IDENTIFICATION OF THE ACQUISITION SYSTEM IN MEDICAL IMAGES BY NOISE ANALYSIS

Presented by

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To obtain the grade of Doctor in Informatics

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BACKGROUND

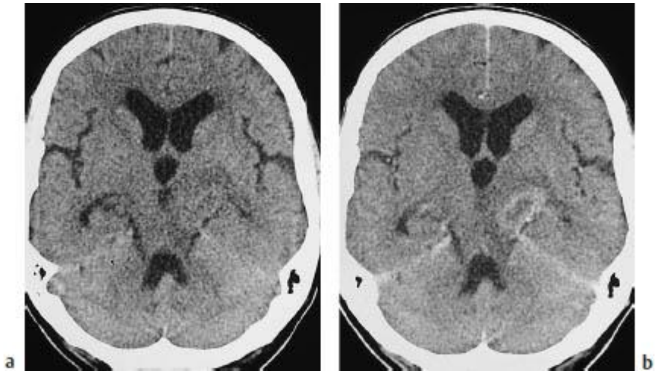
- Digital world!
- Transferred and shared media
- Securing the image
- Medical imaging
- Securing the medical images

BACKGROUND

- **Health assurance**

- **Bank credits**

- **The industrial CT-Scanner (sharing and copyright issues)**



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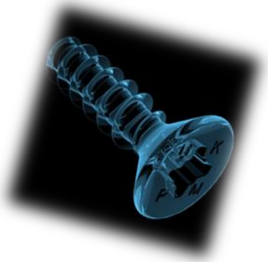
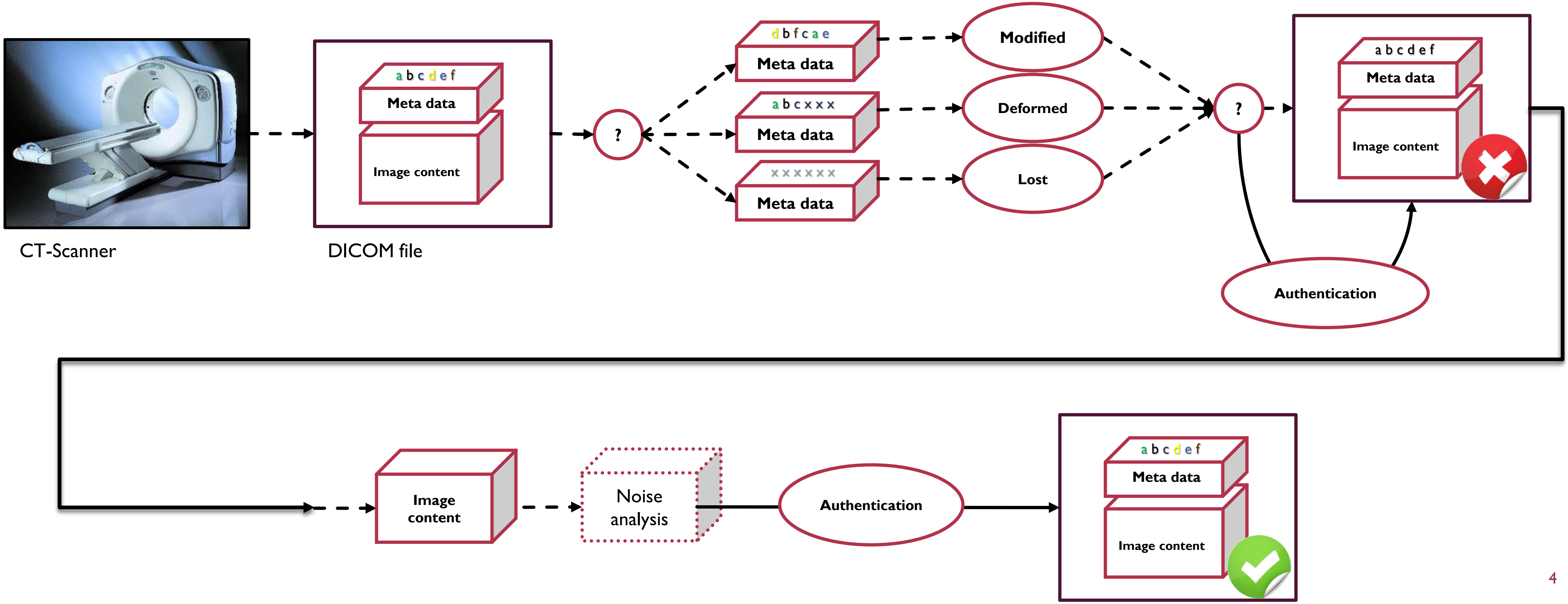
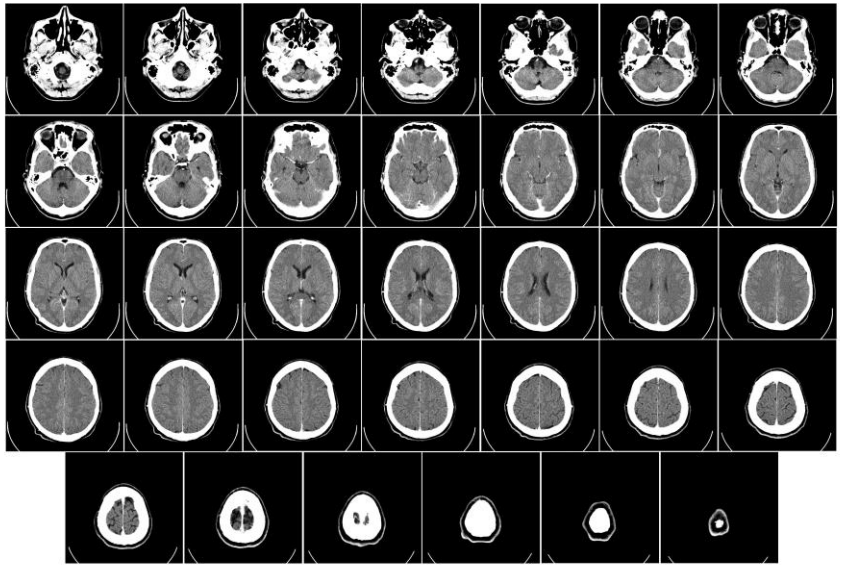
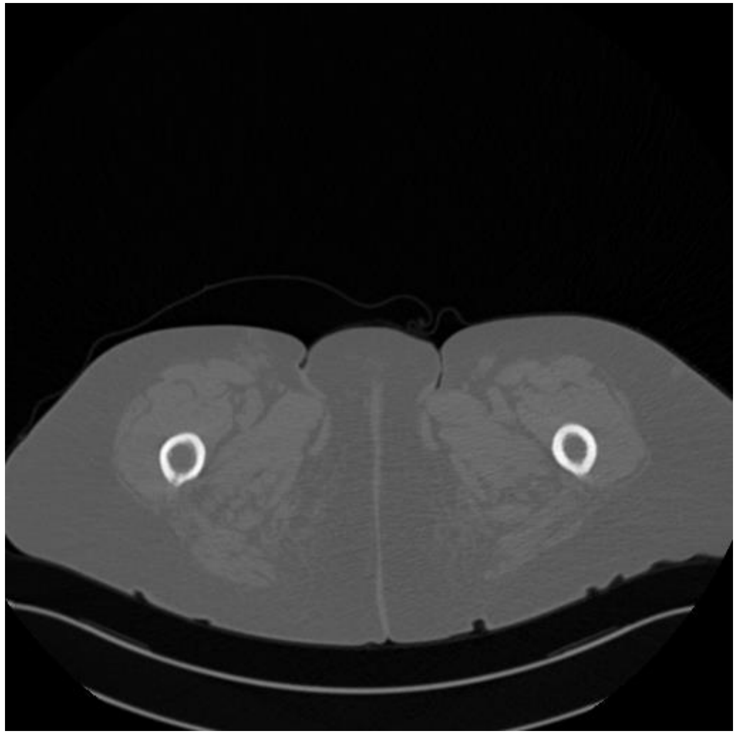


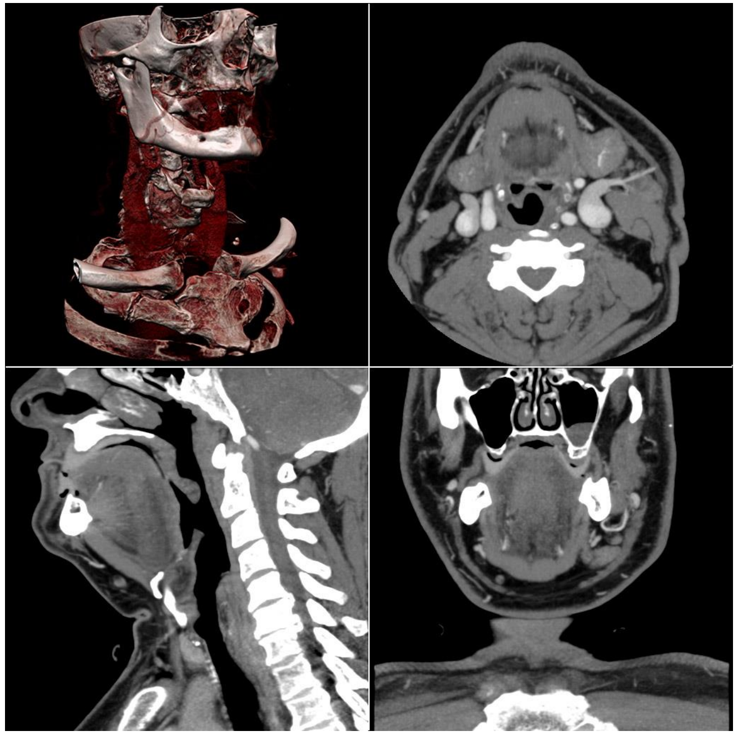
BACKGROUND


CT-Scanner
DICOM file
a b c d e f
Meta data
Image content
?
d b f c a e
Meta data
a b c x x x
Meta data
x x x x x x
Meta data
Modified
Deformed
Lost
?
a b c d e f
Meta data
Image content
Authentication
Image content
Noise analysis
Authentication
a b c d e f
Meta data
Image content

BACKGROUND CT-SCAN IMAGE





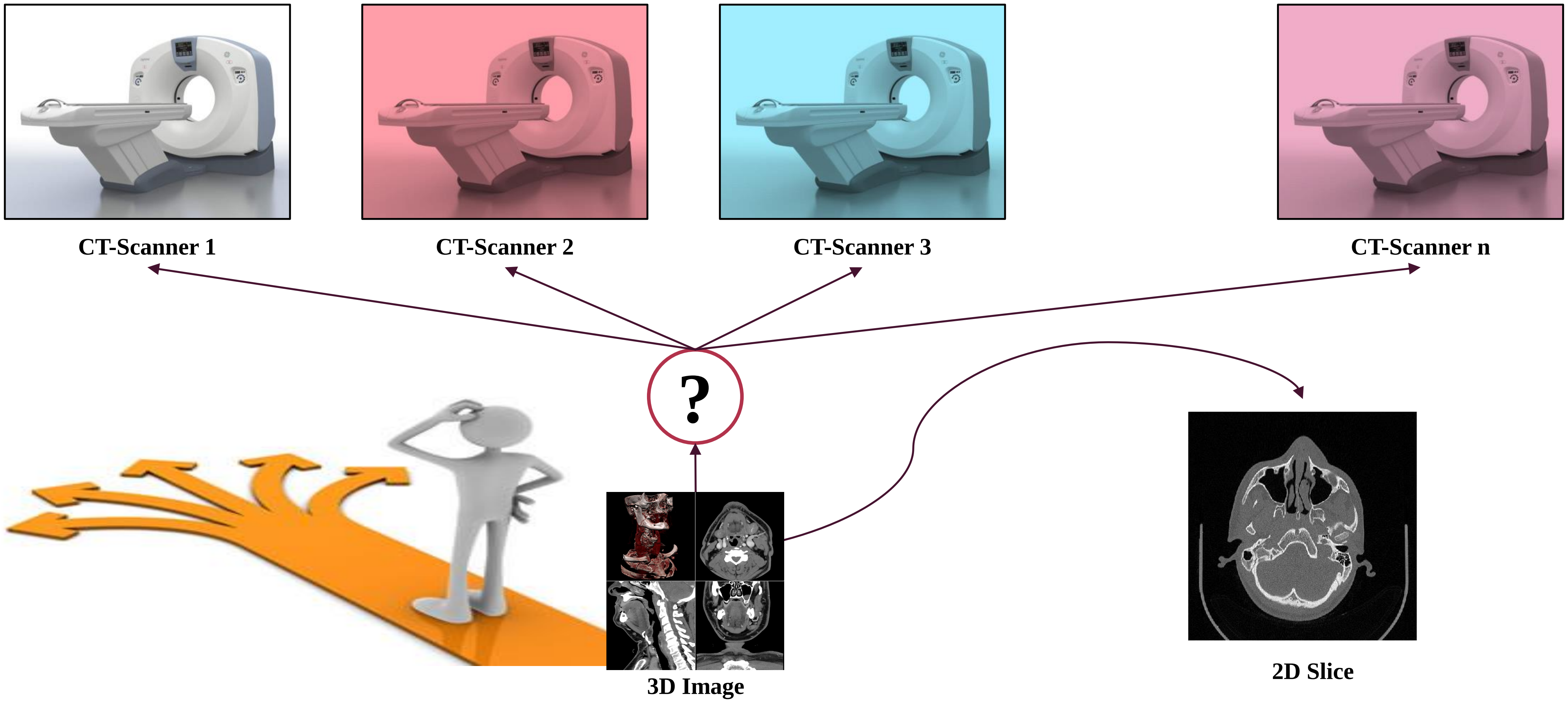


Volume slices

3D volume

3D visualization

PROBLEM: CT-SCAN DEVICE IDENTIFICATION



OUTLINES

- Background
- Problem
- Digital device identification
  - Overview
  - Related work
- Contributions
  - CT-Scanner Identification based on sensor noise analysis
    - Identification based on sensor noise
    - Improving sensor noise analysis
  - New directions for CT-Scanner identification
    - Extending the RPN to the different images axis
    - Using an RPN of different intensity layers
- Conclusion and perspective

OUTLINES

DIGITAL DEVICE IDENTIFICATION

-OVERVIEW- *-RELATED WORK-*

Digital Camera Identification

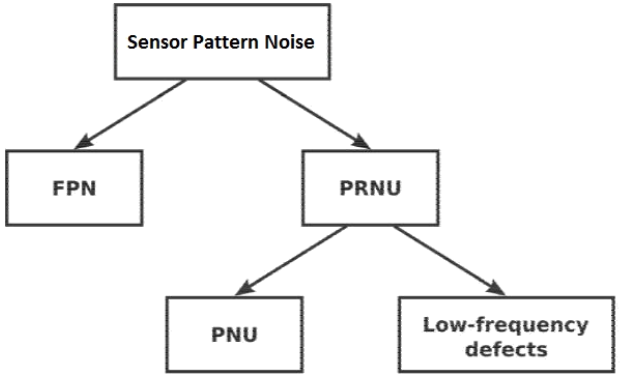
DIGITAL DEVICE IDENTIFICATION

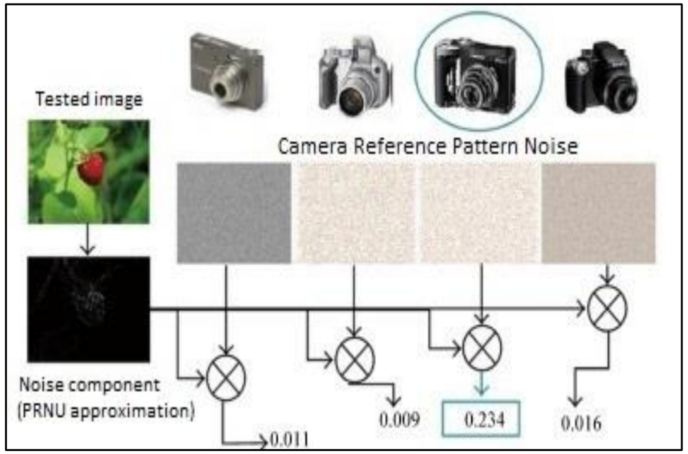
-OVERVIEW- *-RELATED WORK-*

Digital images:

- Camera Identification
  - [1], [2]: Statistical features studies.
  - [3,4,5,6]: Sensor noise-based methods.

- Digital flatbed scanner
  - [7]: Frequency domain.
  - [8]: Spatial domain.





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[2] M. Kharrazi, H.T. Sencar, and N. Memon, "Blind source camera identification," in Image Processing, 2004. ICIP '04. 2004 International Conference on, Oct 2004, vol. 1, pp. 709–712 Vol. 1.
[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] M. Chen, J. Fridrich, M. Goljan, and J. Luk´as, "Determining image origin and integrity using sensor noise," Information Forensics and Security, IEEE Transactions on, vol. 3, no. 1, pp. 74–90, 2008.
[5] X. Kang, Y. Li, Z. Qu, and J. Huang, "Enhancing source camera identification performance with a camera reference phase sensor pattern noise," Information Forensics and Security, IEEE Transactions on, vol. 7, April 2012.
[6] C. T. Li, "Source camera identification using enhanced sensor pattern noise," Trans. Info. For. Sec., vol. 5, no. 2, pp. 280–287, 2010.
[7] N. Khanna, A. K. Mikkilineni, G. T.-C. Chiu, J. P. Allebach, and E. J. Delp, "Scanner identification using sensor pattern noise," in SPIE Conference on Security, Steganography, and Watermarking of Multimedia, 2007, vol. 6505.
[8] C.-H. Choi, M.-J. Lee, and H.-K. Lee, "Scanner identification using spectral noise in the frequency domain," in Image Processing (ICIP), 2010 17th IEEE International Conference on, Sept 2010, pp. 2121–2124.

DIGITAL DEVICE IDENTIFICATION

-OVERVIEW- -RELATED WORK-

Medical images:

- [1]: Modification in medical images.
- [2]: Noise characteristics in CT-Scanner manufacturers (NPS).
- [3]: Device identification in 2D radiography images.
- [4], [5]: CT-Scanner identification.

[1] H. Huang, G. Coatrieux, H. Shu, L. Luo and C. Roux. Blind Integrity Verication of Medical Images. IEEE Transactions on Information Technology in Biomedicine, vol. 16, no. 6, pages 11221126, 2012.
[2] 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.
[3] Y. Duan, G. Coatrieux, and H. Shu, Identification of digital radiography image source based on digital radiography pattern noise recognition, in Image Processing (ICIP), 2014 IEEE International Conference on. IEEE, 2014
[4] Y. Duan, G. Coatrieux and H. Shu. Computed tomography image source identification by discriminating CT-scanner image reconstruction process. 37th Annual International Conference of the IEEE, 2015.
[5] Y. Duan, D. Bouslimi, G. Yang, H. Shu and G. Coatrieux. Computed Tomography Image Origin Identification based on Original Sensor Pattern Noise and 3D Image Reconstruction Algorithm Footprints, *IEEE Journal of Biomedical and Health Informatics*, 2016

OUTLINES

- Background
- Problem and work objectives
- Digital device identification
  - Overview
  - Related work
- **Contributions**
  - CT-Scanner Identification based on sensor noise analysis
    - Identification based on sensor noise
    - Improving sensor noise analysis
  - New directions for CT-Scanner identification
    - Extending the RPN to the different images axis
    - Using an RPN of different intensity layers
- Conclusion and perspectives

CONTRIBUTIONS

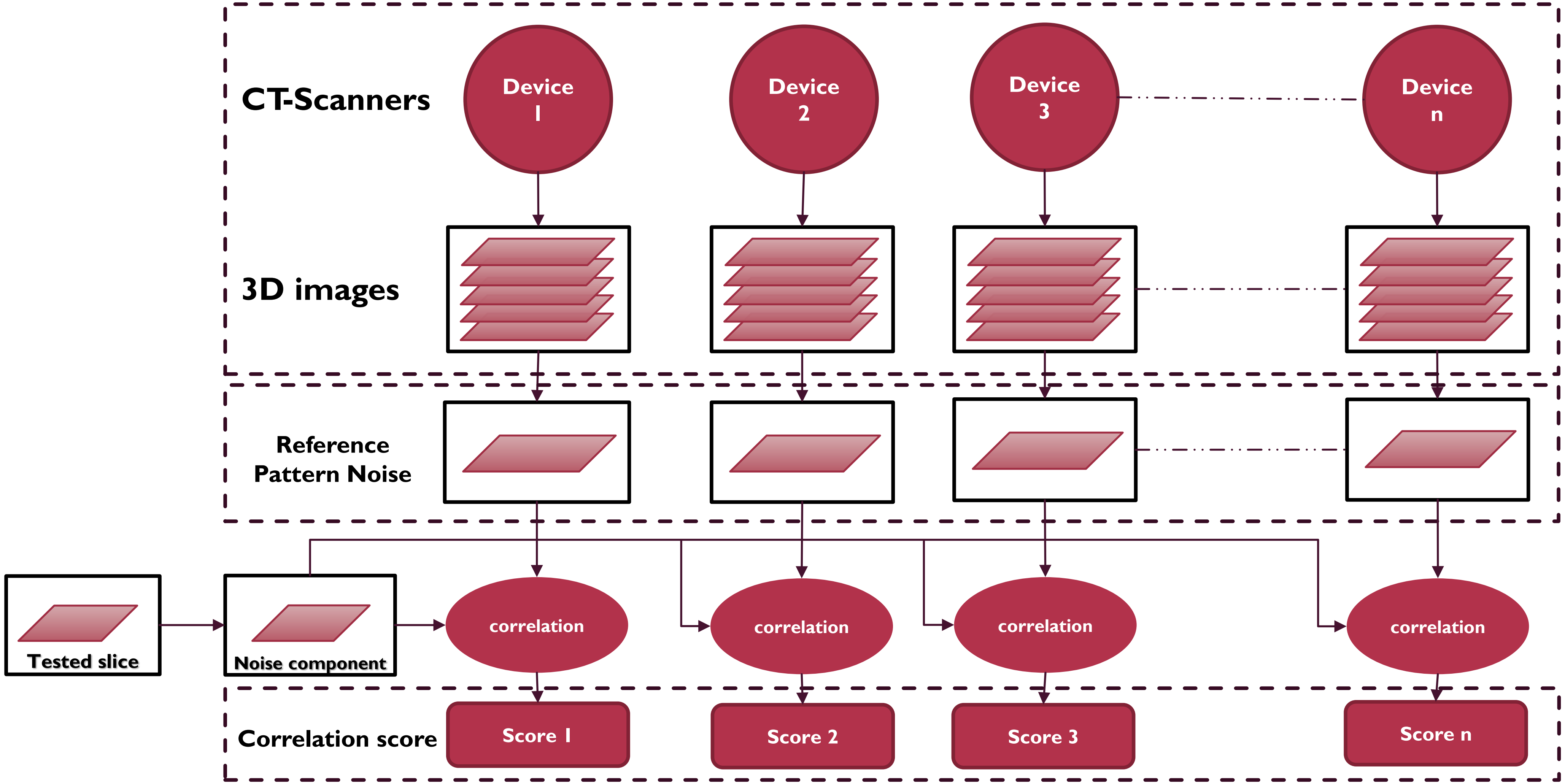
1. CT-Scanner Identification based on sensor noise analysis
   1. Identification based on sensor noise
   2. Improving sensor noise analysis
   3. Conclusion
2. New directions for CT-Scanner identification
   1. Extending the RPN to the different image axes
   2. Using an RPN of different intensity layers
   3. Conclusion

CONTRIBUTIONS

1. CT-Scanner Identification based on sensor noise analysis
    1. **Identification based on sensor noise**
    2. Improving sensor noise analysis
    3. Conclusion
2. New directions for CT-Scanner identification
    1. Extending the RPN to the different image axes
    2. Using an RPN of different intensity layers
    3. Conclusion

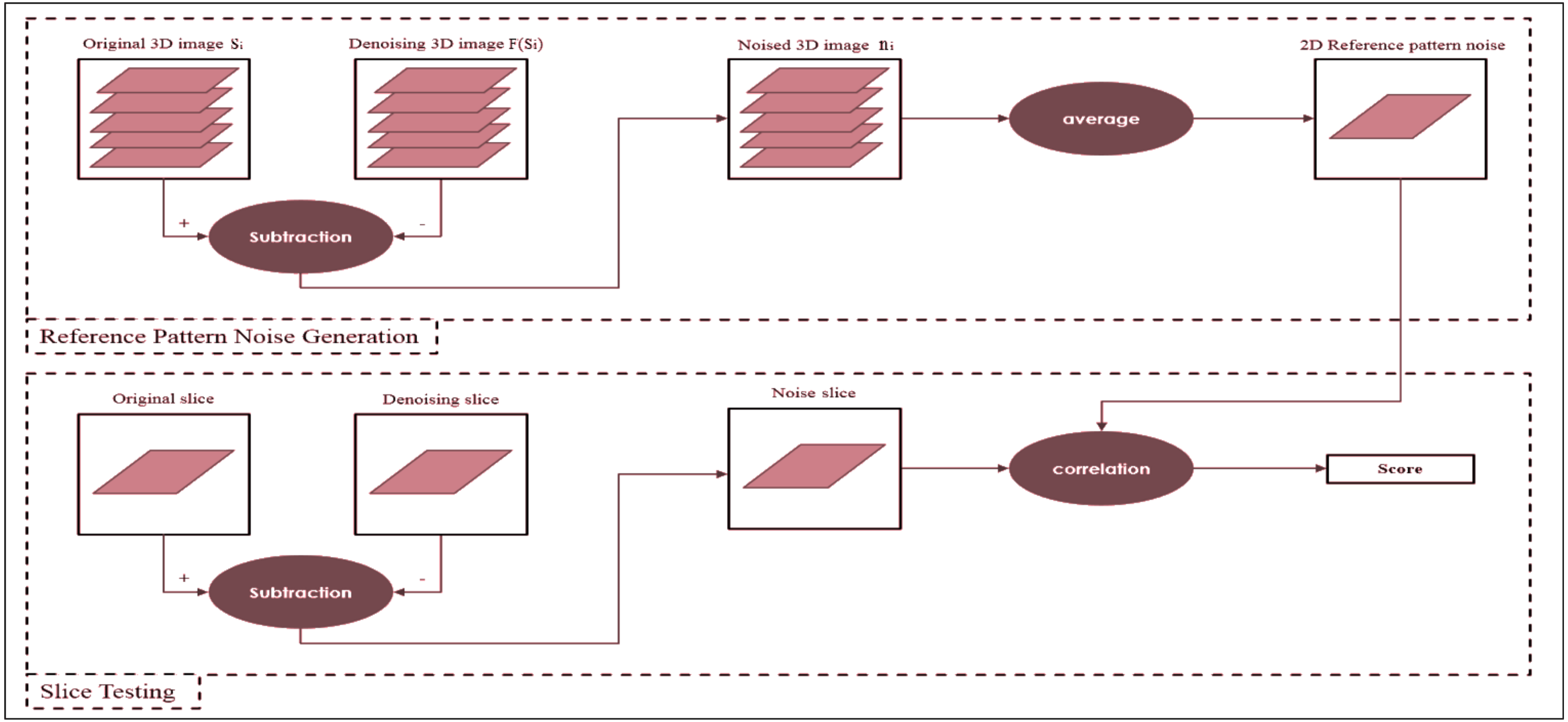
IDENTIFICATION BASED ON SENSOR NOISE

1. IDENTIFICATION METHOD *2. EXPERIMENTS* *3. RESULTS*



IDENTIFICATION BASED ON SENSOR NOISE

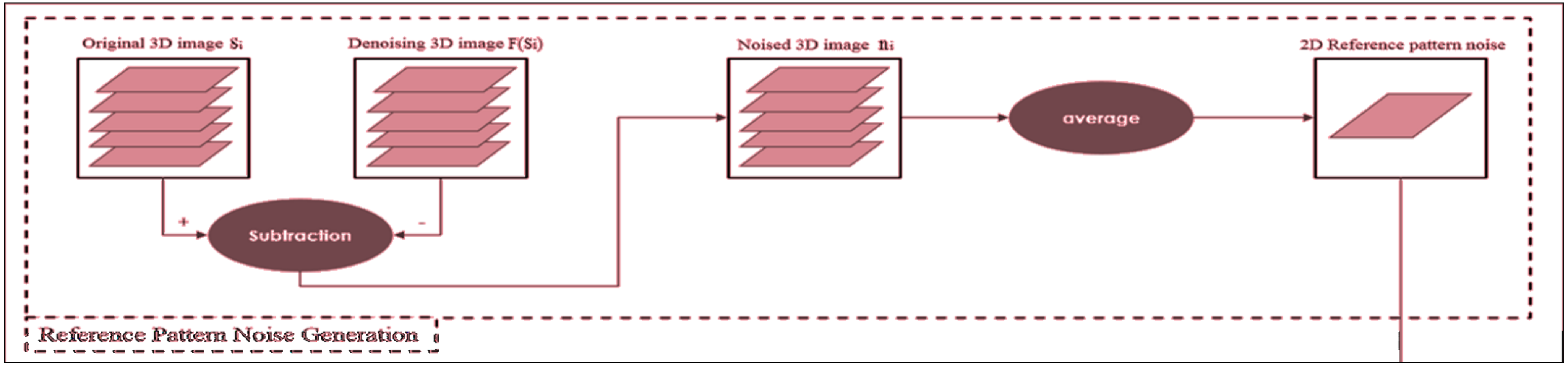
1. IDENTIFICATION METHOD *2. EXPERIMENTS* *3. RESULTS*



[*] 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.

IDENTIFICATION BASED ON SENSOR NOISE

1. IDENTIFICATION METHOD *2. EXPERIMENTS* *3. RESULTS*



1. Extract the Reference Pattern Noise

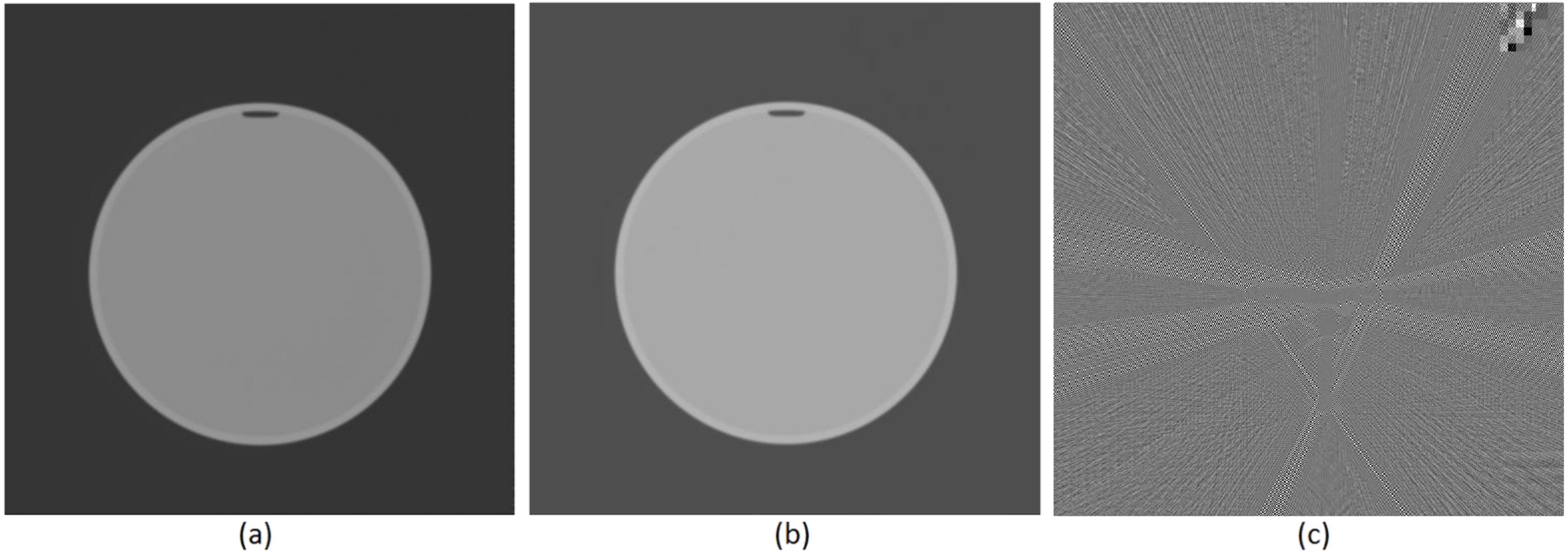
$$n^{(i)} = s^{(i)} - F(s^{(i)})^{*}$$

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

n : Noise component
s : Slice
F() : Denoising function
i : Slice number

RPN : Reference pattern noise
N : Number of noise slices
n : Noise component

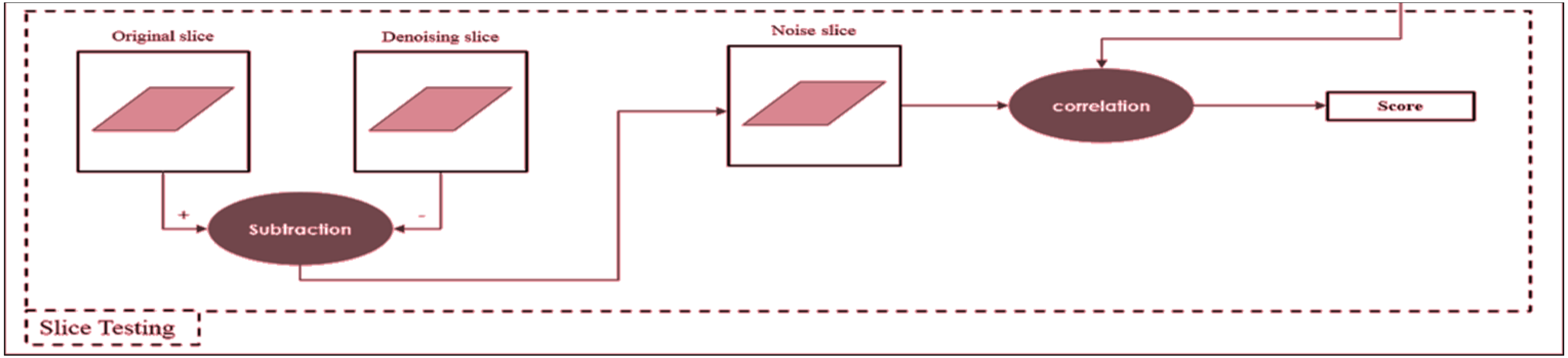
[*] Marian Kazubek. Wavelet domain image denoising by thresholding and Wiener filtering. IEEE Signal Processing Letters, vol. 10, no. 11, pages 324-326, 2003



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

IDENTIFICATION BASED ON SENSOR NOISE

1. IDENTIFICATION METHOD *2. EXPERIMENTS* *3. RESULTS*



2. Extract the noise component for the tested slice

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

n: noise component
s: slice
$F()$: denoising function

3. Decision by correlation

$$corr(n, RPN_i) = \frac{(n - \bar{n}).(RPN_i - \overline{RPN_i})}{\|n - \bar{n}\| \, \|RPN_i - \overline{RPN_i}\|} = score_i$$

n: is the noise component of the tested slice

Device $d = arg_d max(score_i)$

[*] Marian Kazubek. Wavelet domain image denoising by thresholding and Wiener filtering. IEEE Signal Processing Letters, vol. 10, no. 11, pages 324326, 2003

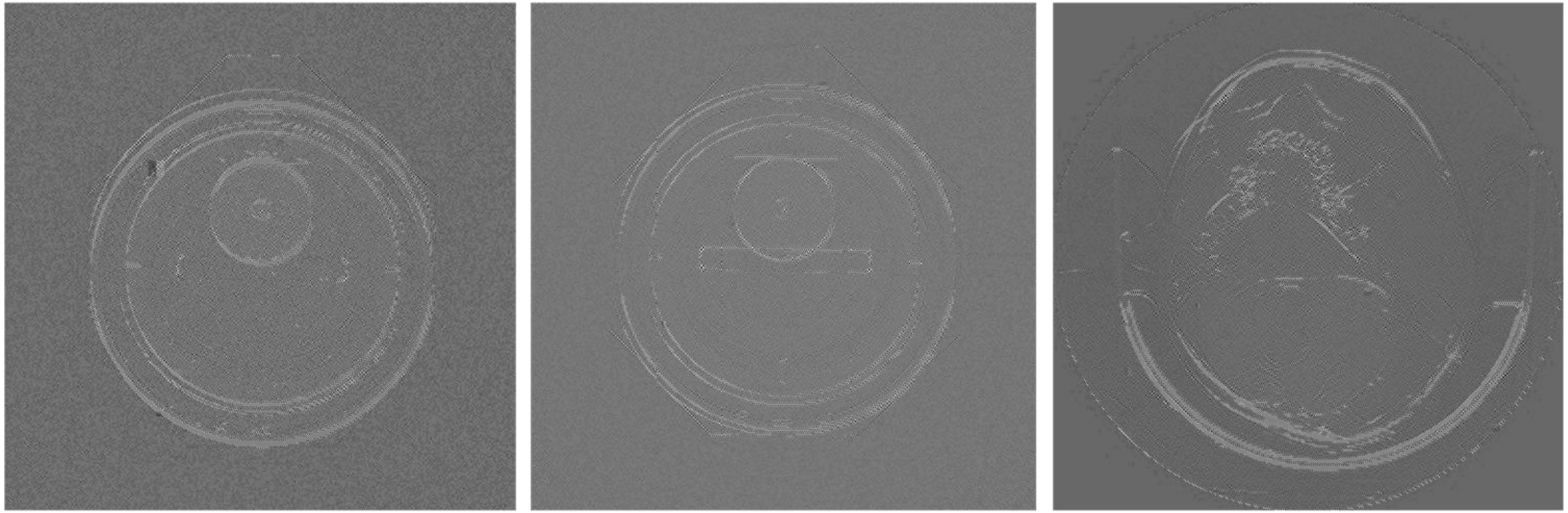
Experimental images*

	Siemens 1	Siemens 2	GE
Content	Phantom	Phantom	skull
Manufacturer model name	SD AS+	SD AS	LS VCT
Nb of images	3	3	2
Nb of slices	420	420	320
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	200

[*] Thanks to IMAIOS, CHU Montpellier, Clinique du Parc

IDENTIFICATION BASED ON SENSOR NOISE

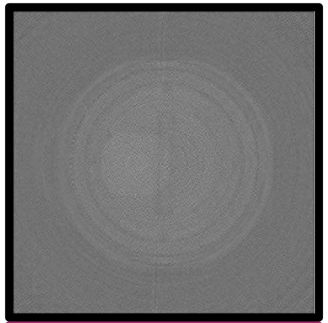
1. IDENTIFICATION METHOD *2. EXPERIMENTS* *3. RESULTS*

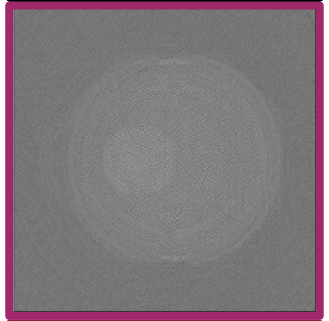


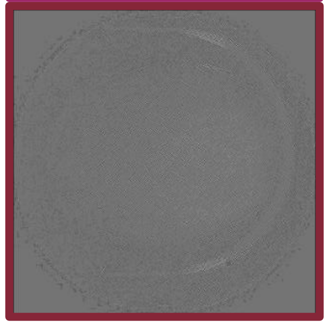
(a) (b) (c)

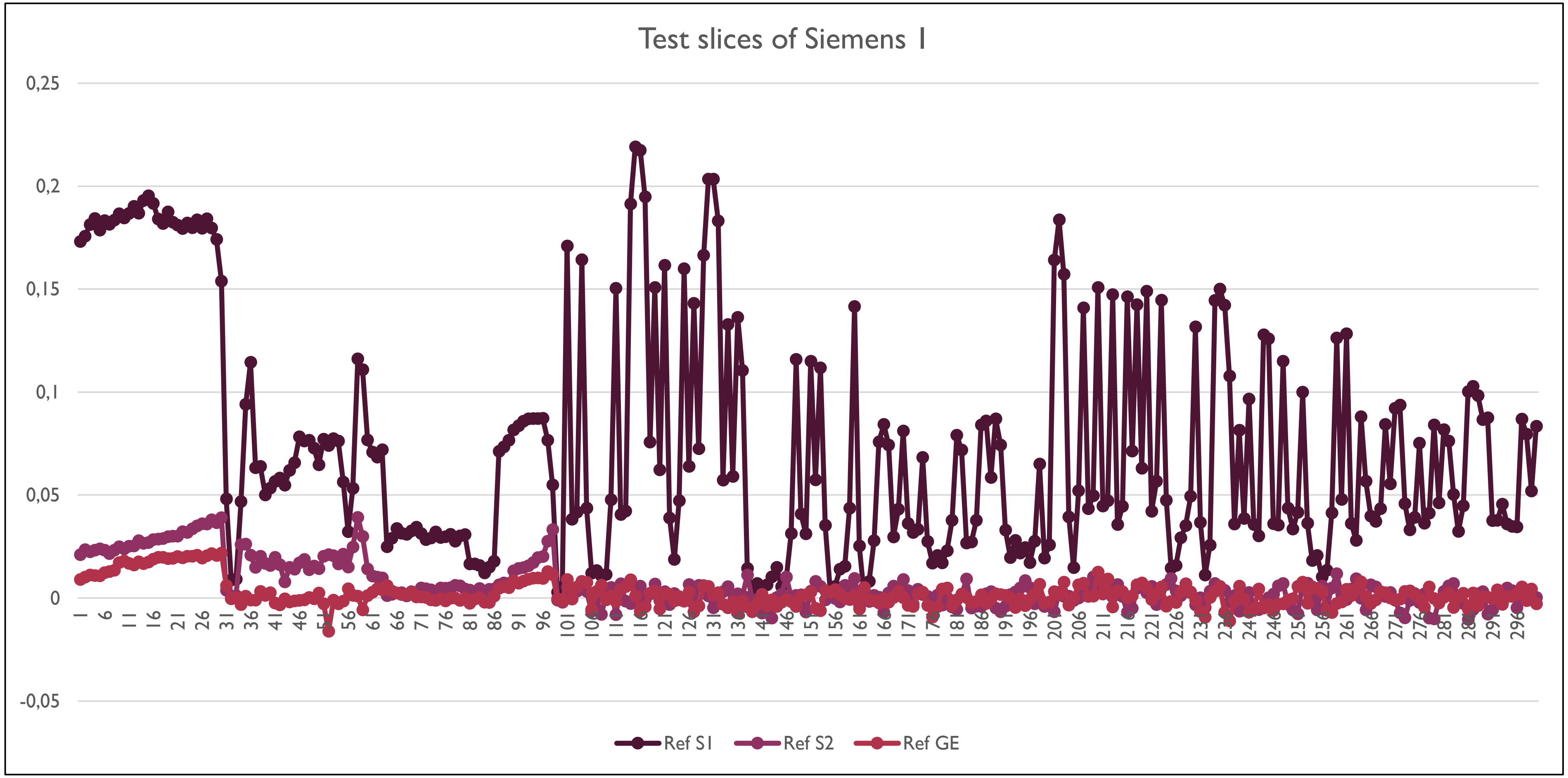
Reference pattern noise from: a) Siemens 1 RPN, b) Siemens 2 RPN, c) General Electric RPN

IDENTIFICATION BASED ON SENSOR NOISE



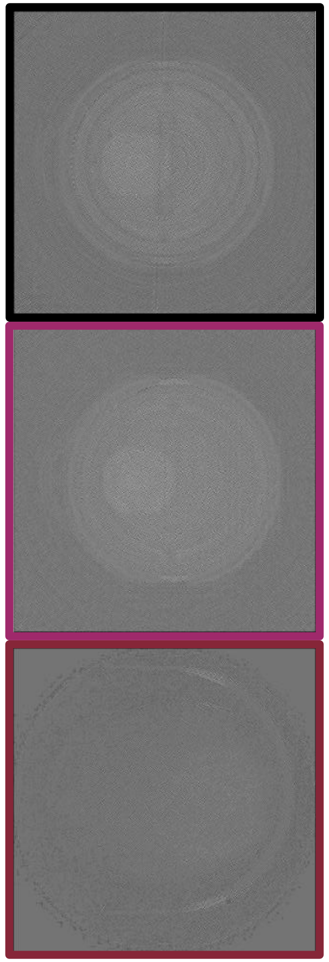


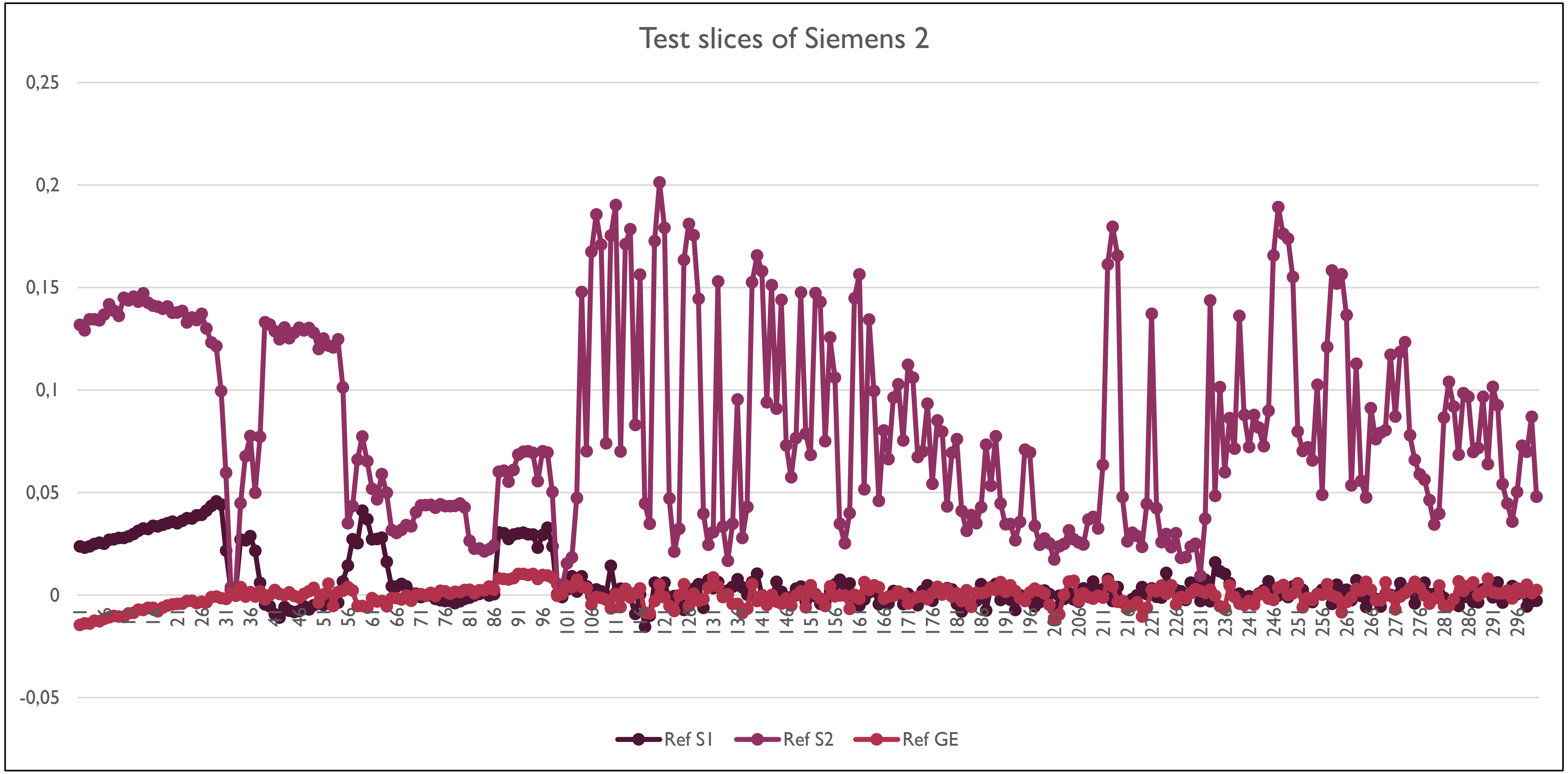




IDENTIFICATION BASED ON SENSOR NOISE

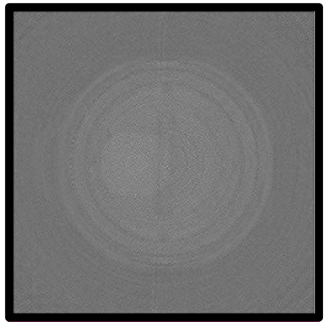
1. IDENTIFICATION METHOD *2. EXPERIMENTS* *3. RESULTS*

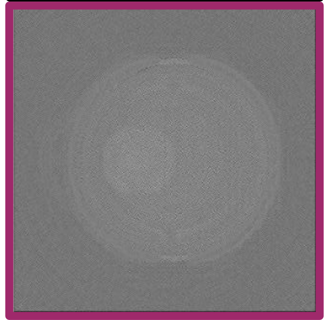


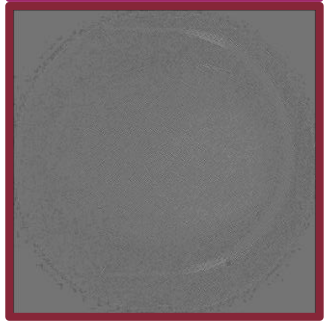


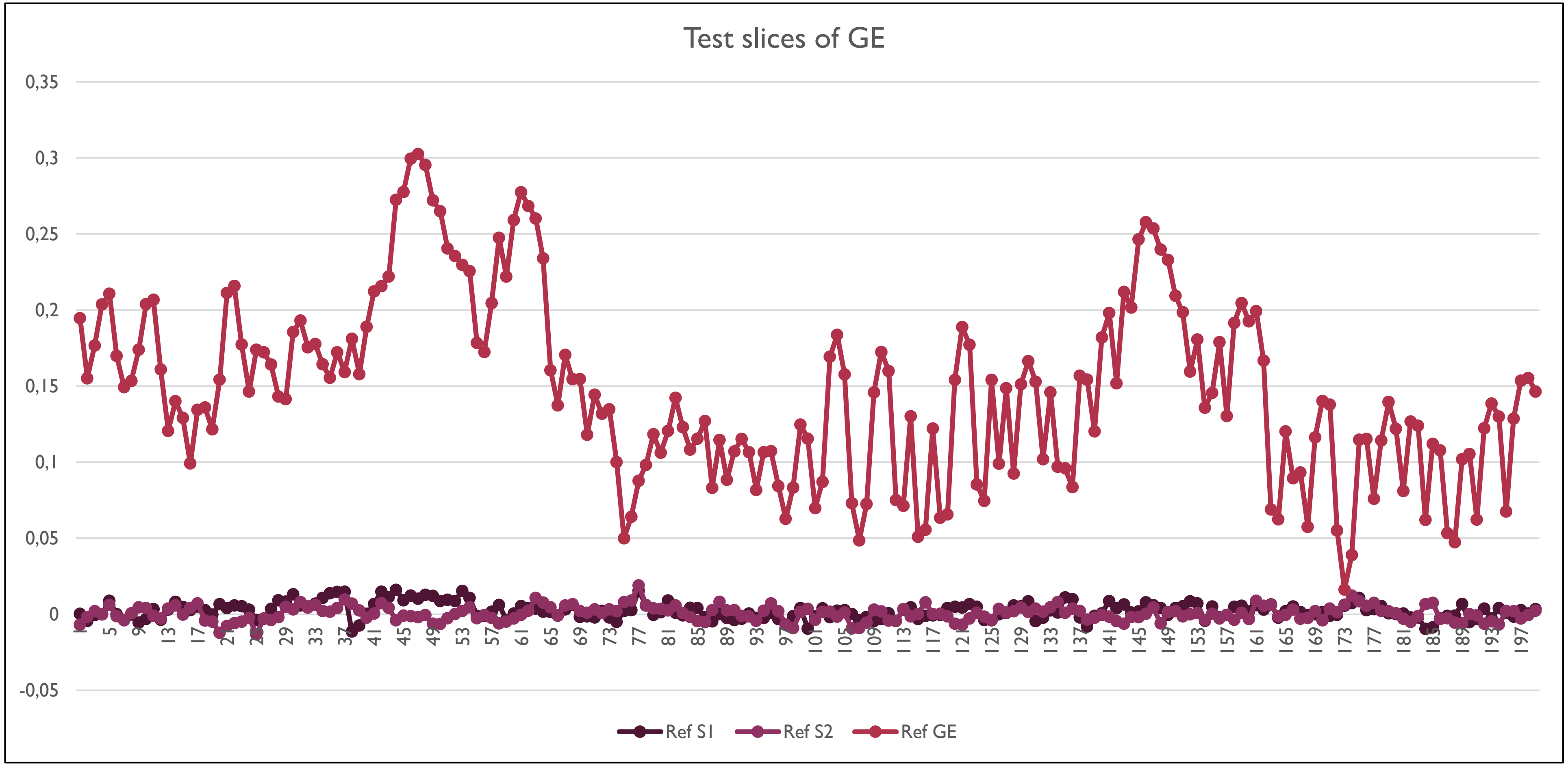
IDENTIFICATION BASED ON SENSOR NOISE

I. IDENTIFICATION METHOD *2. EXPERIMENTS* *3. RESULTS*









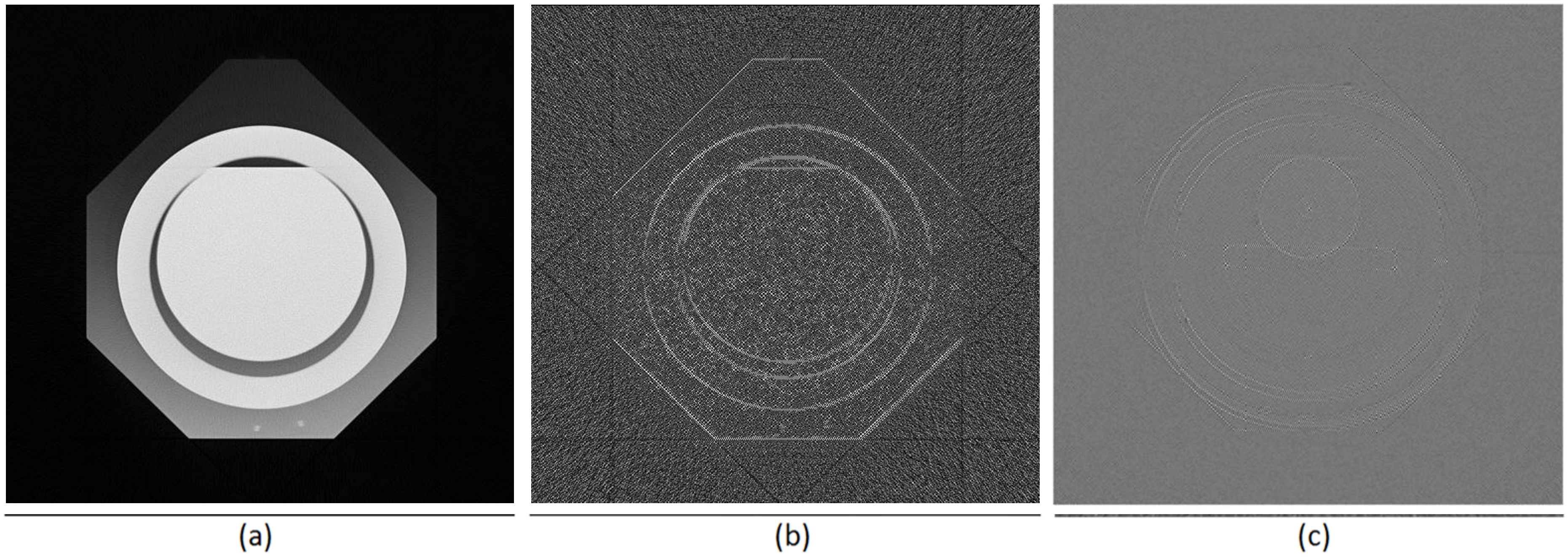
IDENTIFICATION BASED ON SENSOR NOISE

1. IDENTIFICATION METHOD *2. EXPERIMENTS* *3. RESULTS*

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

Identification accuracy

- Small dataset.
- Images of phantoms.
- RPN contains noise and edges artifacts.
- High correlation? Correlation with noise or edges?



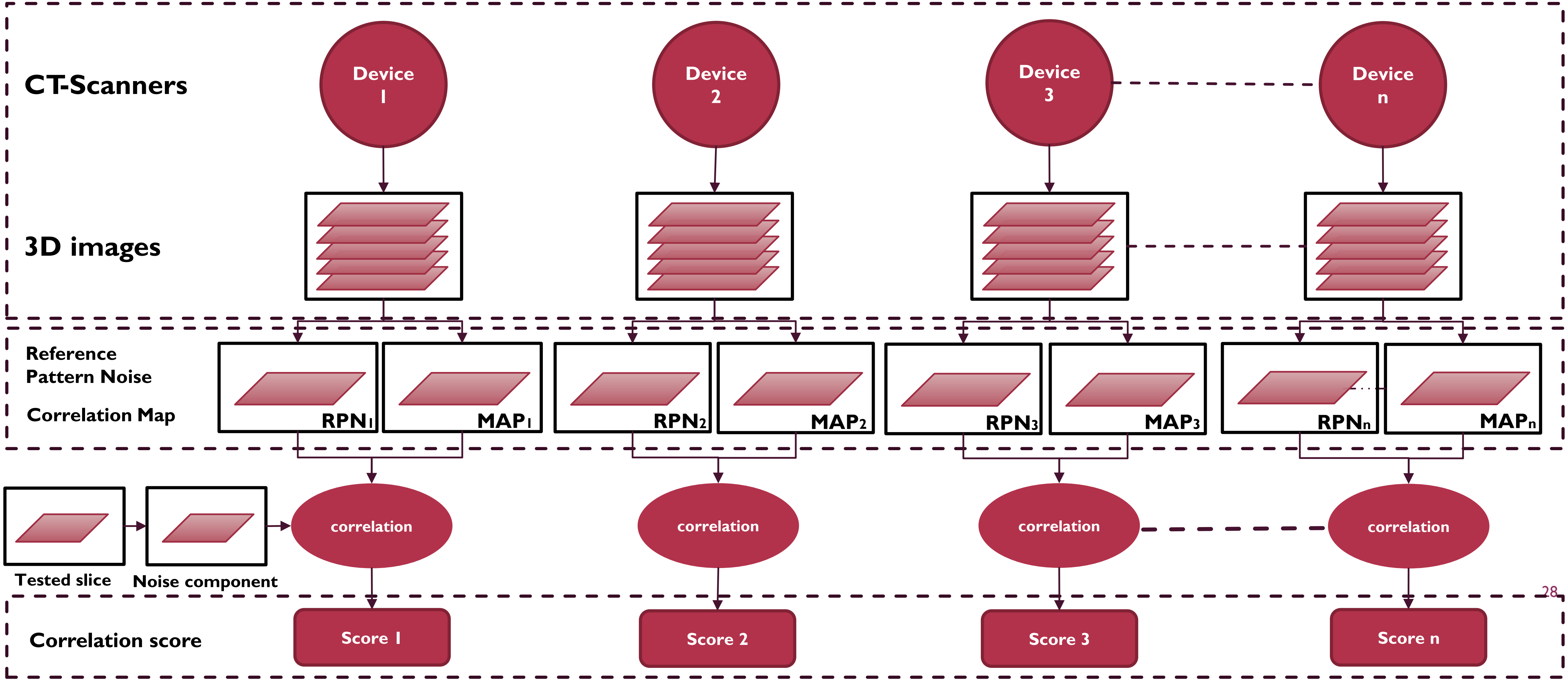
Example: a) Original slice from a Siemens device, b) Its noise component, c) An RPN of a Siemens device

CONTRIBUTIONS

1. CT-Scanner Identification based on sensor noise analysis
   1. Identification based on sensor noise
   2. **Improving sensor noise analysis**
   3. Conclusion
2. New directions for CT-Scanner identification
   1. Extending the RPN to the different image axes
   2. Using an RPN of different intensity layers
   3. Conclusion

IMPROVING SENSOR NOISE ANALYSIS

1. IDENTIFICATION METHOD *2. EXPERIMENTS* *3. RESULTS*



IMPROVING SENSOR NOISE ANALYSIS

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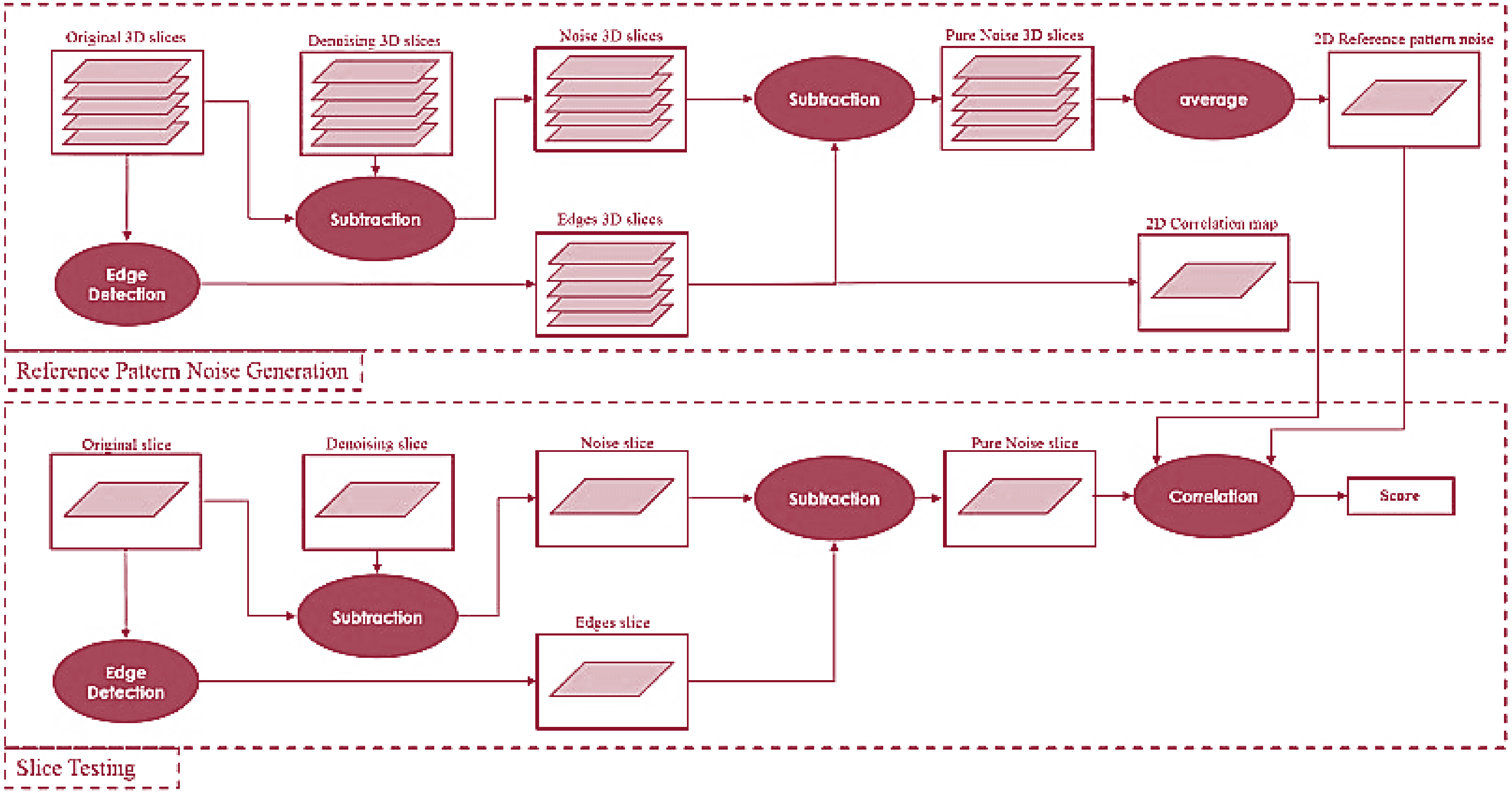
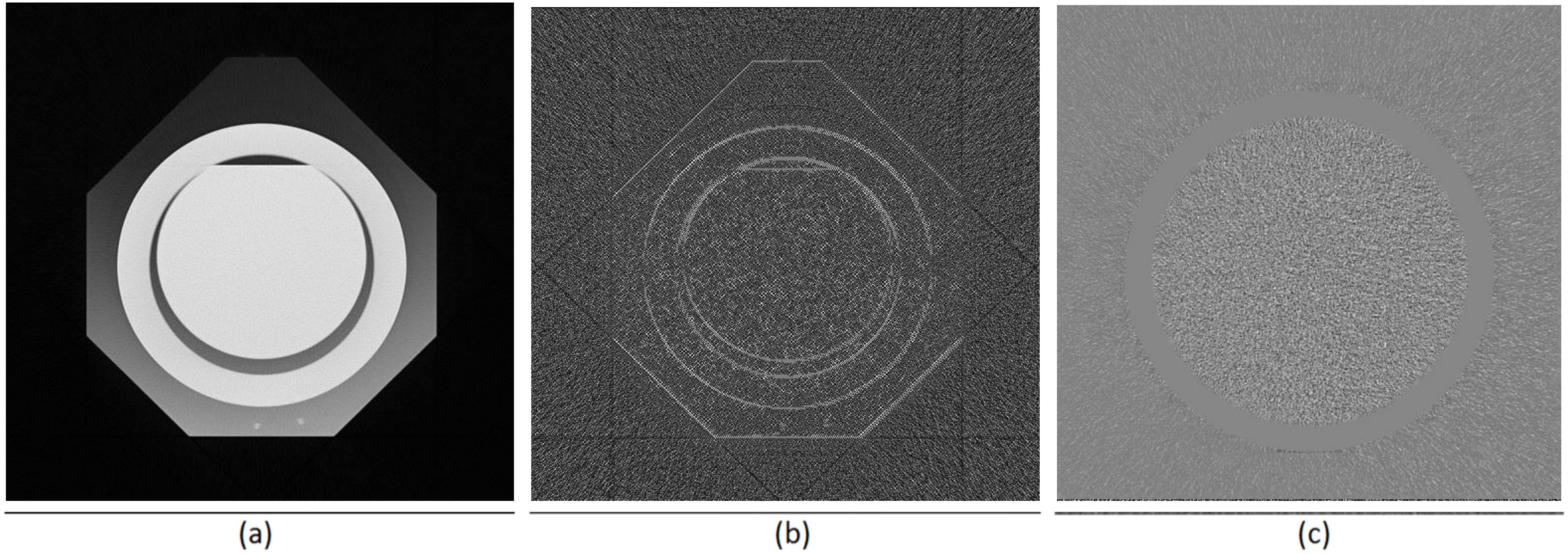


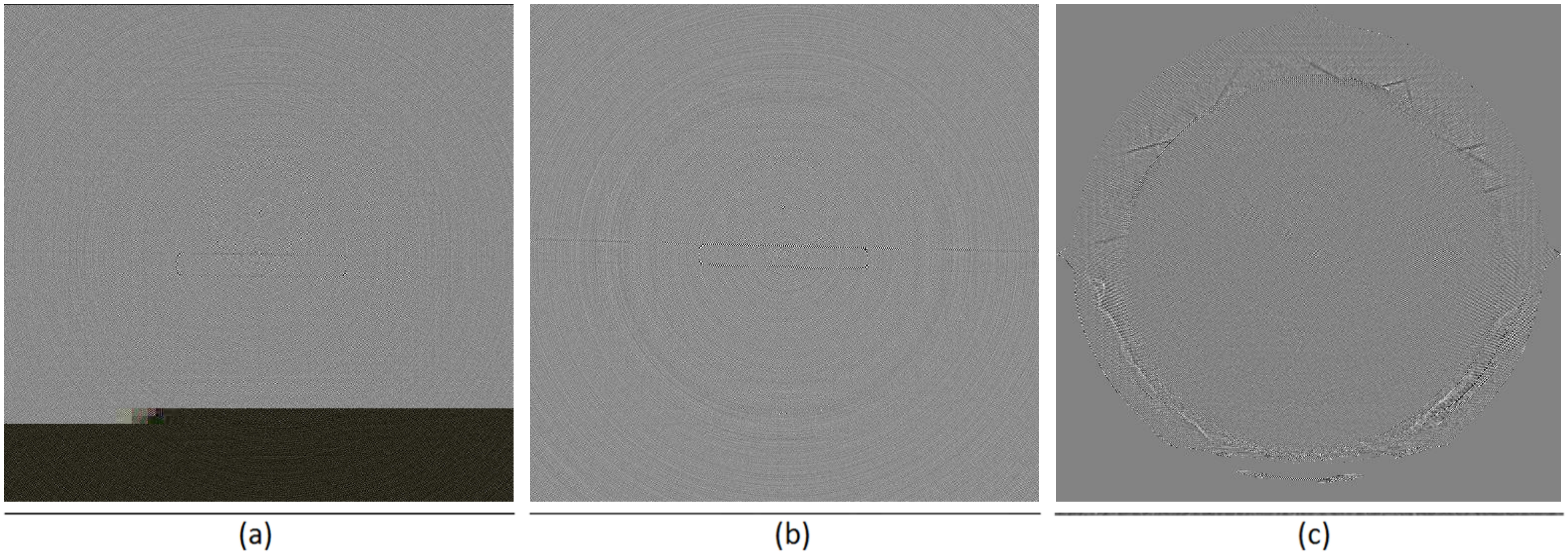


Example: a) Original slice from a Siemens device, b) Its noise component, c) Its “pure" noise component

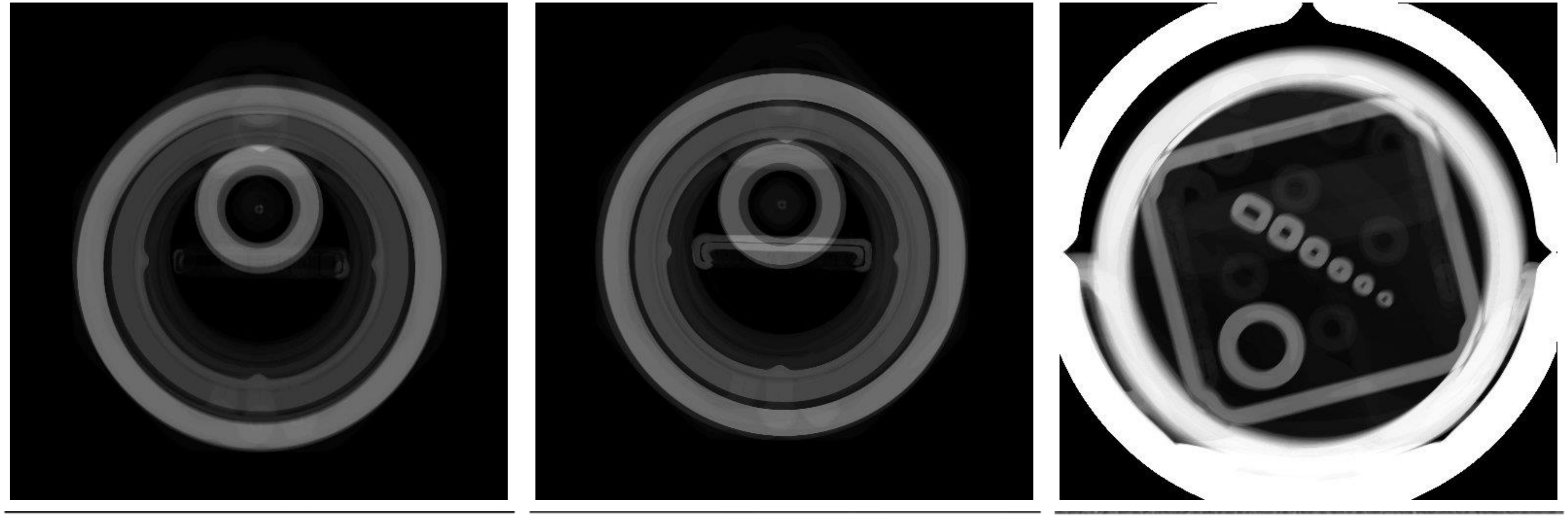
Experimental images

IMAIOS

Parameter \Device	Siemens 1	Siemens 2	General Electric
Content	Phantom	Phantom	Phantom
Nb of images	12	12	16
Nb of slices	1200	1200	1200
Size (Pixels)	512x512	512x512	512x512
Bits per pixel	16	16	16
Beam Energy	(120,140) kv	(120,140) kv	(120,140) kv
Pitch value	(0.5, 1)	(0.5, 1)	(0.5, 1)
Slice thickness	3mm	3mm	3mm
Pixel size	1mm	1mm	1mm
Nb of slices of RPN	200	200	200
Nb of tested slices	1000	1000	1000



The reference pattern noise of each device: a) RPN of S1, b) RPN of S2, c) RPN of GE

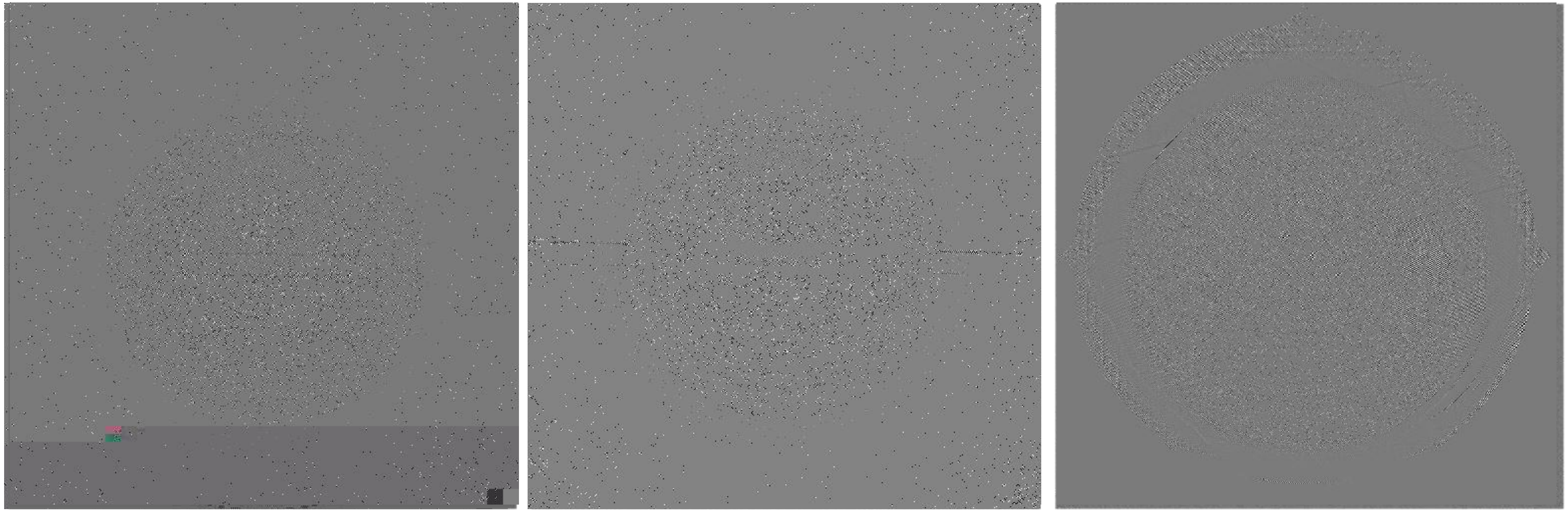


(a) (b) (c)

The correlation map of each device: a) RPN of S1, b) RPN of S2, c) RPN of GE

IMPROVING SENSOR NOISE ANALYSIS

1. IDENTIFICATION METHOD *2. EXPERIMENTS* *3. RESULTS*

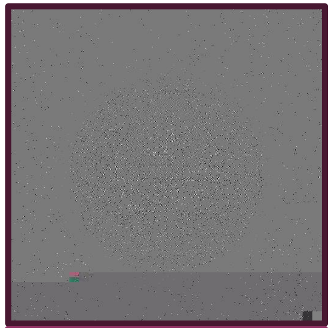


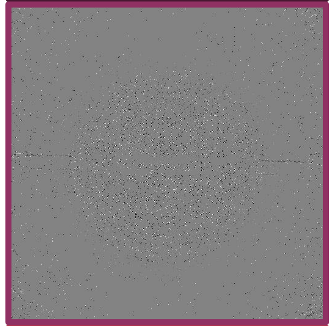
(a) (b) (c)

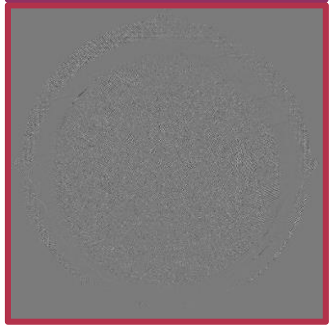
The reference pattern noise of each device: a) RPN of S1, b) RPN of S2, c) RPN of GE

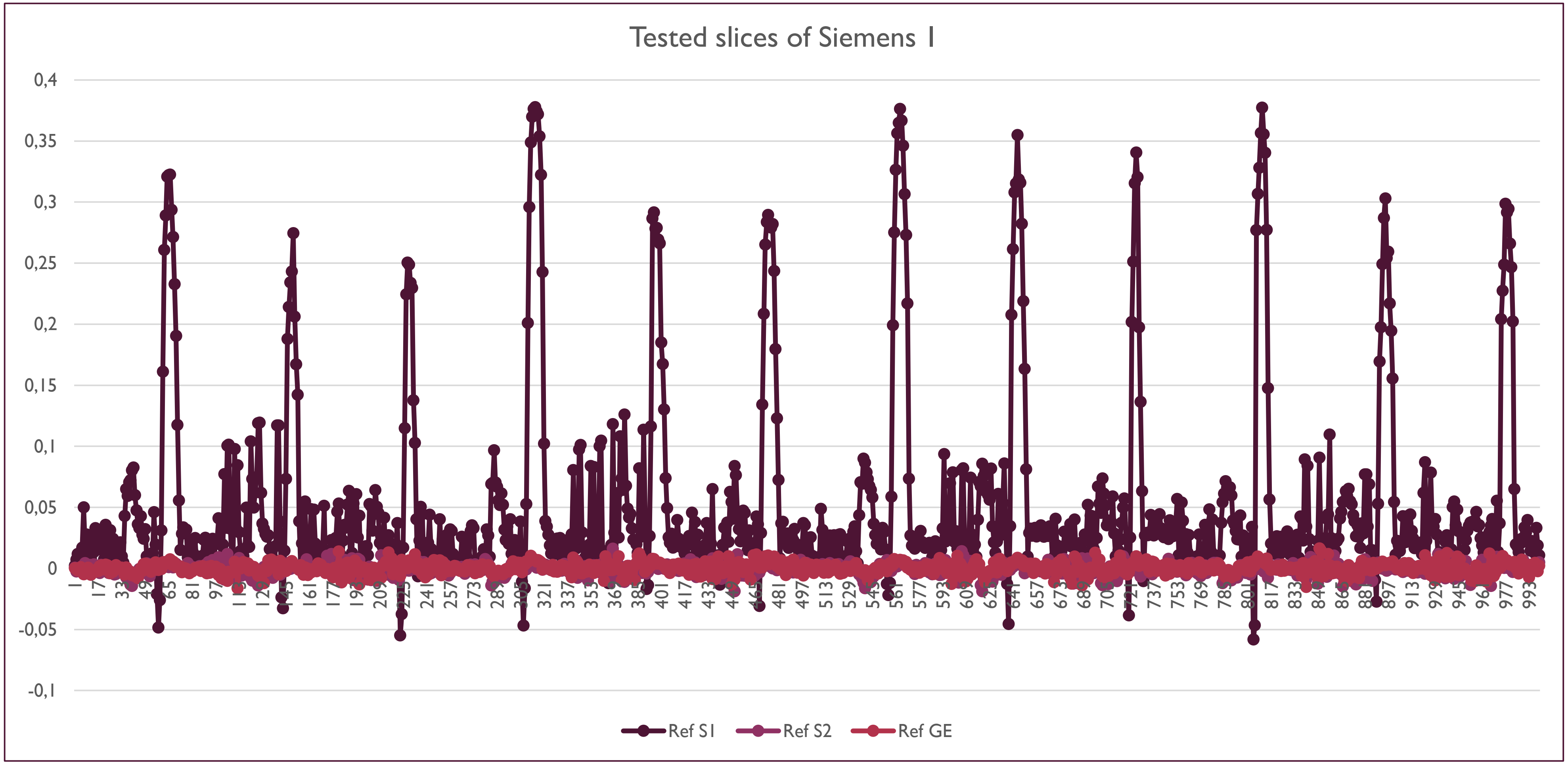
IMPROVING SENSOR NOISE ANALYSIS

1. IDENTIFICATION METHOD *2. EXPERIMENTS* *3. RESULTS*



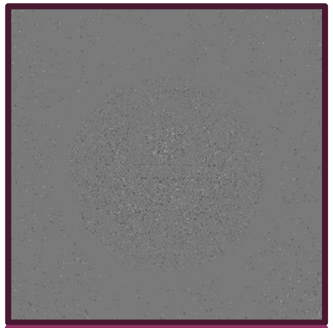


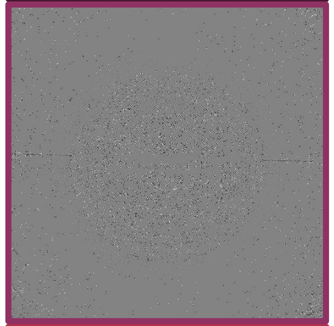


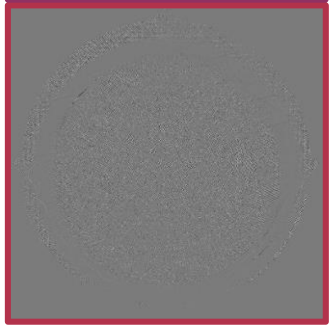


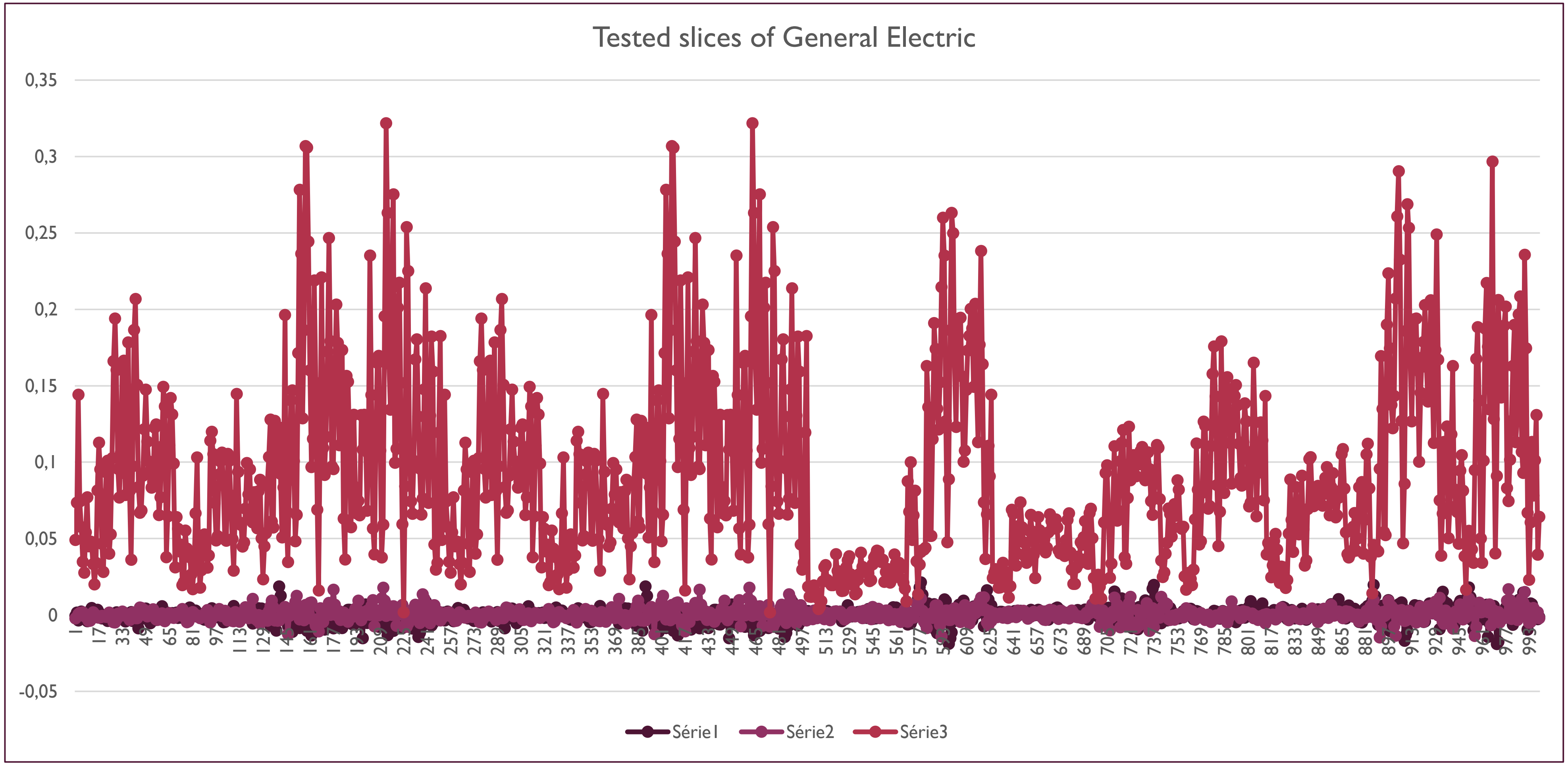
IMPROVING SENSOR NOISE ANALYSIS

1. IDENTIFICATION METHOD *2. EXPERIMENTS* ***3. RESULTS***









	Siemens 1	Siemens 2	GE
Siemens 1	**94.3 %**	2.3 %	0 %
Siemens 2	2.6 %	**95.2 %**	0 %
GE	3.1 %	2.5 %	**100 %**

Identification accuracy

CONTRIBUTIONS

1. CT-Scanner Identification based on sensor noise analysis
    1. Identification based on sensor noise
    2. Improving sensor noise analysis
    3. **Conclusion**
2. New directions for CT-Scanner identification
    1. Extending the RPN to the different image axes
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    3. Conclusion

CT-SCANNER IDENTIFICATION BASED ON SENSOR NOISE ANALYSIS

-CONCLUSION-

- We proposed a first analysis of CT-Scanner identification problem.
- We extract the CT-Scanner fingerprint.
- Detect its presence by correlation.
- Why the RPN:
  - Does not require an access to the sensor output.
  - It could be applied on whatever CT-Scanner.
- In addition to the noise there are some artifacts in high frequency.
- Edge mask and correlation map.
- We were able to identify the CT-Scanner based on its reconstructed images.

[2014] Kharboutly et al. CT-Scanner Identification based on Sensor Noise Analysis, European Workshop on Visual Information Processing, EUVIP, Paris, France

[2014] Kharboutly et al. Identification du Système d'acquisition Scanner-X à partir de l'Analyse du Bruit dans des Images Médicales, CORESA (COmpression et REprésentation des Signaux Audiovisuels), Reims, France

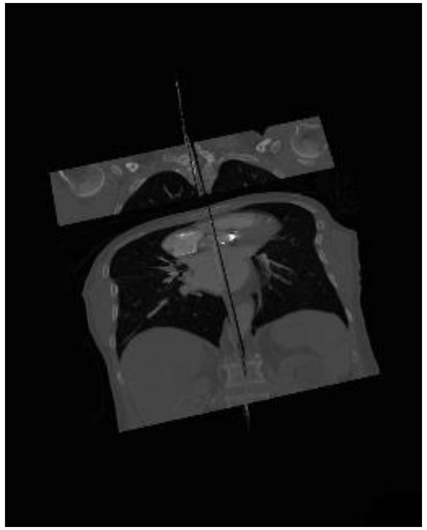
[2015] Kharboutly et al. Improving Sensor Noise Analysis for CT-Scanner Identification, European Signal Processing Conference, EUSIPCO, Nice, France

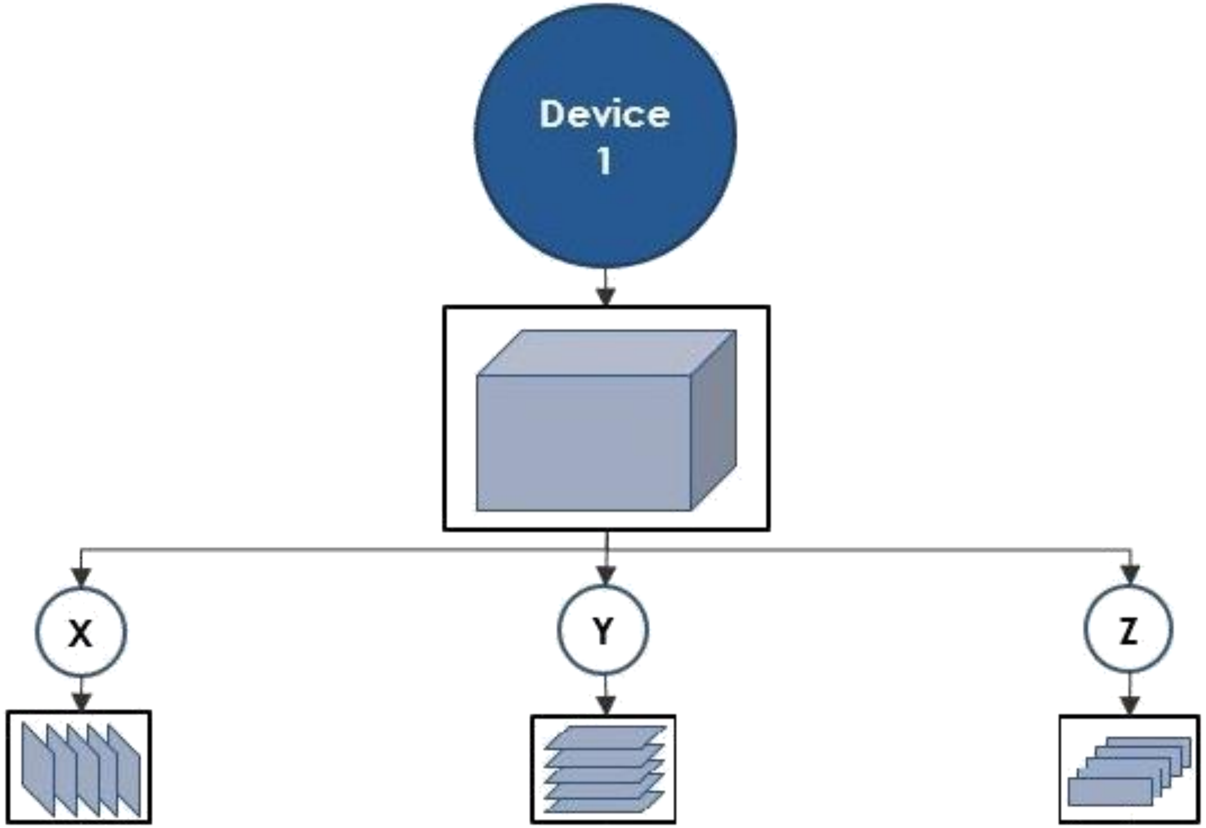
CONTRIBUTIONS

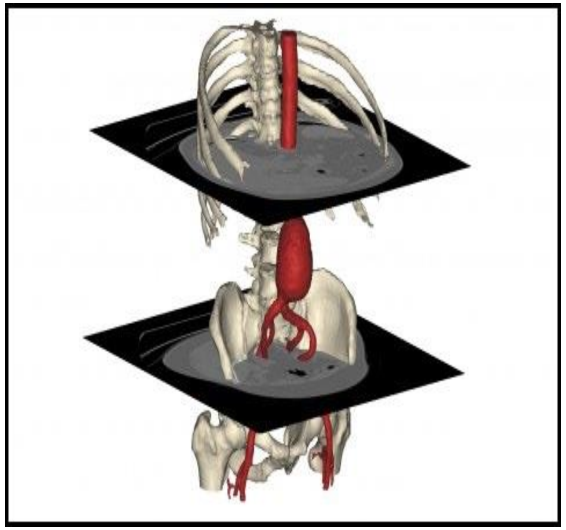
1. CT-Scanner Identification based on sensor noise analysis
    1. Identification based on sensor noise
    2. Improving sensor noise analysis
    3. Conclusion
2. New directions for CT-Scanner identification
    1. **Extending the RPN to the different image axes**
    2. Using an RPN of different intensity layers
    3. Conclusion

EXTENDING THE RPN TO THE DIFFERENT IMAGE AXES

1. IDENTIFICATION METHOD *2. EXPERIMENTS* *3. RESULTS*

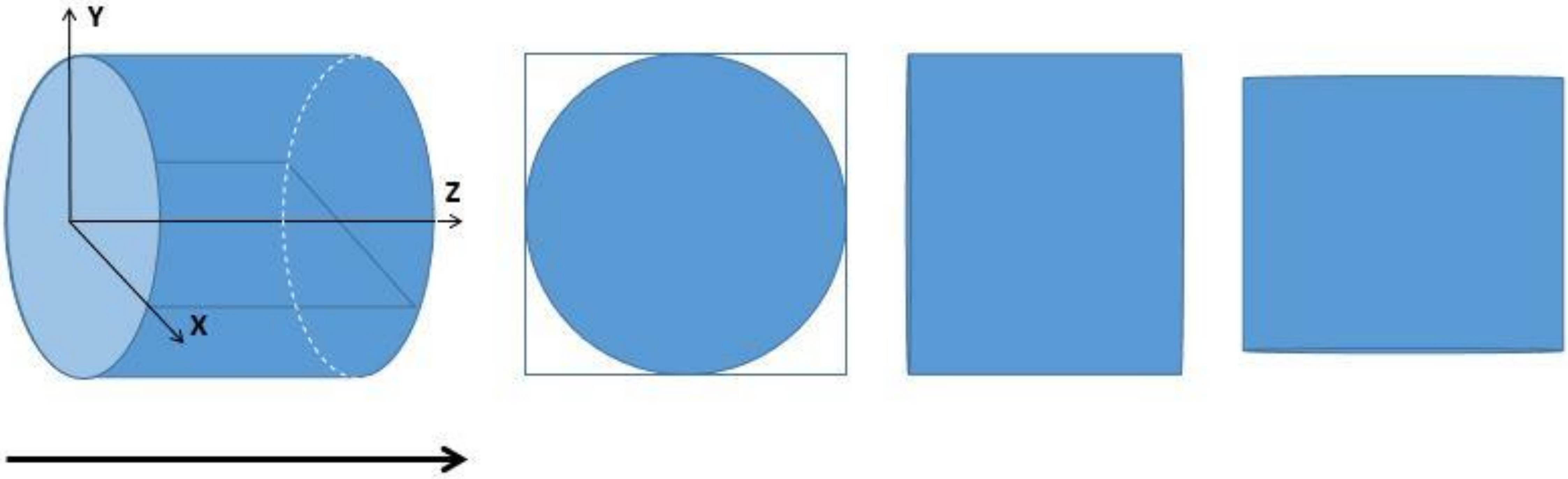






EXTENDING THE RPN TO THE DIFFERENT IMAGE AXES

1. IDENTIFICATION METHOD *2. EXPERIMENTS* *3. RESULTS*



Reconstruction axis
(a)

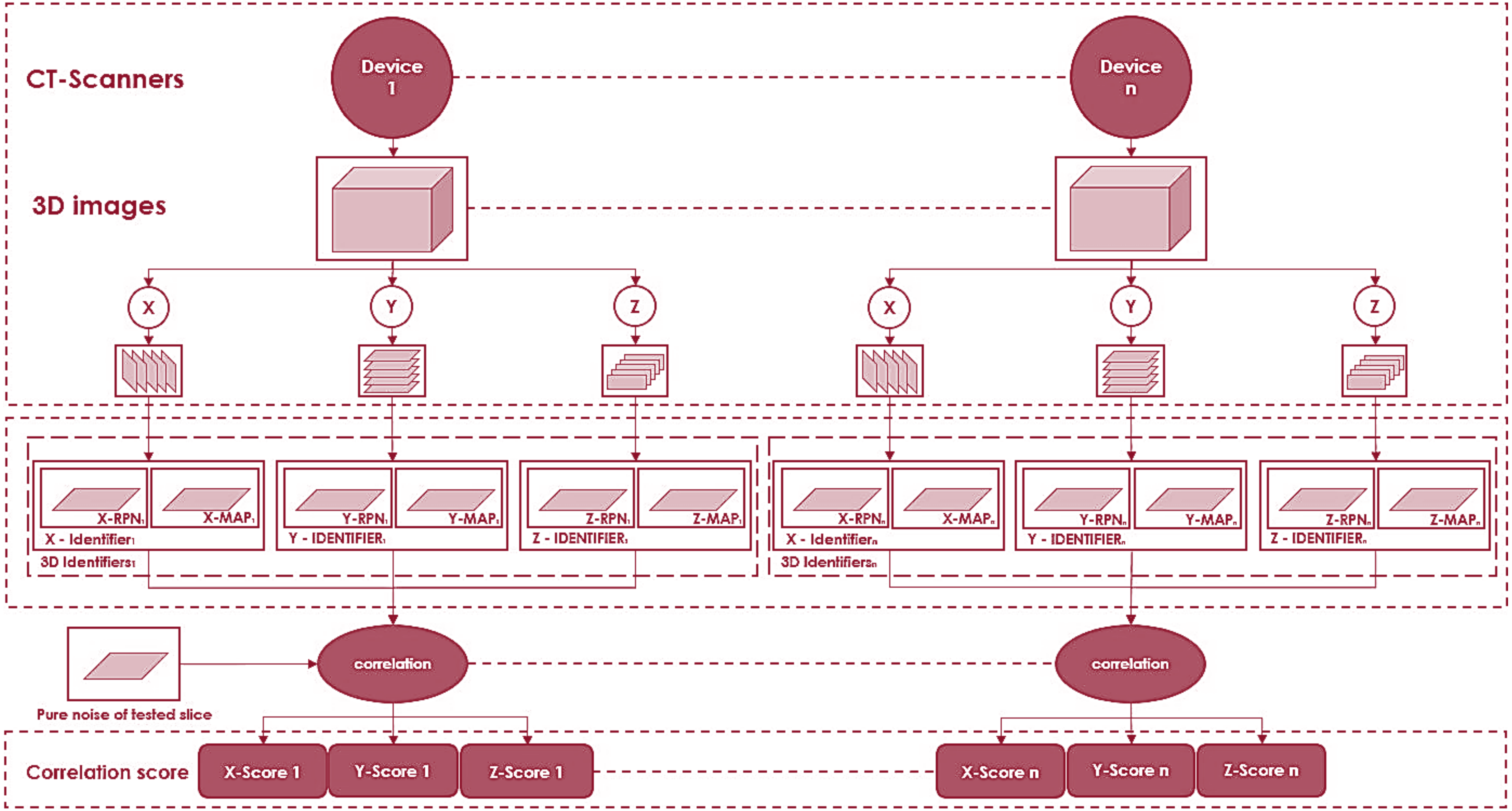
Z Slice
(b)

X Slice
(c)

Y Slice
(d)

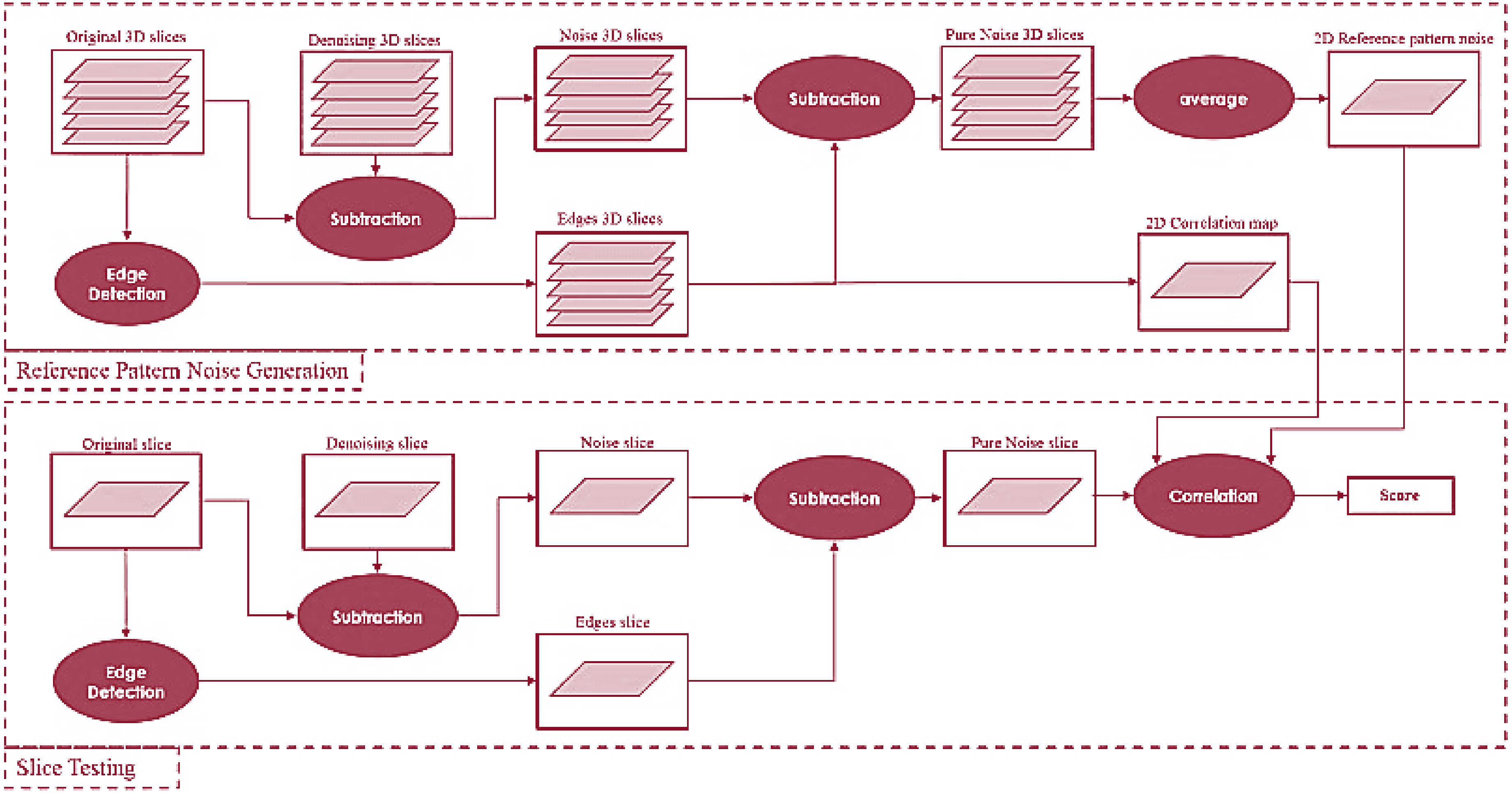
EXTENDING THE RPN TO THE DIFFERENT IMAGE AXES

1. IDENTIFICATION METHOD *2. EXPERIMENTS* *3. RESULTS*



EXTENDING THE RPN TO THE DIFFERENT IMAGE AXES

1. IDENTIFICATION METHOD *2. EXPERIMENTS* *3. RESULTS*



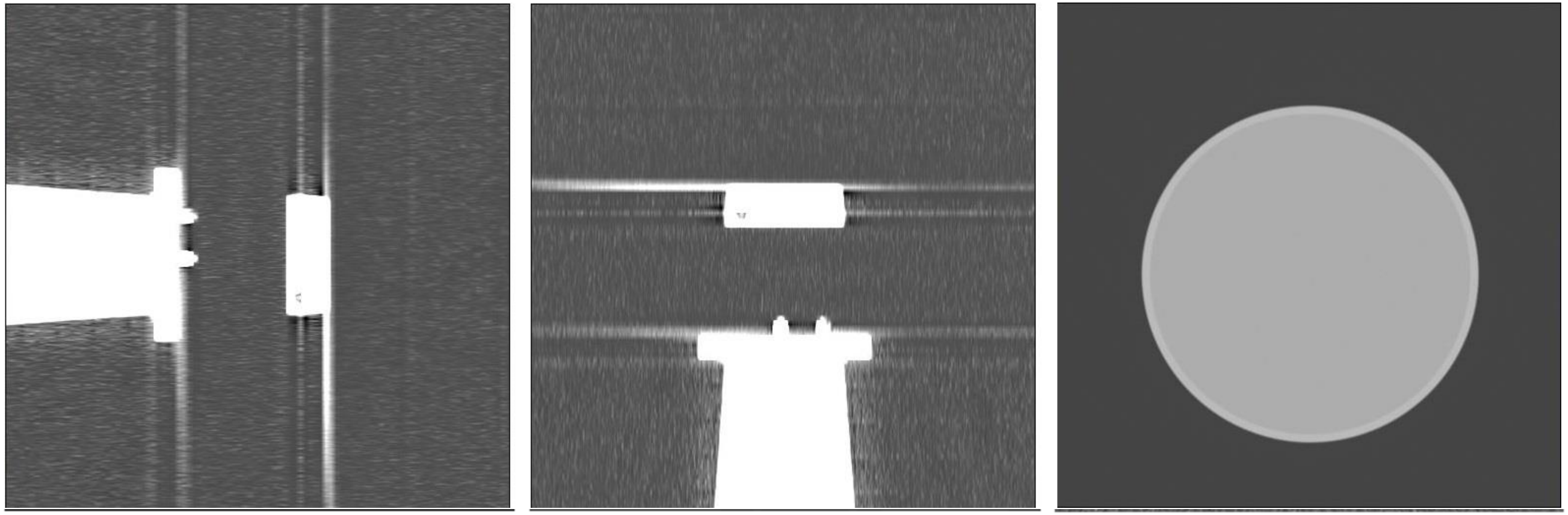
EXTENDING THE RPN TO THE DIFFERENT IMAGE AXES

Experimental images

IMAIOS

Parameter \Device	Siemens 1	Siemens 2	General Electric
Content	Phantom	Phantom	Phantom
Nb of slices	5120	5120	5120
Size (Pixels)	512x512	512x512	512x512
Bits per pixel	16	16	16
Beam Energy	(120,140) kv	(120,140) kv	(120,140) kv
Pitch value	(0.5, 1)	(0.5, 1)	(0.5, 1)
Slice thickness	1mm	1mm	1mm
Pixel size	1mm	1mm	1mm
Voxel Isotropic	yes	yes	yes
Nb of slices of RPN	500	500	500
Nb of tested slices	500	500	500

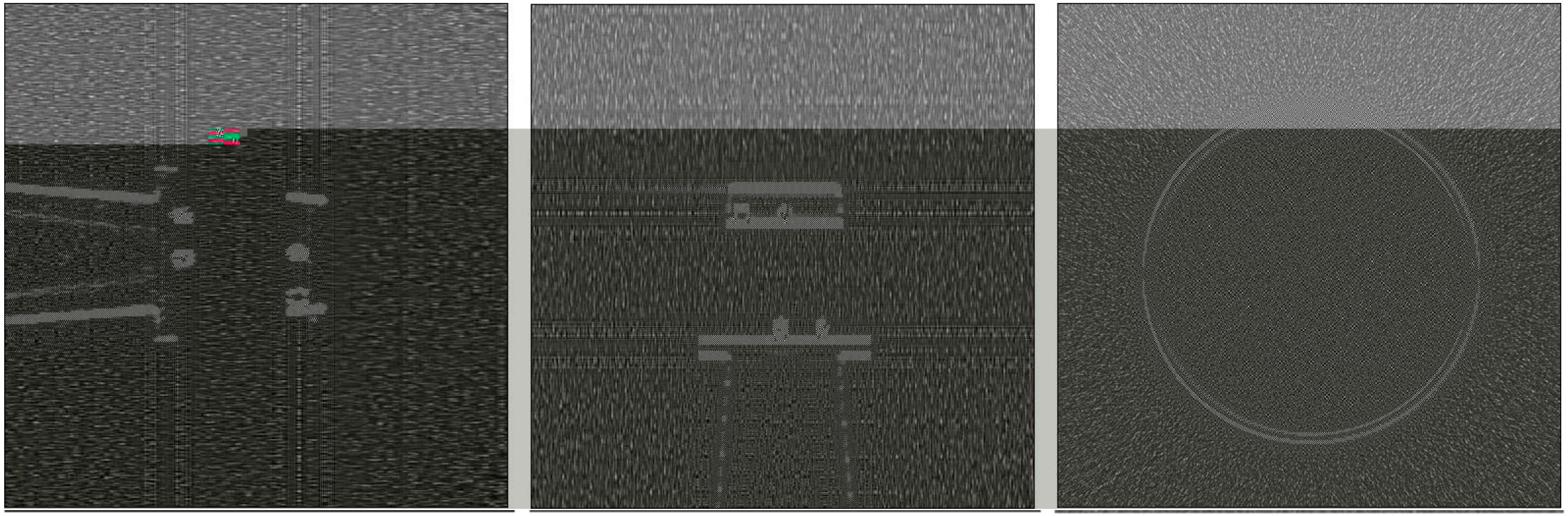
EXTENDING THE RPN TO THE DIFFERENT IMAGE AXES



(a) (b) (c)

Original slices from Siemens 1: a) X directional axis, b) Y directional axis, c) Z directional axis

EXTENDING THE RPN TO THE DIFFERENT IMAGE AXES

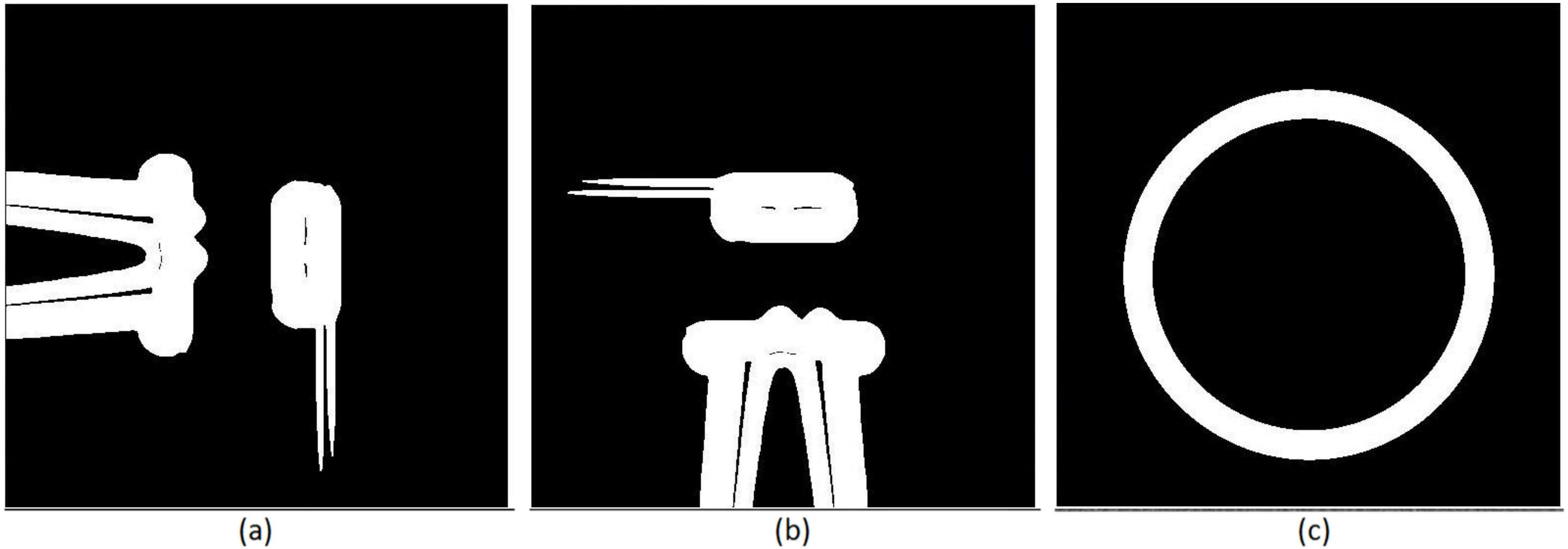


(a) (b) (c)

Noise component from Siemens 1: a) X directional axis, b) Y directional axis, c) Z directional axis

EXTENDING THE RPN TO THE DIFFERENT IMAGE AXES

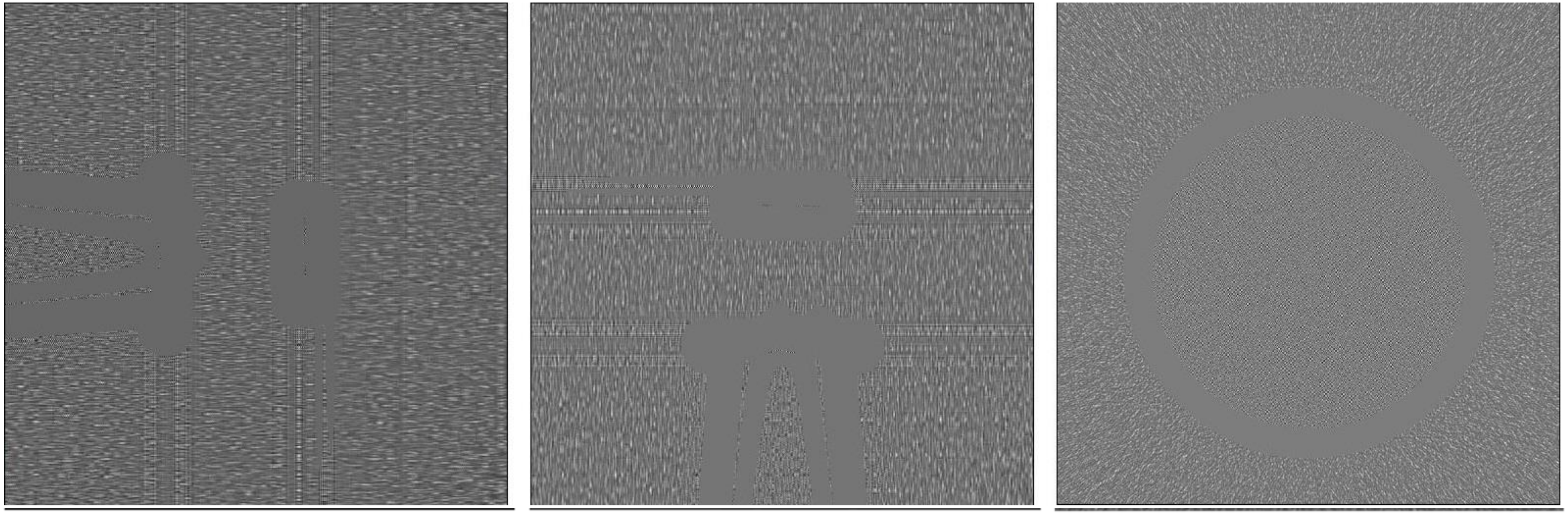
1. IDENTIFICATION METHOD *2. EXPERIMENTS* *3. RESULTS*



Edge mask from Siemens 1: a) X directional axis, b) Y directional axis, c) Z directional axis

EXTENDING THE RPN TO THE DIFFERENT IMAGE AXES

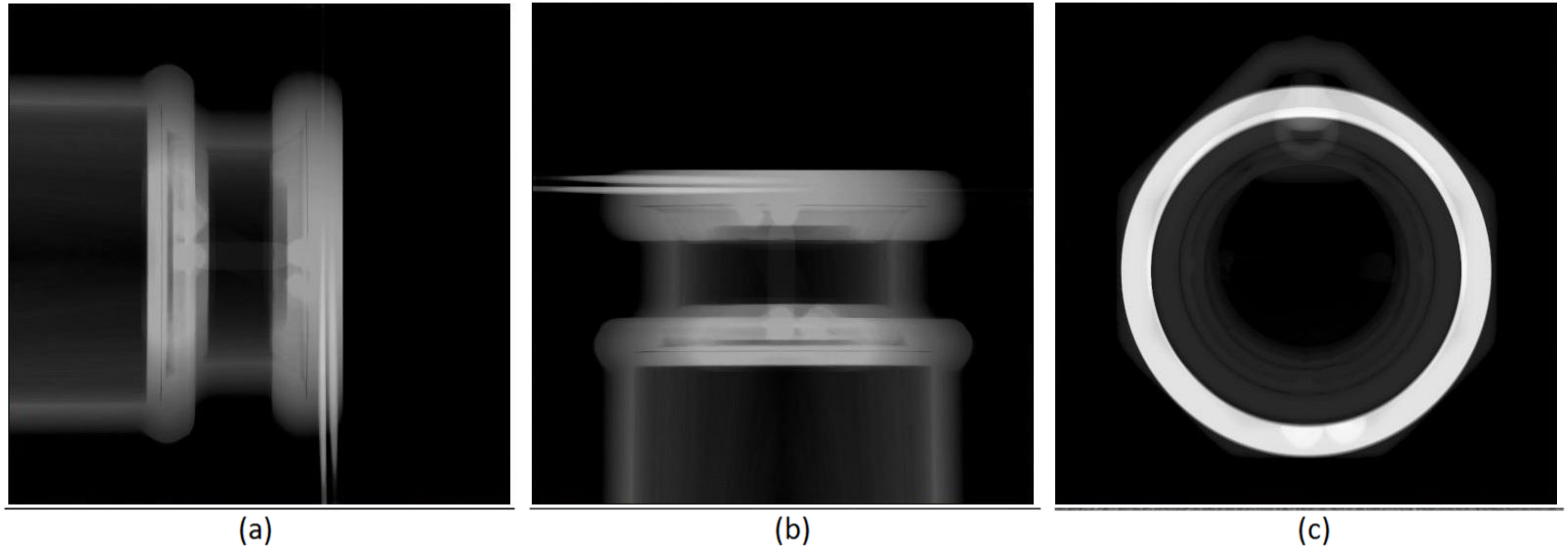
1. IDENTIFICATION METHOD *2. EXPERIMENTS* *3. RESULTS*



(a) (b) (c)

Pure noise component without traces from Siemens 1: a) X directional axis, b) Y directional axis, c) Z directional axis

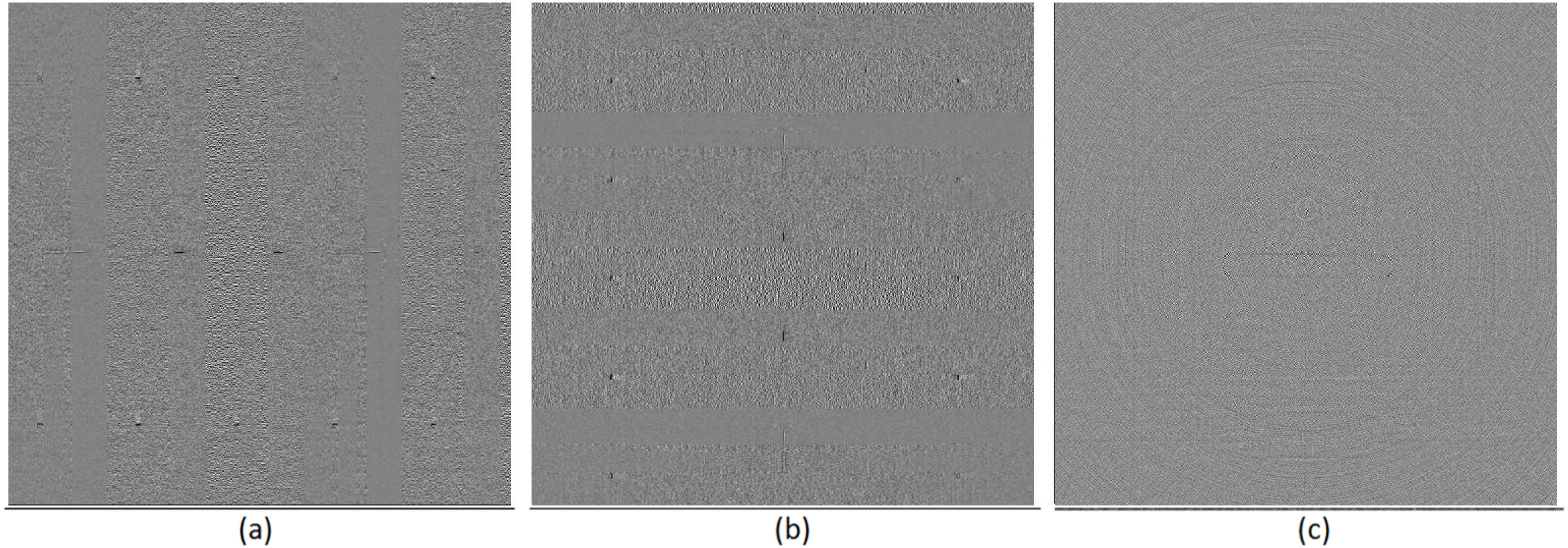
EXTENDING THE RPN TO THE DIFFERENT IMAGE AXES



Three correlation maps from Siemens 1: a) X directional axis, b) Y directional axis, c) Z directional axis

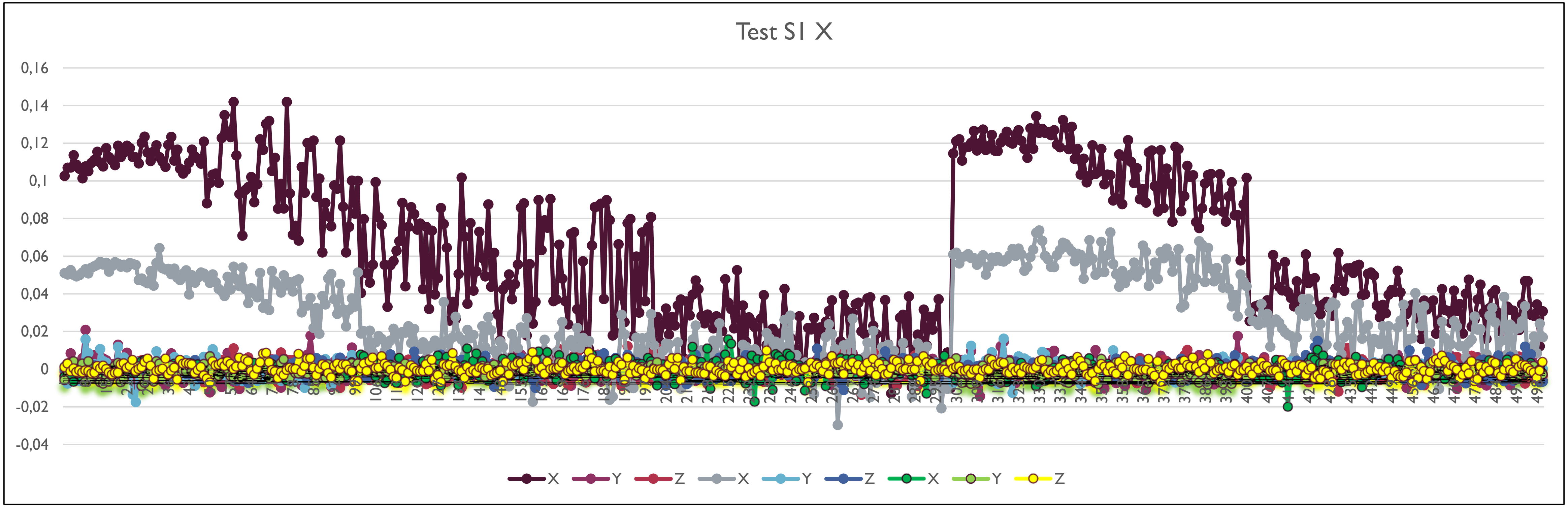
EXTENDING THE RPN TO THE DIFFERENT IMAGE AXES

1. IDENTIFICATION METHOD *2. EXPERIMENTS* *3. RESULTS*



Three RPNs from Siemens 1: a) X directional axis, b) Y directional axis, c) Z directional axis

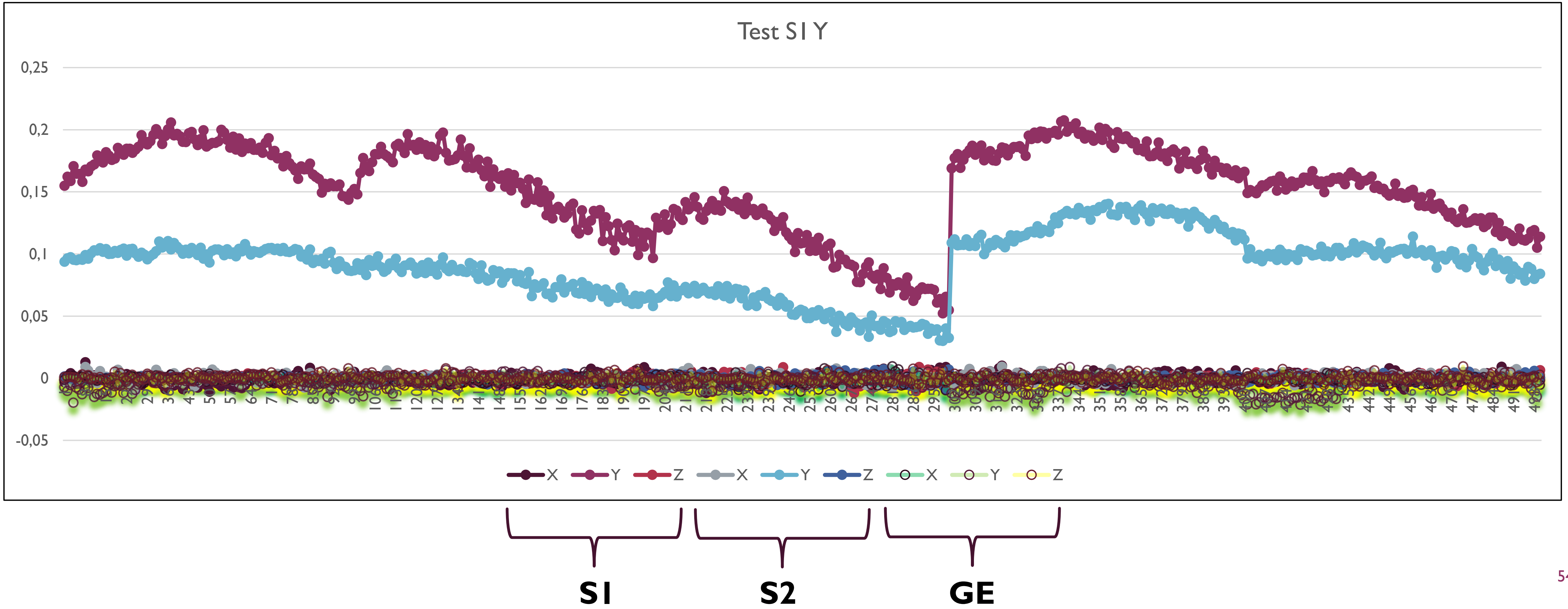
EXTENDING THE RPN TO THE DIFFERENT IMAGE AXES



S1 **S2** **GE**

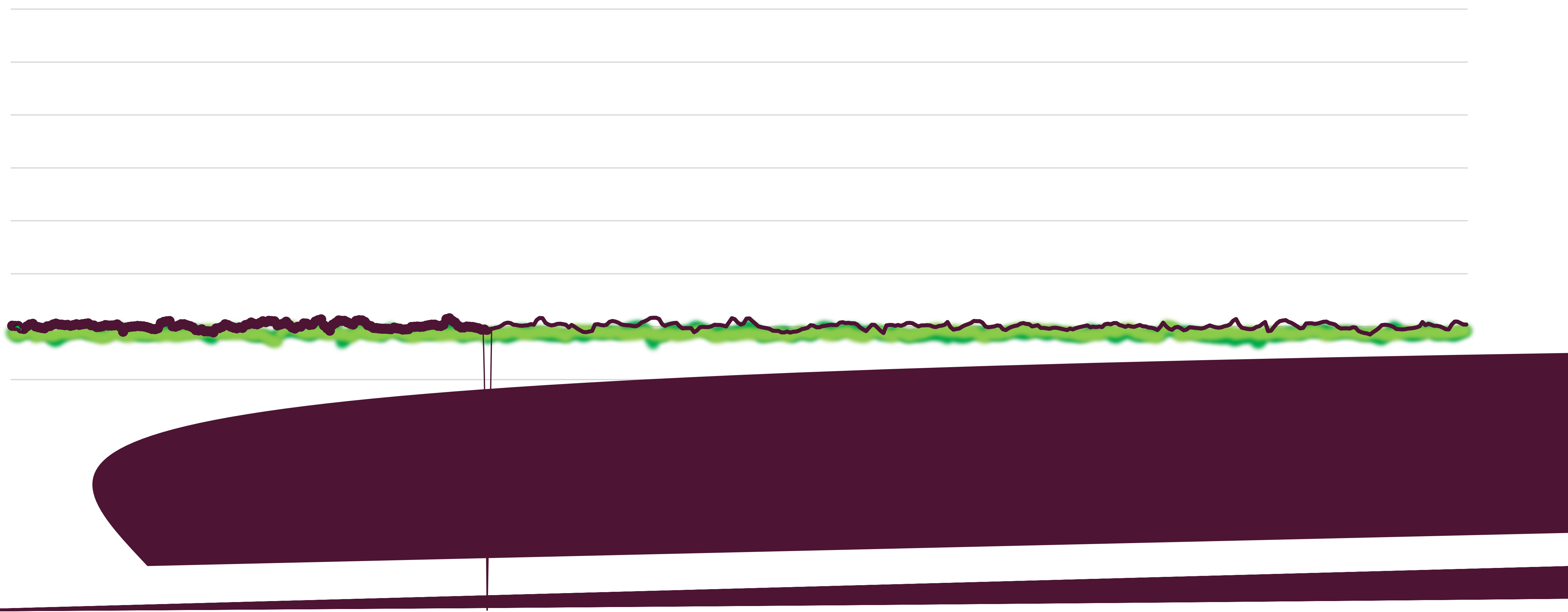
EXTENDING THE RPN TO THE DIFFERENT IMAGE AXES

1. IDENTIFICATION METHOD *2. EXPERIMENTS* ***3. RESULTS***



EXTENDING THE RPN TO THE DIFFERENT IMAGE AXES

1. IDENTIFICATION METHOD *2. EXPERIMENTS* *3. RESULTS*



EXTENDING THE RPN TO THE DIFFERENT IMAGE AXES

1. IDENTIFICATION METHOD *2. EXPERIMENTS* *3. RESULTS*

Ref \ Test	S1 Z	S1 X	S1 Y	S2 Z	S2 X	S2 Y	GE Z	GE X	GE Y
S1 Z	92,2 %	0	0	9 %	0	0	3,4 %	0	0
S1 X	0,2 %	100 %	0	0,2 %	0	0	1,8 %	0	0
S1 Y	0	0	100 %	0,2 %	0	0	3 %	0	0
S2 Z	5,8 %	0	0	88,6 %	0	0	6,6 %	0	0
S2 X	0	0	0	0	100 %	0	0,8 %	0,2 %	0
S2 Y	0,6 %	0	0	0,6 %	0	100 %	4,2 %	0	0
GE Z	0,4 %	0	0	0,8 %	0	0	73 %	0,2 %	0
GE X	0,4 %	0	0	0	0	0	4,4 %	99,6 %	0
GE Y	0,2 %	0	0	0,4 %	0	0	2,2 %	0	100 %

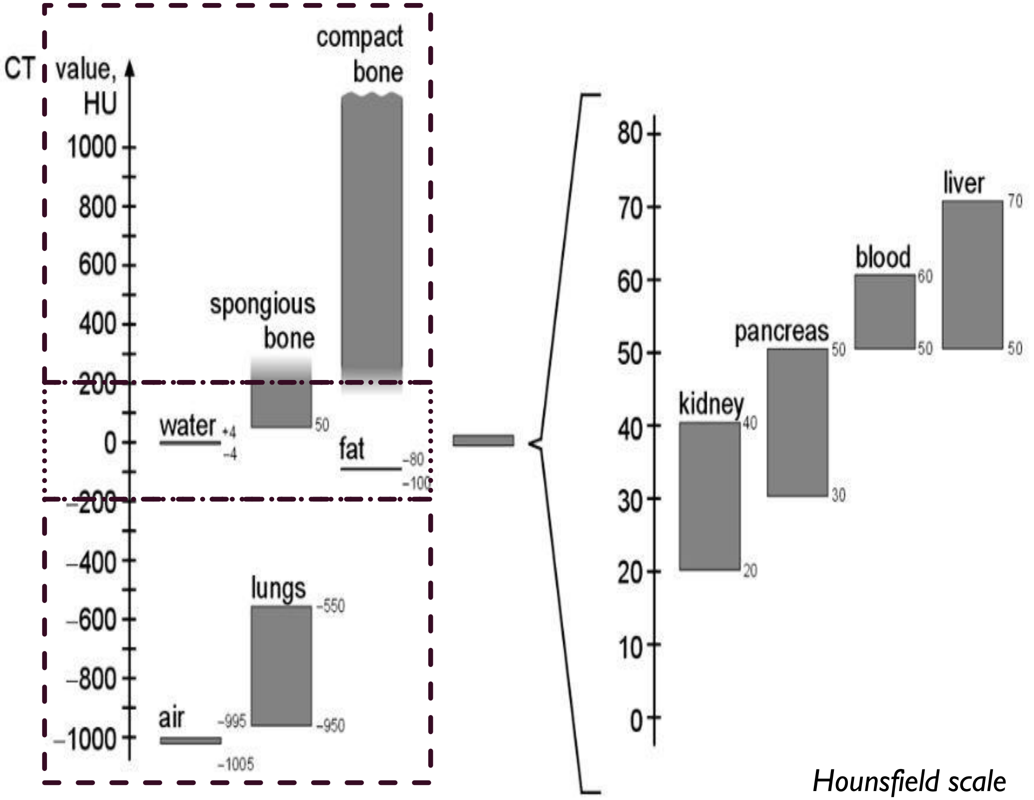
Identification accuracy

CONTRIBUTIONS

1. CT-Scanner Identification based on sensor noise analysis
    1. Identification based on sensor noise
    2. Improving sensor noise analysis
    3. **Conclusion**
2. New directions for CT-Scanner identification
    1. Extending the RPN to the different image axes
    2. **Using an RPN of different intensity layers**
    3. Conclusion

USING AN RPN OF DIFFERENT INTENSITY LAYERS

1. IDENTIFICATION METHOD *2. EXPERIMENTS* *3. RESULTS*



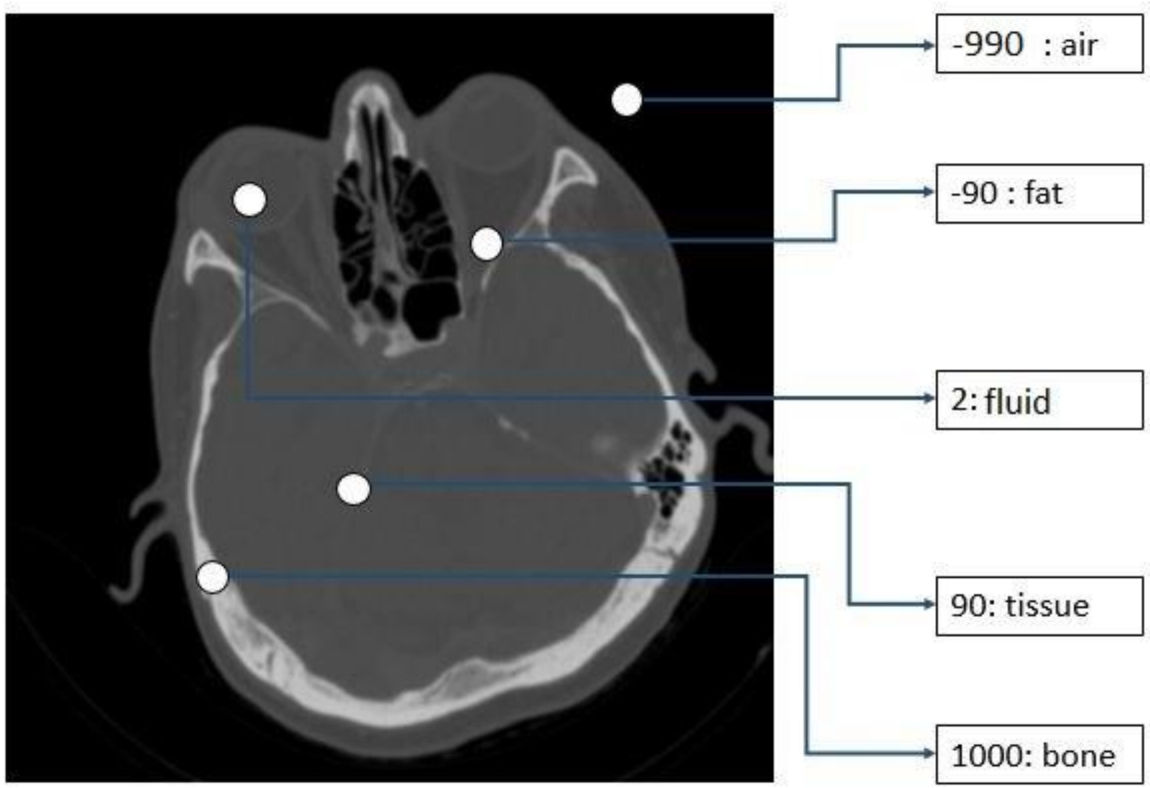
Hounsfield scale

Three homogenous layers!

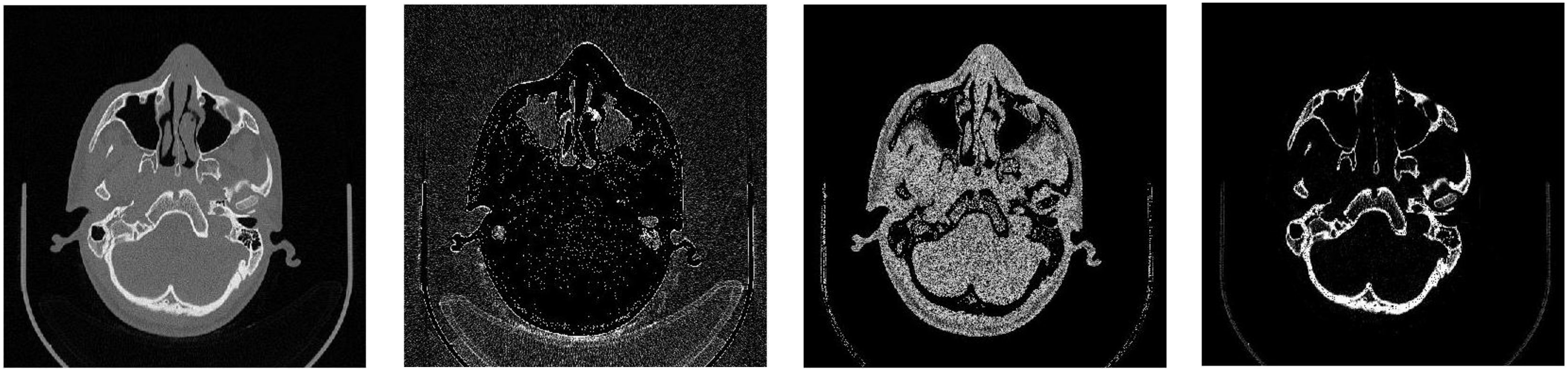
USING AN RPN OF DIFFERENT INTENSITY LAYERS

1. IDENTIFICATION METHOD *2. EXPERIMENTS* *3. RESULTS*

Air layer	:	[-990,-200]
Tissue layer	:	[-200,+200]
Bone layer	:	[+200,+1500]



USING AN RPN OF DIFFERENT INTENSITY LAYERS

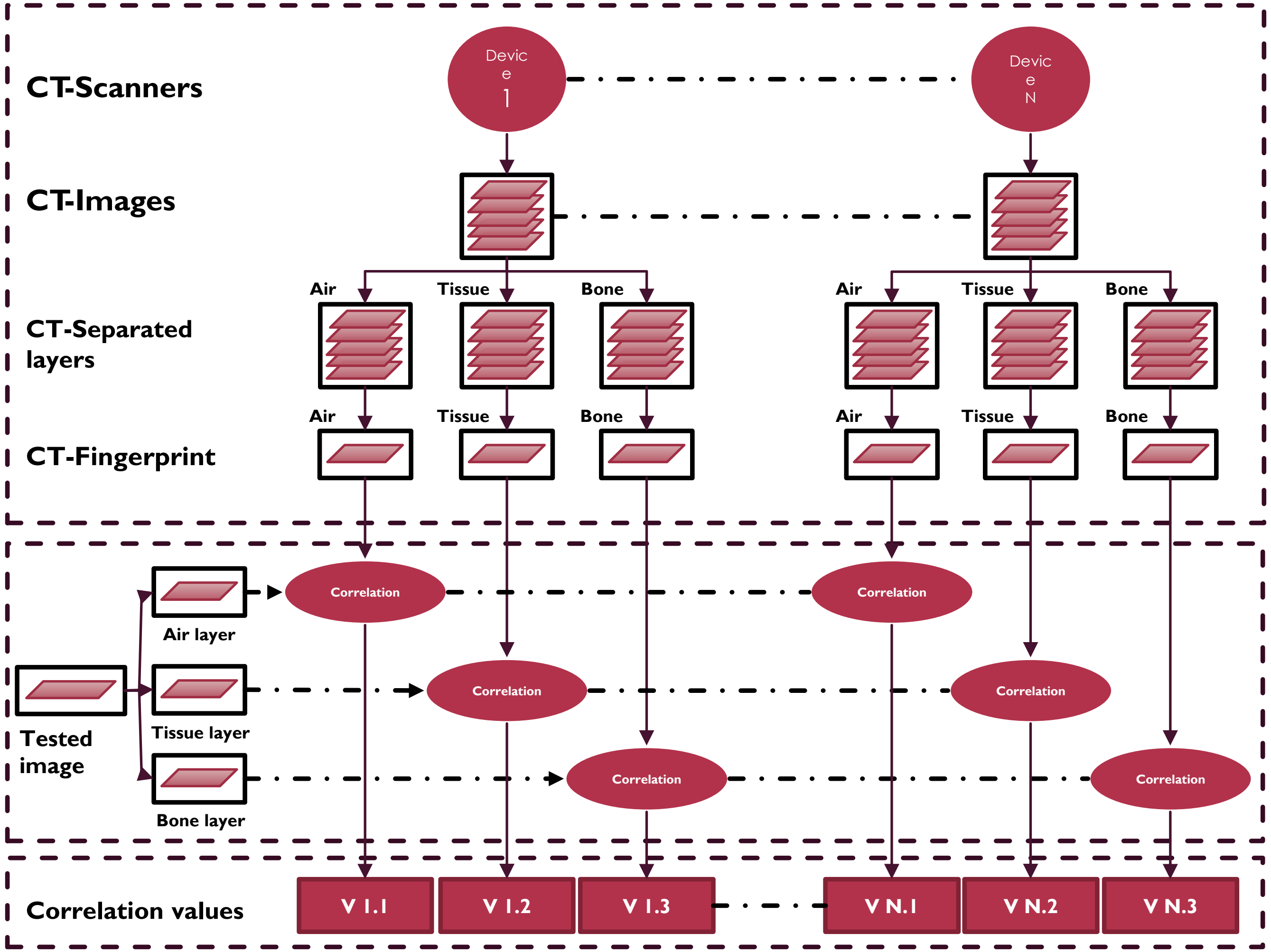


(a) (b) (c) (d)

Original slices of a head and its three layers: a) Original, b) Air layer, c) Tissue layer, d) Bone layer

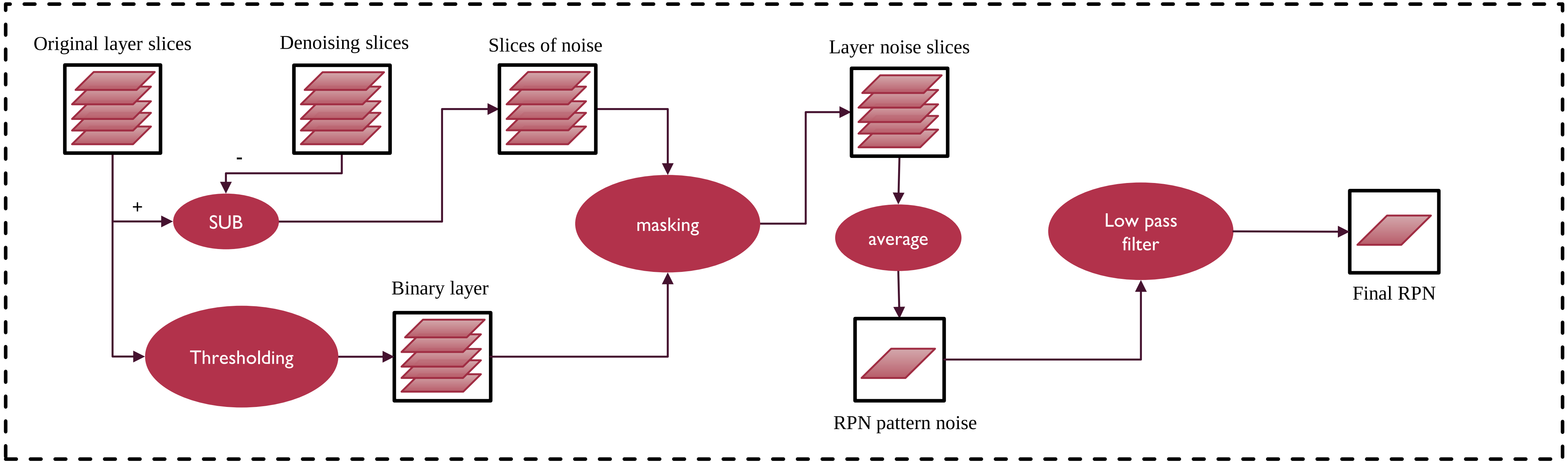
USING AN RPN OF DIFFERENT INTENSITY LAYERS

1. IDENTIFICATION METHOD *2. EXPERIMENTS* *3. RESULTS*



USING AN RPN OF DIFFERENT INTENSITY LAYERS

1. IDENTIFICATION METHOD *2. EXPERIMENTS* *3. RESULTS*



Correlation measure

$$PCE(N_t, RPN_j) = \frac{E_p(N_t, RPN_j)}{E_{cp}(N_t, RPN_j)}$$

Peak to correlation energy*

[*] M. Goljan, J. Fridrich and T. Filler. Large scale test of sensor fingerprint camera identification. In IS&T/SPIE Electronic Imaging, pages 72540I-72540I. International Society for Optics and Photonics, 2009.

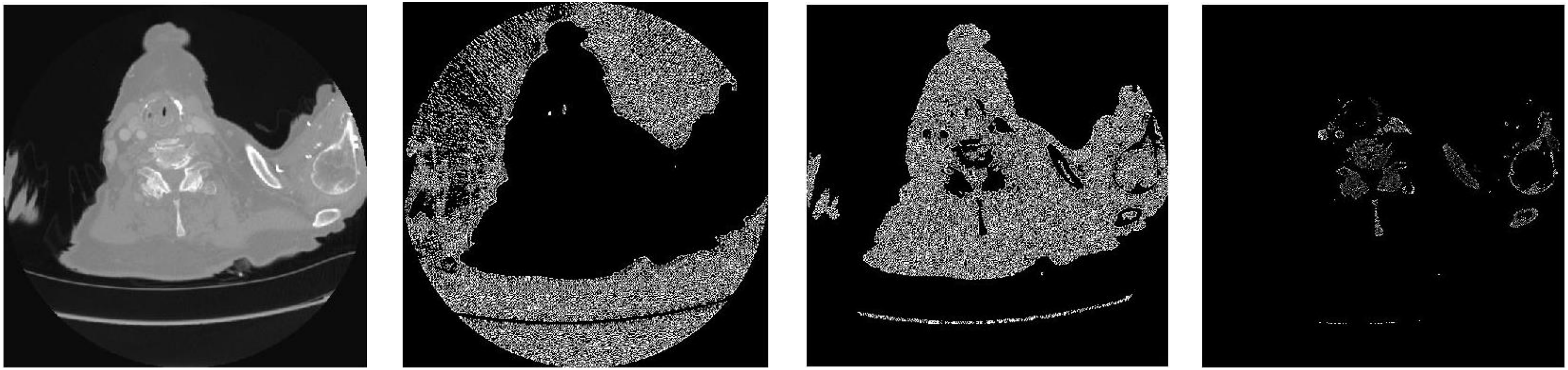
IMAIOS

Experimental images

Parameter \Device	Siemens 1	Siemens 2	General Electric
Content	Real data	Real data	Real data
Nb of 3D images	20	20	20
Nb of slices	7572	7279	5088
Size (Pixels)	512x512	512x512	512x512
Bits per pixel	16	16	16
Nb of slices of RPN	3363	3756	2092
Nb of tested slices	4209	4523	2996

USING AN RPN OF DIFFERENT INTENSITY LAYERS

1. IDENTIFICATION METHOD *2. EXPERIMENTS* *3. RESULTS*

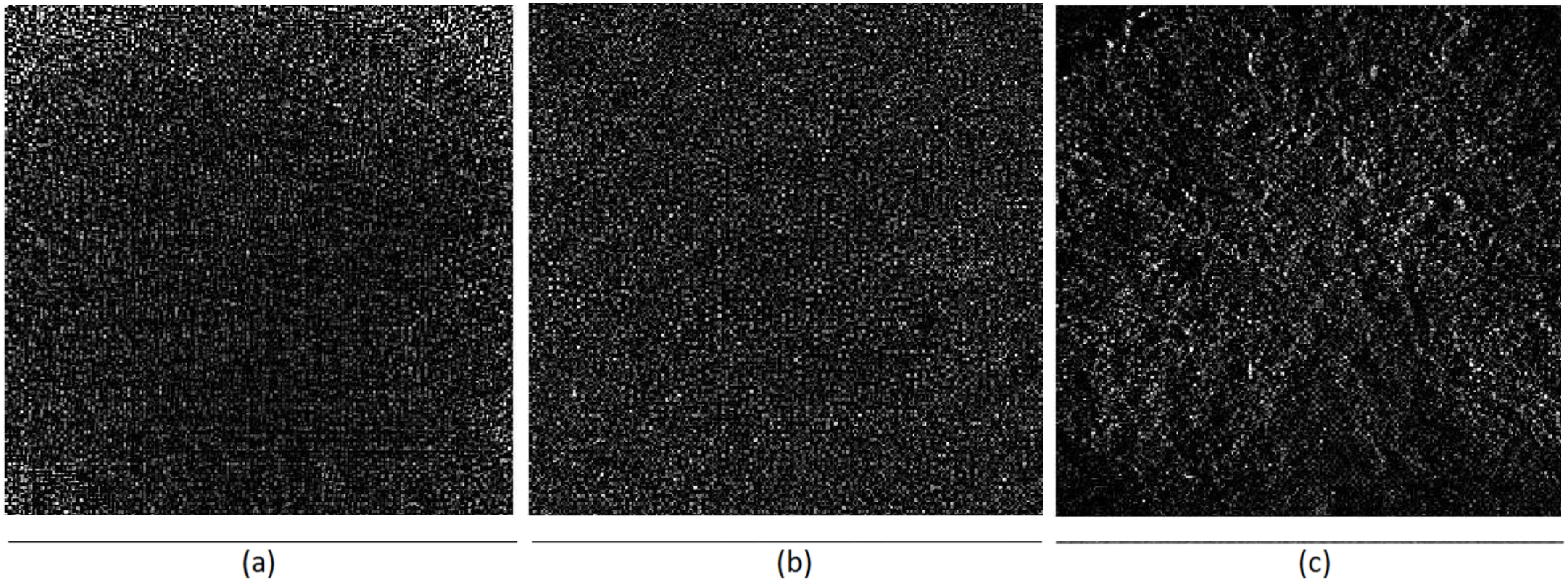


(a) (b) (c) (d)

Original slices of a neck and the noise of its three layers: a) Original, b) Air layer, c) Tissue layer, d) Bone layer

USING AN RPN OF DIFFERENT INTENSITY LAYERS

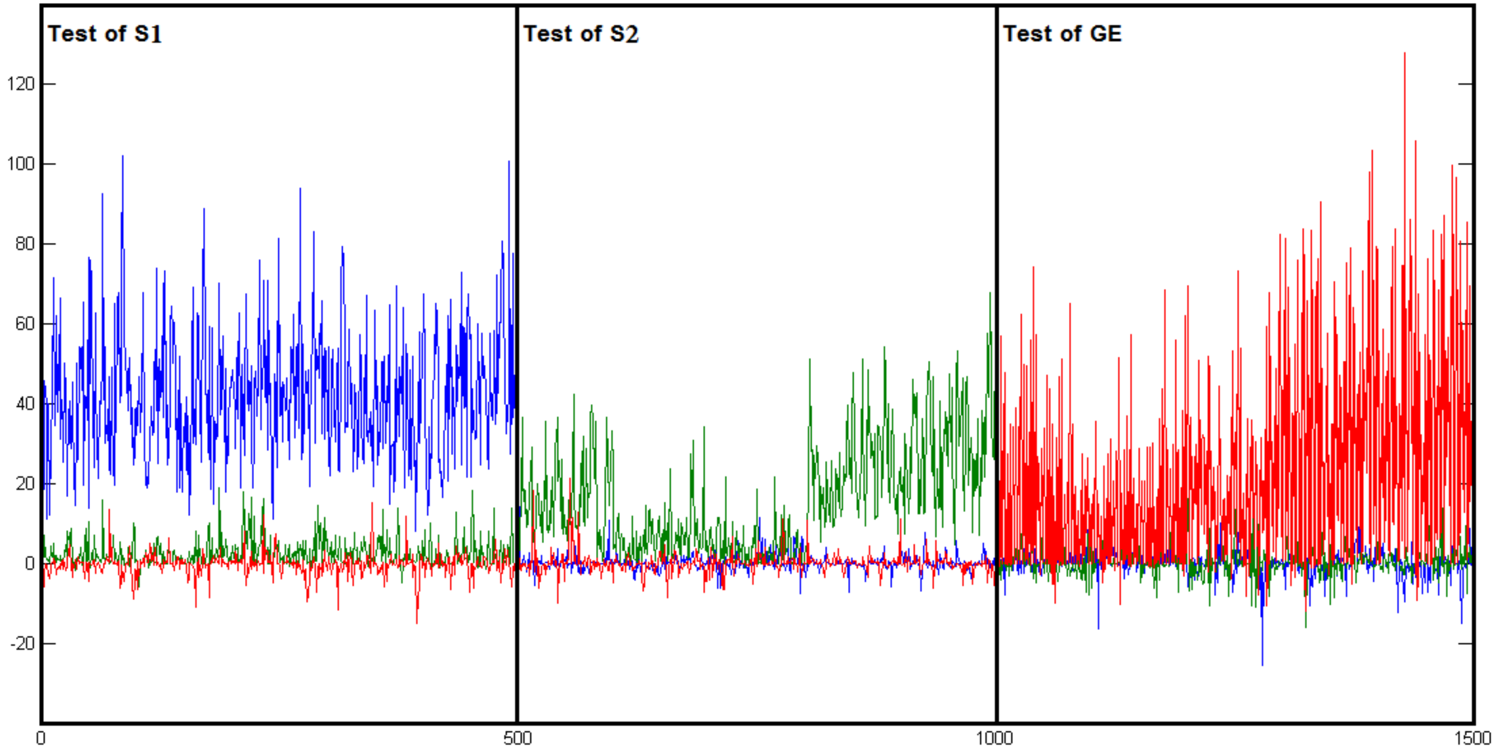
1. IDENTIFICATION METHOD *2. EXPERIMENTS* *3. RESULTS*



RPNs from three different CT-Scanners using different layers: a) S1 air RPN, b) S2 tissue RPN, c) GE Bone RPN

USING AN RPN OF DIFFERENT INTENSITY LAYERS

1. IDENTIFICATION METHOD *2. EXPERIMENTS* *3. RESULTS*



RPN S1 RPN S2 RPN GE

PCEs from the tissue layer of the three CT-Scanners

Device \ Layer	Air	Soft tissue	Bone	Majority
Siemens 1	52 %	83 %	74 %	**81.32 %**
Siemens 2	92 %	72 %	68 %	**83.63 %**
GE	100 %	73 %	42 %	**81.81 %**

Identification accuracy

	Siemens 1	Siemens 2	GE	No ID
Siemens 1	**81.32 %**	9.29 %	3.23 %	6.25 %
Siemens 2	4.75 %	**83.63 %**	4.24 %	7.38 %
GE	5.27 %	4.03 %	**81.81 %**	8.89 %

Identification accuracy

CONTRIBUTIONS

1. CT-Scanner Identification based on sensor noise analysis
   1. Identification based on sensor noise
   2. Improving sensor noise analysis
   3. **Conclusion**
2. New directions for CT-Scanner identification
   1. Extending the RPN to the different image axes
   2. Using an RPN of different intensity layers
   3. **Conclusion**

NEW DIRECTIONS FOR CT-SCANNER IDENTIFICATION

-CONCLUSION-

- Two advanced methods were proposed based on the medical image properties.
- The three directional RPNs that enable the identification along X and Y directional axes also.
- The three layer concept, that divide the CT-Scanner images into homogeny layers

[2015] Kharboutly et al. Advanced Sensor Noise Analysis for CT-Scanner Identification from its 3D Images, IEEE International Conference on Image Processing Theory, Tools and Applications, IPTA, Orléans, France

[2016] Kharboutly et al. Identification du Scanner X à partir d'Empreintes du Capteur, CORESA (COmpression et REprésentation des Signaux Audiovisuels), Nancy, France

[2017] Kharboutly et al. Computed Tomography Scanner Identification Based on Sensor Fingerprint, International Conference on Acoustics, Speech and signal processing, USA *(Under submission)*

[2017] Kharboutly et al. Computed Tomography Scanner Identification Based on Sensor noise, EMB, Journal of Biomedical and Health Informatics *(Under submission)*

OUTLINES

- Background
- Problem and work objectives
- Digital device identification
  - Overview
  - Related work
- Contributions
  - CT-Scanner Identification based on sensor noise analysis
    - Identification based on sensor noise
    - Improving sensor noise analysis
  - New directions for CT-Scanner identification
    - Extending the RPN to the different images axis
    - Using an RPN of different intensity layers
- **Conclusion and perspectives**

CONCLUSION

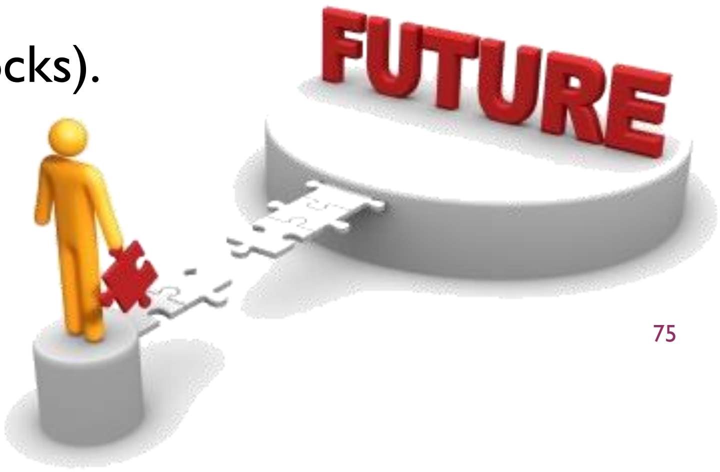
- We proposed two groups of methods
  - First group based on the digital device identification.
  - Second group based on the properties of medical images.
- In the second group we presented new concepts in the medical device identification
- We were able to identify the CT-Scanner and the acquisition axis.
- Our experiments were applied on real data of patients.
- Our proposed methods achieved high identification accuracy

CONCLUSION

	M1	M2	M3	M4
Year	2014	2015	2015	2016
Sensor Nosie	Basic RPN	Improved RPN	Advanced RPN	Advanced RPN
Fingerprint	RPN	RPN + Map	3D RPN + Map	3 layers RPN
Edge problem	**Yes**	No	No	No
Homogenous content	No	No	No	**Yes**
Min performance	95%	91.3%	73%	81.63%
Max performance	97%	100%	100%	83.63%
Data type	phantom	phantom	phantom	**Real data**
Min performance	27%	31.3 %	31.3 %	81.63%
Max performance	37%	33.3%	33.3%	83.63%
Real data	Yes	Yes	Yes	Yes

PERSPECTIVES

- Study the effect of other denoising filters.
- Extend the identification method on 3D images.
- Generalize the separation into layers on the 3D images.
- Study the influence of image compression.
- Study the influence of image modification (by correlation on different blocks).
- Study the case of attacking the CT-Scanner RPN.



PUBLICATIONS

- **International**

  [2014] CT-Scanner Identification based on Sensor Noise Analysis
  Auteurs : **Anas Kharboutly**, William Puech, Gérard Subsol et Denis Hoa
  European Workshop on Visual Information Processing, EUVIP, Paris, France

  [2015] Advanced Sensor Noise Analysis for CT-Scanner Identification from its 3D Images
  Auteurs : **Anas Kharboutly**, William Puech, Gérard Subsol et Denis Hoa
  IEEE International Conference on Image Processing Theory, Tools and Applications, IPTA, Orléans, France

  [2015] Improving Sensor Noise Analysis for CT-Scanner Identification
  Auteurs : **Anas Kharboutly**, William Puech, Gérard Subsol et Denis Hoa
  European Signal Processing Conference, EUSIPCO, Nice, France

  [2017] Computed Tomography Scanner Identification Based on Sensor Fingerprint
  Auteurs : **Anas Kharboutly**, William Puech, Gérard Subsol et Denis Hoa
  International Conference on Acoustics, Speech and Signal Processing, USA
  (In preparation for submission)

PUBLICATIONS

- **National**

  [2014] Identification du Système d'acquisition Scanner-X à partir de l'Analyse du Bruit dans des Images Médicales

  Auteurs : **Anas Kharboutly**, William Puech, Gérard Subsol et Denis Hoa

  CORESA (COmpression et REprésentation des Signaux Audiovisuels), Reims, France

  [2016] Identification du Scanner X à partir d'Empreintes du Capteur

  Auteurs : **Anas Kharboutly**, William Puech, Gérard Subsol et Denis Hoa

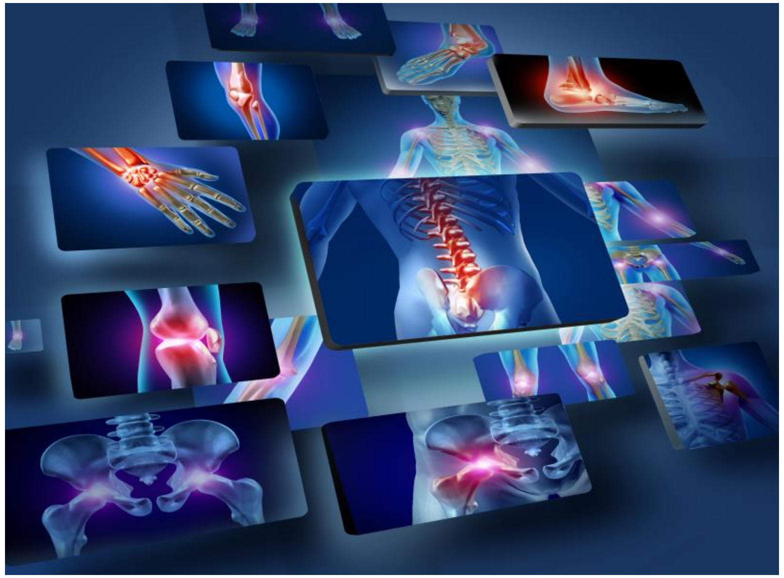
  CORESA (COmpression et REprésentation des Signaux Audiovisuels), Nancy, France

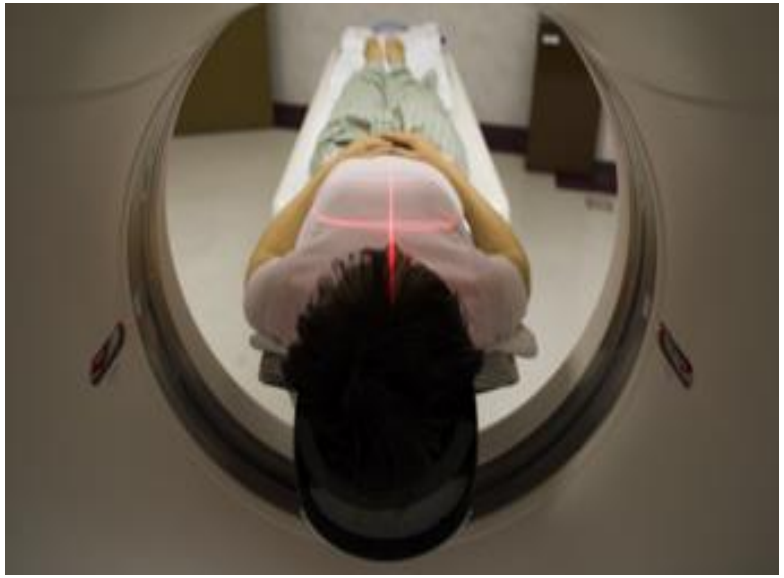
- **Journal**

  [2017] Computed Tomography Scanner Identification Based on Sensor noise

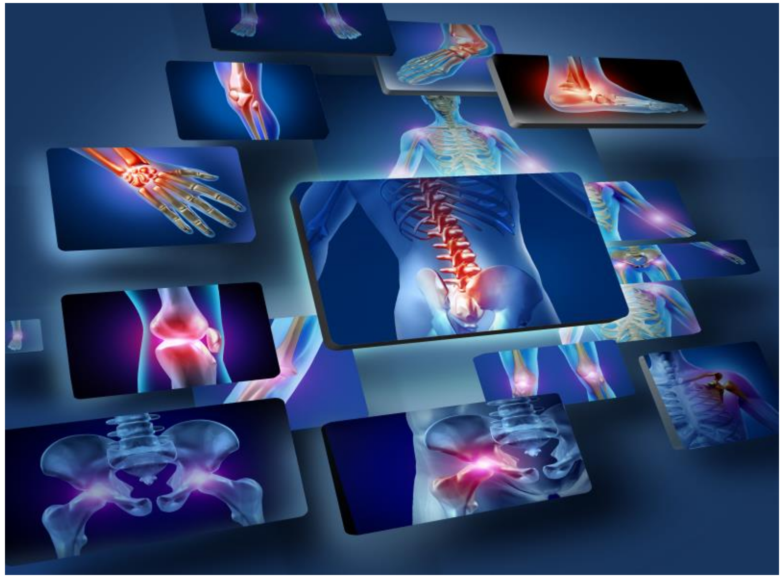
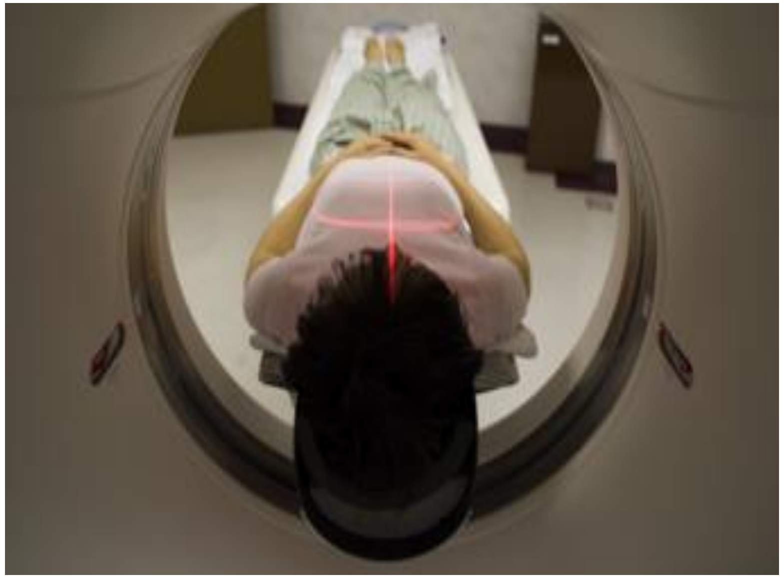
  Auteurs : **Anas Kharboutly**, William Puech, Gérard Subsol et Denis Hoa

  (In preparation for submission)



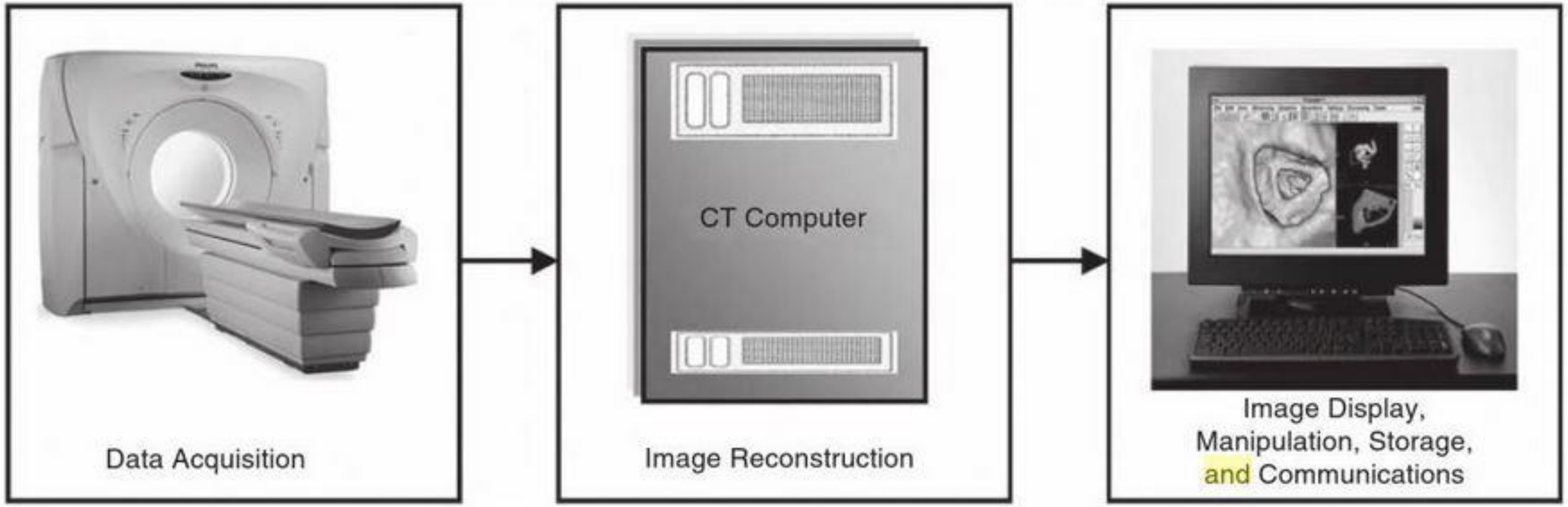


Thank you for your attention!

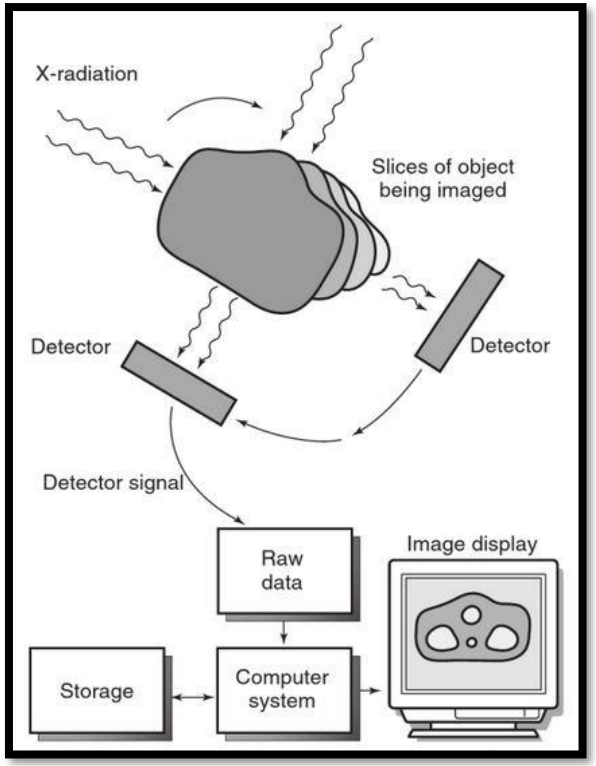

Thank you for your attention!

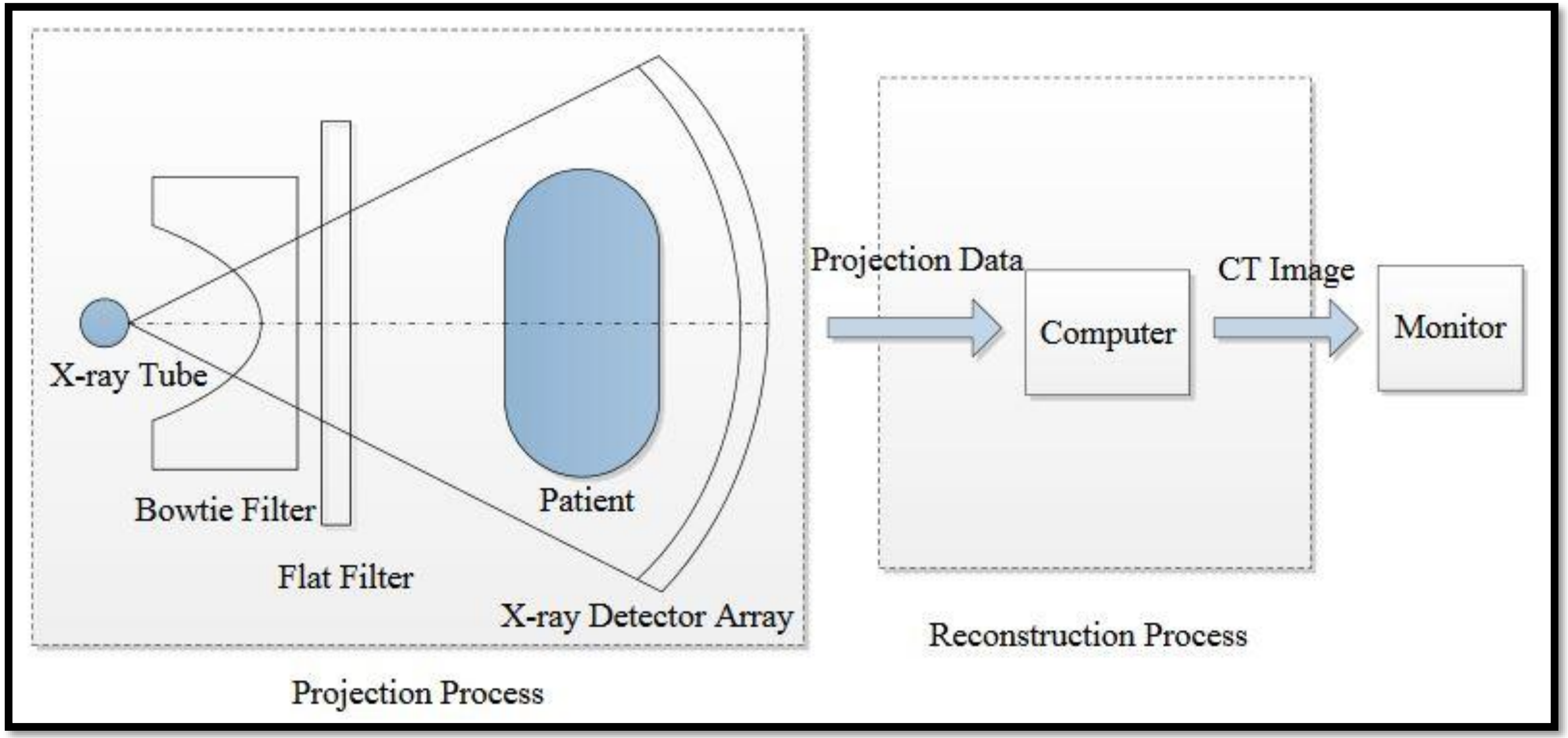
CT-SCANNER ACQUISITION SYSTEM



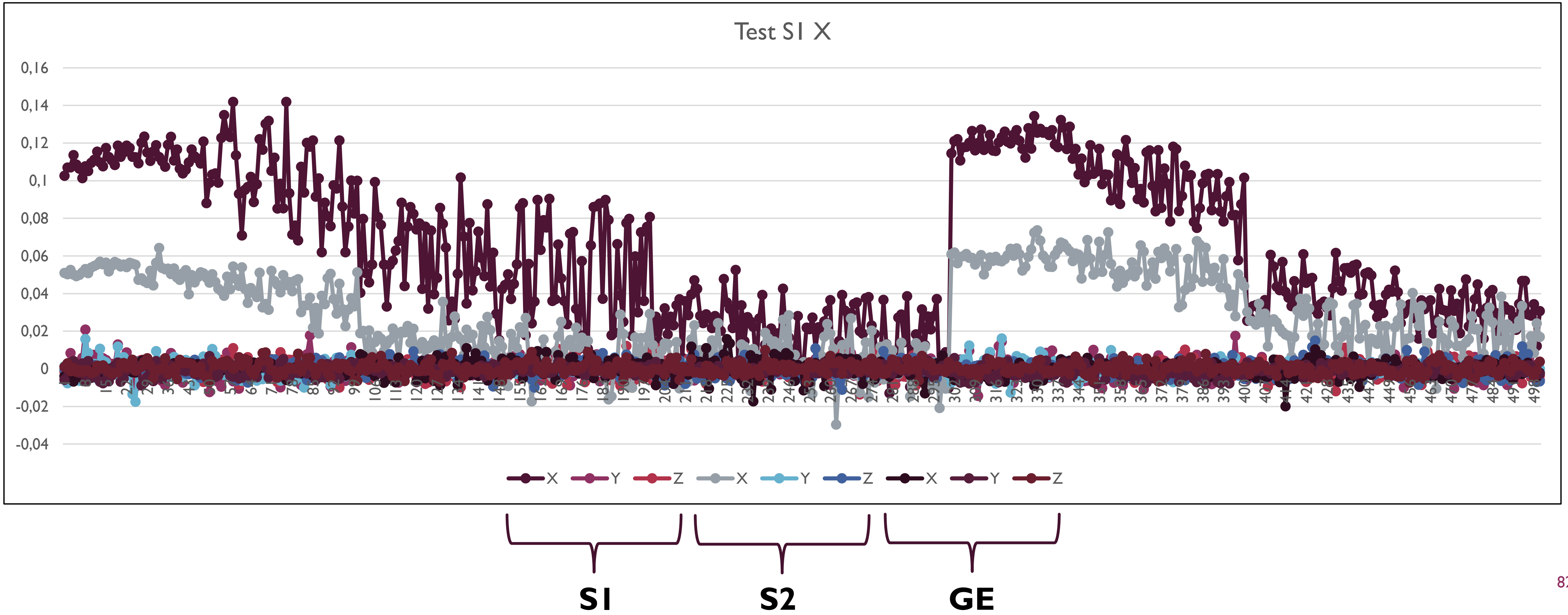
[Seeram 2015] Euclid Seeram. Computed tomography: physical principles, clinical applications, and quality control. Elsevier Health Sciences, 2015.

CT-SCANNER ACQUISITION SYSTEM





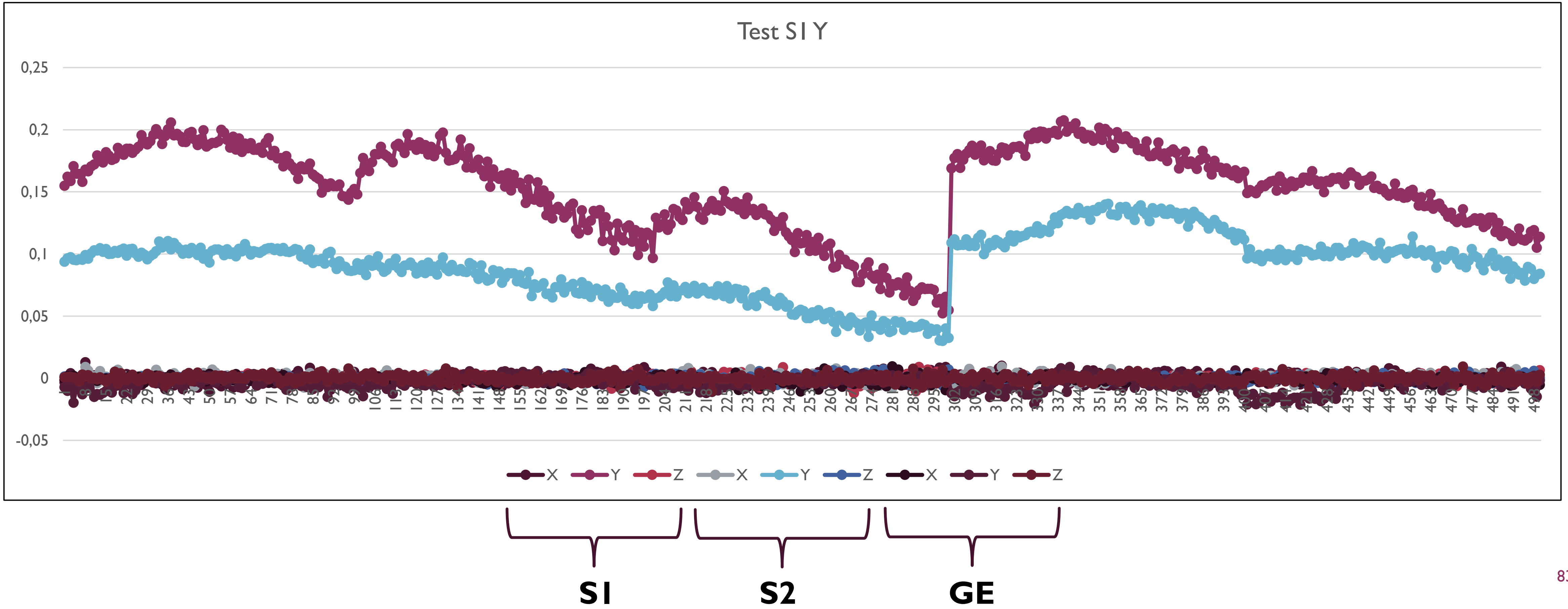
[1] Euclid Seeram. Computed tomography: physical principles, clinical applications, and quality control. Elsevier Health Sciences, 2015.
[2] Y. Duan, G. Coatrieux and H. Shu. Computed tomography image source identification by discriminating CT-scanner image reconstruction process. 37th Annual International Conference of the IEEE, 2015.



Test S1 X
0,16
0,14
0,12
0,1
0,08
0,06
0,04
0,02
0
-0,02
-0,04
X
Y
Z
X
Y
Z
X
Y
Z
S1
S2
GE

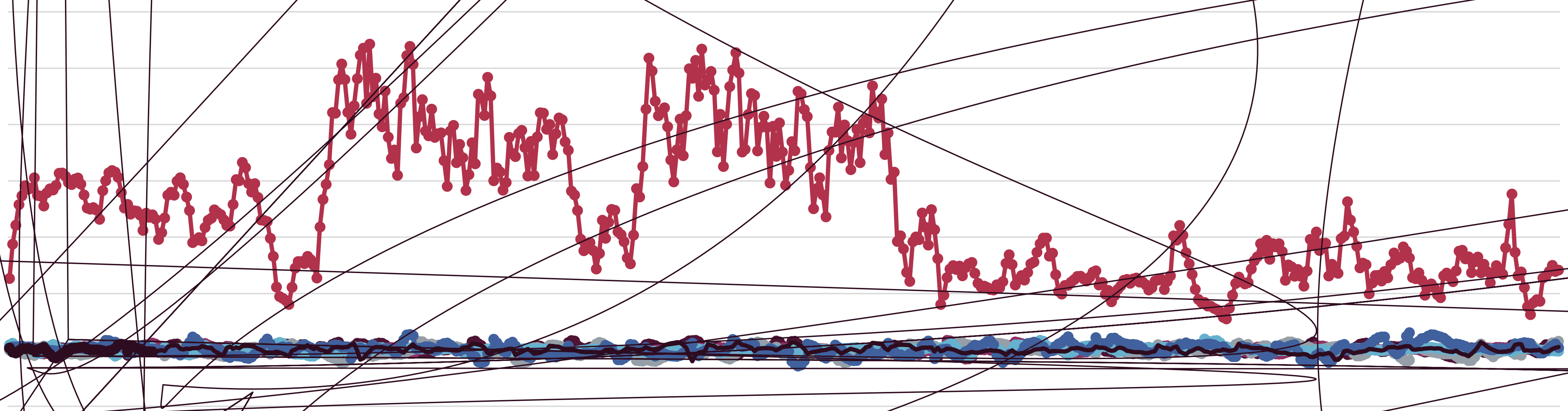
EXTENDING THE RPN TO THE DIFFERENT IMAGE AXES

1. IDENTIFICATION METHOD *2. EXPERIMENTS* *3. RESULTS*



EXTENDING THE RPN TO THE DIFFERENT IMAGE AXES

1. IDENTIFICATION METHOD *2. EXPERIMENTS* *3. RESULTS*



EXTENDING THE RPN TO THE DIFFERENT IMAGE AXES

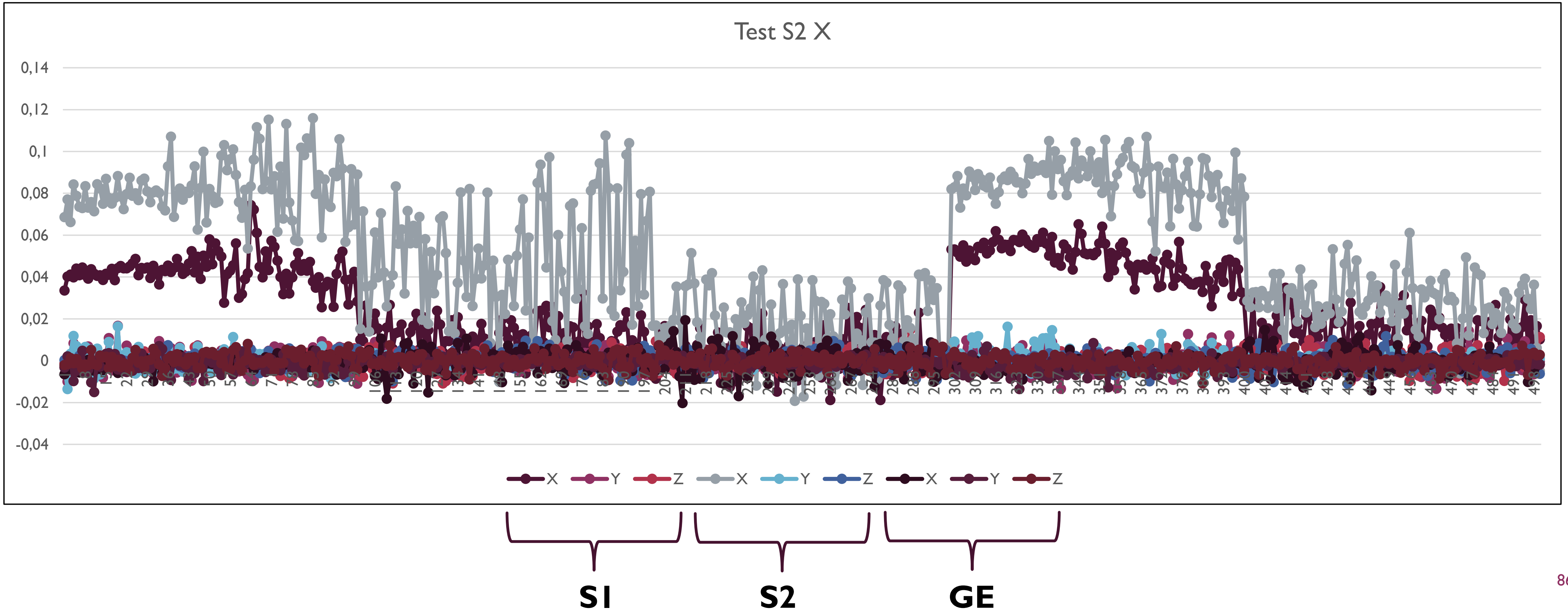
1. IDENTIFICATION METHOD *2. EXPERIMENTS* *3. RESULTS*

Ref\Test	S1 X	S1 Y	S1 Z	S2 X	S2 Y	S2 Z	GE X	GE Y	GE Z
S1 X	**92,2 %**	0	0	9 %	0	0	3,4 %	0	0
S1 Y	0,2 %	**100 %**	0	0,2 %	0	0	1,8 %	0	0
S1 Z	0	0	**100 %**	0,2 %	0	0	3 %	0	0
S2 X	5,8 %	0	0	**88,6 %**	0	0	6,6 %	0	0
S2 Y	0	0	0	0	**100 %**	0	0,8 %	0,2 %	0
S2 Z	0,6 %	0	0	0,6 %	0	**100 %**	4,2 %	0	0
GE X	0,4 %	0	0	0,8 %	0	0	**73 %**	0,2 %	0
GE Y	0,4 %	0	0	0	0	0	4,4 %	**99,6 %**	0
GE Z	0,2 %	0	0	0,4 %	0	0	2,2 %	0	**100 %**

Identification accuracy

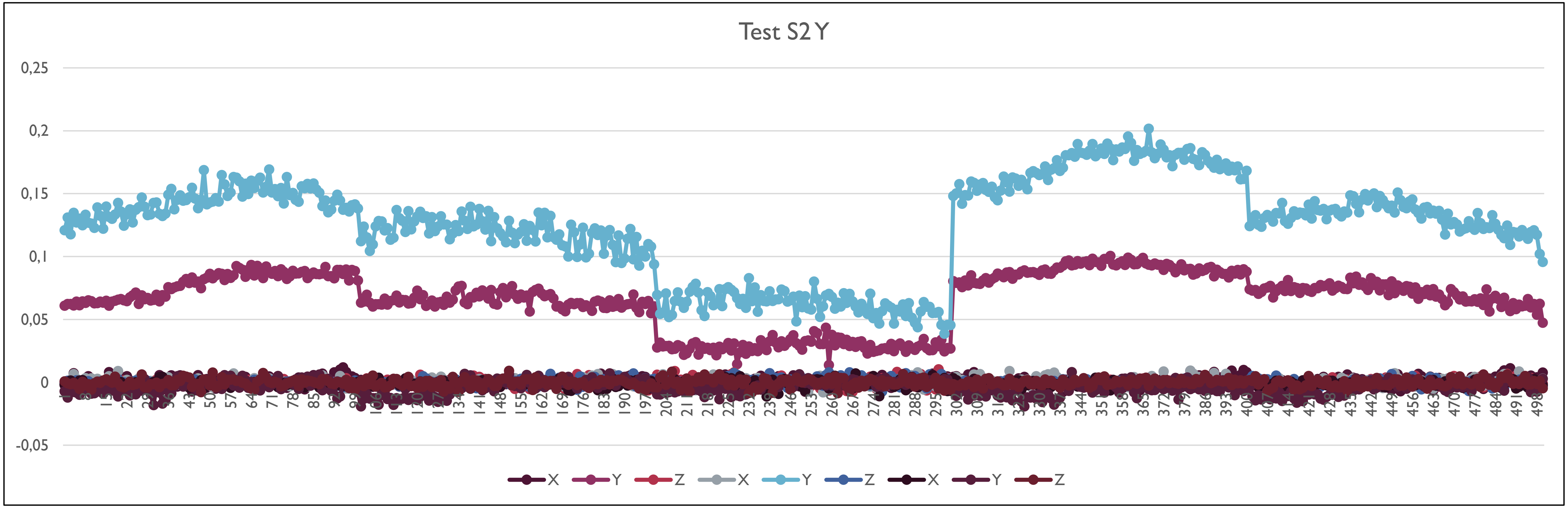
EXTENDING THE RPN TO THE DIFFERENT IMAGE AXES

1. IDENTIFICATION METHOD *2. EXPERIMENTS* *3. RESULTS*



EXTENDING THE RPN TO THE DIFFERENT IMAGE AXES

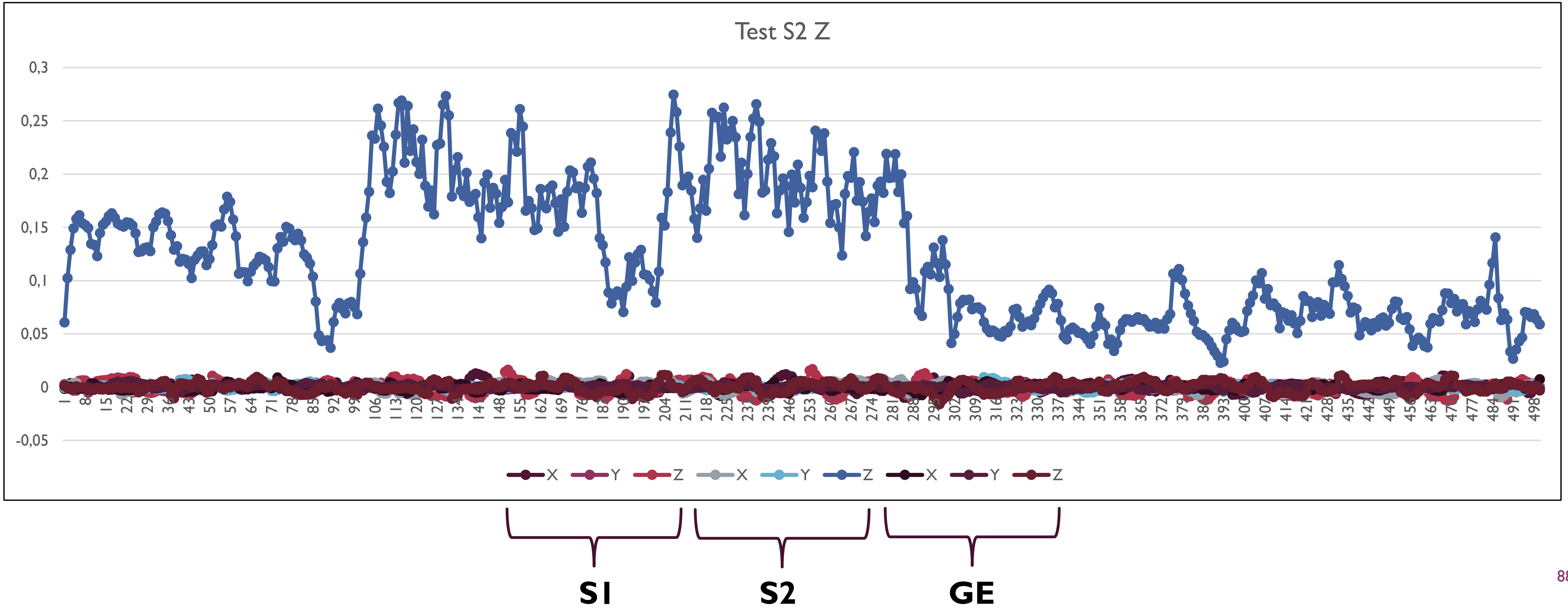
1. IDENTIFICATION METHOD *2. EXPERIMENTS* *3. RESULTS*



S1 **S2** **GE**

EXTENDING THE RPN TO THE DIFFERENT IMAGE AXES

1. IDENTIFICATION METHOD *2. EXPERIMENTS* *3. RESULTS*



EXTENDING THE RPN TO THE DIFFERENT IMAGE AXES

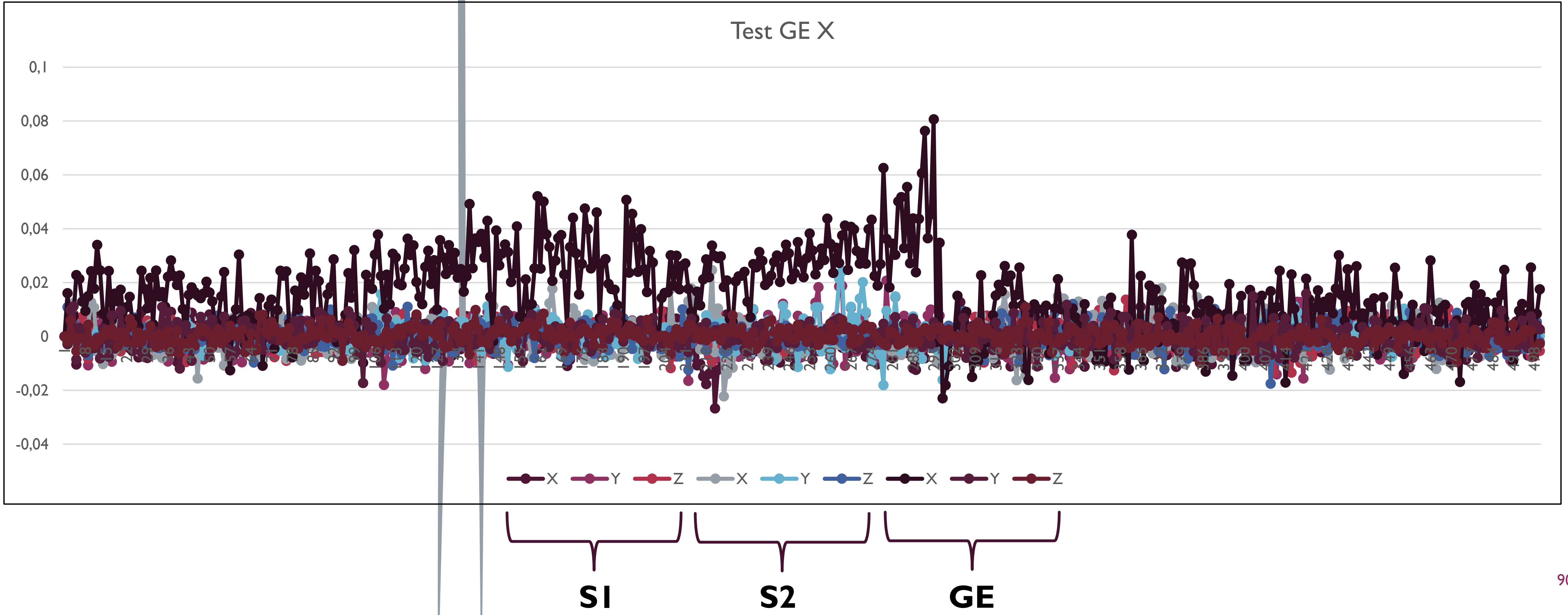
1. IDENTIFICATION METHOD *2. EXPERIMENTS* *3. RESULTS*

Ref\Test	S1 X	S1 Y	S1 Z	S2 X	S2 Y	S2 Z	GE X	GE Y	GE Z
S1 X	92,2 %	0	0	9 %	0	0	3,4 %	0	0
S1 Y	0,2 %	100 %	0	0,2 %	0	0	1,8 %	0	0
S1 Z	0	0	100 %	0,2 %	0	0	3 %	0	0
S2 X	5,8 %	0	0	**88,6 %**	0	0	6,6 %	0	0
S2 Y	0	0	0	0	**100 %**	0	0,8 %	0,2 %	0
S2 Z	0,6 %	0	0	0,6 %	0	**100 %**	4,2 %	0	0
GE X	0,4 %	0	0	0,8 %	0	0	73 %	0,2 %	0
GE Y	0,4 %	0	0	0	0	0	4,4 %	99,6 %	0
GE Z	0,2 %	0	0	0,4 %	0	0	2,2 %	0	100 %

Identification accuracy

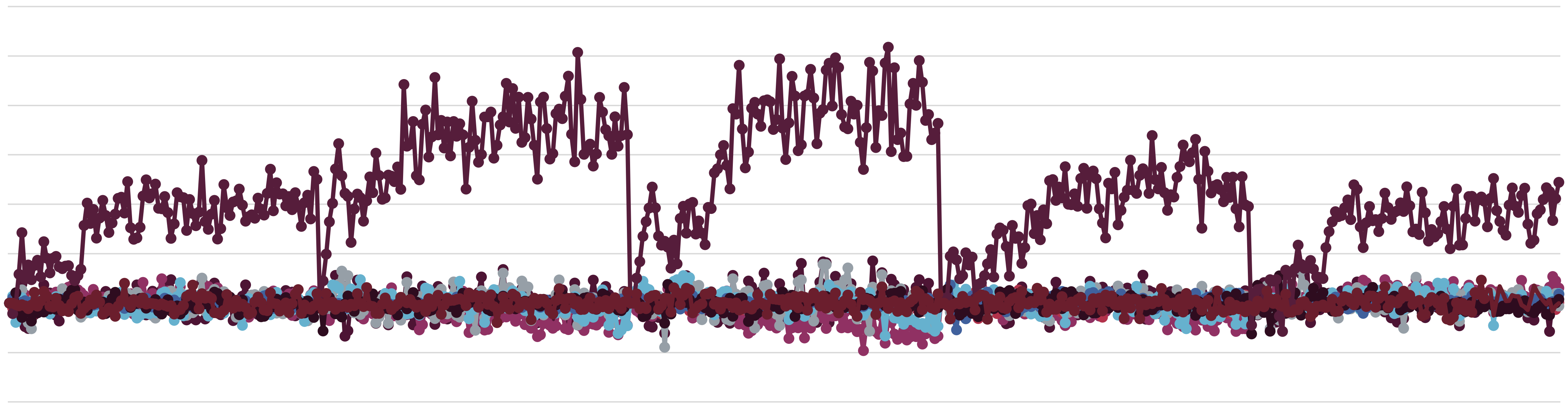
EXTENDING THE RPN TO THE DIFFERENT IMAGE AXES

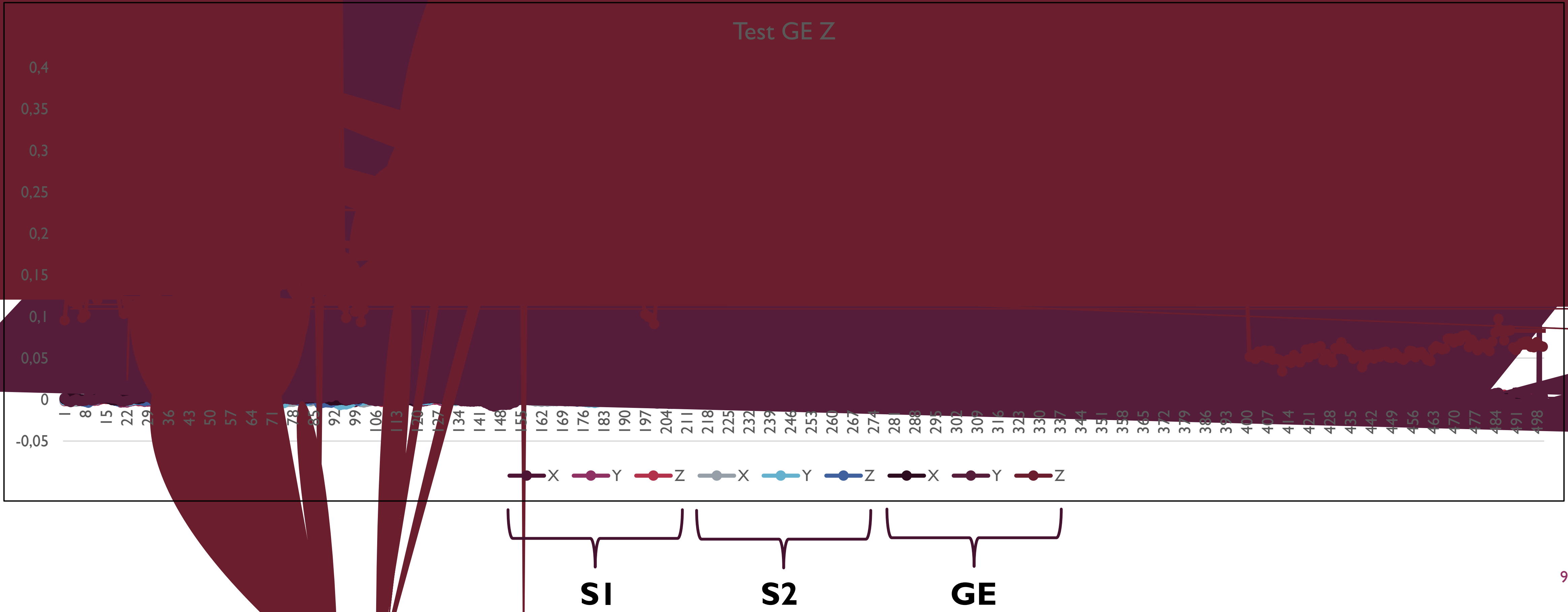
1. IDENTIFICATION METHOD *2. EXPERIMENTS* ***3. RESULTS***



EXTENDING THE RPN TO THE DIFFERENT IMAGE AXES

1. IDENTIFICATION METHOD *2. EXPERIMENTS* *3. RESULTS*




Test GE Z
0,4
0,35
0,3
0,25
0,2
0,15
0,1
0,05
0
-0,05
X
Y
Z
X
Y
Z
X
Y
Z
S1
S2
GE

Ref\Test	S1 X	S1 Y	S1 Z	S2 X	S2 Y	S2 Z	GE X	GE Y	GE Z
S1 X	92,2 %	0	0	9 %	0	0	3,4 %	0	0
S1 Y	0,2 %	100 %	0	0,2 %	0	0	1,8 %	0	0
S1 Z	0	0	100 %	0,2 %	0	0	3 %	0	0
S2 X	5,8 %	0	0	88,6 %	0	0	6,6 %	0	0
S2 Y	0	0	0	0	100 %	0	0,8 %	0,2 %	0
S2 Z	0,6 %	0	0	0,6 %	0	100 %	4,2 %	0	0
GE X	0,4 %	0	0	0,8 %	0	0	**73 %**	0,2 %	0
GE Y	0,4 %	0	0	0	0	0	4,4 %	**99,6 %**	0
GE Z	0,2 %	0	0	0,4 %	0	0	2,2 %	0	**100 %**

Identification accuracy

EXTENDING THE RPN TO THE DIFFERENT IMAGE AXES

1. IDENTIFICATION METHOD *2. EXPERIMENTS* *3. RESULTS*

Ref\Test	S1 X	S1 Y	S1 Z	S2 X	S2 Y	S2 Z	GE X	GE Y	GE Z
S1 X	**92,2 %**	0	0	9 %	0	0	3,4 %	0	0
S1 Y	0,2 %	**100 %**	0	0,2 %	0	0	1,8 %	0	0
S1 Z	0	0	**100 %**	0,2 %	0	0	3 %	0	0
S2 X	5,8 %	0	0	**88,6 %**	0	0	6,6 %	0	0
S2 Y	0	0	0	0	**100 %**	0	0,8 %	0,2 %	0
S2 Z	0,6 %	0	0	0,6 %	0	**100 %**	4,2 %	0	0
GE X	0,4 %	0	0	0,8 %	0	0	**73 %**	0,2 %	0
GE Y	0,4 %	0	0	0	0	0	4,4 %	**99,6 %**	0
GE Z	0,2 %	0	0	0,4 %	0	0	2,2 %	0	**100 %**

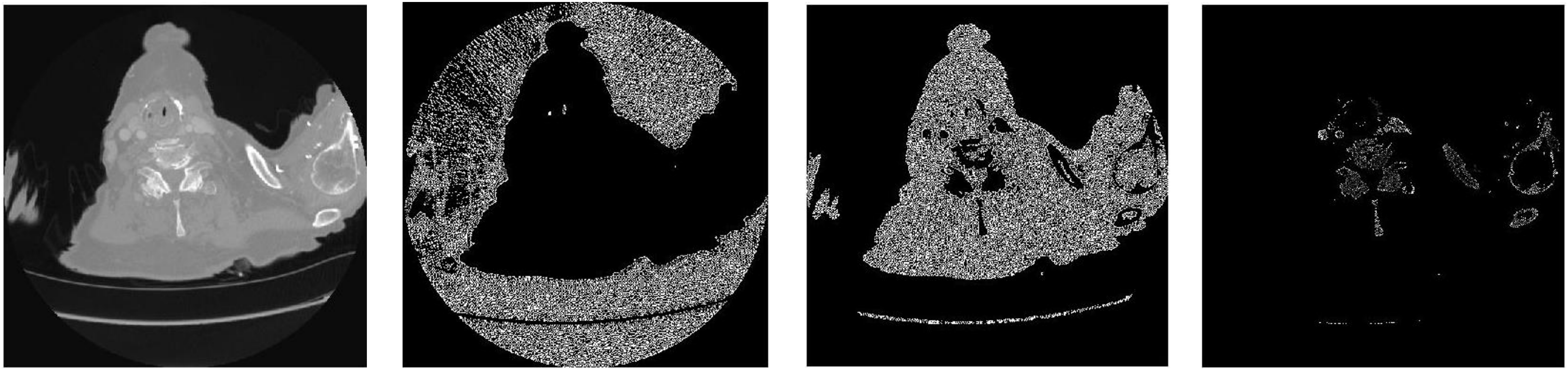
Identification accuracy

Experimental images

Parameter \Device	Siemens 1	Siemens 2	General Electric
Content	Phantom	Phantom	Phantom
Nb of 3D images	20	20	20
Nb of slices	7572	7279	5088
Size (Pixels)	512x512	512x512	512x512
Bits per pixel	16	16	16
Nb of slices of RPN	3363	3756	2092
Nb of tested slices	4209	4523	2996

USING AN RPN OF DIFFERENT INTENSITY LAYERS

1. IDENTIFICATION METHOD *2. EXPERIMENTS* *3. RESULTS*

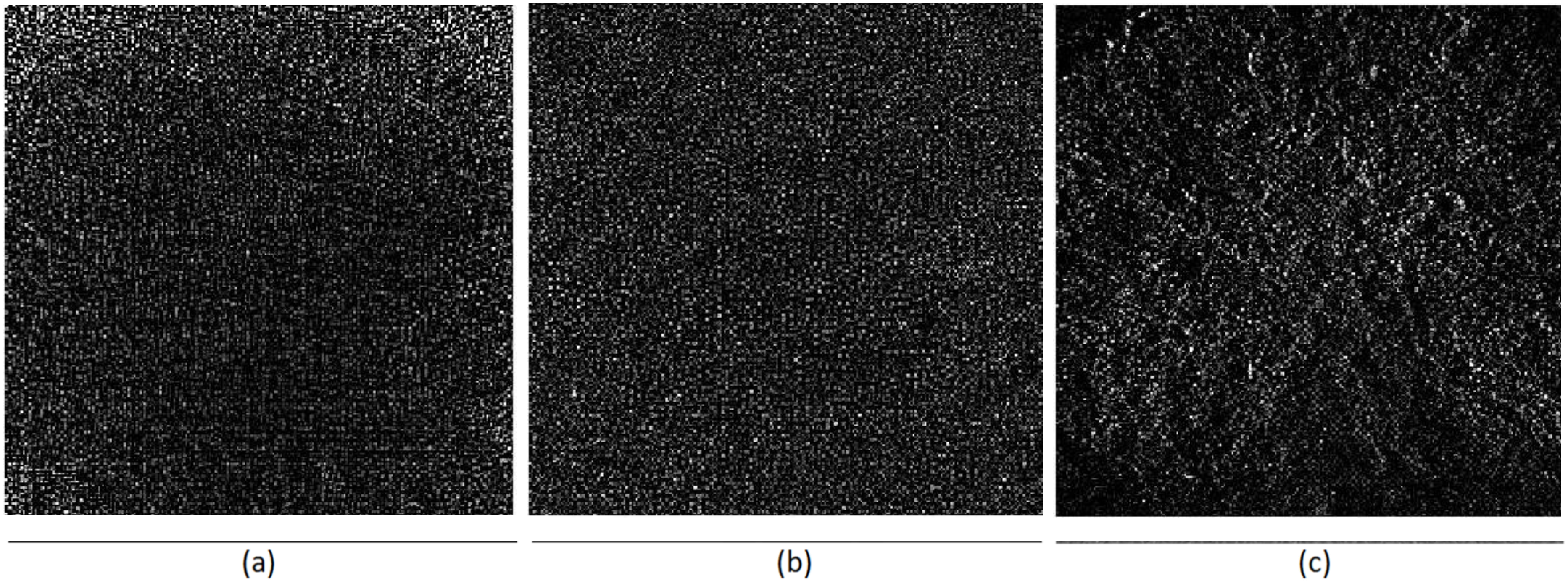


(a) (b) (c) (d)

Original slices of a neck and the noise of its three layers: a) Original, b) Air layer, c) Tissue layer, d) Bone layer

USING AN RPN OF DIFFERENT INTENSITY LAYERS

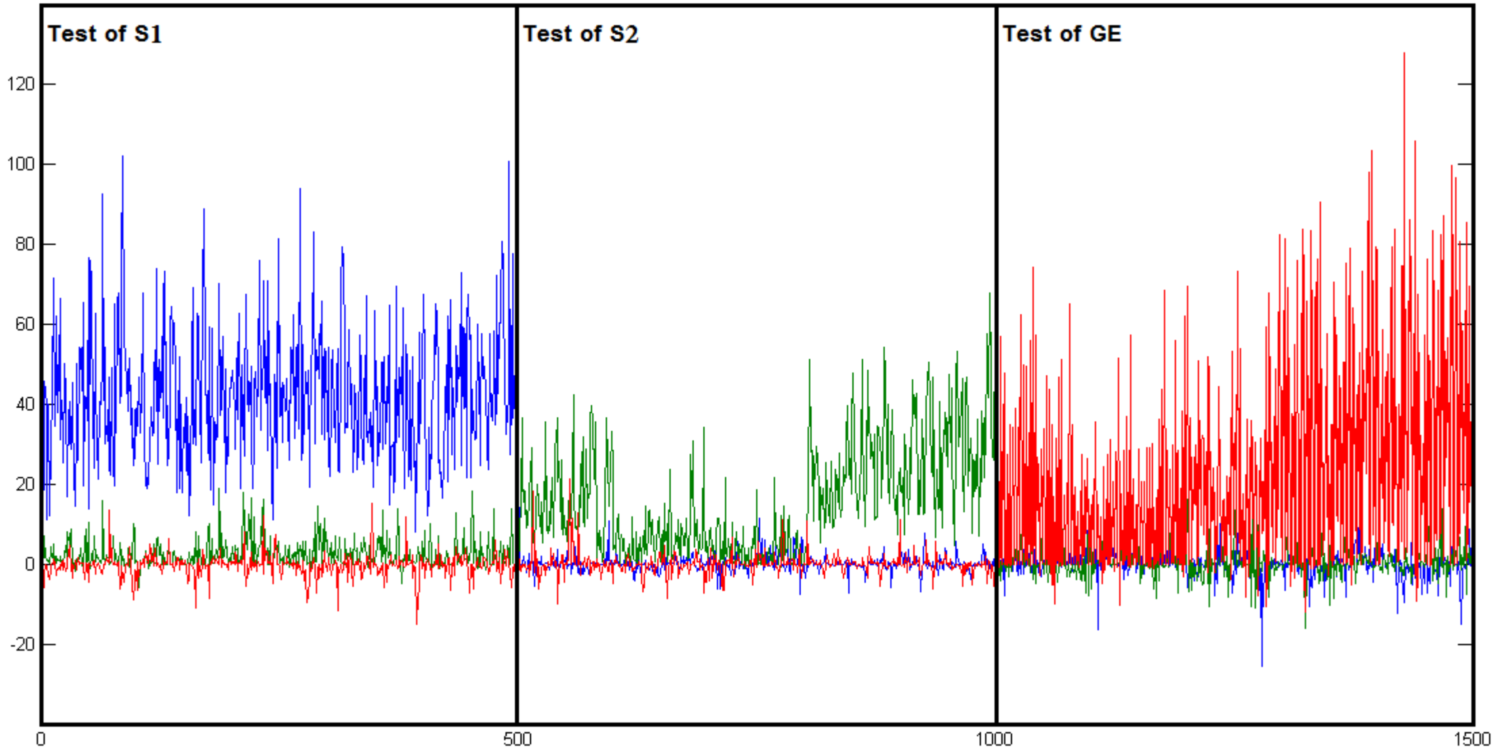
1. IDENTIFICATION METHOD *2. EXPERIMENTS* *3. RESULTS*



RPNs from three different CT-Scanners using different layers: a) S1 air RPN, b) S2 tissue RPN, c) GE Bone RPN

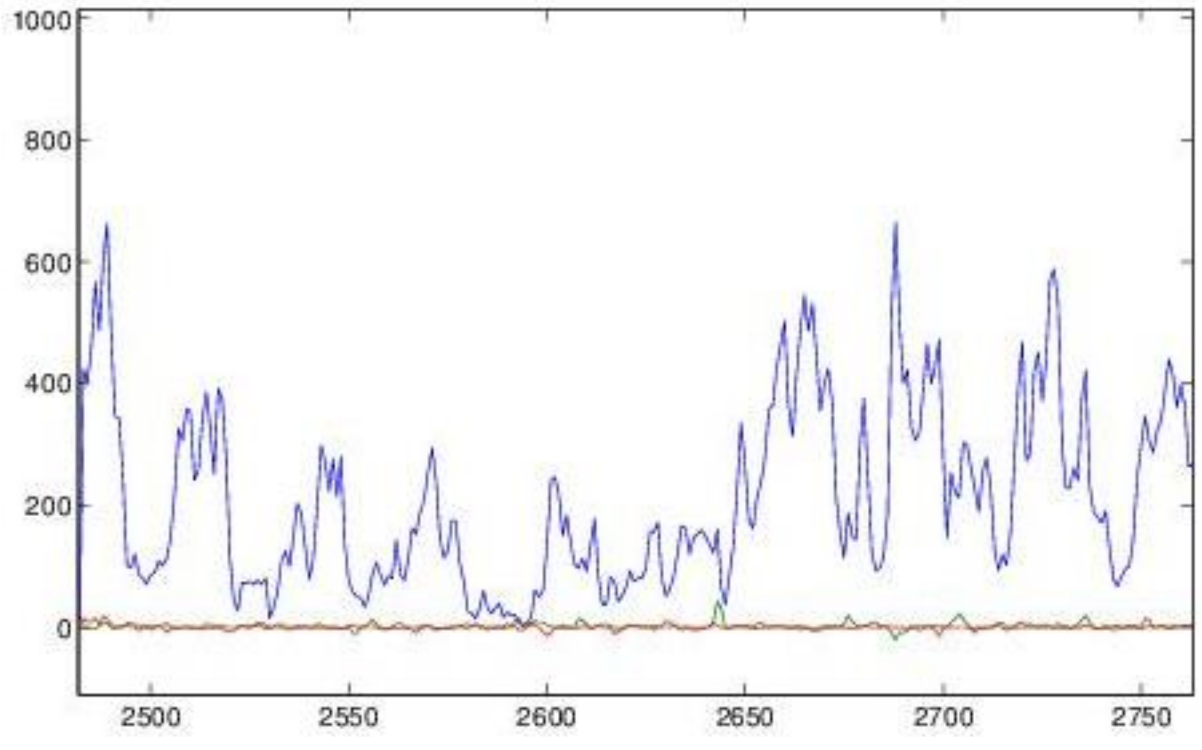
USING AN RPN OF DIFFERENT INTENSITY LAYERS

1. IDENTIFICATION METHOD *2. EXPERIMENTS* *3. RESULTS*

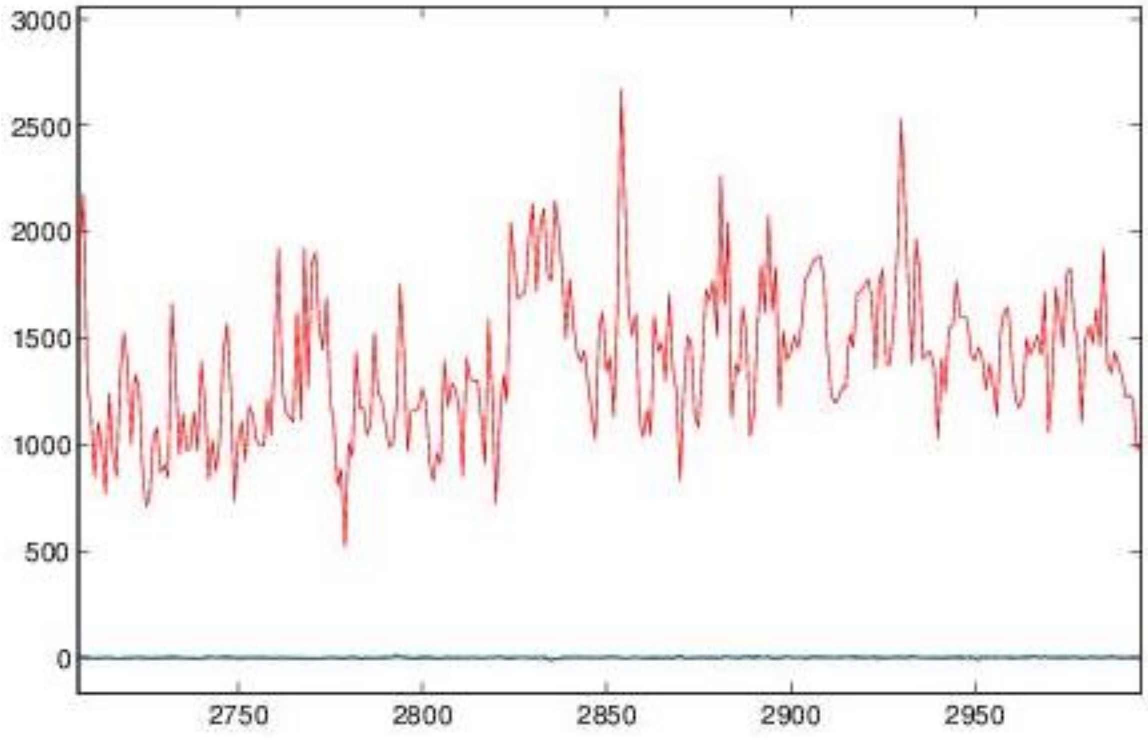


PCEs from the tissue layer of the three CT-Scanners

USING AN RPN OF DIFFERENT INTENSITY LAYERS



PCEs from the bone layer of S1



PCEs from the air layer of GE


TURKEY
SYRIA
LEBANON
★ DAMASCUS
IRAN
IRAQ
JORDAN
ISRAEL
EGYPT
SAUDI ARABIA

Syrie, Alep…









Maintenant, tout n’est qu’un souvenir!