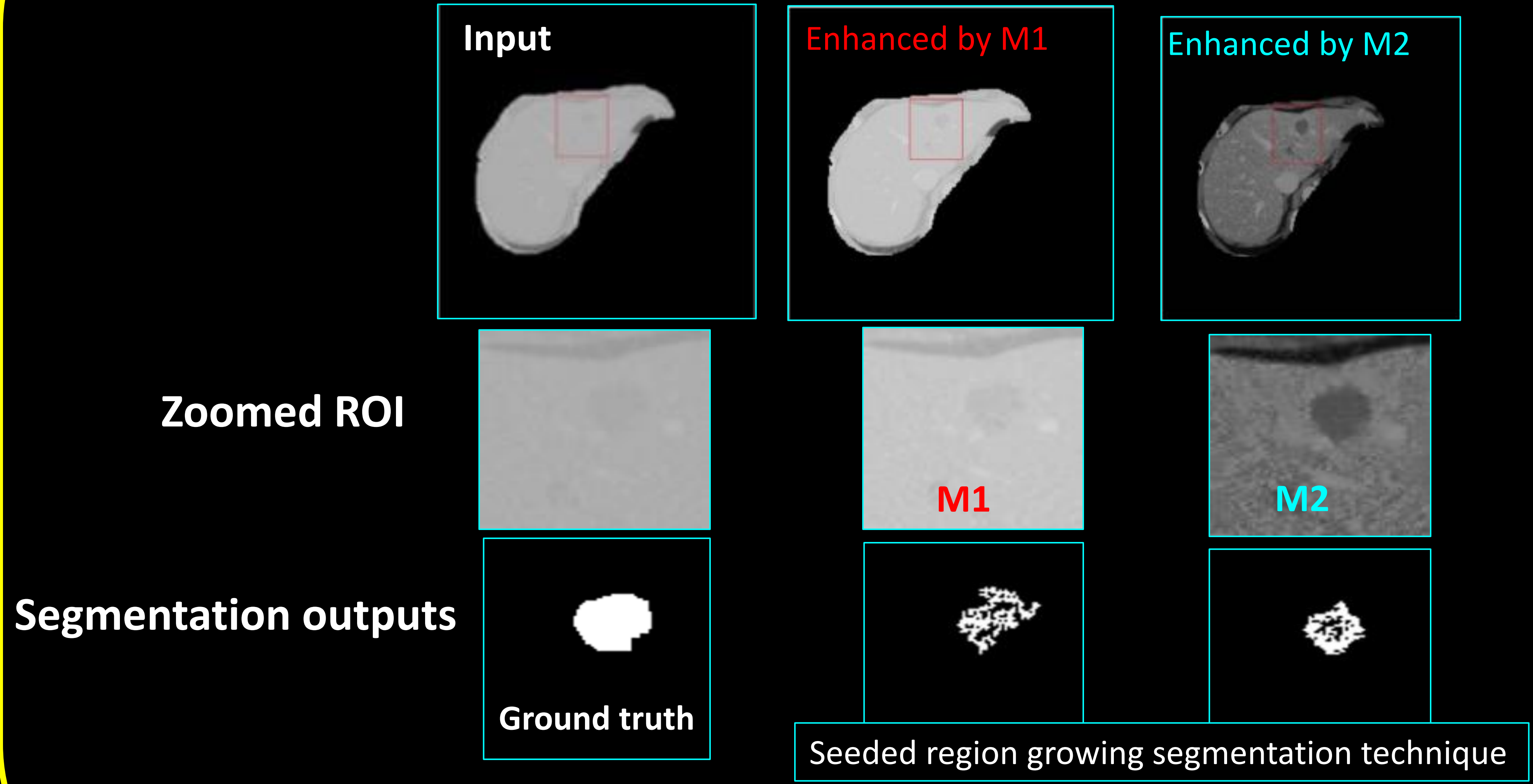
Original

Compressed images

Image Enhancement Evaluation



IQA through Segmentation Performance Analysis



Seeded region growing segmentation technique

Naseem R, Khan ZA, Satpute N, Beghdadi A, Cheikh FA, Olivares J. , « Cross-modality guided contrast enhancement for improved liver tumor image segmentation; IEEE Access. 2021 Aug 24

Image Quality Enhancement in the Context of Medical Imaging and Diagnosis

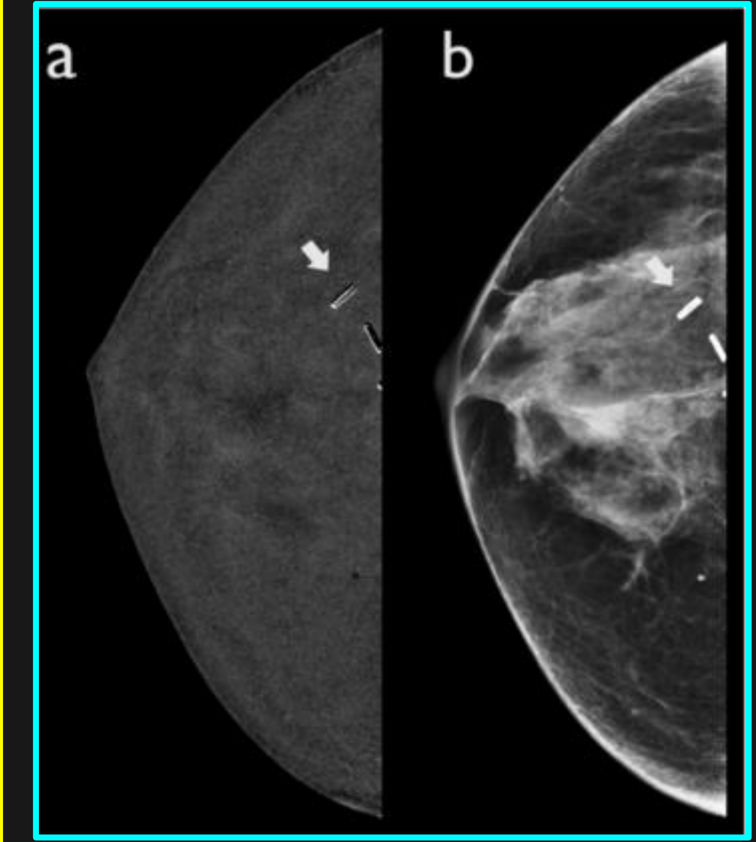


Image contrast enhancement may amplify various artefacts

- ✓ Halo artefact
- ✓ Motion artefact
- ✓ Breast implant artefact.
- ✓ Hair artefact.
- ✓ Contrast splatter artefact
- ✓ Antiperspirant artefacts

………

It is necessary to be familiar with these artefacts to avoid image-based diagnostic errors

Nori et al. Insights into Imaging (2020) 11:16 https://doi.org/10.1186/s13244-019-0811-x

Visual Illusion in Radiology

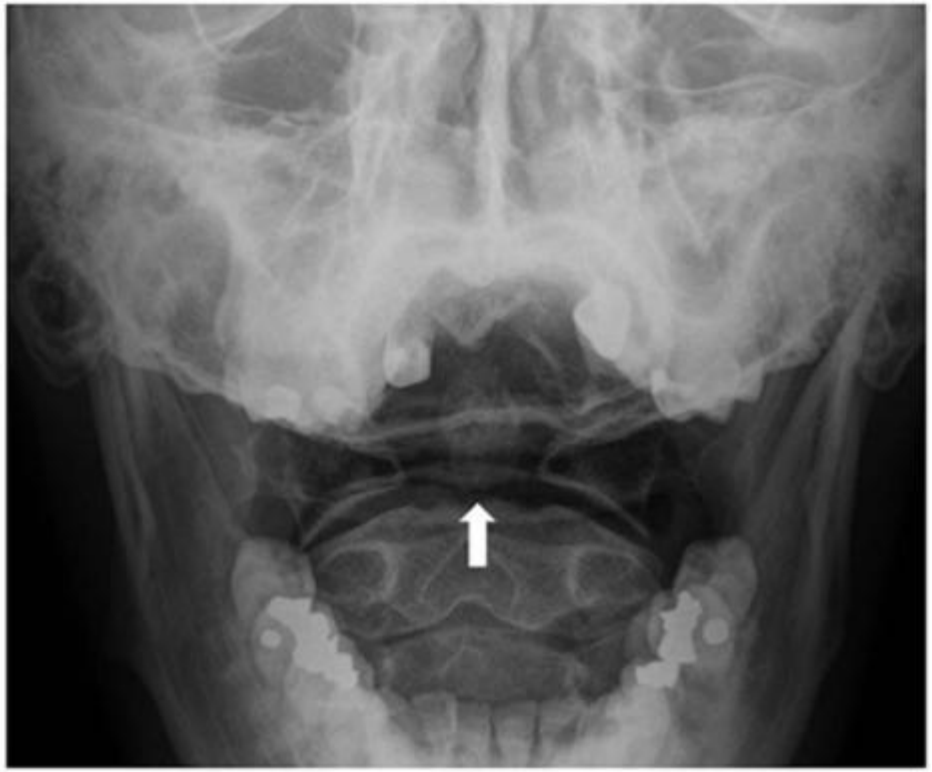


FIGURE 2. Mach bands across the base of the dens (a bone that projects from the spinal vertebra, also known as the “odontoid process”), can be mistaken for fractures (white arrow).

Visual illusion due to Mach bands

Alexander, Robert G., et al. "Visual illusions in radiology: untrue perceptions in medical images and their implications for diagnostic accuracy." Frontiers in Neuroscience 15 (2021)

Visual Illusion in Medical Imaging

How to avoid visual illusions?

Strategies

- to help distinguish reality from illusion is to rely on multiple sources of information for diagnosis
- Use of Adaptive Image quality Enhancement
- Use of Cross-modal Image Quality Enhancement.
- Use CNN-based methods

Visual IllusioVisual Illusions in Radiology: Untrue Perceptions in Medical Images and Their Implications for Diagnostic Accuracy; Front. Neurosci., 11 June 2021

Medical Image Dataset Issues

Collecting/sharing datasets is an important task contributing the development of efficient AI-based solutions for:

✓ Image guided diagnosis, Image/video guided surgery

✓ Image guided radiotherapy, …

➢ Medical image dataset issues:

- scarcity, lack of diversity, poor quality, and high annotation costs.
- Small sample sizes, inconsistent labelling, leading to subjective, noisy, and expensive data
- Data limitations due to physical constraints and side effects on patients exposed to signals such as X-rays
- Ethical constraints limit model generalization, often causing overfitting and biases that hinder clinical deployment

Part III

Selected Real Applications In Medical Imaging Context

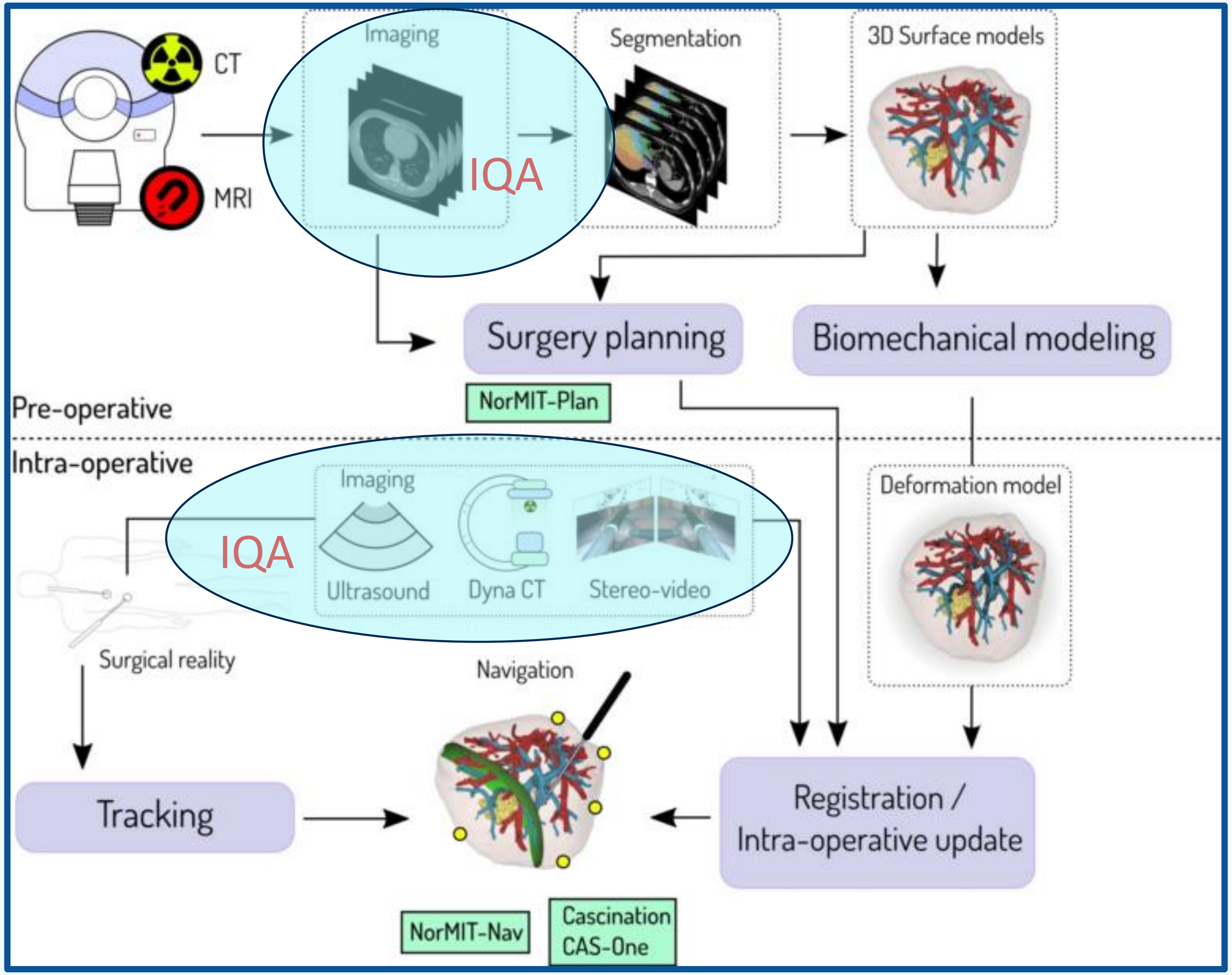
The importance of IQA in the context of

- Video guided surgery
- Low Dose CT
- Wireless Capsule Endoscopy

Video Guided Surgery Navigation Workflow

HiPerNav

Cascination



CT

MRI

Imaging

IQA

Segmentation

3D Surface models

Surgery planning

Biomechanical modeling

NorMIT-Plan

Pre-operative

Intra-operative

Imaging

IQA

Ultrasound

Dyna CT

Stereo-video

Deformation model

Surgical reality

Navigation

Tracking

Registration / Intra-operative update

NorMIT-Nav

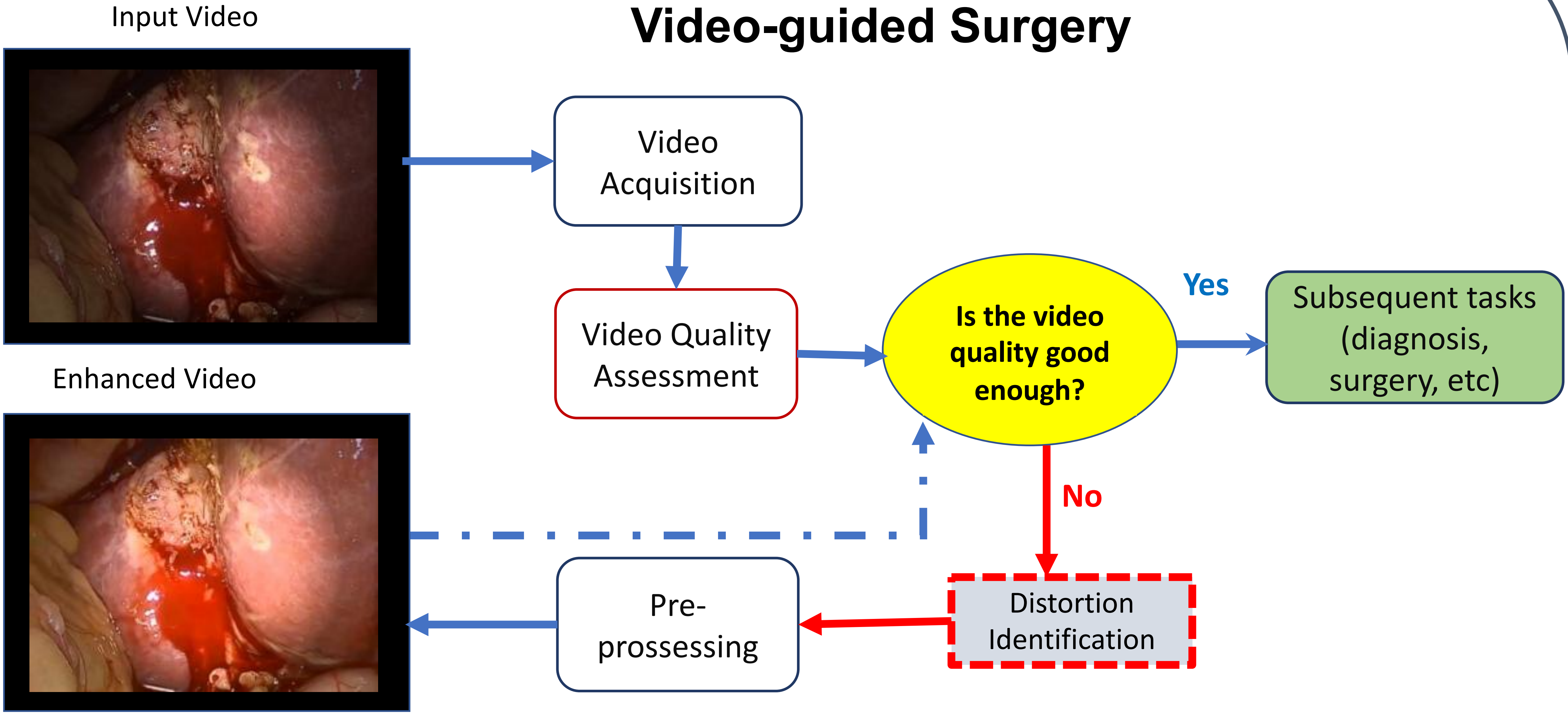
Cascination CAS-One

Warning

The following videos are surgical video sequences that may offend the sensibilities of some of you.

Do not look at or close your eyes if this is the case for you.

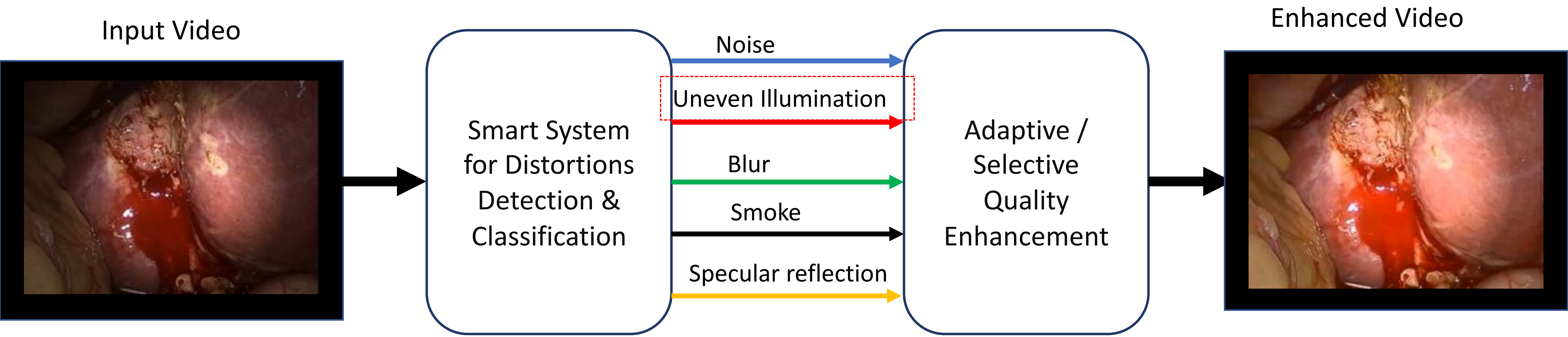
Quality-driven Framework for Video-guided Surgery



A. Beghdadi et al., ICIP 2024 , Kula Lumpur, Malysia

Context and Motivation

Video Guided Laparoscopic Surgery



Smart Video Surgery Distorsions Identification and Quality Enhancement System

- Original Videos are extracted from Cholec80 dataset available at http://camma.u-strasbg.fr/datasets

Real-time Distortion Classification in Laparoscopic Videos

Motivation Challenges

- Several distortions encountered during laparoscopic surgery may cause visual discomfort
- Automated video quality enhancement to remove annoying distortions
- Knowledge of the type of distortion is important for applying the appropriate enhancement solution

Two main problems to be solved in this challenge

- Real-time detection of distortions
- Distortion identification and classification

Some Samples of LVQ Dataset

AWG Noise

Blur

Uneven Illumination

Smoke

Z. A. Khan et al., “Towards a video quality assessment based framework for enhancement of laparoscopic videos”, Medical Imaging: Image Perception, Observer Performance, and Technology Assessment 2020.

Uneven Illumination at different levels

Level 1 – Hard to notice

Level 2 – Just Noticeable

Level 3 – Slightly Annoying

Level 4 – Moderately Annoying

Level 5 – Very Annoying

Z. A. Khan, PhD thesis (in progress), University Sorbonne Paris Nord

Real-time Distortions Detection and Classification

D. Hammou et al.
Winner of the 2nd place in the ICIP2020 Challenge Session

Recent Progress in Low Dose CT Image Quality Assessment and Enhancement

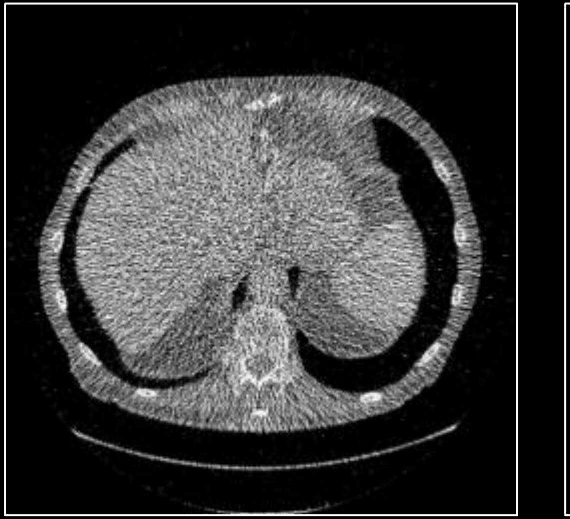
Computational Visual Perception and Learning Framework for Quality-Driven Medical Imaging

Originality of this approach

- **Overcoming Physical Limits of Low-Dose Medical Image Acquisition Systems**
  - **Explainable Deep Learning Solutions (Human in the Loop)**
    - → **Modelling of Retino-Cortical Mechanisms**
- **Medical Image Assessment at Acquisition and Processing Levels**
  - **Diagnostic-Oriented Image Quality Metrics (IQMs)**

Low-Dose Computed Tomography Imaging

5% Dose



10% Dose

25% Dose

100% Dose

Patient Safety ⟷ **Image Quality**

“ALARA ”

ALARA ("**A**s **L**ow **A**s **R**easonably **A**chievable") is the core radiation safety principle in radiology, ensuring patient and staff exposure to ionizing radiation is minimized while maintaining necessary diagnostic image quality.

Prior Works: LDCT Enhancement Models & Loss Functions

- **Advances**
  - Advanced Architectures
  - Competitive and very High IQA metrics

- **Limitations**
  - Over-smoothing
  - Lack of transparency and interpretability
  - Non accurate CT images Quality Assessment

Physics Understanding for Medical Image Quality Enhancement

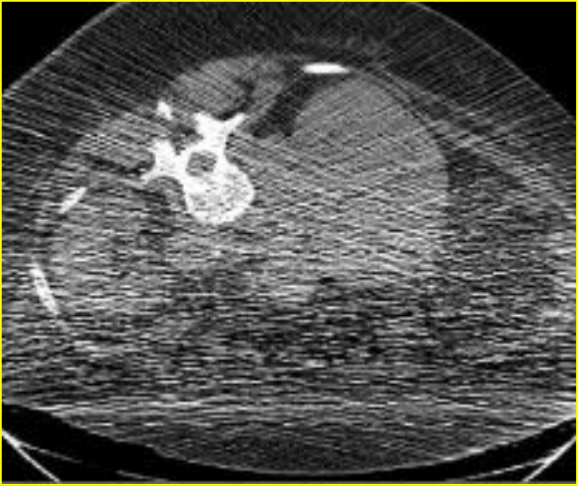
- **Why it Matters**
  - **Targeted artifact correction**
  - **Physics-guided deep learning models**
  - **Improved reconstruction algorithms**
  - **Better generalization across scanners**

Metallic artifact

Noise
due to Photon starvation (LDCT)

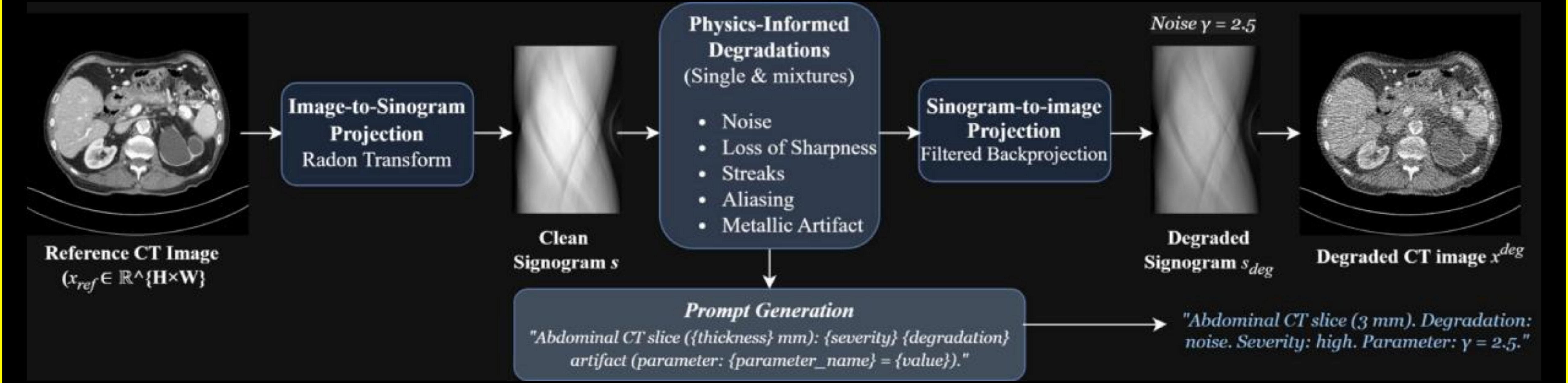
Sparse View CT

Loss of sharpness
(Aquisition Parameters)



Streaks artifact due to Photon starvation

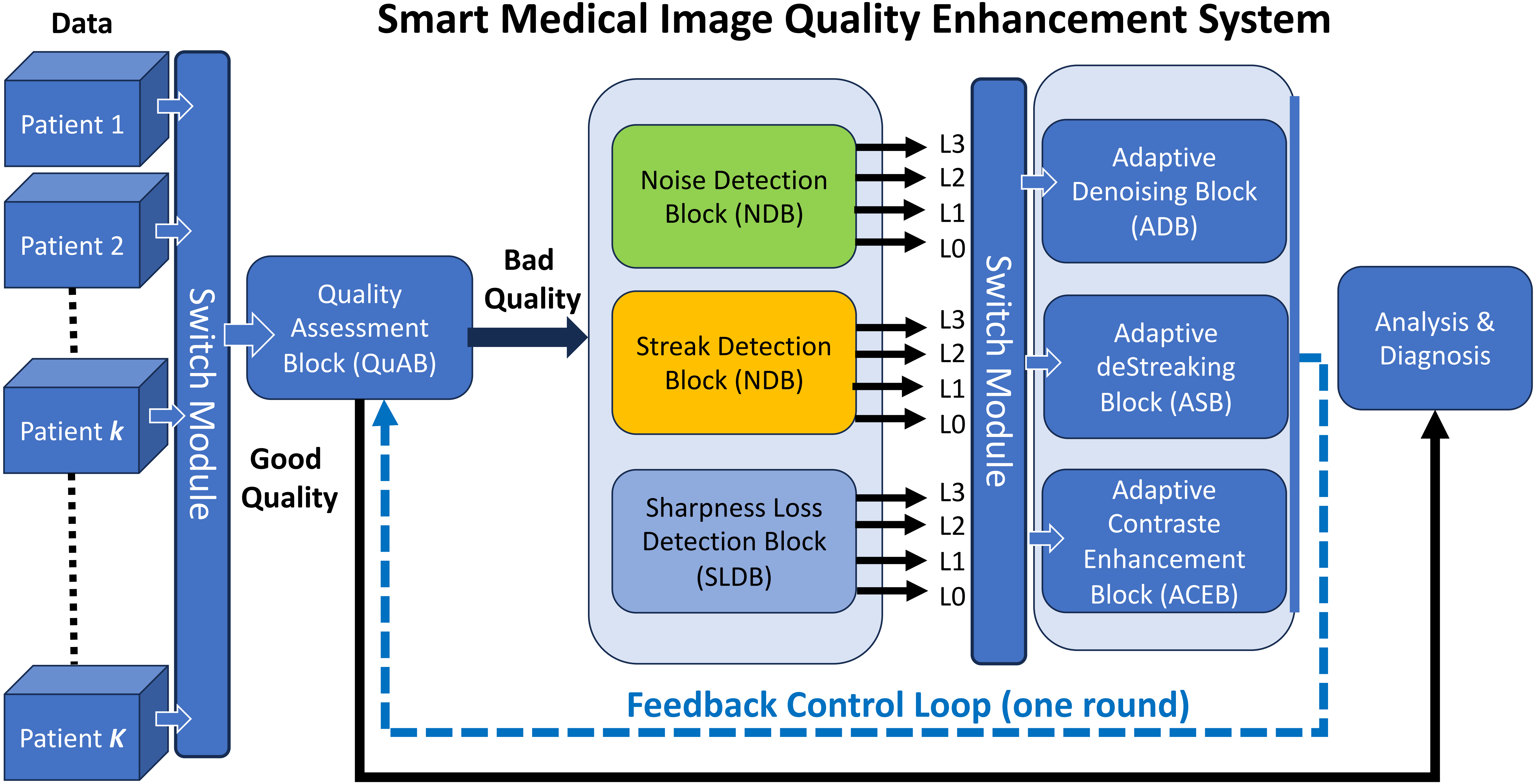
DOSE-CONTROLLABLE PHYSICS-BASED LOW-DOSE CT SYNTHESIS
Workflow



"Abdominal CT slice ({thickness} mm): {severity} {degradation} artifact (parameter: {parameter_name} = {value})."

"Abdominal CT slice (3 mm). Degradation: noise. Severity: high. Parameter: $\gamma = 2.5$."

Smart Medical Image Quality Enhancement System



Data

Patient 1

Patient 2

Patient *k*

Patient *K*

Switch Module

Quality Assessment Block (QuAB)

Bad Quality

Good Quality

Noise Detection Block (NDB)

Streak Detection Block (NDB)

Sharpness Loss Detection Block (SLDB)

L3
L2
L1
L0

Switch Module

Adaptive Denoising Block (ADB)

Adaptive deStreaking Block (ASB)

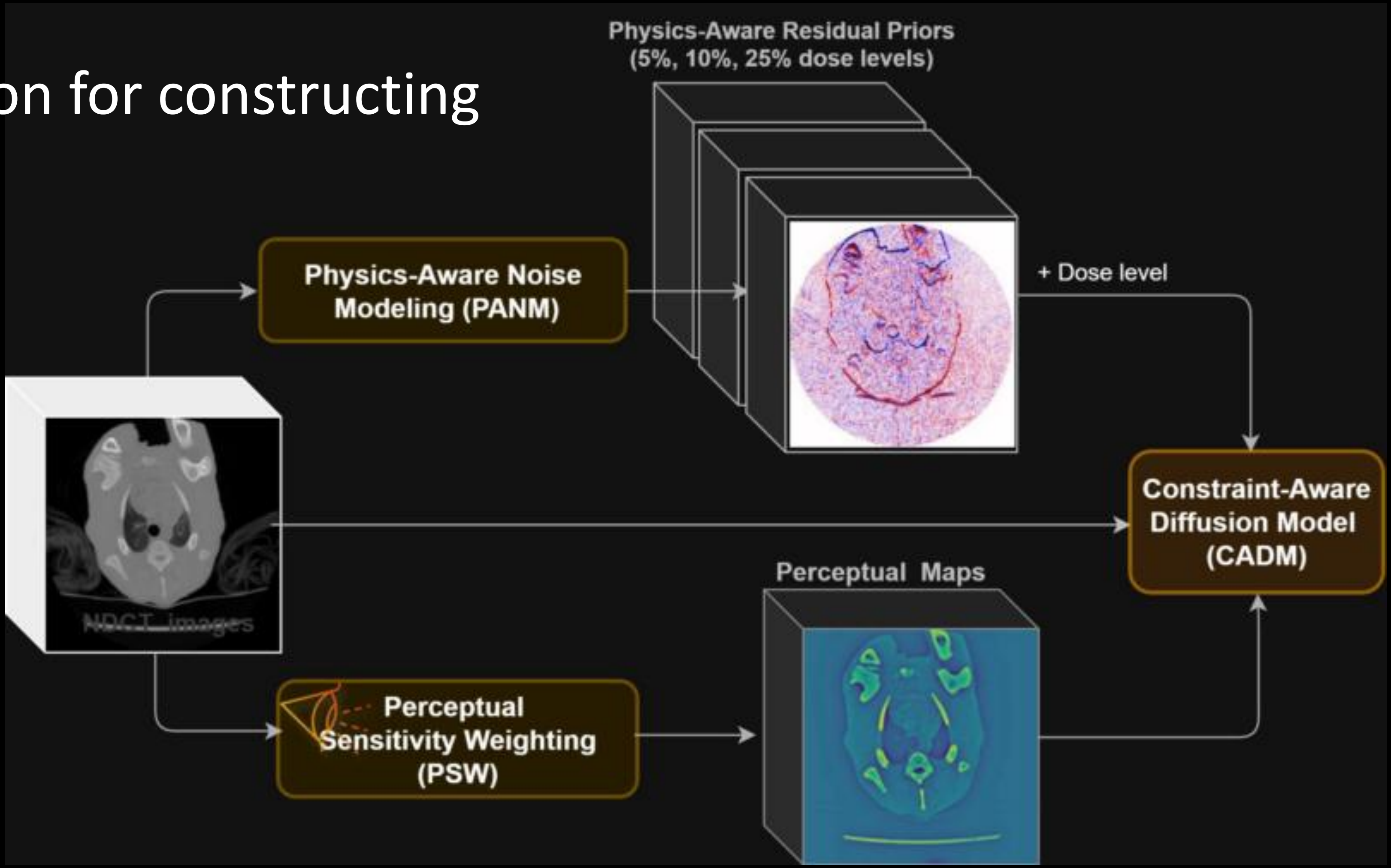
Adaptive Contraste Enhancement Block (ACEB)

Analysis & Diagnosis

Feedback Control Loop (one round)

DOSE-CONTROLLABLE PHYSICS-BASED LOW-DOSE CT SYNTHESIS

Our solution for constructing dataset



Y. Taifour, M. Tliba, A. Beghdadi, A. Chetouani, H. Zaidi, F. Alaya Cheikh, “PHYSHVS-LDCT: Dose-controllable physics-based LDCT synthesis for benchmarking and data augmentation”, accepted in IEEE-ISBI 2026

Physics-Aware Noise Adaptation Modeling Block

1. **Choose the dose level (50% , 25%, 10%, 5%)**
2. Convert NDCT (HU) → linear attenuation coefficients:

$$\mu(x,y) = \mu_{\text{water}} \left(1 + \frac{I_{\text{NDCT}}(x,y)}{1000}\right)$$

3. Apply **Radon transform** :

$$p(s,\theta) = \int_{L(s,\theta)} \mu(x,y)\, dl.$$

$$I_{\text{exp}}(s,\theta) = I_0\, e^{-p(s,\theta)}$$

4. Reduce the Intensity using dose ratio (r) :

$$I_0^{(r)} = r I_0$$

5. Inject Additive Mixed Poisson-Gaussian noise to the signogram

$$I_{\text{noisy}}(s,\theta) \sim \text{Poisson}\left(I_0^{(r)}\, e^{-p(s,\theta)}\right)$$

6. Reconstruct using Filtered Backprojection
7. Compute residual:

$$PARP = I_{NDCT} - I_{LDCT,sim}$$

LDCT Image Quality Enhancement

Recent results

Towards Dose-Agnostic Low-Dose CT Enhancement Using Physics-Disentangled Tri-Teacher Distillation

What’s New?

- We investigated **different loss functions**, including:
  - **Pixel-level similarity** using the **L1 loss**
  - **Latent feature–level similarity**
  - **A joint pixel- and latent-level similarity loss**
- We conduct **simulations and analysis** at **very low and ultra-low dose levels**:
  - **10% dose**
  - **5% dose**

Perceptual Loss Functions

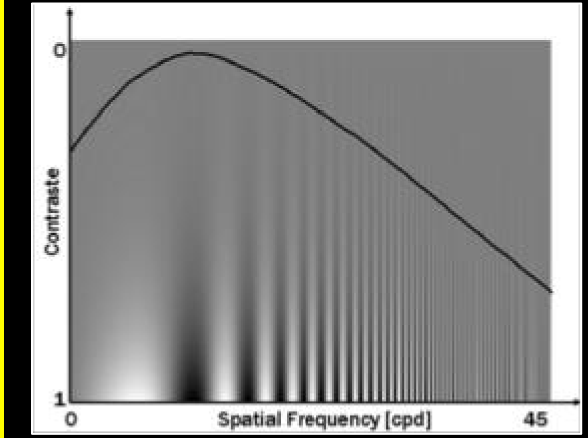
The performance of the DL-based approaches is affected by a multitude of factors. **The loss function is a critical one**.

Perceptual loss functions (PLF): PLFs are designed to capture perceptual differences between images.

- PLF is a powerful tool in the design of Deep Learning based architectures.
- PLFs differ from traditional pixel-wise loss functions:
  - ✓ PLFs compare high-level features extracted from pre-trained convolutional neural networks (CNNs)
  - ✓ Traditional loss functions compare raw pixel values directly.

New approach

- **D-PerceptCT** : a novel perceptual LDCT enhancement model
  - **Deep-Perceptual Relevancy Loss Function (DPRLF)**
    - A recent study* on Deep Perceptual Loss Functions showed that combining features from multiple VGG layers improves performance



Contrast Sensitivity Function

$$\mathcal{L}_{\text{DPRLF}} = \lambda_{\text{low}} \cdot \mathcal{L}_{\text{low}} + \lambda_{\text{mid}} \cdot \mathcal{L}_{\text{mid}} + \lambda_{\text{high}} \cdot \mathcal{L}_{\text{high}},$$

with $* \in \{\text{low}, \text{mid}, \text{high}\}$ corresponding respectively to:

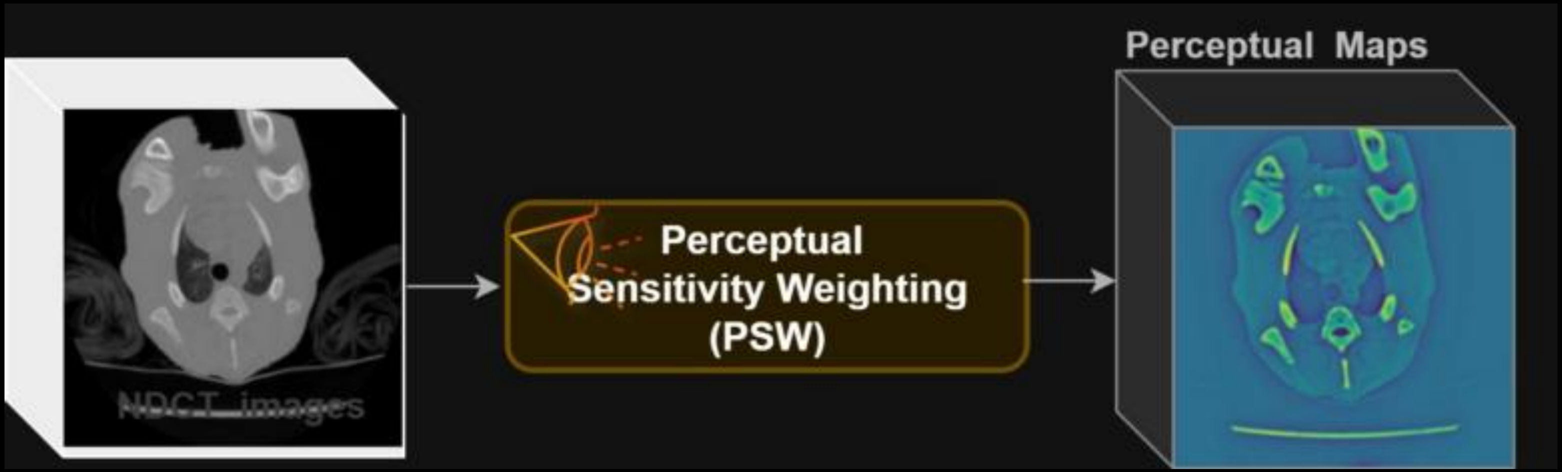
- Low-level features: $\lambda_{\text{low}} = 0.35$,
- Mid-level features: $\lambda_{\text{mid}} = 0.5$,
- High-level features: $\lambda_{\text{high}} = 0.15$.

$$\mathcal{L}_* = \|\phi_*(I_{\text{pred}}) - \phi_*(I_{\text{gt}})\|_2^2$$

* Y. Taifour, A. Beghdadi, M. Luong, Z. Ming, H. Zaidi; MCO 2025, Springer,

PHYSHVS-LDCT

Perceptual Sensitivity Weighting Map (PSW)

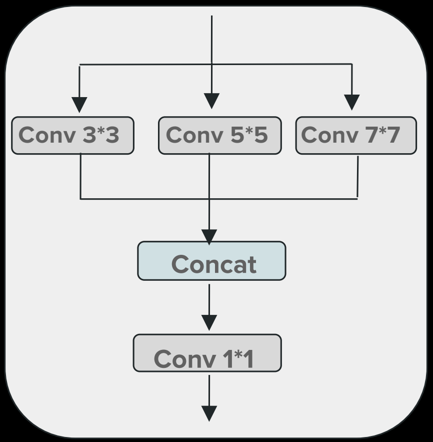


- Uses **Contrast Sensitivity Function (CSF)** (Barten model)
- Weight frequency components of NDCT
- Transform back to spatial domain:

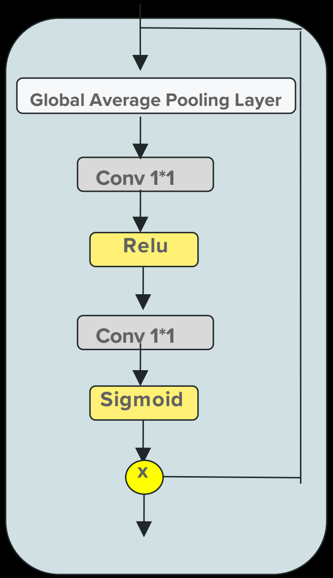
$$PM(x,y) = \mathcal{F}^{-1}(\mathcal{F}(I_{NDCT}) \cdot CSF)$$

New approach

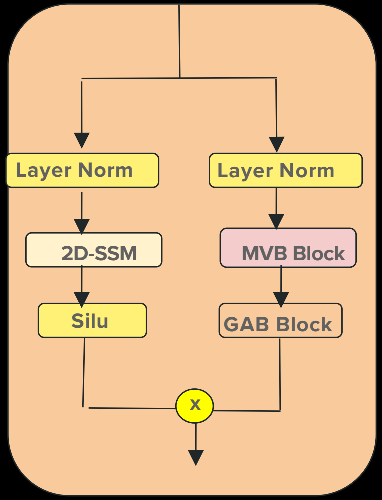
- **D-PerceptCT** : Perceptual LDCT Enhancement Model
  - **Deep-Perceptual Relevancy Loss (DPRLF)**
  - **Vision State space module -> Global–Local State-Space Block (GL2SB)**



(a) Multiscale Vision Block (MVB)



(b) Global Attention Block (GAB)

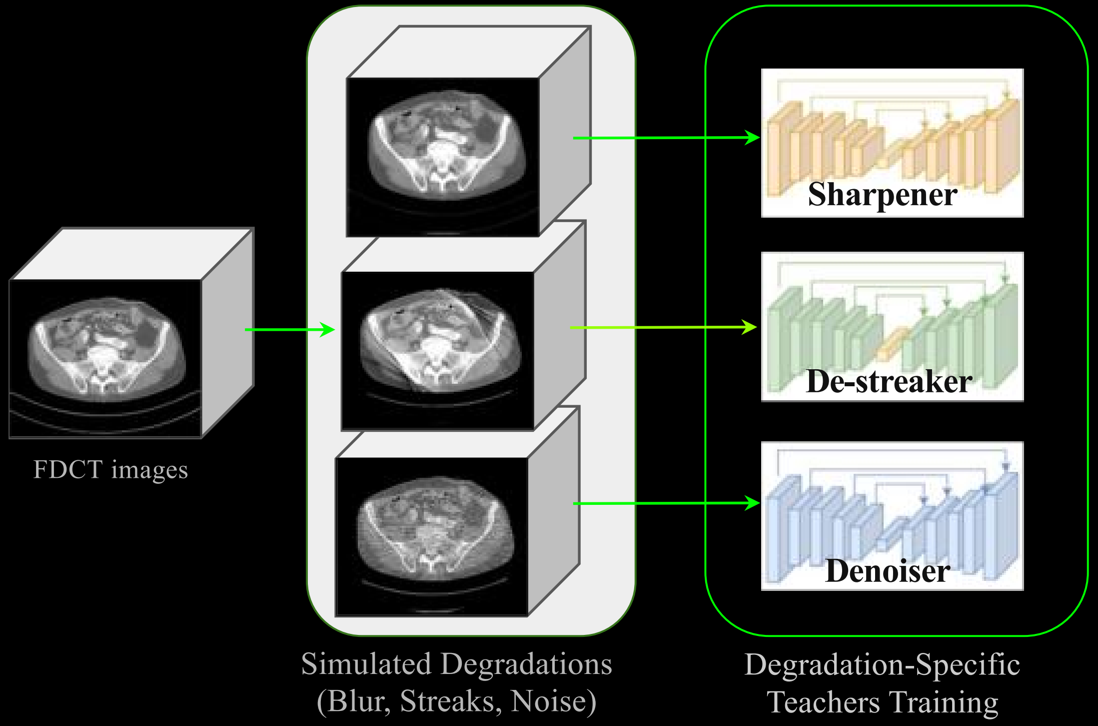


(c) Global–Local State-Space Block (GL2SB)

Y. Taifour, A. Beghdadi, Z. Ming, M. Luong, H. Zaidi, F. Alaya Cheikh IEEE-EUVIP 2025

TriKD-LDCT: MULTI-EXPERT DISTILLATION FOR DEGRADATION-AWARE LOW-DOSE CT ENHANCEMENT

(1) Teachers training (Denoiser, De-streaker,Sharpener)



FDCT images

Sharpener

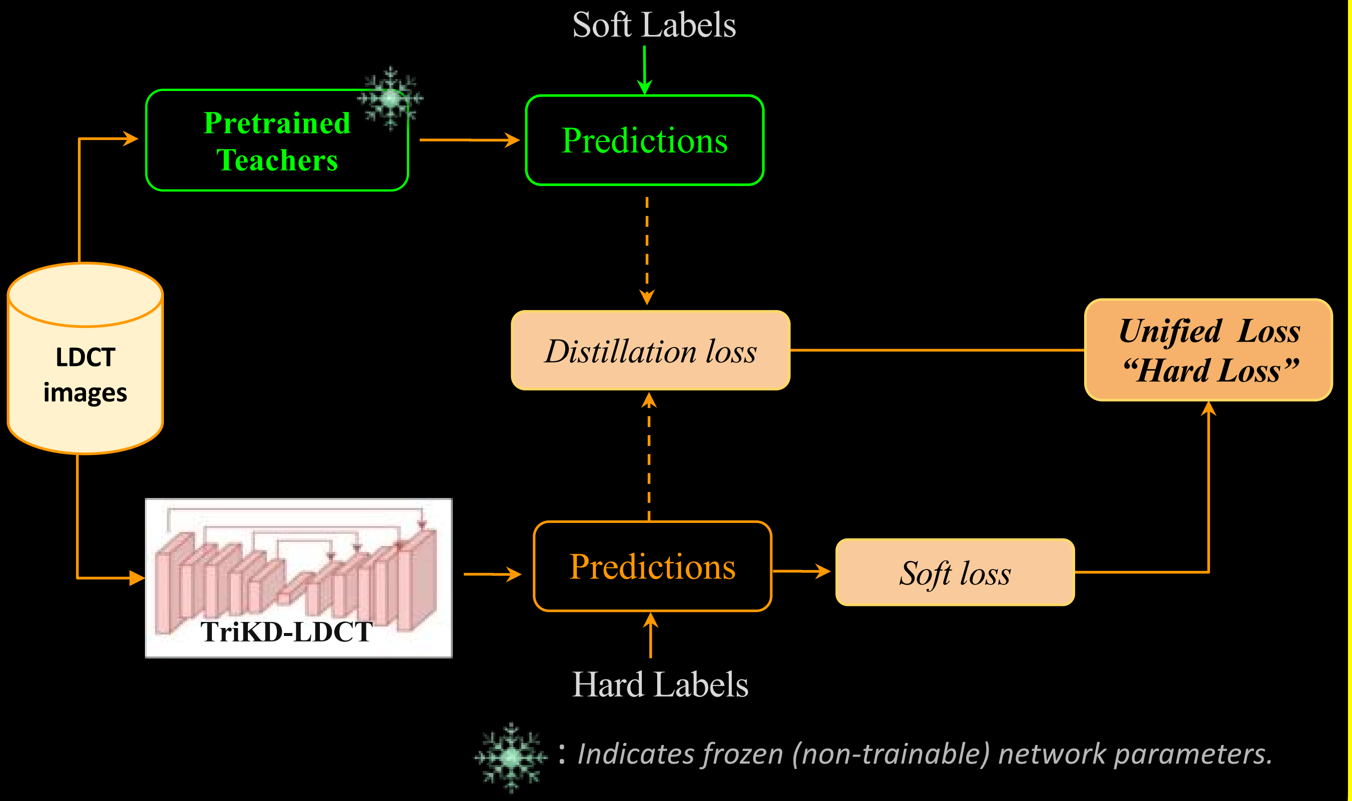
De-streaker

Denoiser

Simulated Degradations
(Blur, Streaks, Noise)

Degradation-Specific
Teachers Training

(2) Knowledge distillation (TriKD-LDCT student model)



Soft Labels

Pretrained Teachers

Predictions

LDCT images

Distillation loss

Unified Loss “Hard Loss”

TriKD-LDCT

Predictions

Soft loss

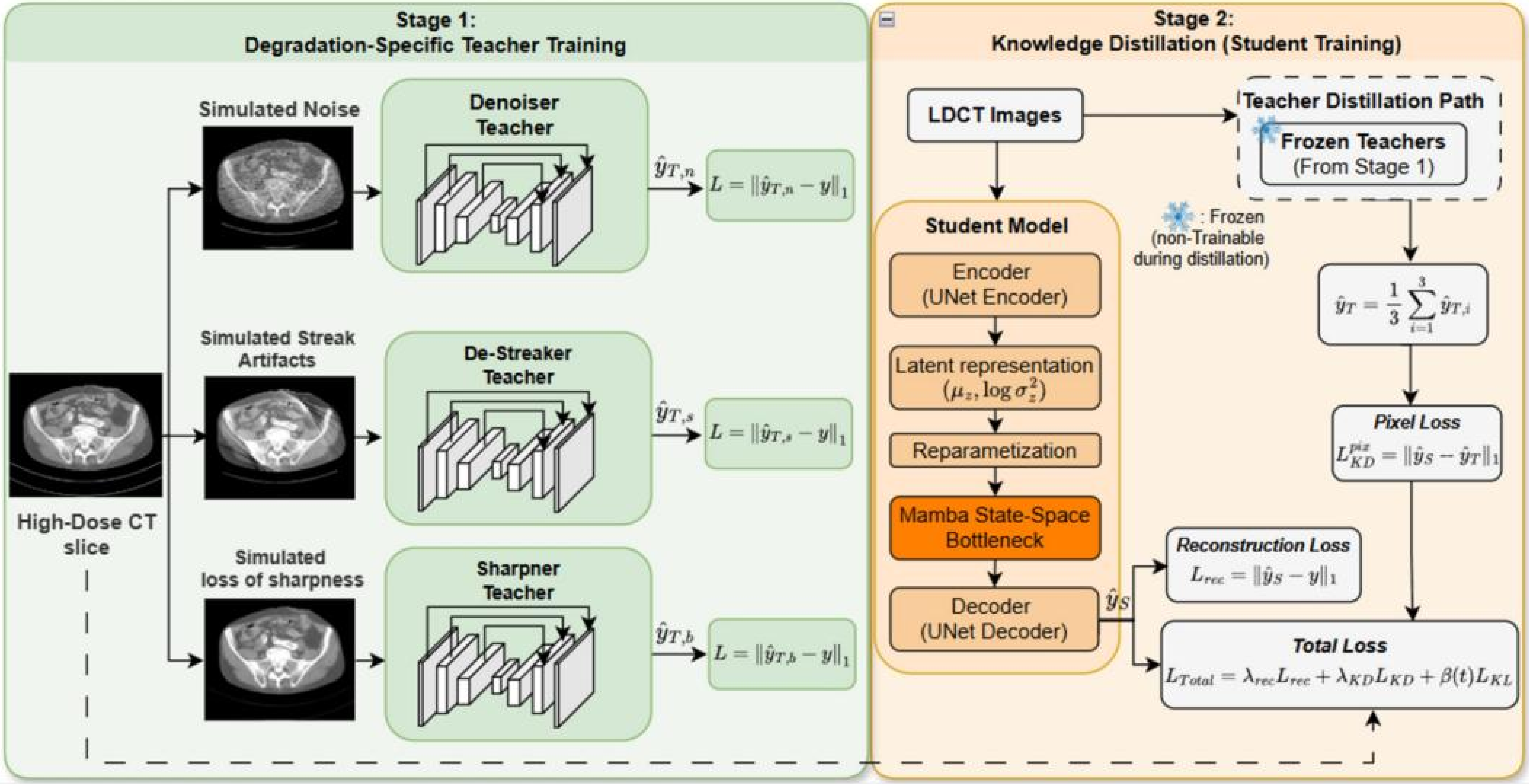
Hard Labels

❄ : *Indicates frozen (non-trainable) network parameters.*

Physics Understanding for Degradations disentanglement

Y. Taifour, M. Tliba, A. Beghdadi, A. Chetouani, Z. Ming, M. Luong, H. Zaidi, F. Alaya Cheikh; “TriKD-LDCT: Multi-expert distillation for degradation-aware LDCT enhancement “, presented in ICASSP2026

Our Proposed Method: TriKD-LDCT



TriKD-LDCT - Variant 3:
1- Qualitative Results:

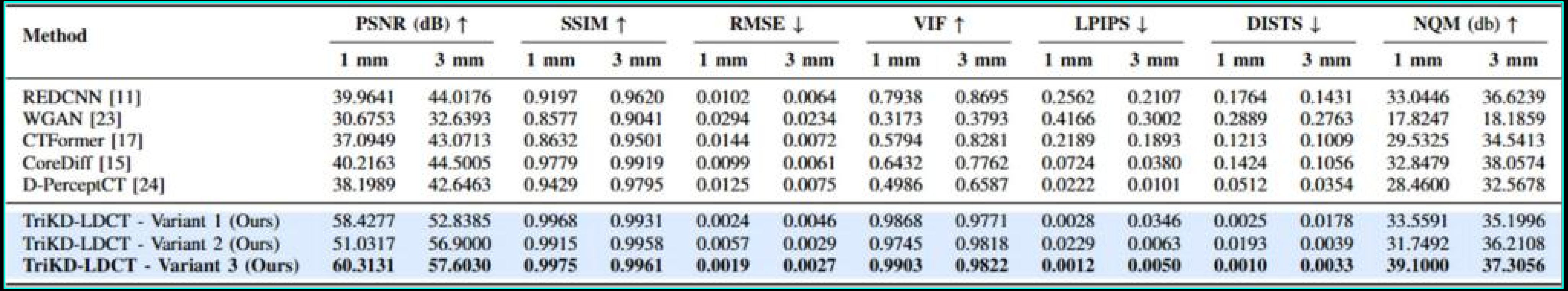
25% Dose CT scan

Enhanced LDCT scan

Full-Dose CT scan

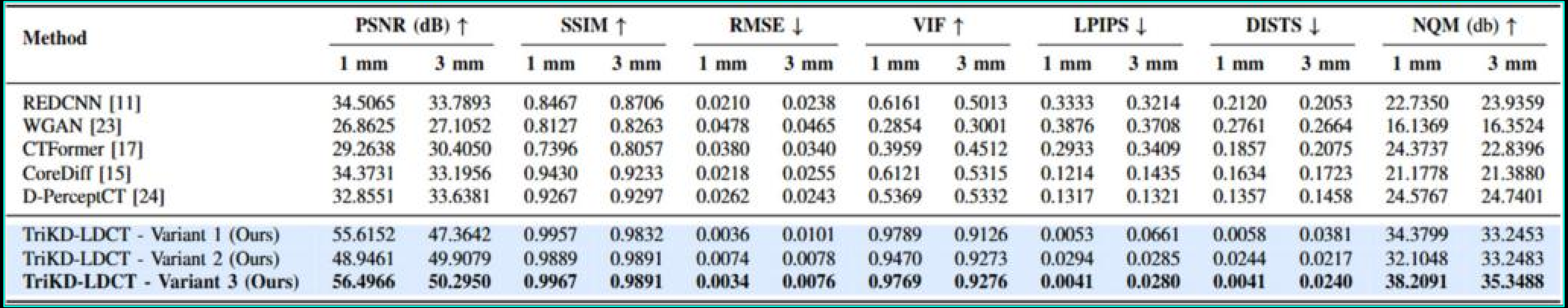
TriKD-LDCT

1- Objective Image Quality Assessment Results



Method	PSNR (dB) ↑		SSIM ↑		RMSE ↓		VIF ↑		LPIPS ↓		DISTS ↓		NQM (db) ↑	
	1 mm	3 mm	1 mm	3 mm	1 mm	3 mm	1 mm	3 mm	1 mm	3 mm	1 mm	3 mm	1 mm	3 mm
REDCNN [11]	39.9641	44.0176	0.9197	0.9620	0.0102	0.0064	0.7938	0.8695	0.2562	0.2107	0.1764	0.1431	33.0446	36.6239
WGAN [23]	30.6753	32.6393	0.8577	0.9041	0.0294	0.0234	0.3173	0.3793	0.4166	0.3002	0.2889	0.2763	17.8247	18.1859
CTFormer [17]	37.0949	43.0713	0.8632	0.9501	0.0144	0.0072	0.5794	0.8281	0.2189	0.1893	0.1213	0.1009	29.5325	34.5413
CoreDiff [15]	40.2163	44.5005	0.9779	0.9919	0.0099	0.0061	0.6432	0.7762	0.0724	0.0380	0.1424	0.1056	32.8479	38.0574
D-PerceptCT [24]	38.1989	42.6463	0.9429	0.9795	0.0125	0.0075	0.4986	0.6587	0.0222	0.0101	0.0512	0.0354	28.4600	32.5678
TriKD-LDCT - Variant 1 (Ours)	58.4277	52.8385	0.9968	0.9931	0.0024	0.0046	0.9868	0.9771	0.0028	0.0346	0.0025	0.0178	33.5591	35.1996
TriKD-LDCT - Variant 2 (Ours)	51.0317	56.9000	0.9915	0.9958	0.0057	0.0029	0.9745	0.9818	0.0229	0.0063	0.0193	0.0039	31.7492	36.2108
TriKD-LDCT - Variant 3 (Ours)	**60.3131**	**57.6030**	**0.9975**	**0.9961**	**0.0019**	**0.0027**	**0.9903**	**0.9822**	**0.0012**	**0.0050**	**0.0010**	**0.0033**	**39.1000**	**37.3056**

TABLE : Quantitative comparison of TriKD-LDCT (Ours) and SOTA methods using full-reference IQA metrics for 1 mm and 3 mm slice thicknesses on **25% dose**. ↑: higher is better; ↓: lower is better.



Method	PSNR (dB) ↑		SSIM ↑		RMSE ↓		VIF ↑		LPIPS ↓		DISTS ↓		NQM (db) ↑	
	1 mm	3 mm	1 mm	3 mm	1 mm	3 mm	1 mm	3 mm	1 mm	3 mm	1 mm	3 mm	1 mm	3 mm
REDCNN [11]	34.5065	33.7893	0.8467	0.8706	0.0210	0.0238	0.6161	0.5013	0.3333	0.3214	0.2120	0.2053	22.7350	23.9359
WGAN [23]	26.8625	27.1052	0.8127	0.8263	0.0478	0.0465	0.2854	0.3001	0.3876	0.3708	0.2761	0.2664	16.1369	16.3524
CTFormer [17]	29.2638	30.4050	0.7396	0.8057	0.0380	0.0340	0.3959	0.4512	0.2933	0.3409	0.1857	0.2075	24.3737	22.8396
CoreDiff [15]	34.3731	33.1956	0.9430	0.9233	0.0218	0.0255	0.6121	0.5315	0.1214	0.1435	0.1634	0.1723	21.1778	21.3880
D-PerceptCT [24]	32.8551	33.6381	0.9267	0.9297	0.0262	0.0243	0.5369	0.5332	0.1317	0.1321	0.1357	0.1458	24.5767	24.7401
TriKD-LDCT - Variant 1 (Ours)	55.6152	47.3642	0.9957	0.9832	0.0036	0.0101	0.9789	0.9126	0.0053	0.0661	0.0058	0.0381	34.3799	33.2453
TriKD-LDCT - Variant 2 (Ours)	48.9461	49.9079	0.9889	0.9891	0.0074	0.0078	0.9470	0.9273	0.0294	0.0285	0.0244	0.0217	32.1048	33.2483
TriKD-LDCT - Variant 3 (Ours)	**56.4966**	**50.2950**	**0.9967**	**0.9891**	**0.0034**	**0.0076**	**0.9769**	**0.9276**	**0.0041**	**0.0280**	**0.0041**	**0.0240**	**38.2091**	**35.3488**

TABLE : Quantitative comparison of TriKD-LDCT (Ours) and SOTA methods using full-reference IQA metrics for 1 mmand 3 mm slice thicknesses on **5% dose**. ↑: higher is better; ↓: lower is better.

Concluding remarks, Challenges and open problems

Traditional approaches Vs ML-based Approaches
Is it relevant and easy to reconcile the two?

- Signal processing/analysis based approaches
  - Still in use in many scientific problems but declining
- ML-based approaches in computer vision
  - Cutting-edge methods to solve many problems but still suffer from a lack of plausible, solid and attractive theoretical foundations
- Combining Perceptual Approaches, Traditional Signal Processing and DL Architectures is the best way to address the challenging problems in computer vision

Traditional approaches Vs ML-based Approaches
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- ➢ Signal processing/analysis based approaches
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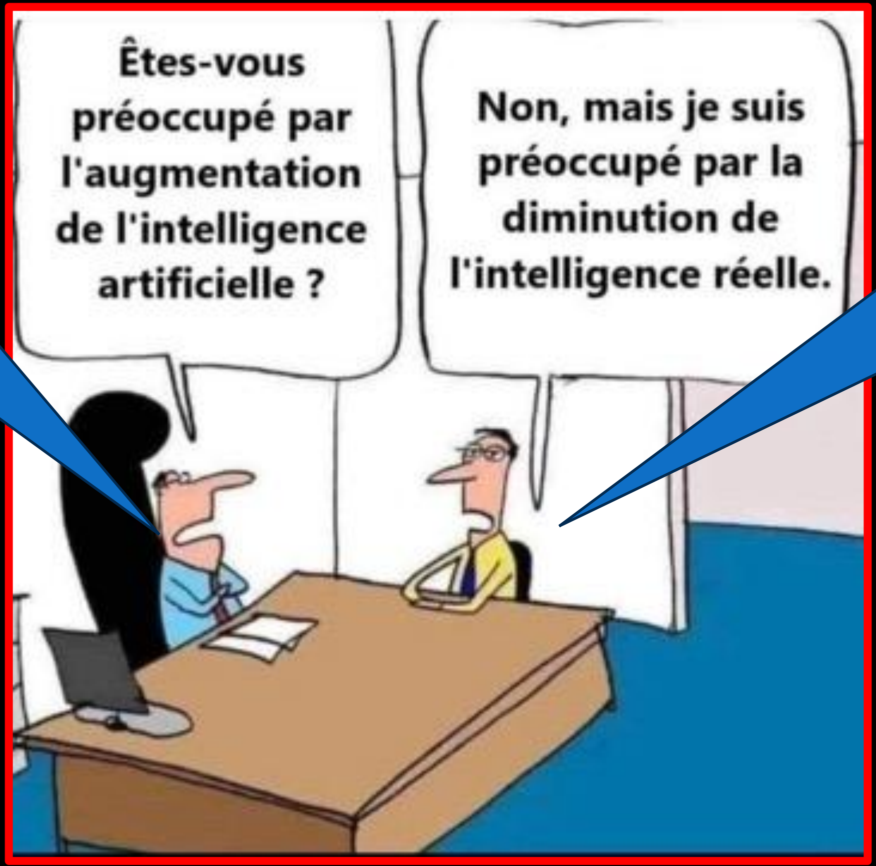
  - ✓ Cutting-edge methods to solve many problems but still suffer from a lack of plausible, solid and attractive theoretical foundations
- ➢ Combining Perceptual Approaches, Traditional Signal Processing and DL Architectures is the best way to address the challenging problems in computer vision and medical imaging

Traditional Approaches Vs ML-based Approaches

Are you worried about the rise of artificial intelligence?



NO …I am worried about the decrease of use of real/human intelligence

Acknowledgements

I would like to thank my PhD students and colleagues who have been involved in one way or another in some parts of this work.