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Introduction

- 1 Single pixel camera
- 2 Motivation
- 3 Problem
- 4 State of the art

Materials and methods

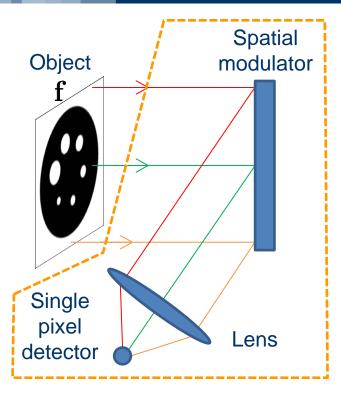
- 1 Experimental setup
- 2 Wavelet decomposition
- 3 ABS-WP strategy
- 4 Extension to TR measurements

Results

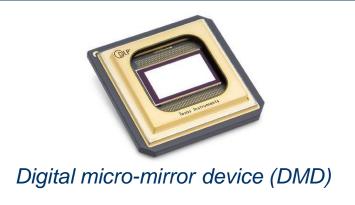
- 1 Temporal resolution
- 2 Application to FLIM
- 3 Multispectral TR measurements

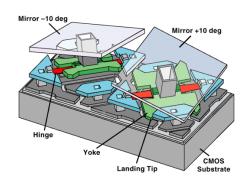
Conclusion





Single-pixel camera (SPC)



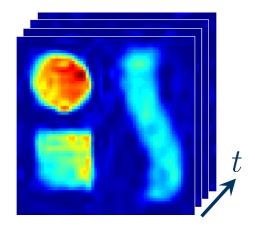


Two mirrors of 13.7 µm (Texas Instruments)

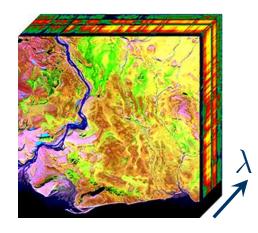
- Spatial modulator: SLM, LCD, DMD (Digital Micro-mirror Device)
- DMD: array mirrors that can independently be tilted in two states



➤ Multi-dimensional acquisitions → management of huge datasets



Stack of time images



Stack of spectral images (Wikipedia)

- ➤ Single pixel camera (SPC) → partial **compression** at the hardware level
 - Infrared or multispectral imaging [Edgar et al., Scientific Reports, 5, 2015]
 - Low cost time-resolved system [Pian et al., Biomedical Optics, 2016]

COUPLE COMPRESSION TECHNIQUES (SOFTWARE LEVEL)
WITH THE SPC (HARDWARE LEVEL)



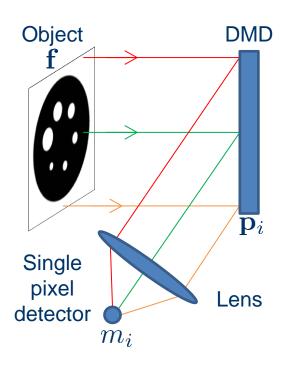


Image of size $N \times N$: **f**

I patterns of size $N \times N$: \mathbf{p}_i

 $\Rightarrow I \text{ measurements: } m_i = \mathbf{f}^\top \mathbf{p}_i$

 \triangleright Sequential measurements m_i for different patterns \mathbf{p}_i

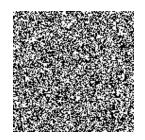
> Problems

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



Introduction > 4 - State of the art

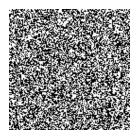
- Compressive sensing [Duarte et al., IEEE SPM, 25, 2008]
 - P1 Random ±1 Bernoulli variables
 - ilables (C
 - P2 Restoration by *I*₁-minimization



Random pattern

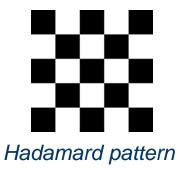
Introduction > 4 - State of the art

- Compressive sensing [Duarte et al., IEEE SPM, 25, 2008]
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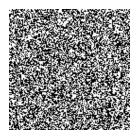
Random pattern

- Basis scan [Zhang et al., Nature Comm., 6, 2015]
 - P1 **№** patterns in a basis (Hadamard, Fourier, etc.)
 - P2 Chosen basis inverse transform (**)





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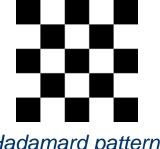


Random pattern

- Basis scan [Zhang et al., Nature Comm., 6, 2015]
 - P1 **N**² patterns in a basis (Hadamard, Fourier, etc.)



P2 – Chosen basis inverse transform

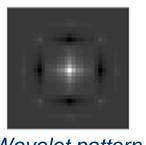


Hadamard pattern

- ➤ Adaptive basis scan [Dai et al., Applied Optics, 53 (29), 2014]
 - P1 − I << N² patterns in a chosen basis



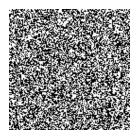
- P2 Chosen basis inverse transform
 - → **Prediction** of the *I* patterns based on previous measures



Wavelet pattern



- ➤ Compressive sensing [Duarte et al., IEEE SPM, 25, 2008]
 - P1 Random ±1 Bernoulli variables
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Random pattern

- Basis scan [Zhang et al., Nature Comm., 6, 2015]
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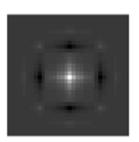


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Wavelet pattern



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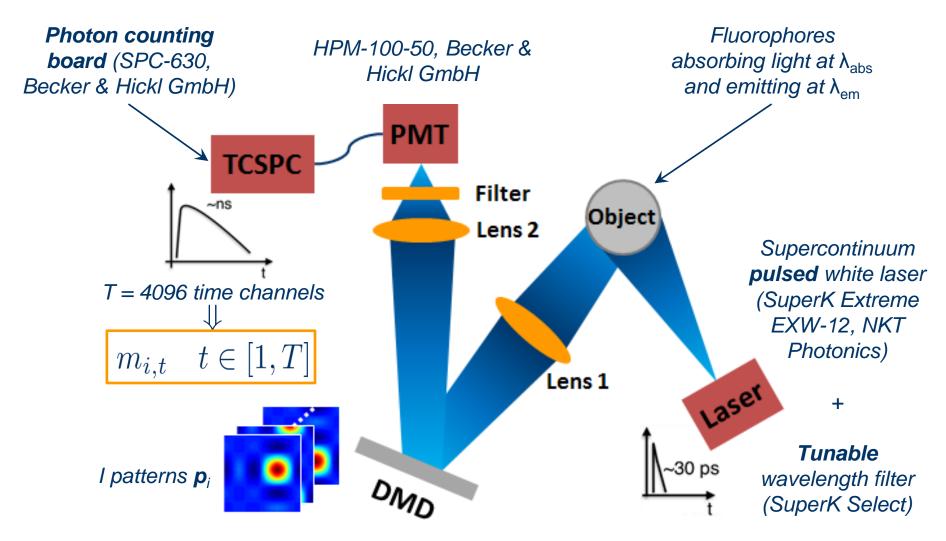
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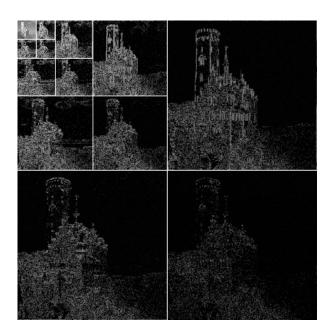
1024×768 **DMD** (DLP7000-V7001, Vialux)



- Adaptive approach in the wavelet domain
- \succ One wavelet coefficient: $c = \mathbf{f}^{ op} \quad \Leftrightarrow$ one SPC measurement
- ➤ Non-linear approximation: retains a percentage of the strongest wavelet coefficients and shows excellent image recovery [Mallat, Academic Press, 2008]



Ground truth 512 x 512 image



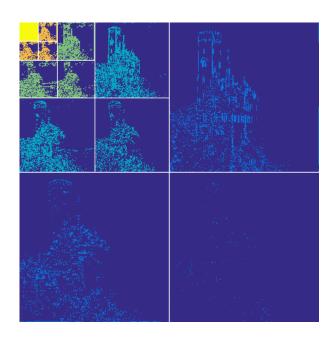
4-level wavelet decomposition 512 x 512



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Ground truth 512 x 512 image



10% of the strongest coefficients



Materials and methods > 2 – Wavelet decomposition

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Ground truth 512 x 512 image



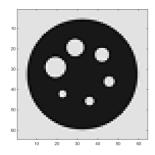
Restored image with 10% of the coefficients



- ➤ ABS-WP: Adaptive Basis Scan by Wavelet Prediction [Rousset et al., IEEE TCI, in press, 2017]
- Multiresolution approach: non-linear approximation idea applied on each of the j = 1...J scales of the J-level wavelet decomposition
- > Steps: example for a 128 x 128 pixel image for J = 1

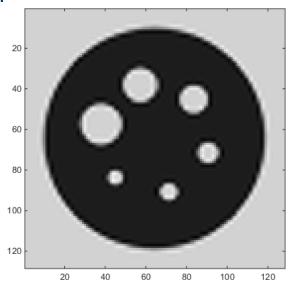


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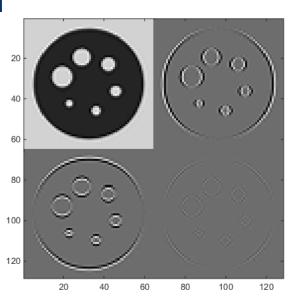


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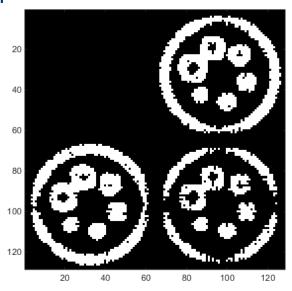


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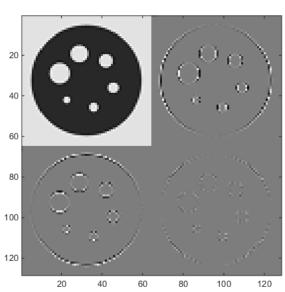
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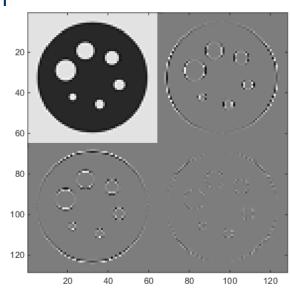


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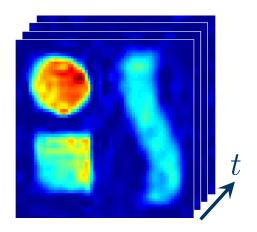
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ightharpoonup Set of percentages $\mathcal{P}=\{p_J,...,p_1\}$ to control the compression rate (CR)



 \triangleright N×N single image $f \rightarrow$ 2D+t stack of T images $f_1, ..., f_T$ of size N×N



$$\mathbf{F}_{1...T} = (\mathbf{f}_1, ..., \mathbf{f}_T) \in \mathbb{R}^{N^2 \times T}$$

Vector of time measurements directly obtained by the TR-SPC

$$\mathbf{m}_i^ op = \mathbf{p}_i^ op \mathbf{F}_{1...T}$$

$$\mathbf{m}_i^{\top} = \mathbf{p}_i^{\top} \mathbf{F}_{1...T}$$
 $\mathbf{m}_i = (m_{i,1}, ..., m_{i,T})^{\top} \in \mathbb{R}^{T \times 1}$

Prediction performed on the continuous-wave (CW) measures

$$m_i = \sum_{t=1}^{T} m_{i,t}$$



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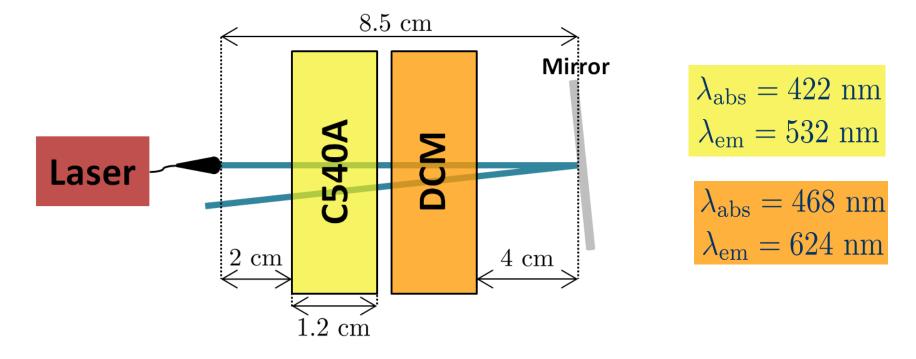
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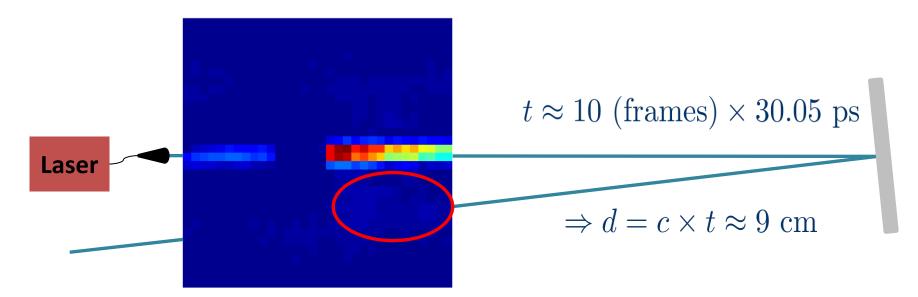
Cuvettes with different solutions of dyes (Coumarin 540A or DCM) in ethanol



- Illumination: wavelengths ranging from 455 to 485 nm with a 5 nm step
- Detection: long-pass filter at 500 nm (FEL0500, ThorLabs)



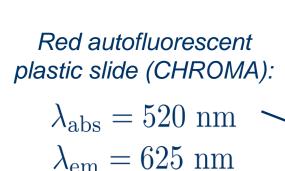
- High temporal resolution with a minimum of 3.05 ps per time channel
- ➤ In practice → binning of the time channels to reduce the noise influence
- > Acquisition of the cuvettes with a binning of 10 (30.05 ps per time channel):

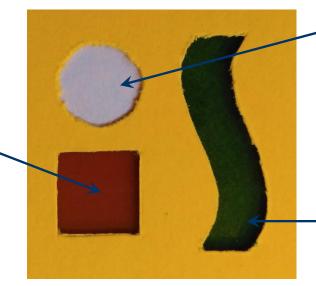


Ability to detect the laser beam travelling at the speed of light



Phantom with different fluorophores





Solution of DCM in ethanol:

$$\lambda_{\rm abs} = 468 \ {\rm nm}$$

$$\lambda_{\rm em} = 624 \text{ nm}$$

Green autofluorescent plastic slide (CHROMA):

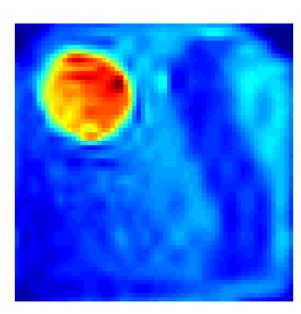
$$\lambda_{\rm abs} = 464 \text{ nm}$$

$$\lambda_{\rm em} = 525 \text{ nm}$$

- ➤ Illumination: 455 to 485 nm with a 5 nm step
- ➤ Detection: long-pass filter at 500 nm (FEL0500, ThorLabs)
- ightharpoonup T = 72 time channels: 0 to 21.66 ns (0.305 ns time step)



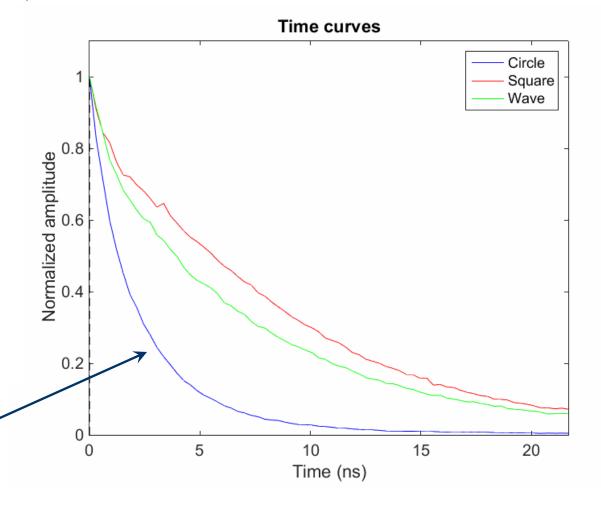
➤ Total of 72 images of size 64×64 acquired and restored with ABS-WP using Daubechies wavelet (Db5) with a **CR of 93** %:



SPC recovered stack

> Fluorescence decay

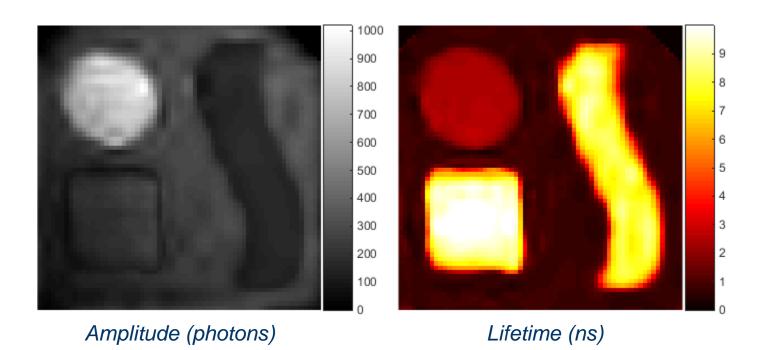
$$I(t) = Ae^{\frac{-t}{\tau}}$$





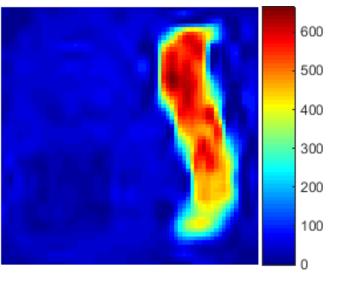
- > $I(t) = Ae^{\frac{-t}{\tau}}$ depicted by experimental curves $\hat{I}(t)$ for each pixel of the image
- ➤ Fitting of the model for each pixel → amplitude and lifetime maps

$$(A^*, \tau^*) = \arg\min \|\hat{I}(\mathbf{t}) - Ae^{\frac{-\mathbf{t}}{\tau}}\|_2^2$$

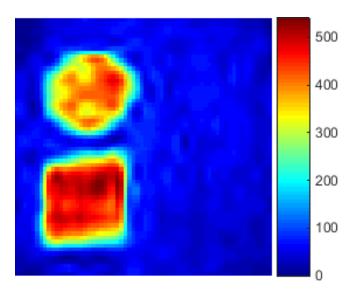




- New experimental setup: addition of a **grating** with $\Lambda = 16$ parallel detectors (*PML-16-1*, *Becker & Hickl GmbH*) \rightarrow possibility to obtain $\Lambda \times T$ images
- Images obtained with ABS-WP with the same parameters:







CW image for $\lambda = 625 \text{ nm}$

> Ability to discern the 3 fluorophores using the time and spectral information



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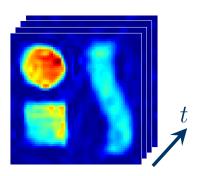
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- \triangleright Proposed system to acquire 2D + $t + \lambda$ images by a SPC:
 - Adaptive technique
 - Wavelet patterns
 - Bi-cubic interpolation prediction
 - Multiresolution approach



- Faster than CS for equivalent image quality [Rousset et al., IEEE TCI, in press, 2017] www.creatis.insa-lyon.fr/~ducros/single_pixel_imaging
- Efficient yet low cost (multispectral) time-resolved system, transposable on a microscope

> Perspectives

- Investigate prediction based only in certain time channels
- Method to divide the acquisition time by 2



CREATIS

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ANR-11-LABX-0063 / ANR-11-IDEX-0007



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Wavelet pattern creation

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

$$\mathbf{p} = \mathbf{W}^{-1}\mathbf{e}$$

$$\mathbf{W} \in \mathbb{R}^{P \times P}$$

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:

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



Computation times

➤ Average computation times (acquisition time excluded), 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