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ADAPTIVE ACQUISITIONS IN BIOMEDICAL OPTICAL IMAGING BASED ON SINGLE PIXEL CAMERA: COMPARISON WITH COMPRESSIVE SENSING

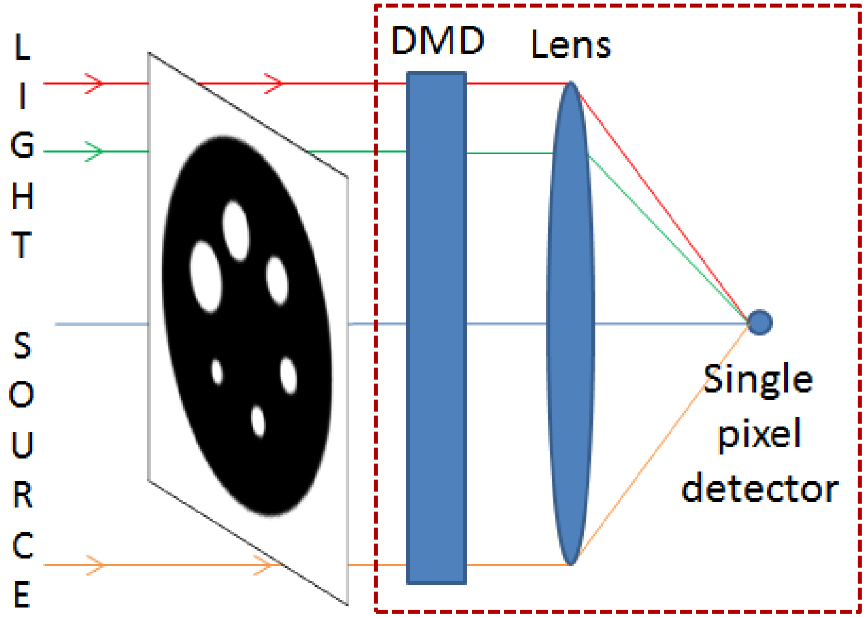
Florian Rousset[1,2], Nicolas Ducros[1], Andrea Farina[2]
Cosimo D'Andrea[2], Françoise Peyrin[1]

florian.rousset@creatis.insa-lyon.fr

[1]Univ Lyon, INSA Lyon, CNRS 5220, INSERM U1206, CREATIS – Villeurbanne, France
[2]Politecnico di Milano, Dipartimento di Fisica – Milan, Italy

OVERVIEW

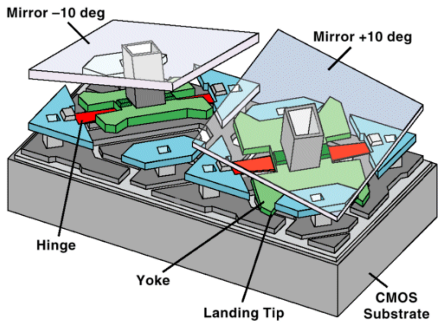
I. Introduction



Single-pixel camera (SPC)

➢ **DMD:** millions of mirrors that can independently tilt in two positions → can be used as a **spatial filtering device**

Digital micro-mirror device

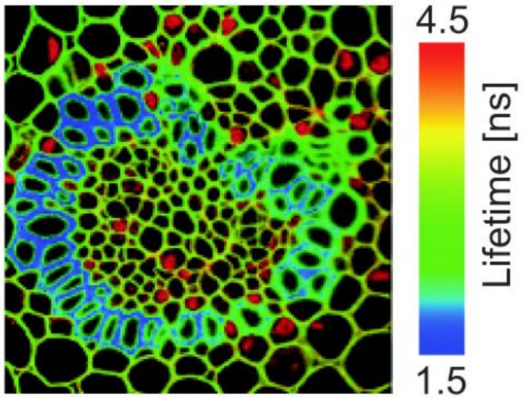


Two mirrors of 13.7 µm (Texas Instruments)

I. Introduction

- Several advantages:
  - **Infrared** or **multispectral** imaging
  - **High quantum efficiency**: able to detect weak intensity light changes
  - **Low cost** time-resolved system (one photon counting board)

Fluorescence lifetime imaging (PicoQuant)

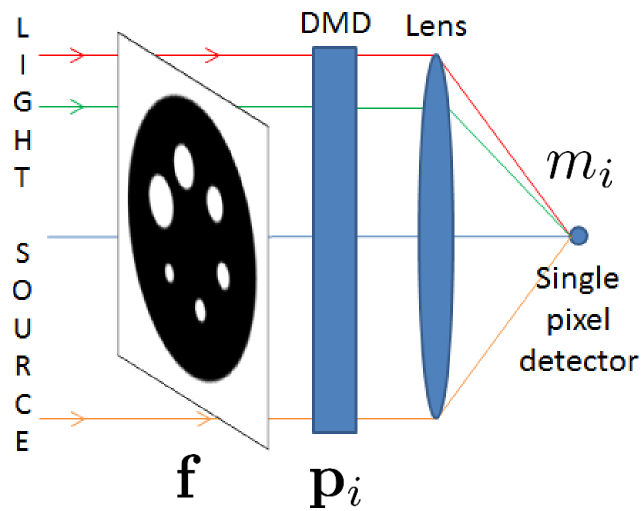


- Possible **applications in medical imaging:**
  - Fluorescence molecular tomography *[Intes 2015]*
  - Fluorescence lifetime imaging
  - Per-operatory imaging (oxygenation or fluorescence)

I. Introduction

- SPC acquisition:
  - Image of size $N \times N = P$ $\mathbf{f} \in \mathbb{R}^{P \times 1}$
  - I patterns of size $N \times N = P$ $\mathbf{p}_i \in \mathbb{R}^{P \times 1}$

→ I measures m_i with $m_i = \mathbf{f}^\top \mathbf{p}_i$



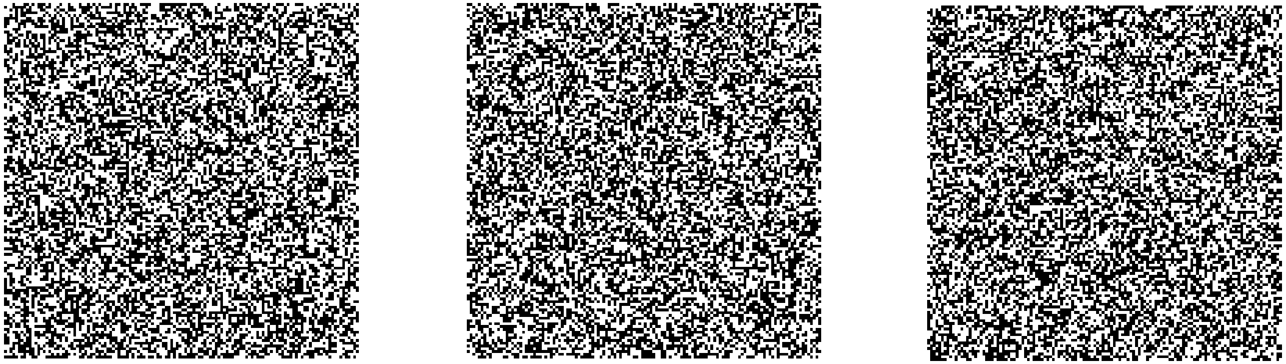
- **Problems:**
  - P1 – Choice / design of the patterns $\mathbf{p}_i$
  - P2 – Restoration of the image **f** from the measures m_i knowing $\mathbf{p}_i$

OVERVIEW

II. State of the art

II.1 – Compressive sensing

- Acquisition based on the **compressive sensing** (CS) *[Donoho 2006, Duarte 2008]*
- P1 – Patterns chosen as independent realizations of **random ±1 Bernoulli variables**
- P2 – Perfect restoration, in theory, by l_1-minimization in a basis (e.g. wavelets). In practice: **TV-minimization** (Total Variation) for faster image recovery *[Takhar 2006, Duarte 2008]*



Example of 3 random patterns

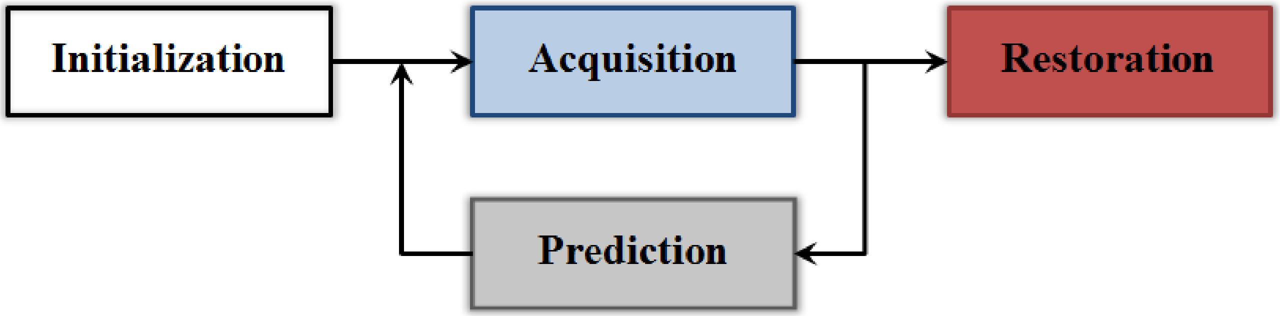
- ***Non-adaptive*** approach: same set of patterns regardless of the image

II.2 – Adaptive acquisition

- **Acquisition directly in a given basis** (Fourier, DCT, wavelets, etc…) *[Deutsch 2009, Averbuch 2012, Dai 2014]*

- P1 – Patterns of the chosen basis, some are **determined during the acquisition** based on measures already performed (prediction step)

- P2 – Almost **instant** image **restoration** using the chosen basis inverse transform *[Mallat 2008]*



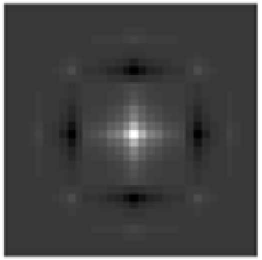
General framework of an adaptive approach

- ***Adaptive*** approach: different set of patterns depending on the object

OVERVIEW

F. Rousset

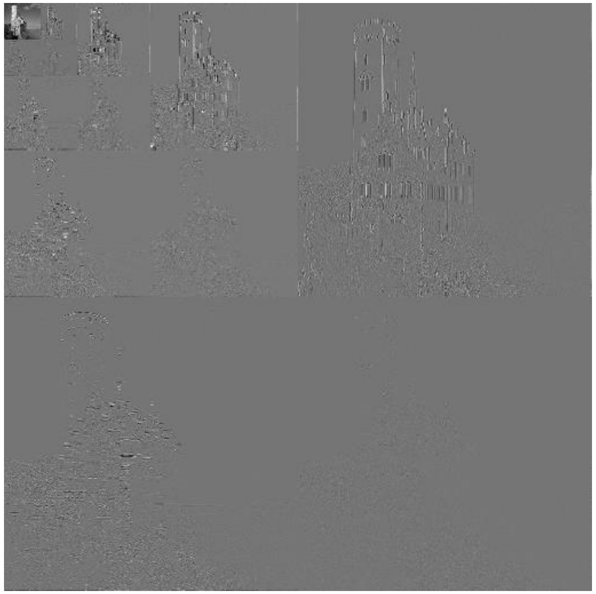
III.1 – Wavelet decomposition



$\mathbf{p}$

- Choice of an ***adaptive*** approach in the wavelet domain
- Coefficient: $c = \mathbf{f}^\top \mathbf{p}$ $\Leftrightarrow$ one SPC measurement
- Non-linear approximation: retains a given percentage of the **strongest coefficients** and shows excellent image recovery *[Mallat 2008]*

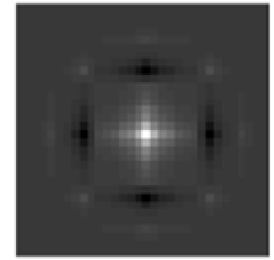
Ground truth 512 x 512 *image*



4-level wavelet decomposition

III. Proposed acquisition strategy: ABS-WP

III.1 – Wavelet decomposition



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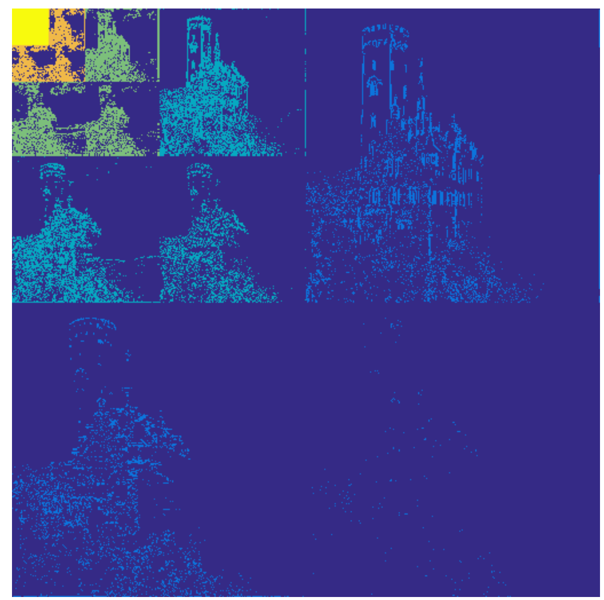

10% of the strongest coefficients

III. Proposed acquisition strategy: ABS-WP

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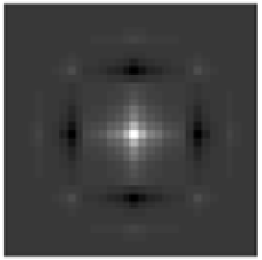

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Ground truth 512 x 512 *image*

Restored image with 10% of the coefficients

III. Proposed acquisition strategy: ABS-WP

III.2 – ABS-WP strategy

- **ABS-WP:** Adaptive Basis Scan by Wavelet Prediction *[Rousset 2015 - 2016]*

- **Multiresolution** approach: non-linear approximation idea applied on each of the $j = 1 \ldots J$ scales of the J-level wavelet decomposition

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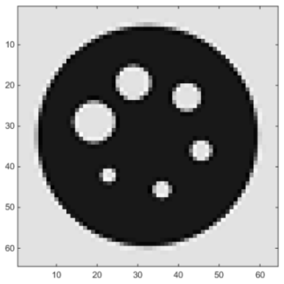
- **Steps:** example for a 128 x 128 pixel image for $J = 1$

  1 – Approximation image acquisition



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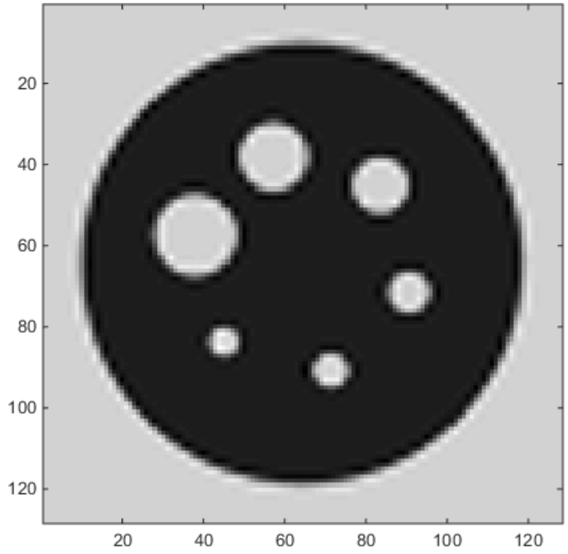
  1 – Approximation image acquisition

  2 – Over-sampling by a factor 2 by a bi-cubic interpolation *[Keys 1981]*



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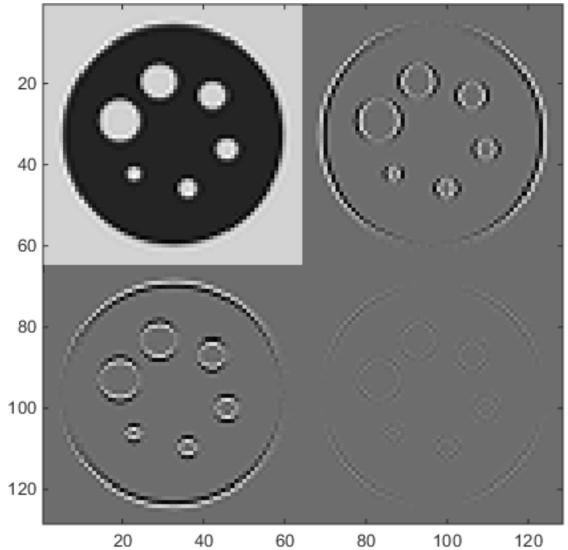
  3 – 1-level wavelet transform



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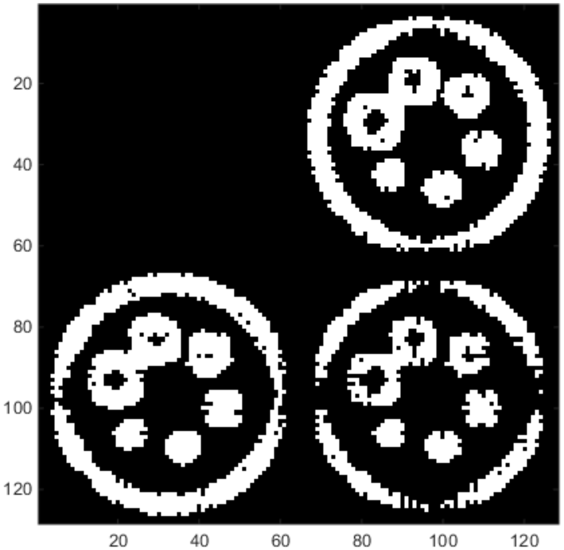
  4 – A percentage p_j of the strongest detail wavelet coefficients is retained



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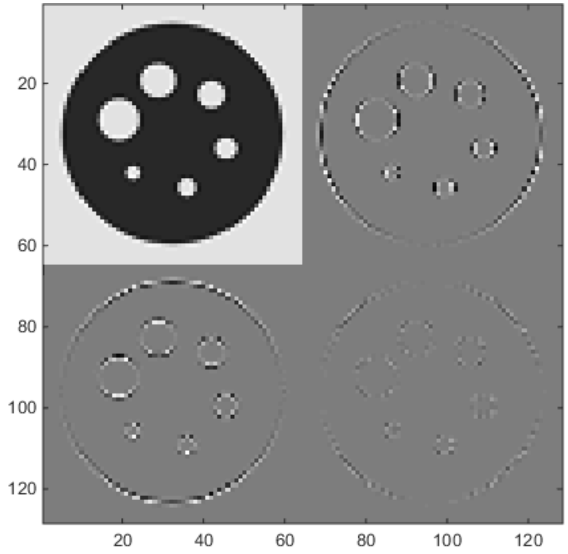
  4 – A percentage p_j of the strongest detail wavelet coefficients is retained

  5 – The “predicted” significant coefficients are experimentally acquired



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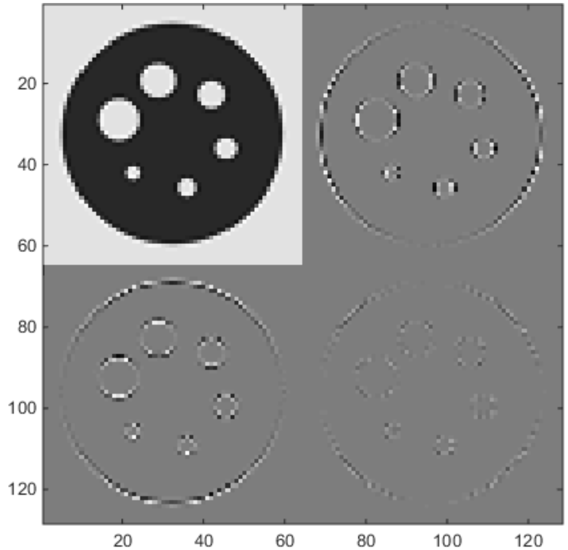


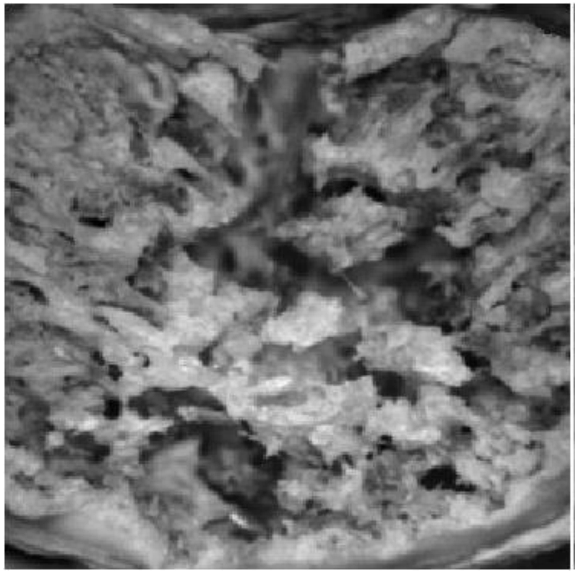
- Set of percentages $\mathcal{P} = \{p_J, \dots, p_1\}$ to control the compression rate (CR)

OVERVIEW

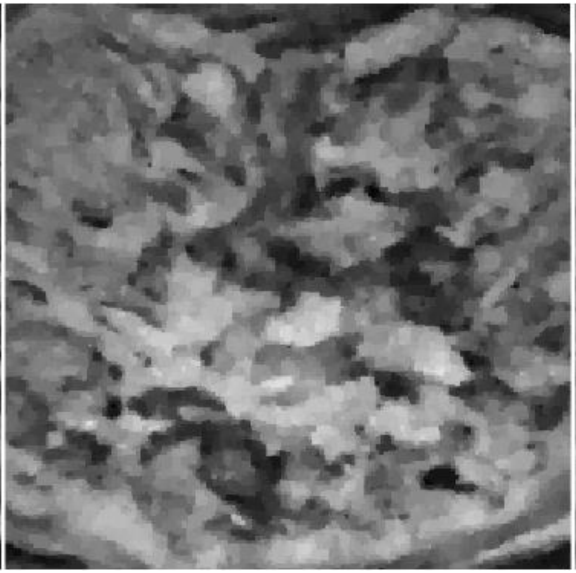
IV. Results and comparisons

IV.1 – Simulations on real images

- Histological image of bone structures
- Simulations for **CR = 80 %**
  - CS : restoration by TV-minimization
  - ABS-WP : Le Gall’s wavelet employed (CDF 5/3)



Reference 256 x 256



CS
PSNR = 29.4 dB
t = 214 s

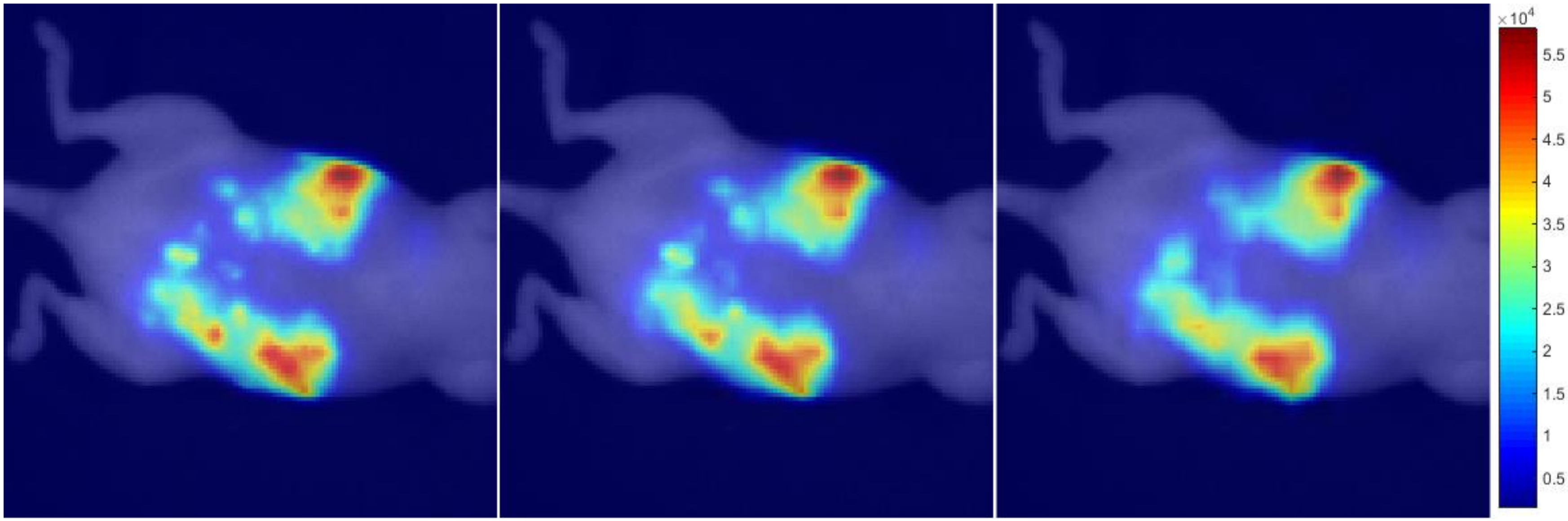
ABS-WP
PSNR = 31.2 dB
t = 0.4 s

IV. Results and comparisons

IV.1 – Simulations on real images

- Bioluminescence image of a mouse over the ambient light image (images provided by V. Josserand et J.L. Coll) *[Coll 2010]*

- **ABS-WP** simulations (Le Gall) on the bioluminescence image:



Reference 128 x 128

CR = 95 %
PSNR = 41.2 dB

CR = 98 %
PSNR = 35.3 dB

- **High compression** rates for **smooth images**

IV. Results and comparisons

IV.1 – Simulations on real images

- **PSNRs** obtained for 4 tests images for **CS** or our method **ABS-WP** for a **85 %** compression rate:

Image	PSNR (dB)	
	CS	ABS-WP
Lena (256 x 256)	27.89	**29.59**
Peppers (256 x 256)	32.96	**34.83**
Bone structures (256 x 256)	28.14	**30.29**
Mouse (128 x 128)	41.41	**48.58**

- **Set of percentages** used for ABS-WP **identical** for each image:

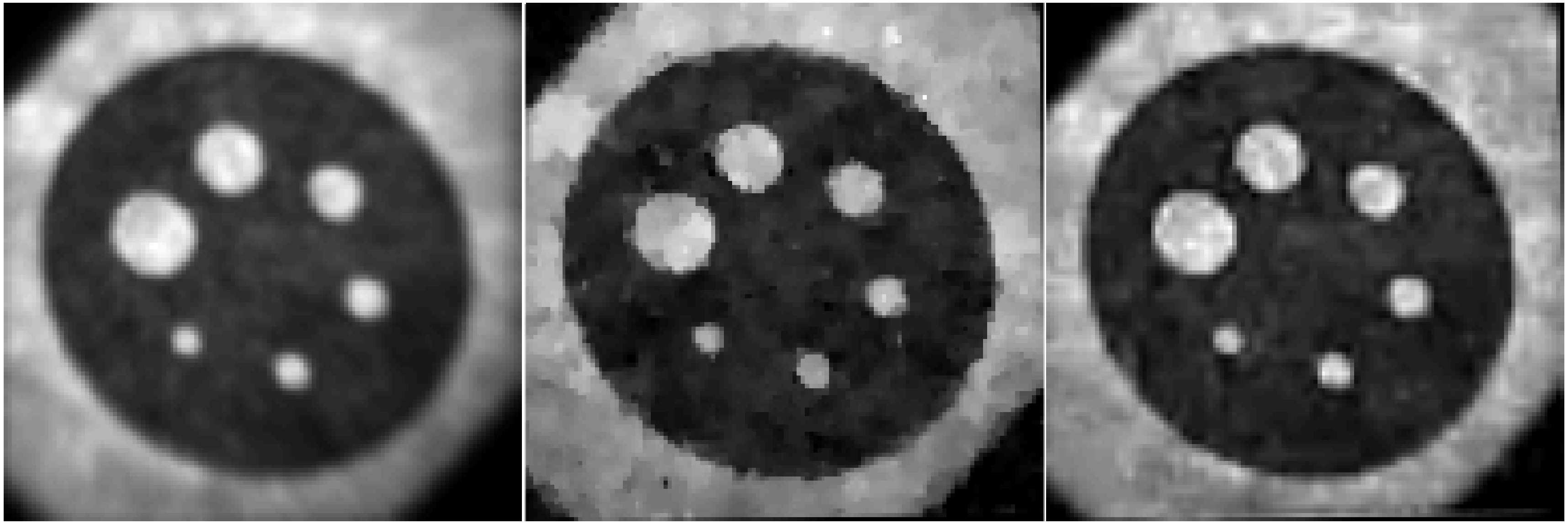
$$\mathcal{P}_{85\%} = \{0.90, 0.80, 0.45, 0.019\}$$

- **Adaptivity** of ABS-WP to different types of images

IV. Results and comparisons

IV.2 – Experimental data

- Jaszczak target printed on a paper and then employed as object
- Acquisitions for **CR = 80 %**
  - CS : restoration by TV-minimization
  - ABS-WP : Le Gall's wavelet



Experimental CCD
128 x 128 *image*

CS
PSNR = 21.2 dB
t = 14 s

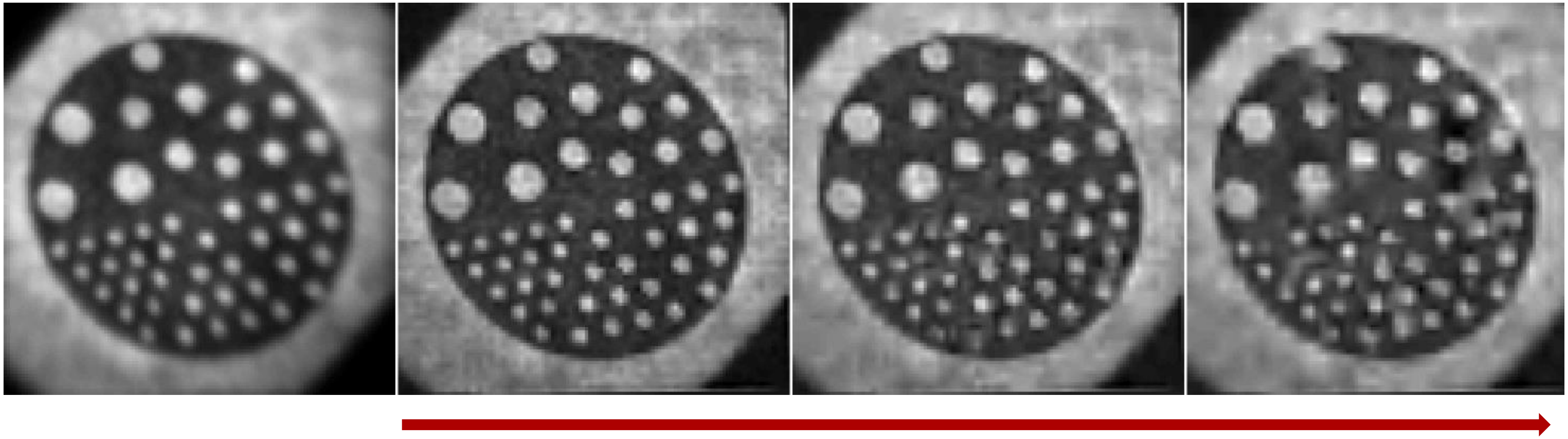
ABS-WP
PSNR = 21.7 dB
t = 0.2

IV. Results and comparisons

IV.2 – Experimental data

- Other Jaszczak target printed on paper and employed as an object to judge the system's spatial resolution. $\varnothing = [1;3]\ \mathrm{mm}$

- Acquisitions for **ABS-WP** (Le Gall) :



Experimental CCD 128 x 128 image	**CR = 75 %** **PSNR = 22.4 dB**	**CR = 85 %** **PSNR = 21.5 dB**	**CR = 90 %** **PSNR = 20.9 dB**

- Measured pixel pitch of **210 µm**. It can be easily modified by changing the optics or the size of the patterns.

OVERVIEW

V. Conclusion

- Proposed method to acquire images by a SPC:
  - **Adaptive** technique
  - **Wavelet** patterns
  - Bi-cubic interpolation **prediction**
  - **Multiresolution** approach

- **Favorable** comparison with compressive sensing:

Type of comparison	CS	ABS-WP
Restoration	**Perfect in theory**	Perfect if CR = 0%
Complexity	Expensive computation	**Direct restoration**
Computation time	x 10-100	**1**
Parameters	Several parameters for the TV-minimization	Choice of the wavelet + set of percentages

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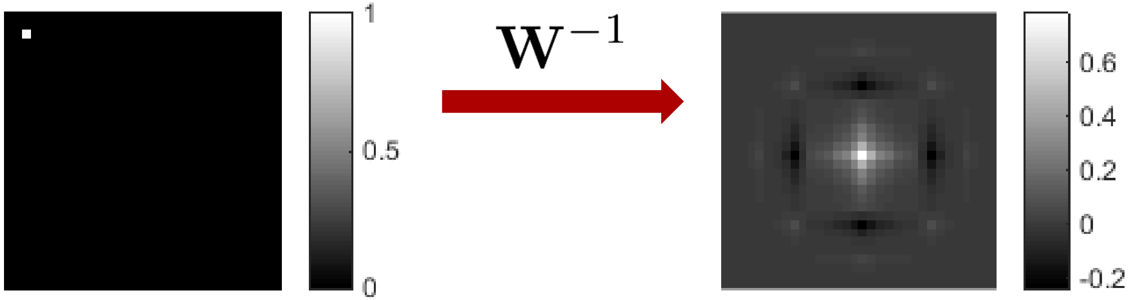
Questions

Wavelet pattern creation

- We note **W** an orthonormal operator so that one wavelet pattern **p** can be obtained as

$$\mathbf{p} = \mathbf{W}^{-1}\mathbf{e} \qquad \mathbf{W} \in \mathbb{R}^{P \times P}$$

with **e** a unit vector chosen from the canonic basis :



- Obtained patterns have real positive and negative values. The DMD can only receive b-bits patterns

→ **uniform quantization** of the patterns and positive/negative separation:

$$q_f = \frac{\max(|\mathbf{p}|)}{2^b - 1} \qquad \hat{\mathbf{p}} = \left\lfloor \frac{1}{q_f}\mathbf{p} \right\rfloor \qquad c \approx q_f \mathbf{f}^\top \hat{\mathbf{p}} = q_f \left(\mathbf{f}^\top \hat{\mathbf{p}}^+ - \mathbf{f}^\top \hat{\mathbf{p}}^- \right)$$

Computation times

- **Average computation times** for the simulations + experimental data (acquisition time excluded). It includes TV-minimization for CS and the prediction step + restoration for ABS-WP :

Image size	Time (s)	
	CS	ABS-WP
128 x 128	13.18	**0.18**
256 x 256	213.62	**0.42**

- **TV-minimization** demands **expensive computations**, time increases quickly with the number of measures and the image size

- For ABS-WP, **bi-cubic interpolation** and the **wavelet transform** are **optimized** and **fast** operations

- **Real time** possible for our technique