



Laboratoire
Informatique
Robotique
Microélectronique
Montpellier

EUVIP 2014



CT-SCANNER IDENTIFICATION BASED ON SENSOR NOISE ANALYSIS

10 – 12 December 2014
Paris, France

A. Kharboutly¹, W. Puech¹, G. Subsol¹ et D. Ho²

¹LIRMM (860 rue Saint Priest, Montpellier)

²IMAIOS (MIBI-672, rue du Mas de Verchant, Montpellier)

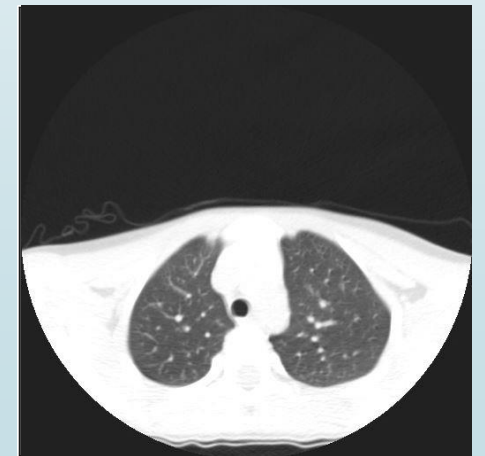


Context

- Medical image stored as a DICOM file:
meta data + image content
 - Meta data may be distorted, modified or lost.
 - Image content may be falsified modified (e.g. mixing different images)
- Authentication of the acquisition device in medical image by noise analyzing



CT-Scanner



2D Slice

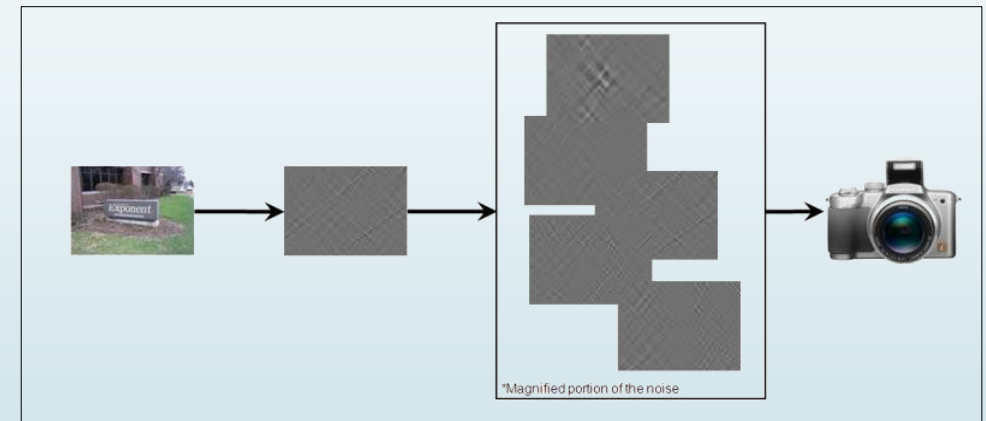
[*] Jerrold T. Bushberg, J. Anthony Seibert, Edwin M. Leidholdt Jr., and John M. Boone, The Essential Physics of Medical Imaging, Third Edition, LWW, third, north american edition edition, 12 2011.

[*] Klaus D. Toennies, Guide to Medical Image Analysis - Methods and Algorithms, Advances in Computer Vision and Pattern Recognition. Springer, 2012.

Context

Digital image forensics:

- Forgeries tracing
 - [1] General digital photography
 - [2] Digital blind forensics
- Device identification
 - [3] Digital camera identification
 - [4] Medical image characteristics
 - [5] Identification of digital radiography images



Camera identification

[1] H. T. Sencar and N. Memon, Digital Image Forensics: There is More to a Picture Than Meets the Eye, Springer, 2013.

[2] H. Huang, G. Coatrieux, H. Shu, L. Luo, and C. Roux, "Blind integrity verification of medical images," IEEE Transactions on Information Technology in Biomedicine, vol. 16, no. 6, pp. 1122–1126, 2012.

[3] J. Lukas, J. Fridrich, and M. Goljan, "Digital camera identification from sensor pattern noise," IEEE Transactions on Information Forensics and Security, vol. 1, no. 2, pp. 205–214, 2006.

[4] J. B. Solomon, O. Christianson, and E. Samei, "Quantitative comparison of noise texture across CT scanners from different manufacturers," Medical physics, vol. 39, no. 10, pp. 6048–55, October 2012.

[5] Y. Duan, G. Coatrieux and H. Shu, "Identification of digital radiography image source based on digital radiography pattern noise recognition" IEEE ICIP 2014, pp. 5372-5376, Paris, France.



CT-Scanner 1



CT-Scanner 2

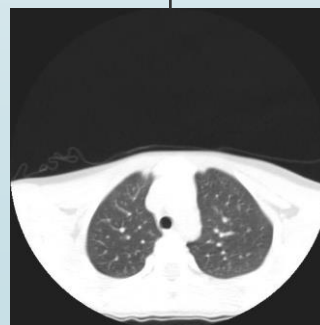


CT-Scanner 3

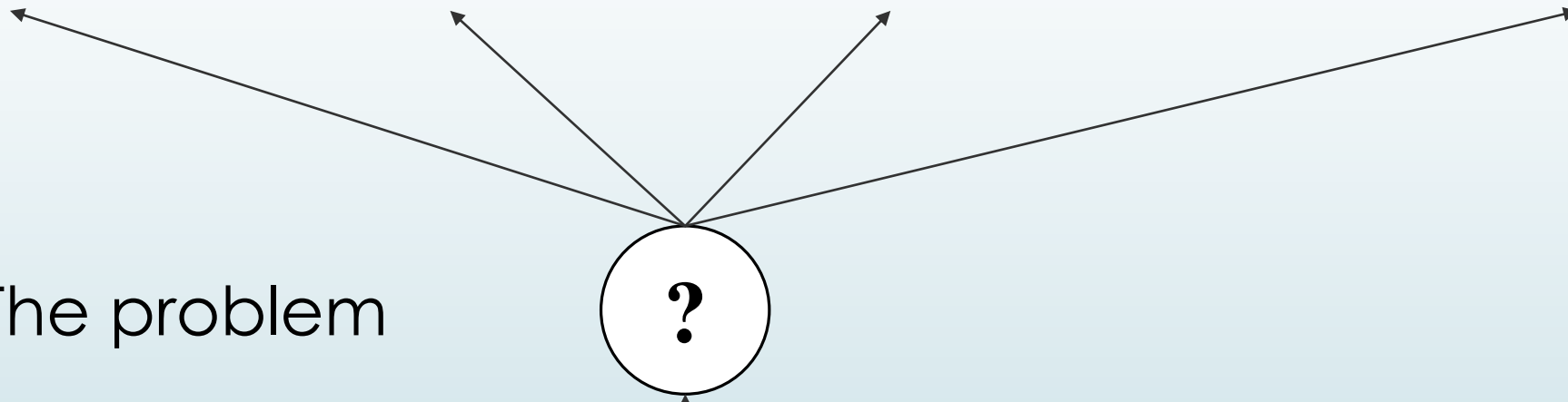


CT-Scanner n

The problem



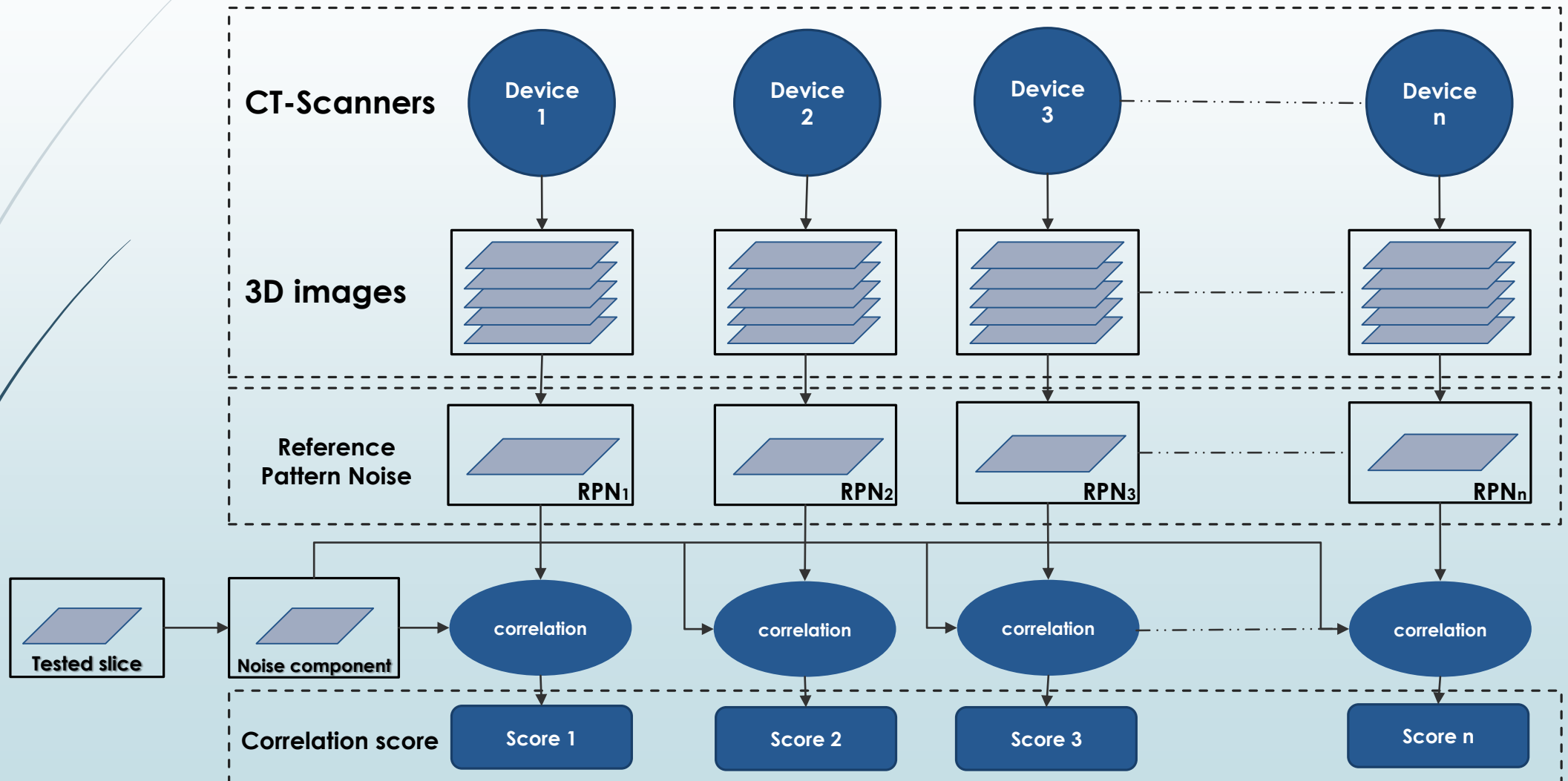
2D Slice



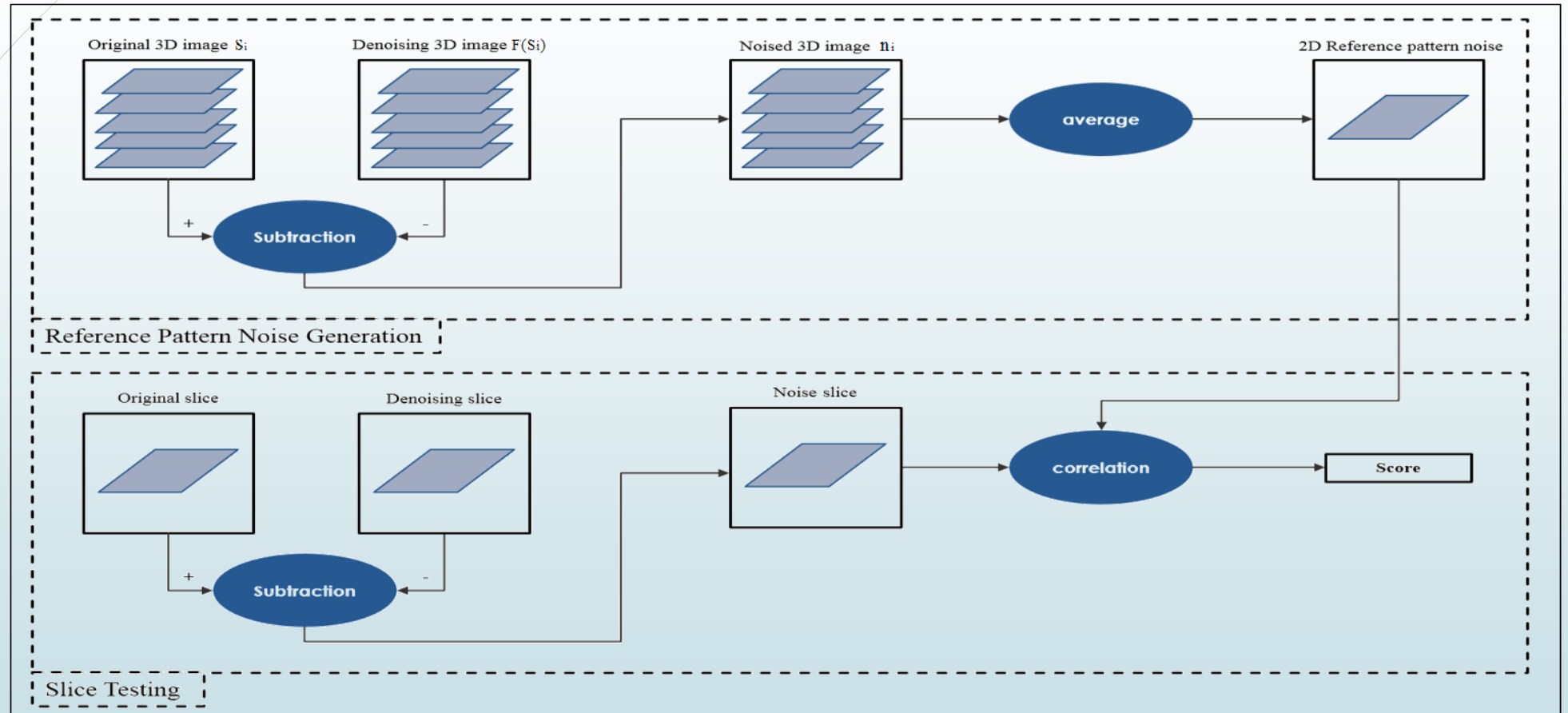
Outlines

- Context
- **Presentation of the identification method**
- Experimental results
- Conclusion and future work

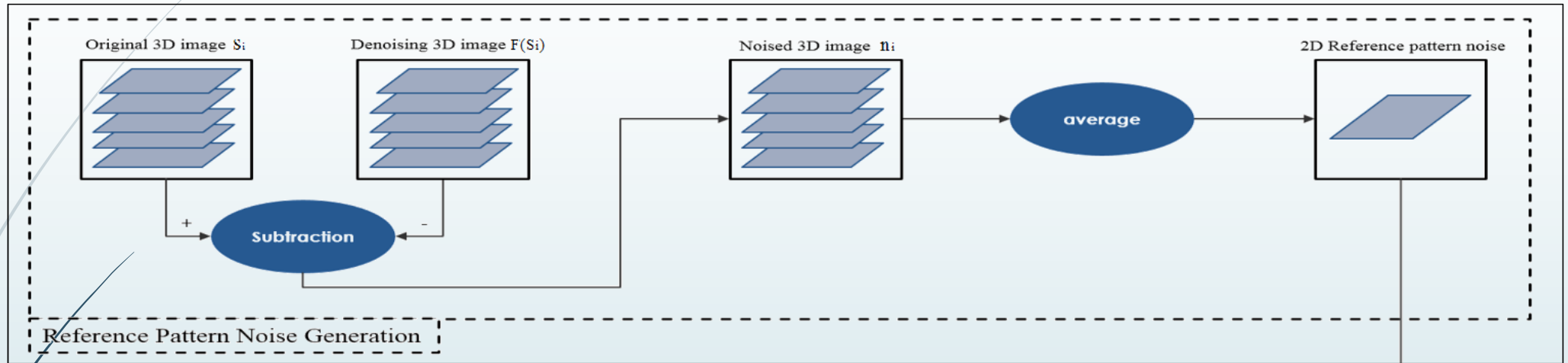
Identification method



For each device



RPN Generation



1. Extract the Reference Pattern Noise

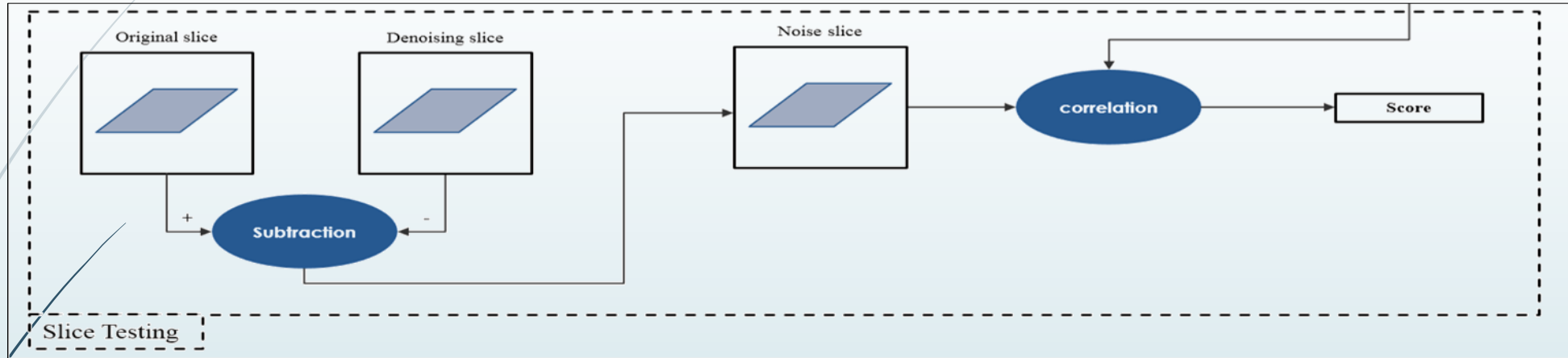
$$n^{(i)} = s^{(i)} - F(s^{(i)})$$

n: noise component
s: slice
F(): denoising function
i: slice number

$$RPN = \frac{1}{N} \sum_{i=1}^N n^{(i)}$$

RPN: reference pattern noise
N: number of noise slices
n: noise component

Noise extraction



2. Extract the noise component for the tested slice

$$n = s - F(s)$$

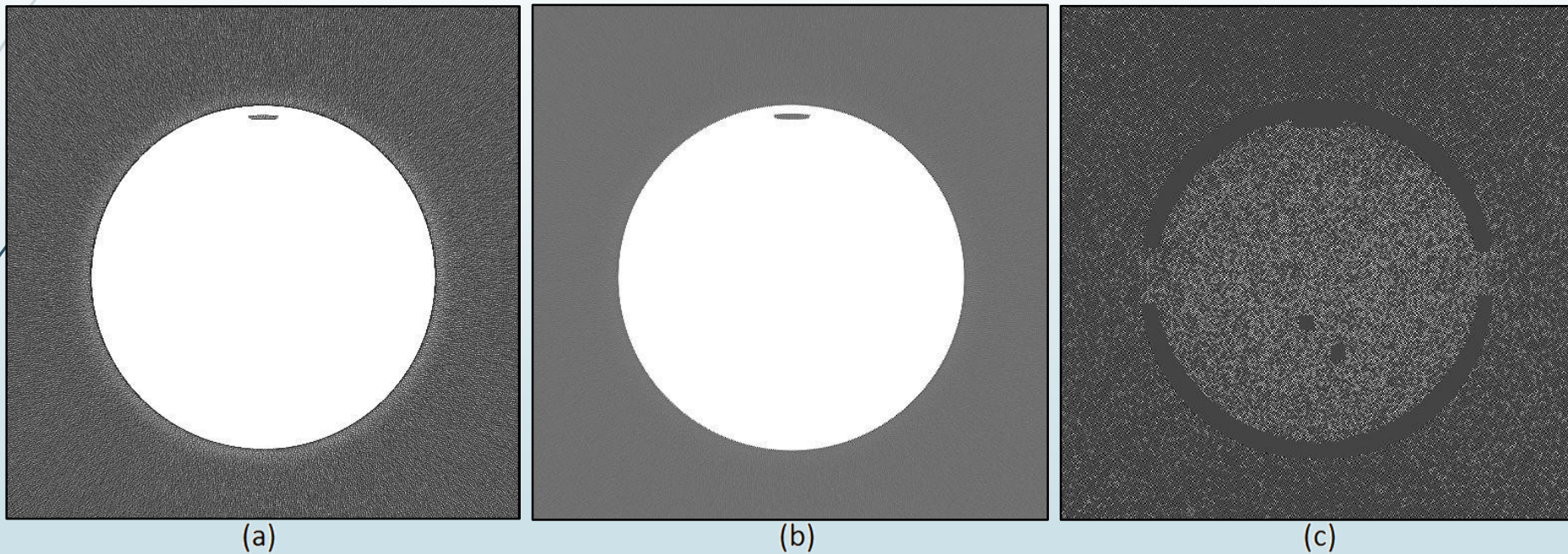
n: noise component

s: slice

F(): denoising function

Noise extraction

Extract the noise component



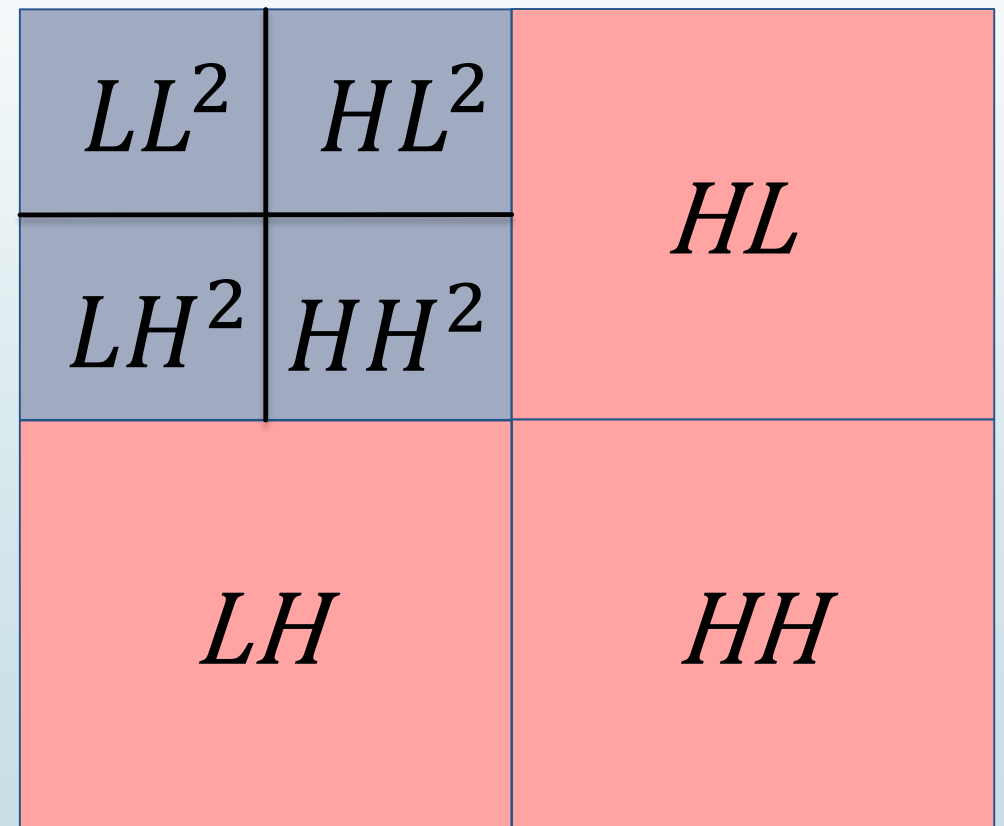
Example: a) Original slice from a Siemens device, b) Its denoised component, c) The noise component

Denoising algorithm

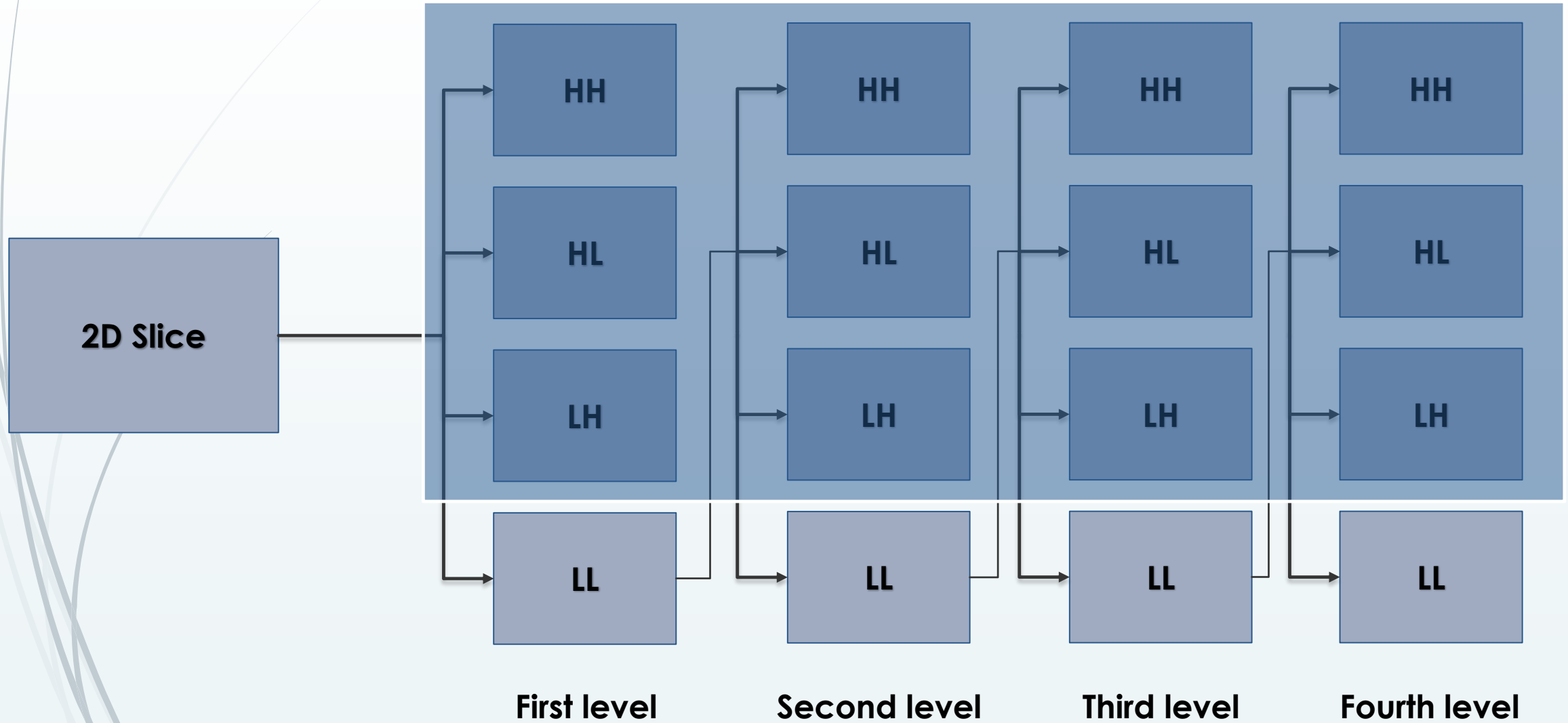
1. Four levels of wavelet decomposition
2. Denote the vertical, horizontal, and diagonal subbands
3. Estimate the local variance for each wavelet coefficient for 4 sizes of a square $W \times W$ neighborhood N , for $W \in \{3, 5, 7, 9\}$ and take the minimum of the 4 variances as the final estimate
4. Denoised wavelet coefficients using the Wiener filter
5. Apply the inverse wavelet transform to the denoised wavelet coefficients

1. Wavelet Decomposition

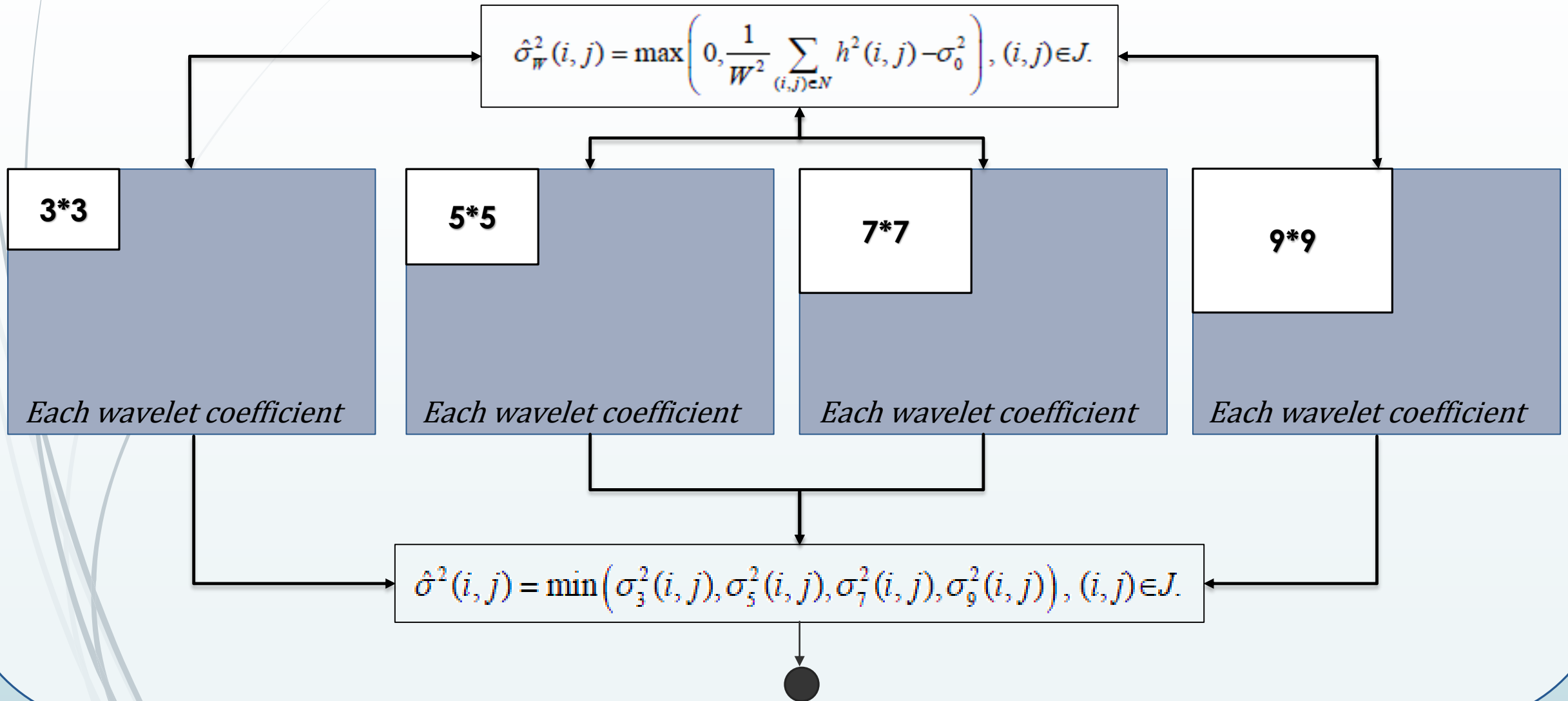
- Example of two levels of wavelet decomposition



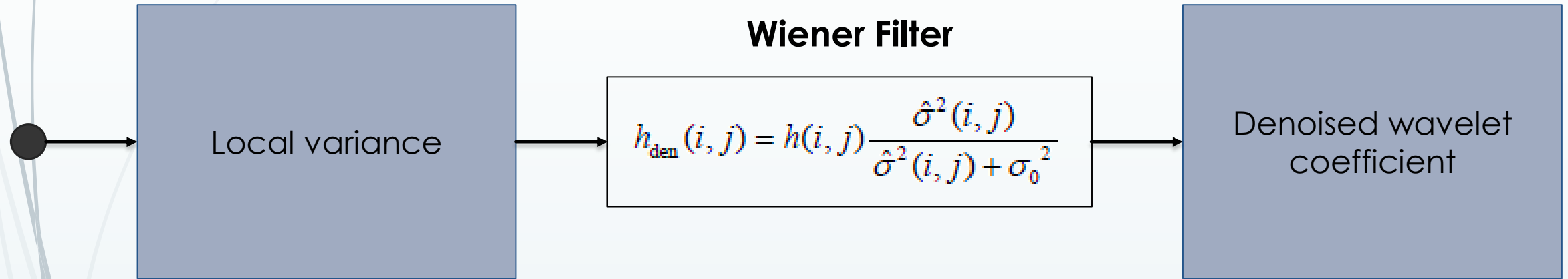
2. Wavelet Levels



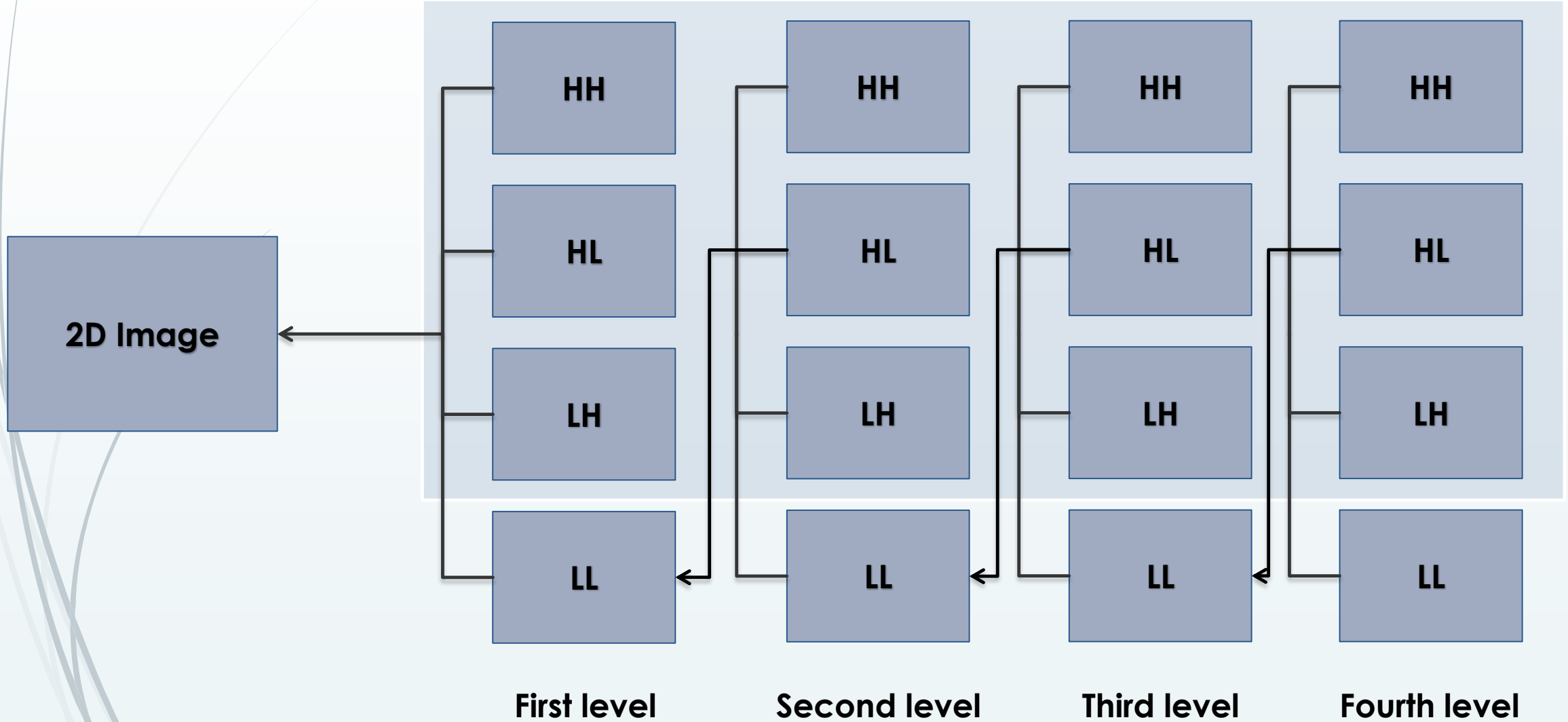
3. Local Variance Estimation



4. Wiener Filter

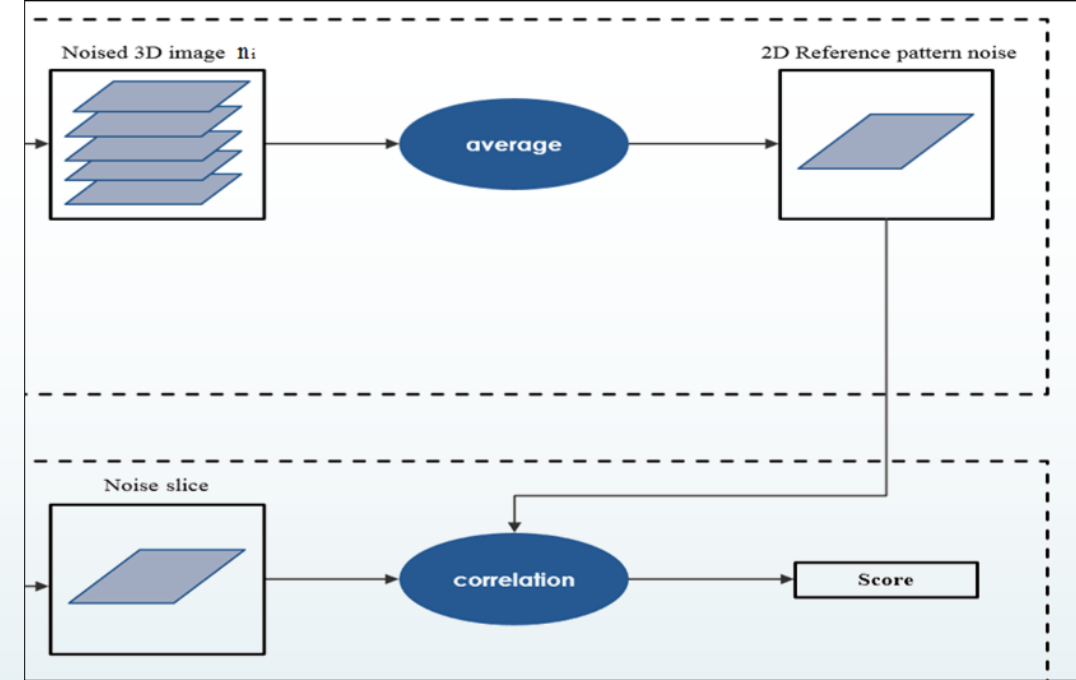


5. Inverse Wavelet



Correlation

3. Decision by correlation



$$\text{corr}(n, RPN_i) = \frac{(n - \bar{n}) \cdot (RPN_i - \overline{RPN_i})}{\|n - \bar{n}\| \|RPN_i - \overline{RPN_i}\|} = \text{score}_i$$

\mathbf{n} : is the noise component of the tested slice

$$\text{Device } d = \text{arg}_d \max(\text{score}_i)$$

\mathbf{i} : is the identified device

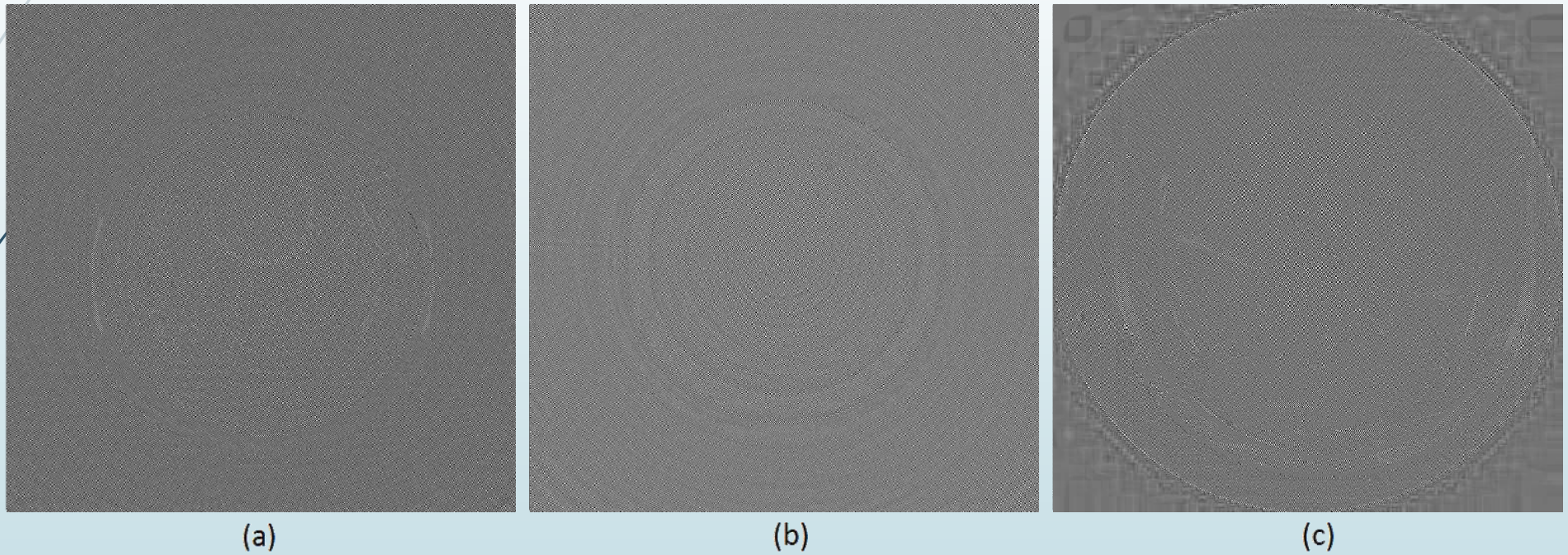
Outlines

- Context
- Presentation of the identification method
- **Experimental results**
- Conclusion and future work

Experimental images

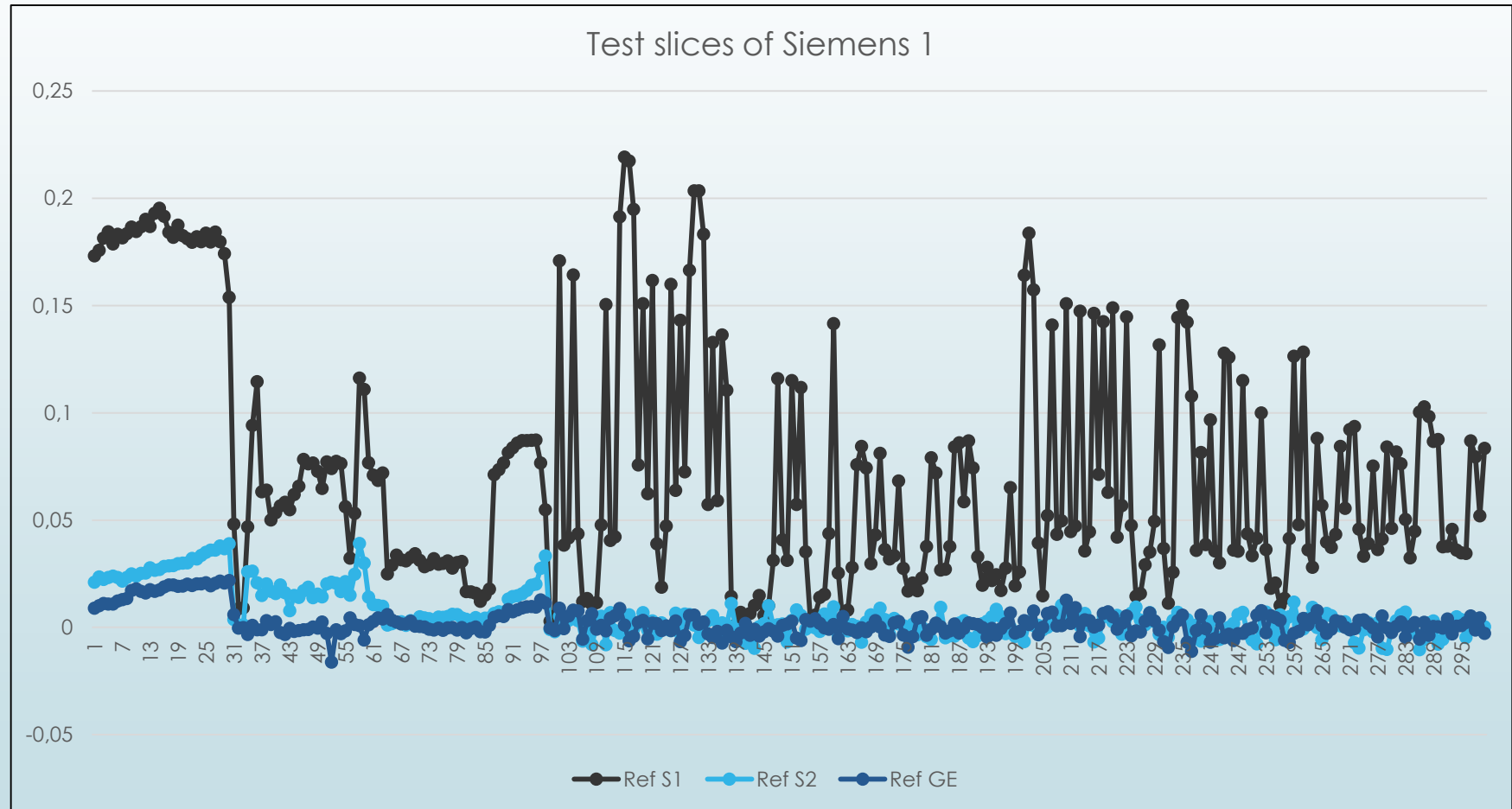
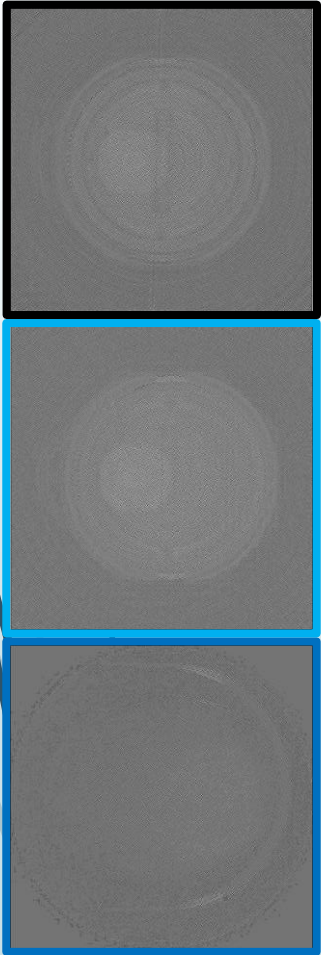
	Siemens 1	Siemens 2	GE
Content	Phantom	Phantom	skull
Nb of images	3	3	2
Nb of slices	300	300	200
Size (pixels)	512x512	512x512	512x512
Bits per pixel	16	16	16
Slice thickness	3mm	3mm	3mm
Pixel size	1mm	1mm	1mm
Nb of slices to compute RPN	120	120	120
Nb of tested slices	300	300	300

Results

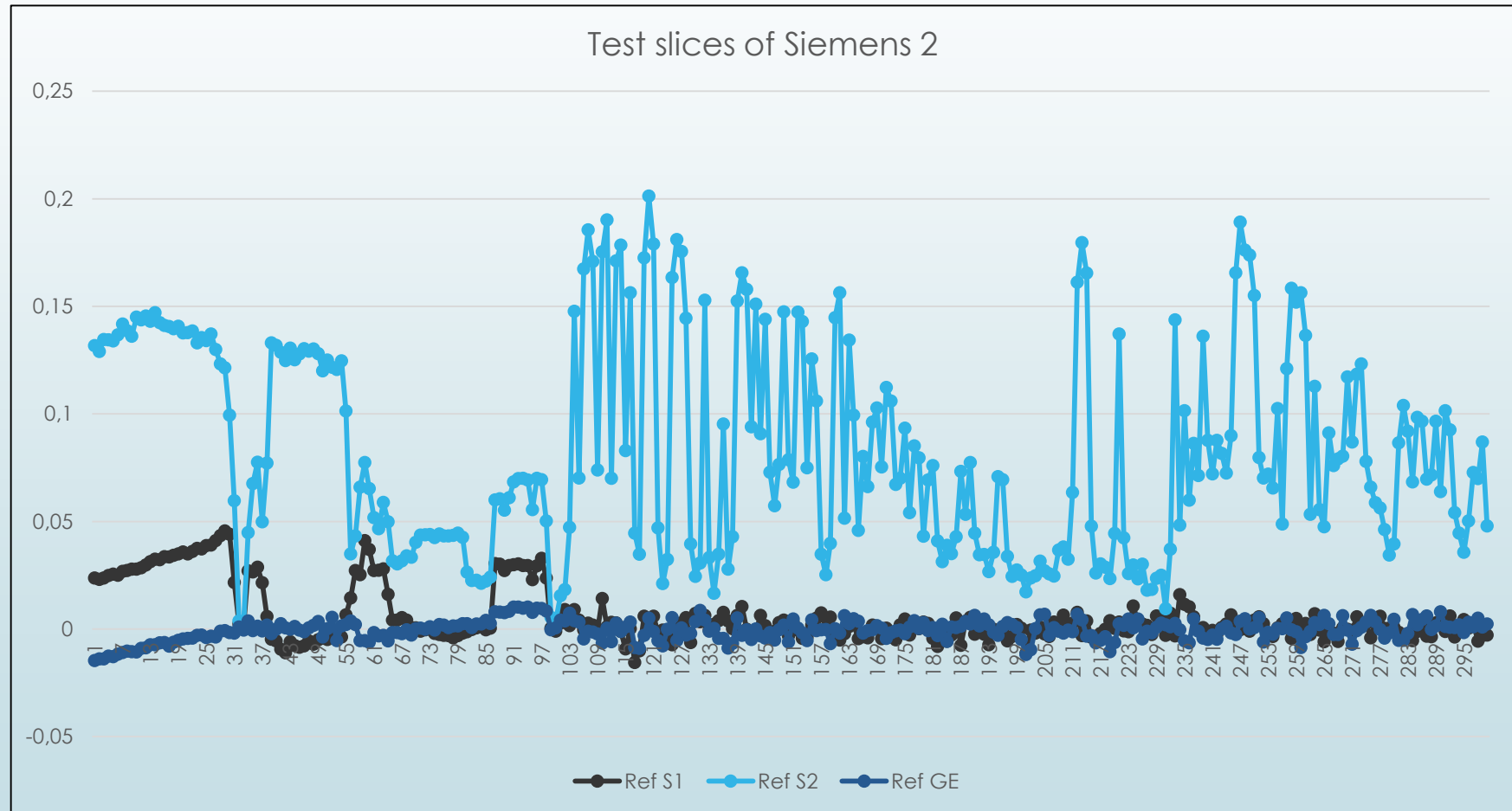
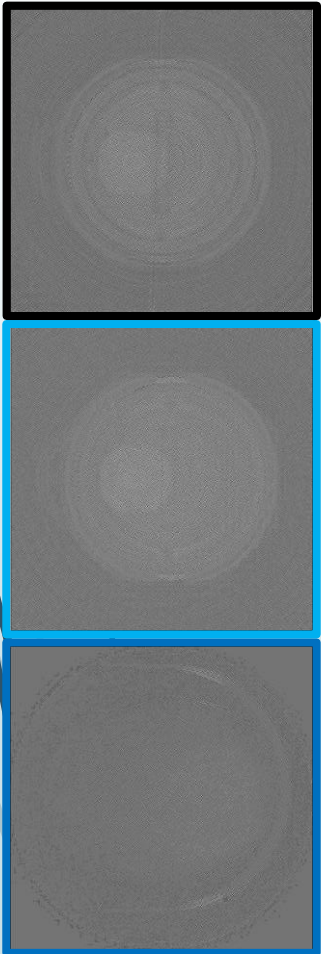


Reference pattern noise from: a) Siemens device Ref S1, b) Siemens device Ref S2, c) General Electric Ref GE

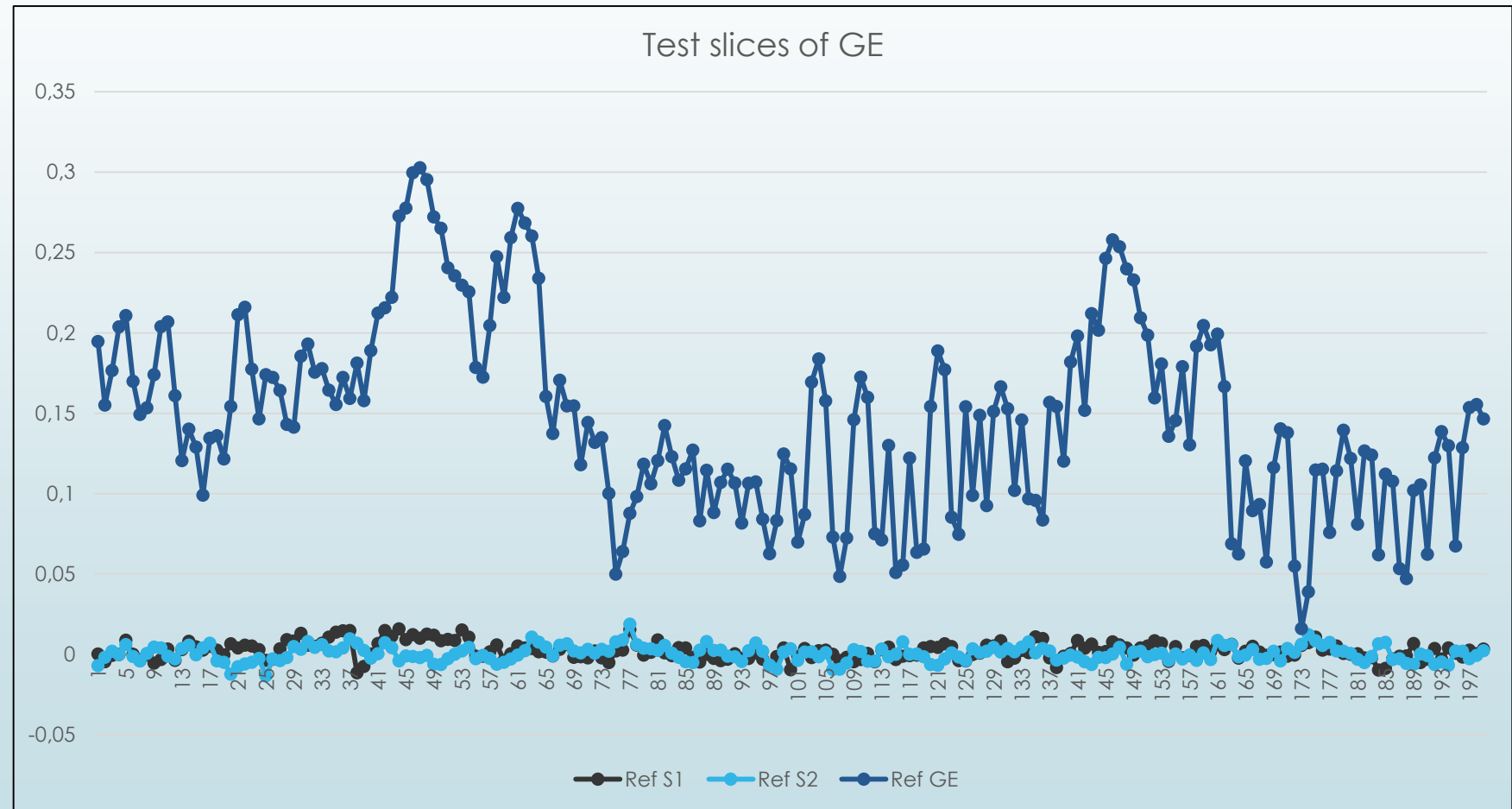
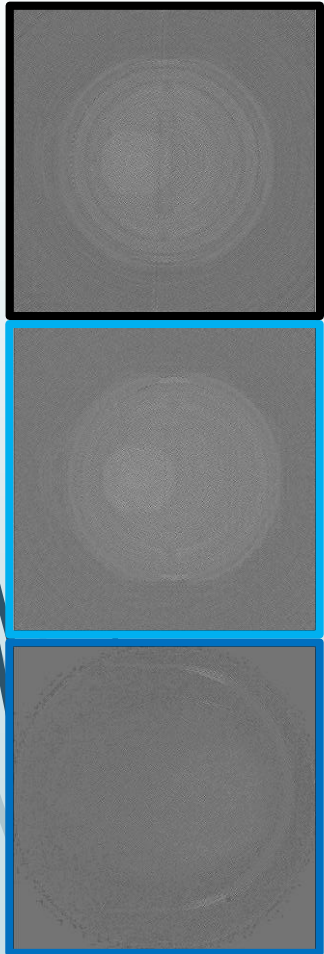
Results



Results



Results



Identification accuracy

	Siemens 1	Siemens 2	GE
Siemens 1	99.3 %	0 %	0 %
Siemens 2	0.7 %	100 %	0 %
GE	0 %	0 %	100 %

Outlines

- Context
- Presentation of the identification method
- Experimental results
- Conclusion and future work

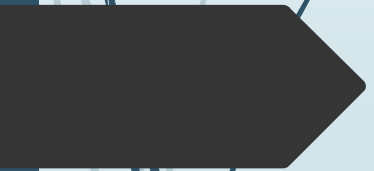
Conclusion

- Preliminary results on CT-Scanner identification based on sensor noise analyzing.

Future work

- Working with more images and more devices
- Generalize the work in 3D
- Analyze the noise model.
- Study the influence of acquisition parameters [Solomon et al. 2013]
- Study the possibility of classifying the images that are acquired by one device but in different acquisition parameters
- Study the influence of image compression on the CT-Scanner identification

Thank you for your attention



CT-SCANNER IDENTIFICATION BASED ON SENSOR NOISE ANALYSIS

