

#### **V POLITECNICO DI MILANO**

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## Time-resolved waveletbased acquisitions using a single pixel camera

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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



### Introduction > 1 – Single pixel camera



Single-pixel camera (SPC)

Two mirrors of 13.7 µm (Texas Instruments)

Landing Tip

Yoke

Digital micro-mirror device (DMD)

Mirror +10 deg

CMOS

Substrate

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

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#### ➤ Multi-dimensional acquisitions → management of huge datasets



Stack of time images



Stack of spectral images (Wikipedia)

- > Single pixel camera (SPC)  $\rightarrow$  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)

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Image of size  $N \times N$ : **f**  *I* patterns of size  $N \times N$ : **p**<sub>i</sub>  $\Rightarrow I$  measurements:  $m_i = \mathbf{f}^\top \mathbf{p}_i$ 

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

#### > Problems

- P1 Choice / design of the patterns p<sub>i</sub>
- P2 Restoration of the image **f** from the measures  $m_i$  knowing  $\mathbf{p}_i$

- Compressive sensing [Duarte et al., IEEE SPM, 25, 2008]
  - P1 Random ±1 Bernoulli variables (2)
  - P2 Restoration by  $I_1$ -minimization 🙁





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- Basis scan [Zhang et al., Nature Comm., 6, 2015]
  - P1 № patterns in a basis (Hadamard, Fourier, etc.)
  - P2 Chosen basis inverse transform (2)







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#### Hadamard pattern

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- Compressive sensing [Duarte et al., IEEE SPM, 25, 2008]
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- Adaptive basis scan [Dai et al., Applied Optics, 53 (29), 2014]
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    - $\rightarrow$  **Prediction** of the *I* patterns based on previous measures



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Introduction > 4 – State of the art

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1024×768 DMD (DLP7000-V7001, Vialux)

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- Adaptive approach in the wavelet domain
- One wavelet coefficient:
- $c = \mathbf{f}^\top \mathbf{p} \quad \Leftrightarrow \text{ one SPC measurement}$
- 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

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4-level wavelet decomposition 512 x 512

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10% of the strongest coefficients

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Restored image with 10% of the coefficients

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- 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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3 - 1-level wavelet transform



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#### > N×N single image $f \rightarrow 2D+t$ stack of T images $f_1, \ldots, f_T$ 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

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

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

Prediction performed on the continuous-wave (CW) measures

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



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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)

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- > High temporal resolution with a minimum of 3.05 ps per time channel
- > In practice  $\rightarrow$  **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



Red autofluorescent

 $\lambda_{\rm abs} = 520 \text{ nm}$ 

 $\lambda_{\rm em} = 625 \text{ nm}$ 

Solution of DCM in ethanol:

 $\lambda_{\rm abs} = 468 \text{ nm}$  $\lambda_{\rm em} = 624 \text{ nm}$ 

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)

 $\succ$  T = 72 time channels: 0 to 21.66 ns (0.305 ns time step)

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





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

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



Amplitude (photons)

Lifetime (ns)

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



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



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> 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

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### Rhône Alpes





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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:

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

**Computation times** 

Average computation times (acquisition time excluded), includes TVminimization 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