Intelligent signal processing and learning in imaging

Panos Tsakalides

Signal Processing Laboratory (SPL)

Institute of Computer Science (ICS)

Foundation for Research and Technology-Hellas (FORTH)

http://www.ics.forth.gr/spl/

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Overview

Introduction

- FORTH
- Signal Processing Lab

Signal Modeling

- Compressed Sensing
- Matrix Completion

Applications

- Active Range Imaging
- Hyperspectral Imaging
- Image Denighting
- High Dynamic Range Imaging

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Institute of Computer Science (ICS)	Institute of Molecular Biology and Biotechnology
Institute of Electronic Structure and Laser	Institute of Applied and Computational Mathematics
Institute for Mediterranean Studies	The Institute of Chemical Engineering Sciences

- FORTH-ICS has ranked *top* among all Greek ICT institutes.
- FORTH ranked 15th among all European RCs in FP7 signed grant agreements in terms of counts of participations for the period 2007-2012.
- From a total of 38 ERC grants awarded to scientists hosted at Greek institutions, one third are located at FORTH.

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Signal Processing Lab - Key personnel

Prof. P. Tsakalides, Head,
Statistical Signal Processing

Prof. A. Mouchtaris
Audio and Speech Processing

N. Stefanakis, PhD
Audio Signal
Processing

G. Tzagkarakis, PhD
Statistical Signal
Processing

A. Panousopoulou, PhD
Wireless Sensor
Networks

G. Tsagkatakis, PhD
Imaging
Technologies

SPL: Mission

Research in SPL aspires to be at the forefront of signal processing with fundamental work on the development of image, audio, and speech signal processing theory based on non-Gaussian statistics, sinusoidal modeling, sparse representations, and compressed sensing

During the past 5 years, SPL members have been active and productive in original research in 6 major axes:

1. Compressive sensing (CS) and its applications
2. Distributed signal processing for wireless sensor networks
3. Multichannel audio coding and transmission
4. Remote sensing/imaging
5. Non-Gaussian modeling and multiscale Bayesian processing for various signal modalities
6. Wireless network traffic modeling and location sensing

SPL at a glance

	2005-2012	2013 - today
Personnel (total current number)		21
Number of publications in refereed journals and proceeding of International Conferences (full paper reviewed)	167	56
Number of papers in other conferences (abstract reviewed)	4	1
Book chapters in collective volumes	9	3
Number of doctoral theses carried out in the Lab	10	6
Number of master theses carried out in the Lab	30	12
Number of patents and patent applications	5	3
Awards - Prizes - distinctions	8	2
National projects	7	1
European projects	7	3
Other projects	2	-
Incoming funds from projects	3.700.000 Euros	1.300.000 Euros
Incoming funds from services to third parties	203.000 Euros	-

SPL: Research and Technological Development Directions (1)

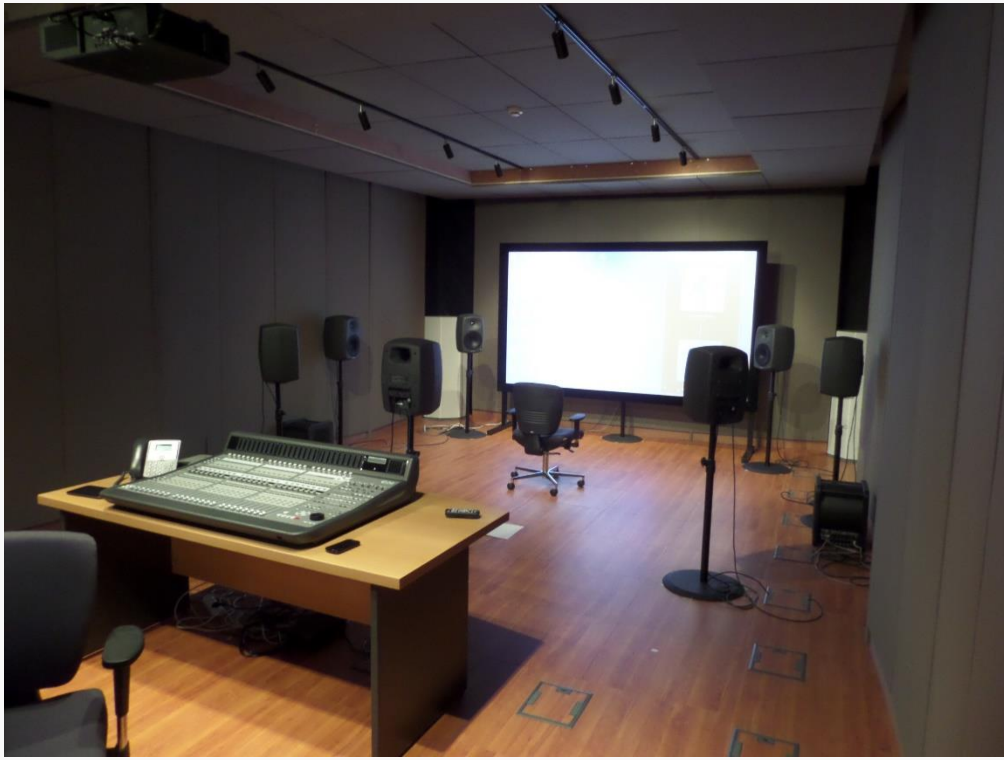
- Sparse signal processing and applications
  - Objectives: develop innovative signal processing algorithms based on the compressed sensing and matrix completion frameworks
  - Applications: audio & video coding, location sensing, remote imaging
  - Past & Present projects: PHYSIS, CS-ORION, ASPIRE
- Distributed signal processing for wireless sensor networks
  - Objectives: Collaborative detection, classification, and tracking, information fusion for intelligent learning and decision making
  - Past & Present projects: HYDROBIONETS
- Non-Gaussian modeling and Bayesian processing
  - Objectives: accurate characterization of the data statistics (e.g., using alpha-stable models). Subsequently, design of novel Bayesian algorithms
  - Applications: image retrieval, fusion, and watermarking; SAR image denoising and autofocus; underwater acoustic signal classification; and biomedical (ultrasound, microarray, miRNA) signal enhancement and classification
  - Past & Present projects: ASPIRE, PENED

SPL: Research and Technological Development Directions (2)

- Spatial sound acquisition and rendering
  - Objectives: develop innovative signal processing algorithms for the robust acquisition, low-bitrate transmission, and 3D rendering of any sound scene
  - Past & Present projects: AVID-MODE, MUSE, ENTER
- Audio signals analysis and modeling
  - Objectives: analyze and exploit properties of audio signals, for compression, sound source separation and enhancement, music analysis and retrieval
  - Past & Present projects: AVID-MODE, NONEUR
- Sensor networks for immersive environments
  - Objectives: capture and transmit audio content through multiple wireless sensors, so that immersive presence can be facilitated to any listener
  - Past & Present projects: ASPIRE, SeNSE

SPL: Infrastructure

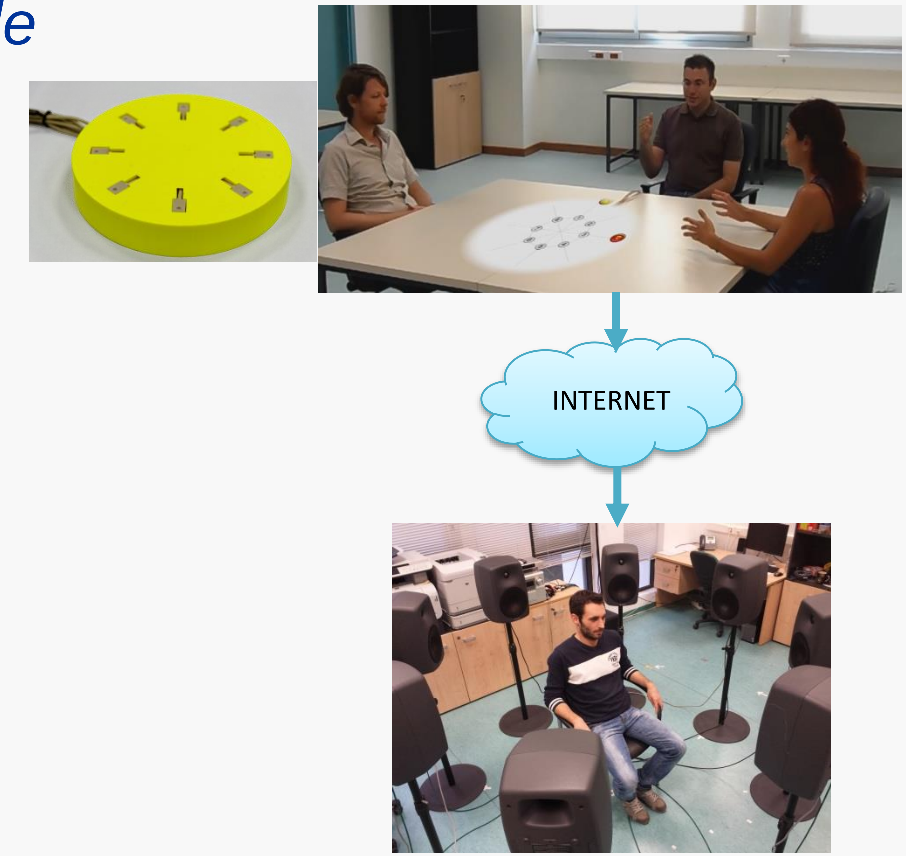
- Immersive Audio Facility
  - Contains 18 loudspeakers, professional studio recording/rendering equipment, cinema layout
  - Room-in-Room design for soundproofing, semi-anechoic
  - Follows ITU-R-BS.1116 for listening rooms
  - Completed April 2014.
- Surround sound equipment, specialized recording equipment, specialized processing platforms



SPL: Scientific & Technical Achievements

Spatial Audio Capture & Reproduction

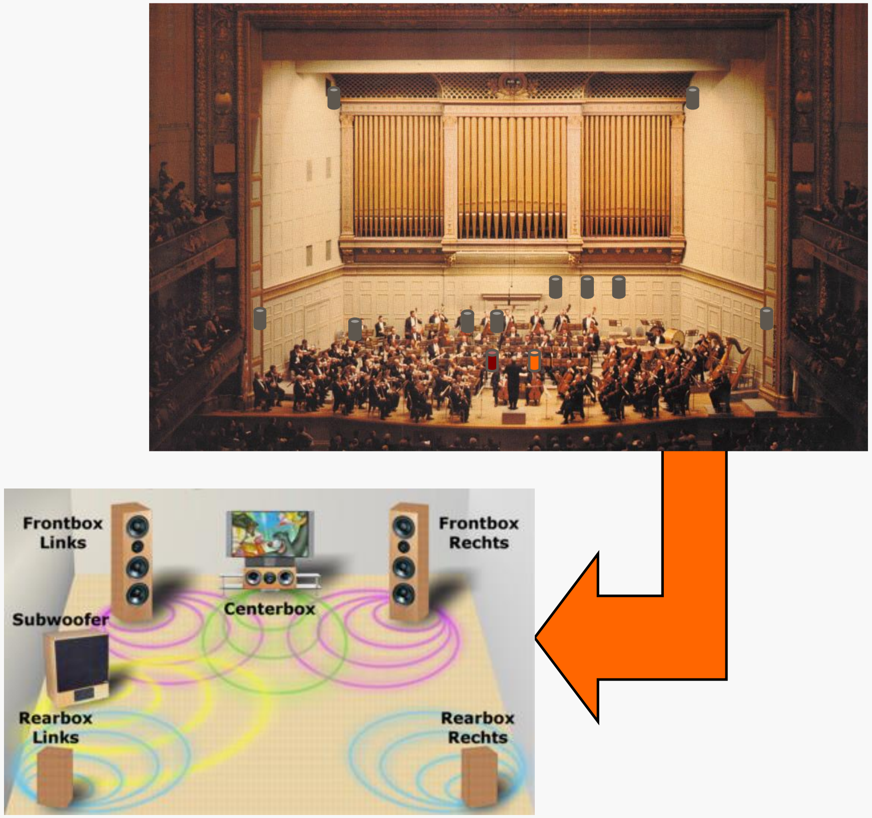
- Microphone arrays for *multiple sound localization*
- Robust counting of the simultaneous sources
- Real-time, low-resource indoor/outdoor operation
- Innovative *low-bitrate directional* coding scheme
- 3D interactive rendering
- 3 US patents pending
- http://www.avid-mode.eu/



SPL: Scientific & Technical Achievements

Audio Coding for Immersive Applications

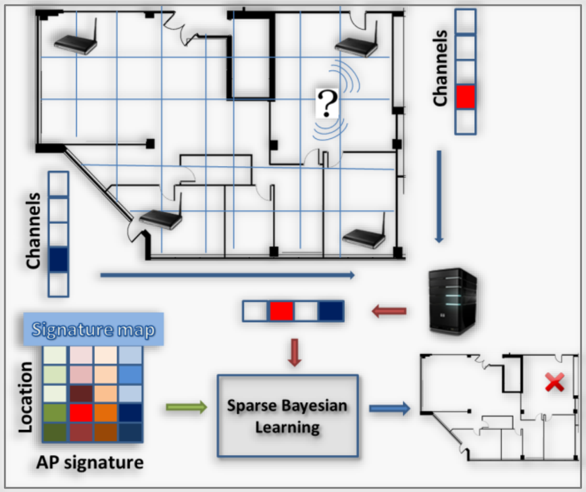
- Audio coding focused on immersive applications
- Low-bitrate audio coding for exploiting harmonic and sparse structure of audio signals
- Encodes the individual audio streams (vs. their mixed content) for interactive presentation at the decoder
- 2 US patents issued



SPL: Scientific & Technical Achievements

Indoor Location Sensing

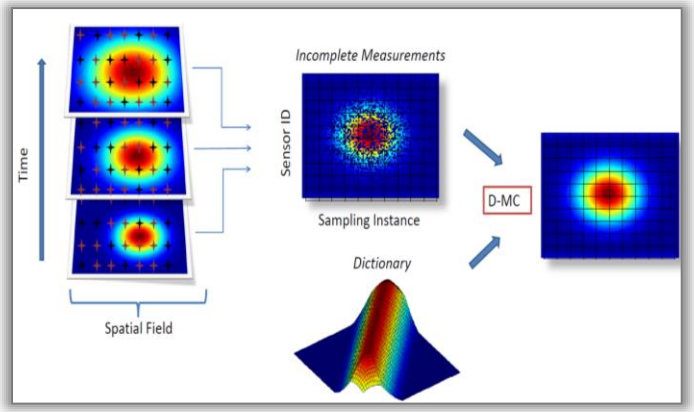
- Assisted living technologies can be aided by location information in order to provide context aware services
- Accurate indoors smartphone localization via the IEEE 802.11 infrastructure
- Efficient management of multiple communication channels
- Compressed fingerprint collection
- Dynamic update of the fingerprint map

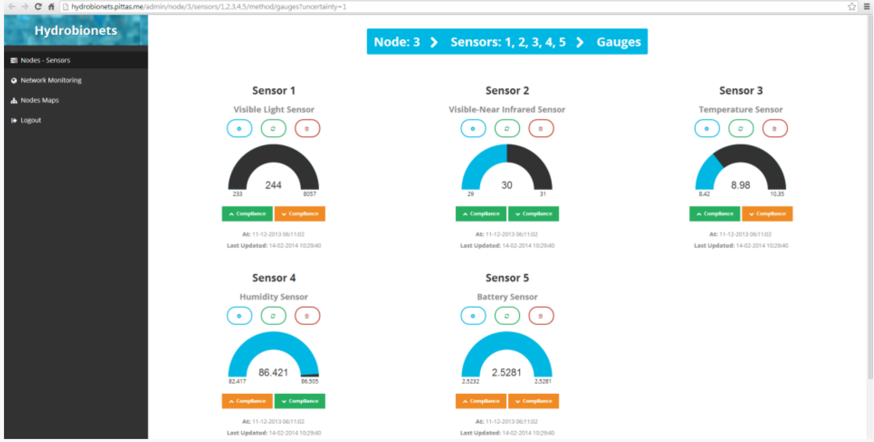


SPL: Scientific & Technical Achievements

Distributed Sensing Platforms in Industrial Environments

- Efficient sampling, storage and reconstruction of spatio-temporal fields via Matrix Completion
- Distributed network management services and cooperative parameters estimation



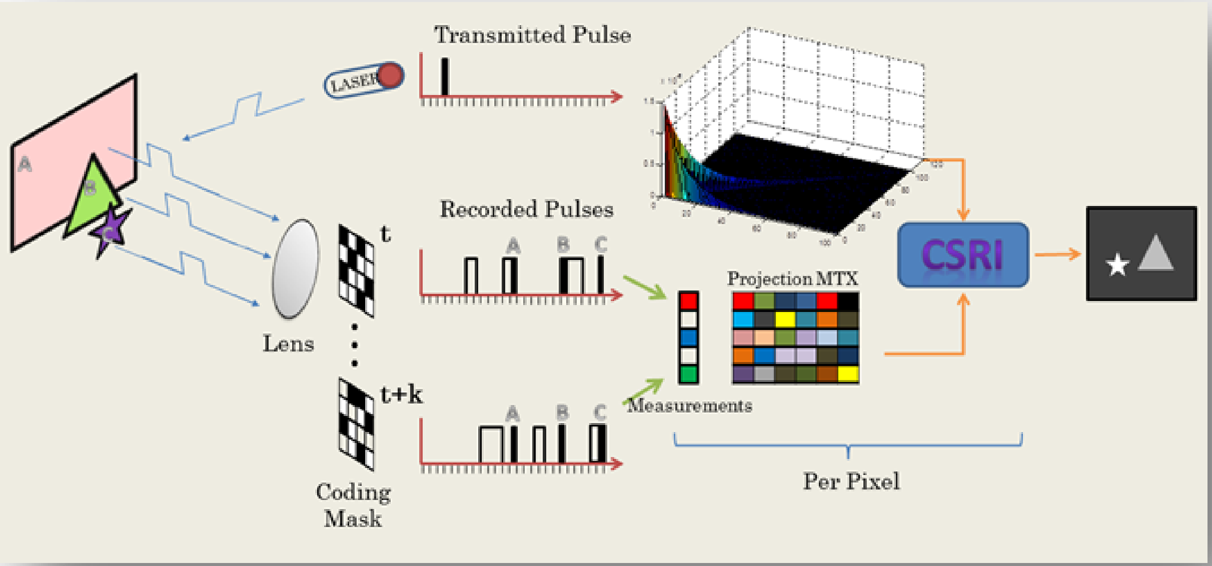


- Visualization of industrial processes and environmental conditions
- Uncertainty quantification and automated alerting
- http://www.hydrobionets.eu/

SPL: Scientific & Technical Achievements

Compressed Sensing Range Imaging

- Active range imaging systems are constrained by the need for a large number of frames in order to generate high resolution depth maps. Our proposed scheme utilizes computational tools in order to extract the same level of detail from a dramatically smaller number of frames
  - Low sampling rate
  - Random sampling pattern
  - Multiple reflection decoding



http://www.cs-orion.eu/

SPL: Impact

- International conference and workshop organization:
  - 1st International Workshop on Cyber-Physical Systems for Smart Water Networks (CySWater) in conjunction with CPS Week 2015. Seattle, April 13, 2015.
  - Winter School on Speech & Audio Processing for Immersive Environments - part of IEEE SPS Seasonal Schools in Signal Proc.
  - 5th Astronomical Data Analysis (ADA V) Conference (summer 2008)
- Since 2006, SPL was awarded the coordination of 3 prestigious Marie Curie Institutional grants (FP6 & FP7), each with a budget exceeding 1.2 M€
- International Dimension:
  - Active collaborations: CEA/Saclay, SAGEM (FR), U. of Valencia (ES), USC, Princeton (US), KTH (SE), Cidana (CN), U. Bristol & Essex (UK)…
  - International research group: 8 foreign postdoctoral fellows since 2006
- 5 US Patents (submitted and awarded)

SPL: Objectives and Prospects for the next 5 years

- Continue to conduct basic research based on the solid ground of Mathematical Signal Processing, i.e., the set of tools and algorithms from statistics and applied harmonic analysis, including signal transformations, sampling theory, and sparse representations

- In Cyber-Physical Systems (CPS), information gathering, processing and computing of massive amounts of data generated from and delivered to highly distributed devices (e.g., sensors and actuators) creates new signal processing challenges. We plan to address exciting emerging problems such as positioning, distributed compression, sampling, and big data processing

- Hyperspectral Imaging Systems: robust and adaptive mathematical methods, able to efficiently recover real-world hyperspectral data with specific constraints and noise/perturbation models which appear commonly in the field of surveillance/security imaging

SPL: Objectives and Prospects for the next 5 years

- Wireless Acoustic Sensor Networks (WASNs)
  - Achieve immersive presence in extended venues (attending a concert, emergency response, surveillance, …)
  - Extend our spatial audio and model-based/sparsity approaches
  - Focus on resource/energy constraints, collaborative processing
  - Very challenging problem, so far few practical deployments have been implemented for WSN-based multimedia streaming

- SPL will place emphasis in continuing its successful track record of attracting European R&D funding

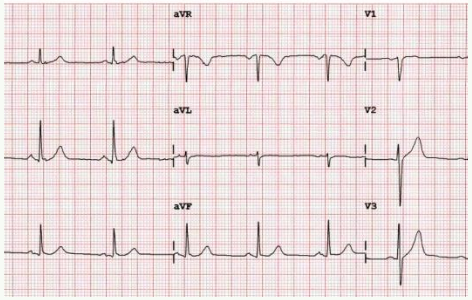
- SPL will actively seek to perform technology transfer to established as well as start-up companies in order to commercially exploit its mature technologies

Signal Processing Lab - projects

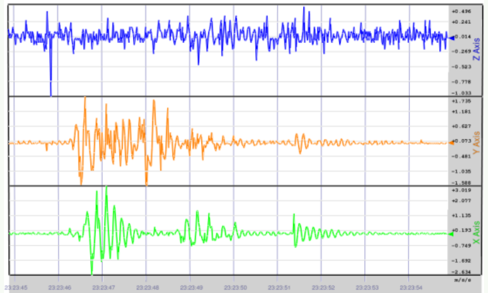
- **PHySIS**: *Sparse Signal Processing Technologies for HyperSpectral Imaging Systems*, H2020, *1.1 M€*, 2015-2017.
- **SeNSE**: *Wireless Sensor Networks for Dense Sampling and Replaying Events*, GSRT, *616 K€*, 2013-2015.
- **CS-ORION**: *Compressed Sensing for Remote Imaging in Aerial and Terrestrial Surveillance*, FP7, *1.2 M€*, 2010-2014.
- **HYDROBIONETS**: *Autonomous Microbiological Control of Water Quality based on Heterogeneous Self-Organized Wireless BioMEM Sensor and Actuator Networks*, FP7, *3.2 M€*, 2011-2014.

Signal Models & Properties

Sparse Signals



Biological



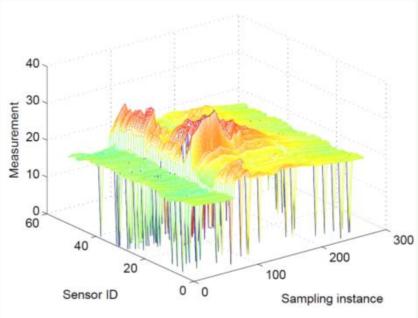
Environmental

Astronomical

Compressible Signals

Images

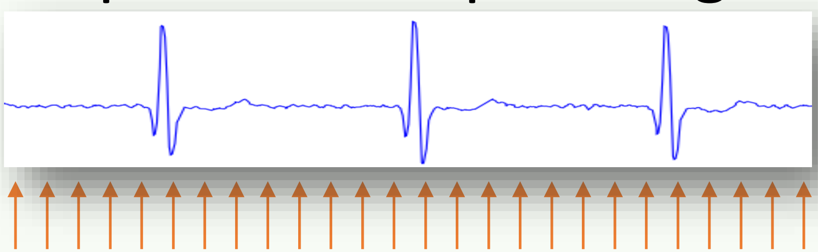
Sound



Cyber Physical

Classical Signal Sampling

Acquisition of sparse signals



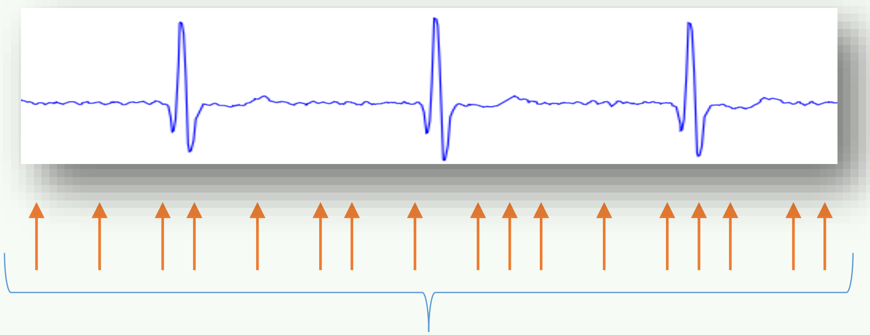
Nyquist–Shannon

Limitations

- Requirements: high quality and costly ADCs
- Power/battery: consumption due to sampling
- Storage/Bandwidth: more data than necessary
- Calibration: Sensor drift requiring recalibration

Compressed Signal Sensing

Acquisition of sparse signals



Compressed Sensing (CS)

CS projects the data in a space incoherent with the data's structure, so that the data can be recovered perfectly with a very low sampling rate under some sparsity assumptions (i.e., the data are sparse or compressible in a known dictionary).

$$\min \ \|\mathbf{s}\|_0 \quad \text{s.t.} \quad \mathbf{y} = \mathbf{\Phi}\mathbf{s}$$

$\| * \|_0$ is NP-hard

$$\min \ \|\mathbf{s}\|_1 \quad \text{s.t.} \quad \mathbf{y} = \mathbf{\Phi}\mathbf{s}$$

$\boldsymbol{s} \in R^n$ is $k - \mathit{sparse}$ if $\|\boldsymbol{s}\|_0 = k, \ \boldsymbol{y} \in R^m; \ m \ll n$

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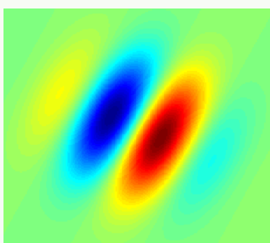
Compressed Sensing

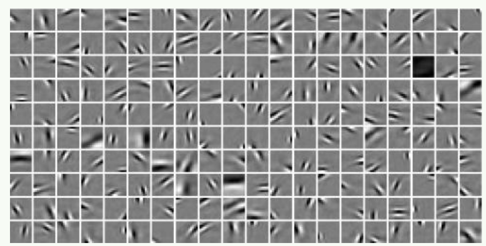
Restricted Isometry Property (RIP): Φ preserves the distance between any pair of k-sparse vectors.

$$(1-\delta_k)\|x\|_2^2 \leq \|\Phi x\|_2^2 \leq (1+\delta_k)\|x\|_2^2$$

Introduction of Dictionaries



Basis



Overcomplete

$$\min_{\mathbf{x}} \|\mathbf{x}\|_1 \quad \text{subject to} \quad \|\mathbf{y} - \mathbf{\Phi D x}\|_2^2 < \epsilon$$

$m > C\, k \log(n)$

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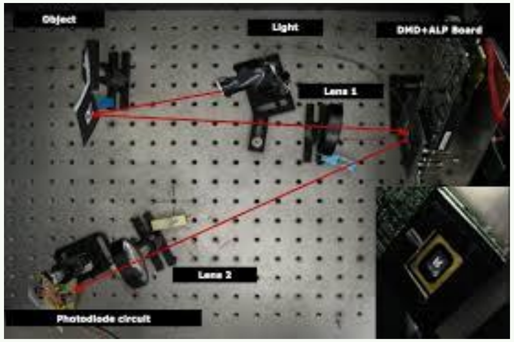
Compressed Sensing properties

- Fast, simple, and efficient compression/coding that is perfectly suitable for systems whose front-end has to run with minimal CPU load, memory, and power requirements.
- Fully linear compression that allows very efficient data fusion (*i.e.*, summing different reconstructed datasets to improve the signal to noise ratio), contrary to non-linear compression methods (*e.g.*, JPEG, MPEGx) that nearly prevent data fusion.
- Full decoupling between the compression/coding stage and the decompression/reconstruction stage, implying that the second stage can be continuously improved even if the first stage is fixed, and can also include priors to improve the reconstruction.
- Since the signal is projected on a random set of measurement vectors, what is transmitted is robust to bit losses that could happen in the case of usually adverse operating remote sensing environments.
- Compressed sensing measurements can be viewed as "weakly encrypted" for an attacker without knowledge of the measurement matrix.

Compressed Sensing in Imaging

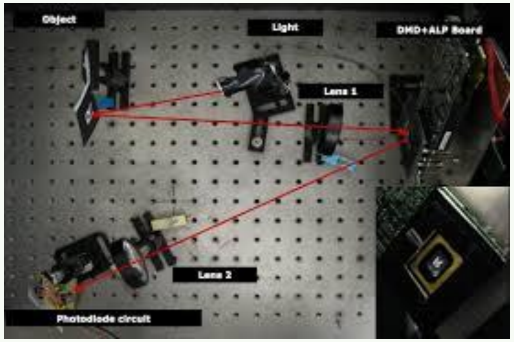
Single Pixel Camera, Rice 2011



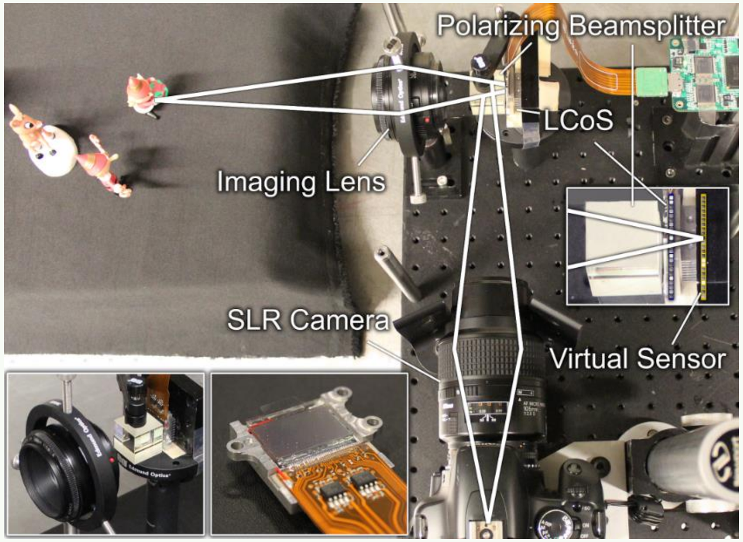
- Directly acquires random projections of a scene without first collecting the pixels/voxels
- The camera architecture employs a digital micromirror array to optically calculate linear projections of the scene onto pseudorandom binary patterns.
- Its key hallmark is its ability to obtain an image or video with a single detection element (the "single pixel") while measuring the scene fewer times than the number of pixels/voxels.
- Since the camera relies on a single photon detector, it can also be adapted to image at wavelengths where conventional CCD and CMOS imagers are blind.

Compressed Sensing in Imaging

Single Pixel Camera, Rice 2011



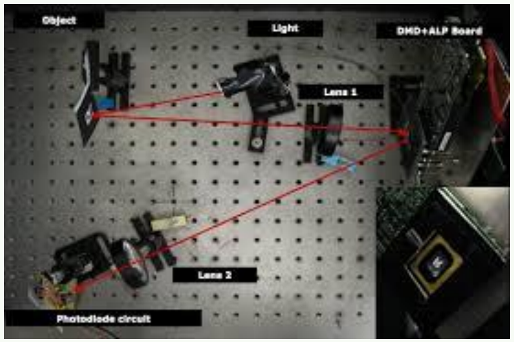
Coded Light Field Cameras, MIT 2013



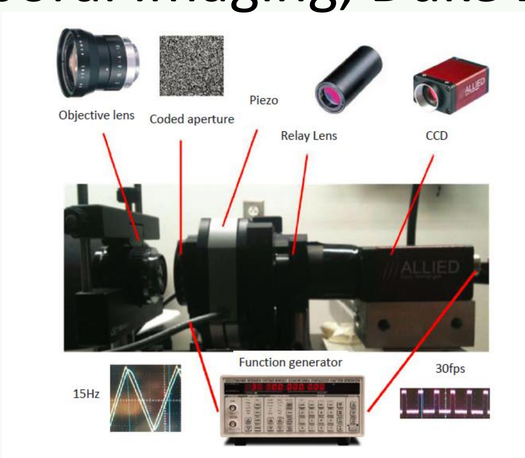
- The compressive light field camera allows for higher-resolution light fields to be recovered than previously possible from a single image.
- The architecture comprises three key components:
  - ➢ light field atoms for a sparse representation of natural light fields
  - ➢ an optical design that allows for capturing optimized 2D light field projections
  - ➢ robust sparse reconstruction methods to recover a 4D light field from a single coded 2D projection.

Compressed Sensing in Imaging

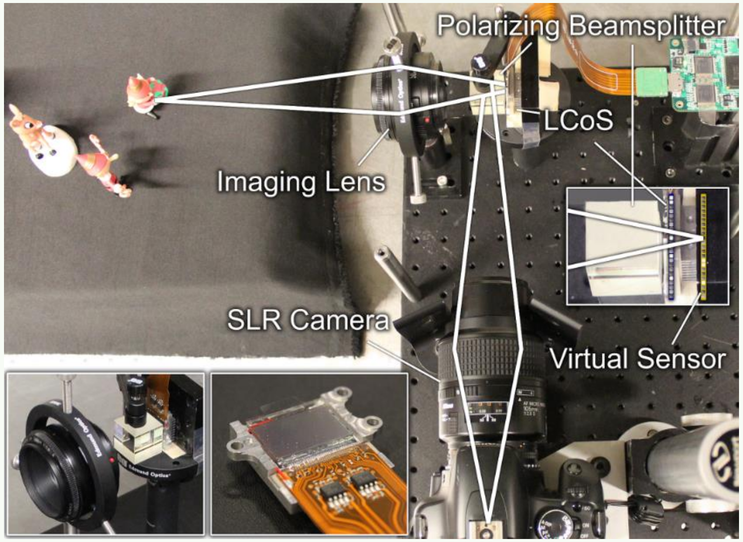
Single Pixel Camera, Rice 2011



Coded Aperture Compressive Temporal Imaging, Duke 2013



Coded Light Field Cameras, MIT 2013

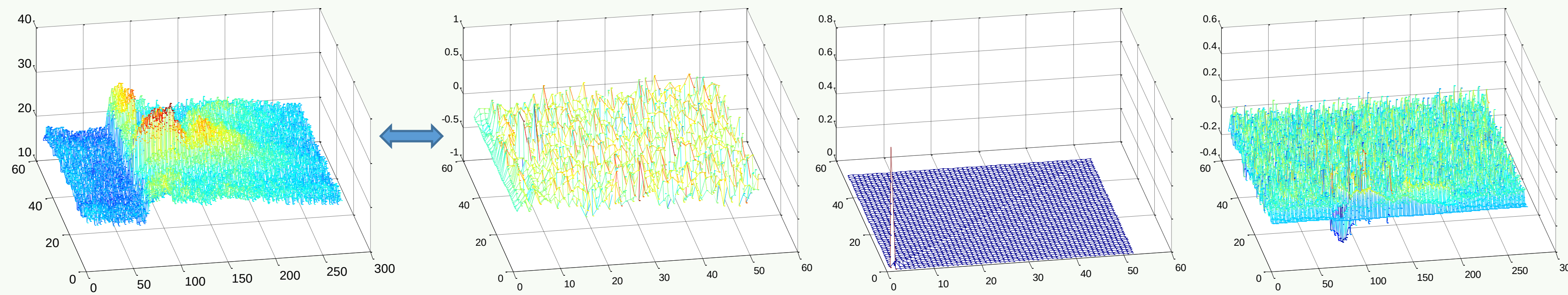


Mechanical translation of a coded aperture for code division multiple access compression of video.

Sparsity of Singular Values

Measurements matrix $\mathbf{X} = [X_0, ..., X_1] \in R^{n \times s}$

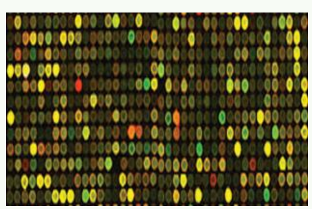
Singular Value Decomposition



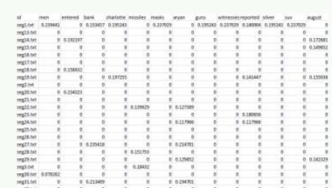
$$\mathbf{X} = \mathbf{U} \quad \mathbf{S} \quad \mathbf{V}^T$$

Correlations $\leftrightarrow$ Low Rank $\leftrightarrow$ Sparse Singular Values

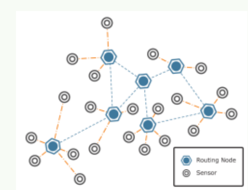
Imaging
(HDR, video inpainting)



Biological
(genome
expression)



Machine
Learning
(rec. engines)



Sensor Networks
(spatio-temporal
sampling)

Matrix Completion

Sampling $$A_{ij}(\mathbf{M}) = \begin{cases} M_{ij}, & \text{if } ij \in S \\ 0, & \text{otherwise} \end{cases}$$

Recovery of **X** is possible from *k<<ns* random entries if matrix **X** is *low rank, r,* and $k \geq Cn^{6/5} r log(n)$

To recover the unknown matrix, solve:

$$\boxed{\min\{\ rank(\mathbf{M}) \ : \ \mathcal{A}(\mathbf{X}) = \mathcal{A}(\mathbf{M})\}}$$

$$\|\mathbf{X}\|_* = \sum \lambda_i$$

$rank$ is NP-hard

$$\boxed{\min\{\ \|\mathbf{M}\|_* \ : \ \mathcal{A}(\mathbf{X}) = \mathcal{A}(\mathbf{M})\}}$$

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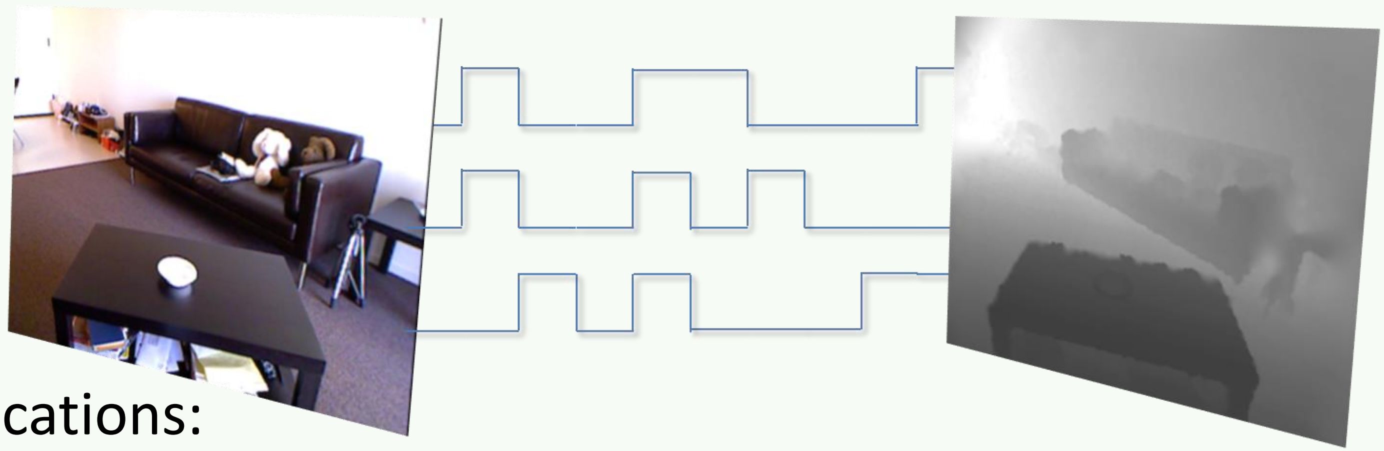
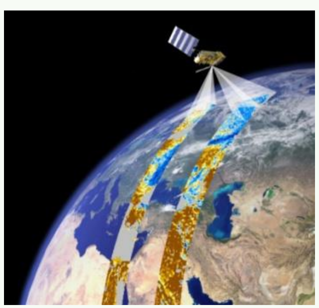
Range Imaging

- Generate a 2D depth map of a scene. Produce a 2D image showing the distance to objects in a scene from a specific point.



- Applications:



Remote Sensing: Altimetry, archeology, geology

Human-Computer Interface: Gaming, Kinect

Consumer photography: 3D photo acquisition

Range Imaging: state-of-the-art

	Stereo	Structured Light	Depth-from-Defocus	ToF
Depth map quality	High	Medium	Low	High
Hardware requirements	Multiple cameras	Projector-camera	Relative motion	Laser-camera
Setup	Disparity	Indoors	Multiple Frames	None
Portability	Low	High	High	High
Illumination sensitivity	High	High	High	Low
Processing complexity	High	Medium	Medium	Low
Resolution	High	Medium	Medium	High

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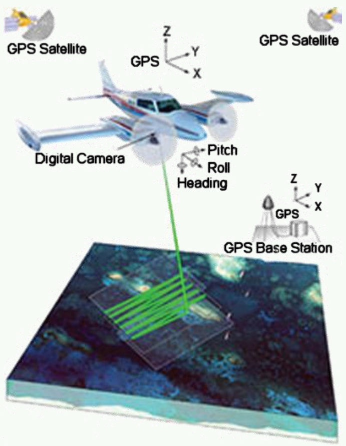
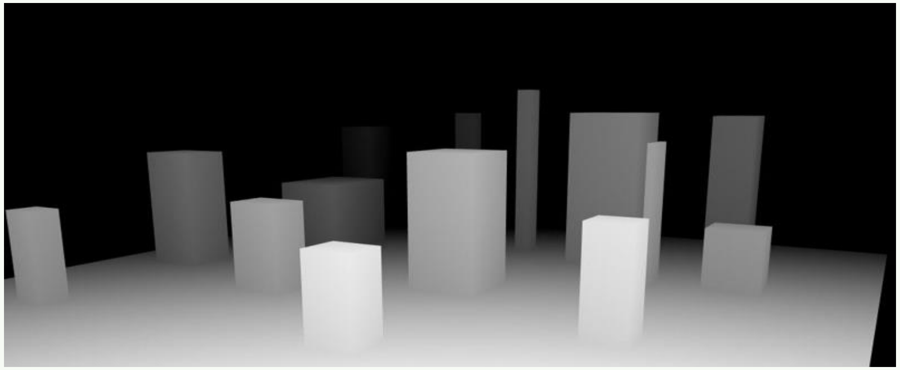
ToF Cameras

- Measure the absolute time that a light pulse needs to travel from a light emitter to a targeted object and back to a detector
- Constant speed of light/sound/RF
- LIght Detection And Ranging (LIDAR)
- Characteristics
    - ➢Direct measurement
    - ➢Limited influence on the environment
    - ➢High accuracy time measurements
    - ➢**Large number of frames necessary**





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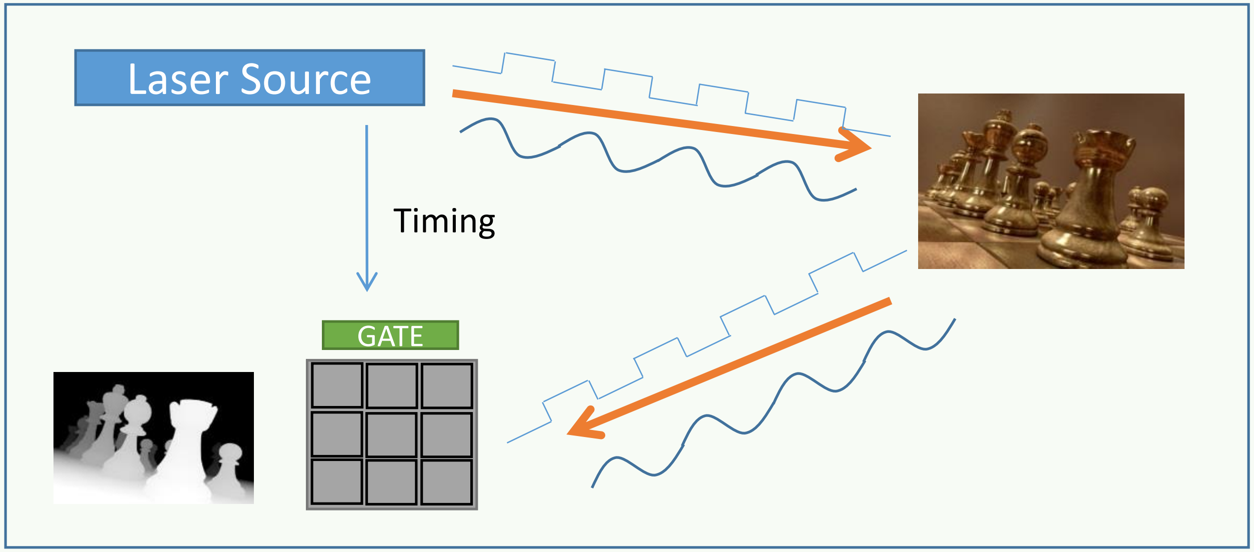
Gated Range Imaging

Process	Techniques
➢ Emit light	• Time Slicing - Classical
➢ Encode reflection	• Gate Coding - Deterministic
➢ Extract depth	• Compressed Sensing

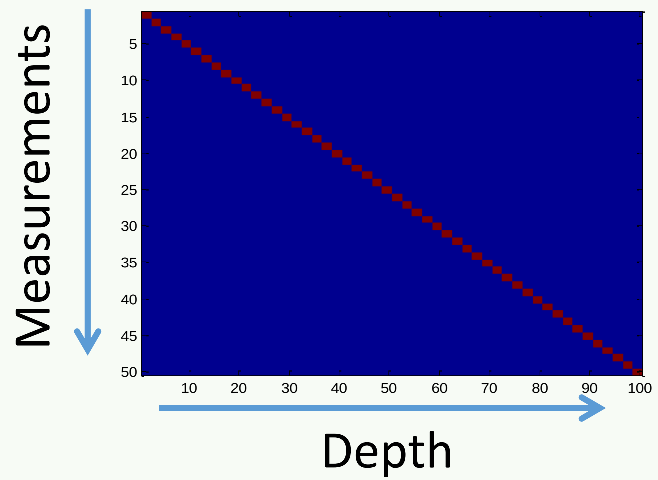


Active Range Imaging

Time Slicing (TS)

- Single depth per image
- Baseline approach
- Single object

$$Z = max(m_0, m_1, ..., m_k)$$

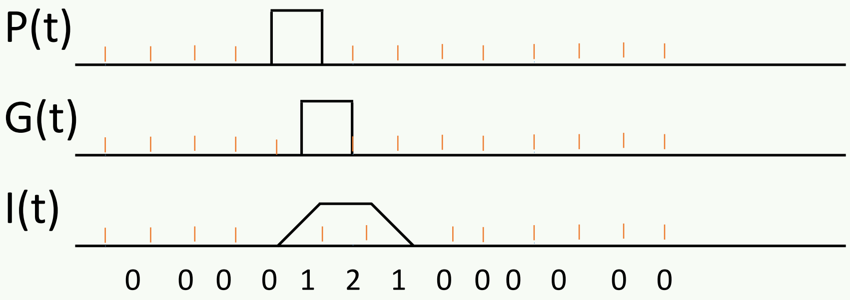


- Each frame encodes a specific distance range by opening and closing the gate during the corresponding interval.
- Benchmark method for depth extraction via GRI: The resolution of the depth map (number of depth bins) is directly proportional to the number of captured frames since each frame encodes depth information from a specific range only.
- <u>Drawback</u>: waste of resources due to the acquisition of a large number of "empty frames", that is, frames that do not capture any reflected pulse.

Active Range Imaging

Gate Coding (GC)

- Exploit pulse and gate rectangular profiles.
- Enhanced coding: the detector is capable of recording three distinct values, 0 for no signal, 1 for a plateau, and 0.5 for a rising or falling edge.
- Super-resolved depth map estimation: the three values produce a constrained ternary code, able to encode $3^n - 2^{n+1} + 1$ valid combinations in *n* images.



The intensity of a single pixel corresponding to an object at distance z_k, or equivalent time t_k, is given by the convolution of the laser pulse profile and the gate profile.

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Why Compressed Sensing

Classical range sampling is limited by the Nyquist-sampling theorem: Depth resolution is limited by the sensor gate delay step size.

Limitations of Classical imaging

- Large number of frames required: resolution?
- Single depth per pixel: transparent objects, foliage smoke fog?
- Robustness to natural phenomena/noise?

Compressed Gated Range Sensing

- Range information is a sparse signal and only a small number of returns are expected for each pixel.
- CS-based imaging samples multiple ranges at the same time with a certain weighting (pseudorandom or coded sampling)

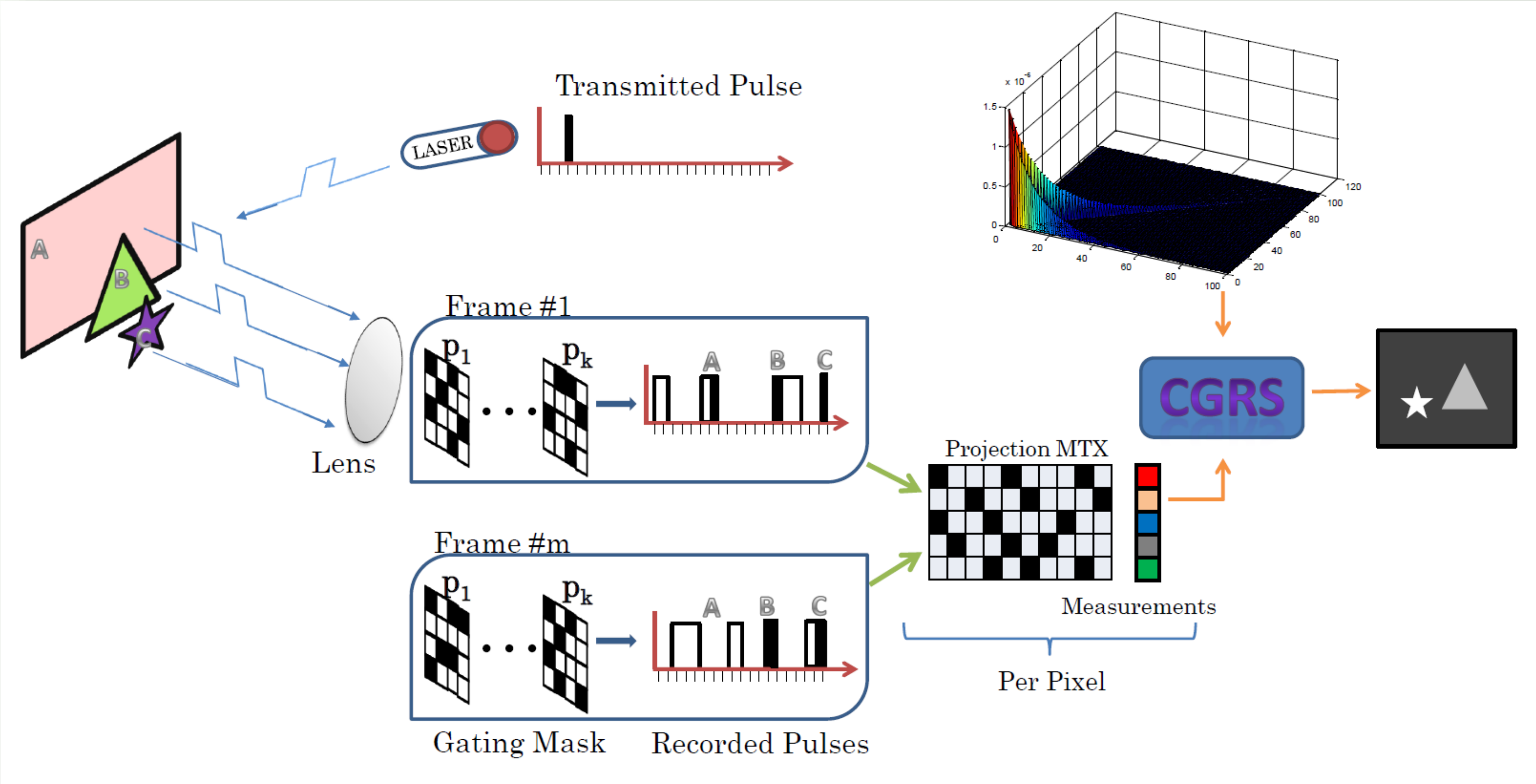
Compressed Gated Range Sensing (CGRS)

High depth resolution comes at the cost of a large number of frames: *r* = acquired #frames / requested #bins.

CGRS:

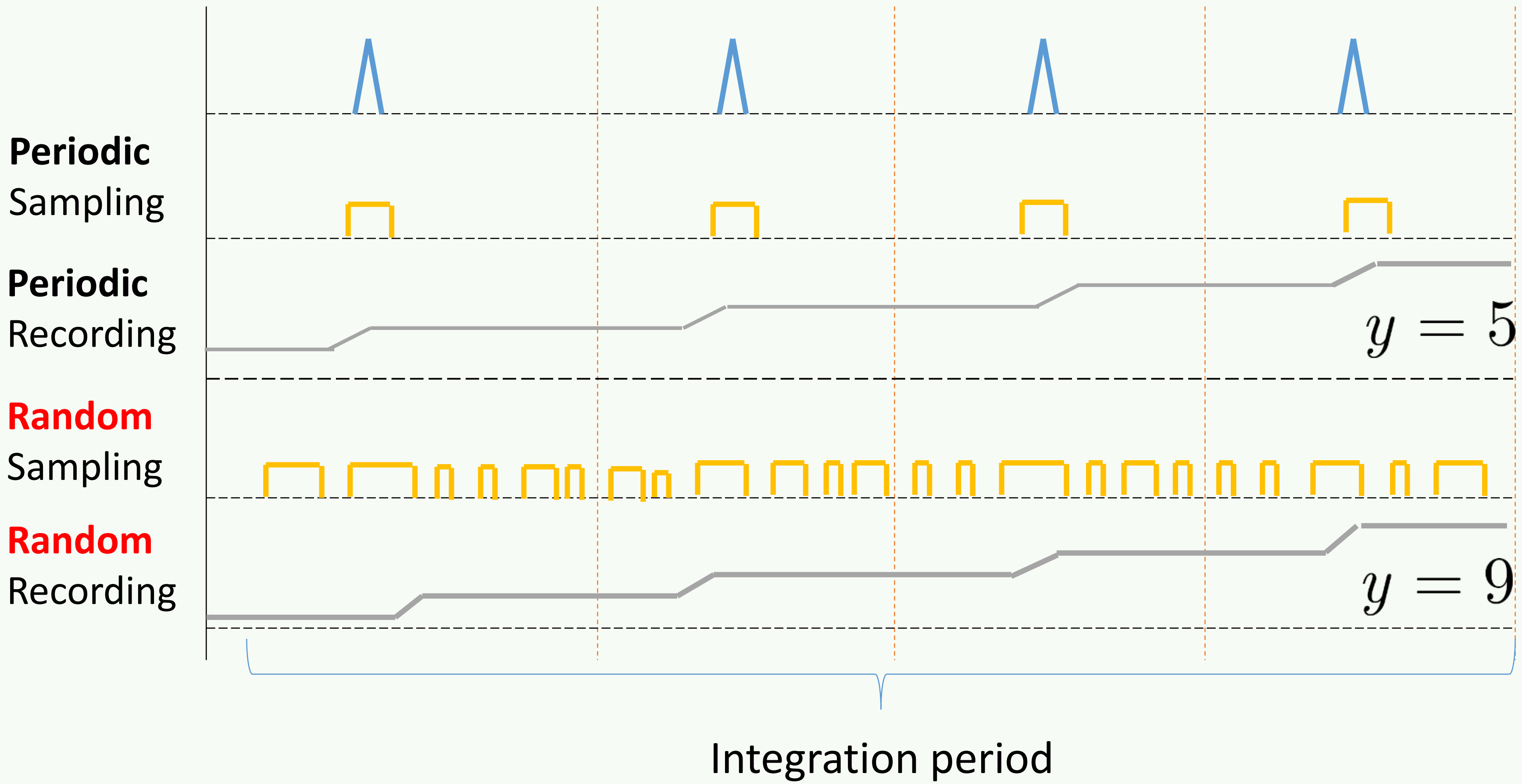
- requires a significantly smaller number of frames for a specific depth resolution.
- offers the capability of capturing multiple reflected pulses at each sensor element.
- relies on electronic multiplexing of the depth signals and not on mechanical interaction, e.g., rotating mirrors.
- exploits prior knowledge concerning the imaging conditions by introducing an appropriately designed dictionary.

The CGRS System



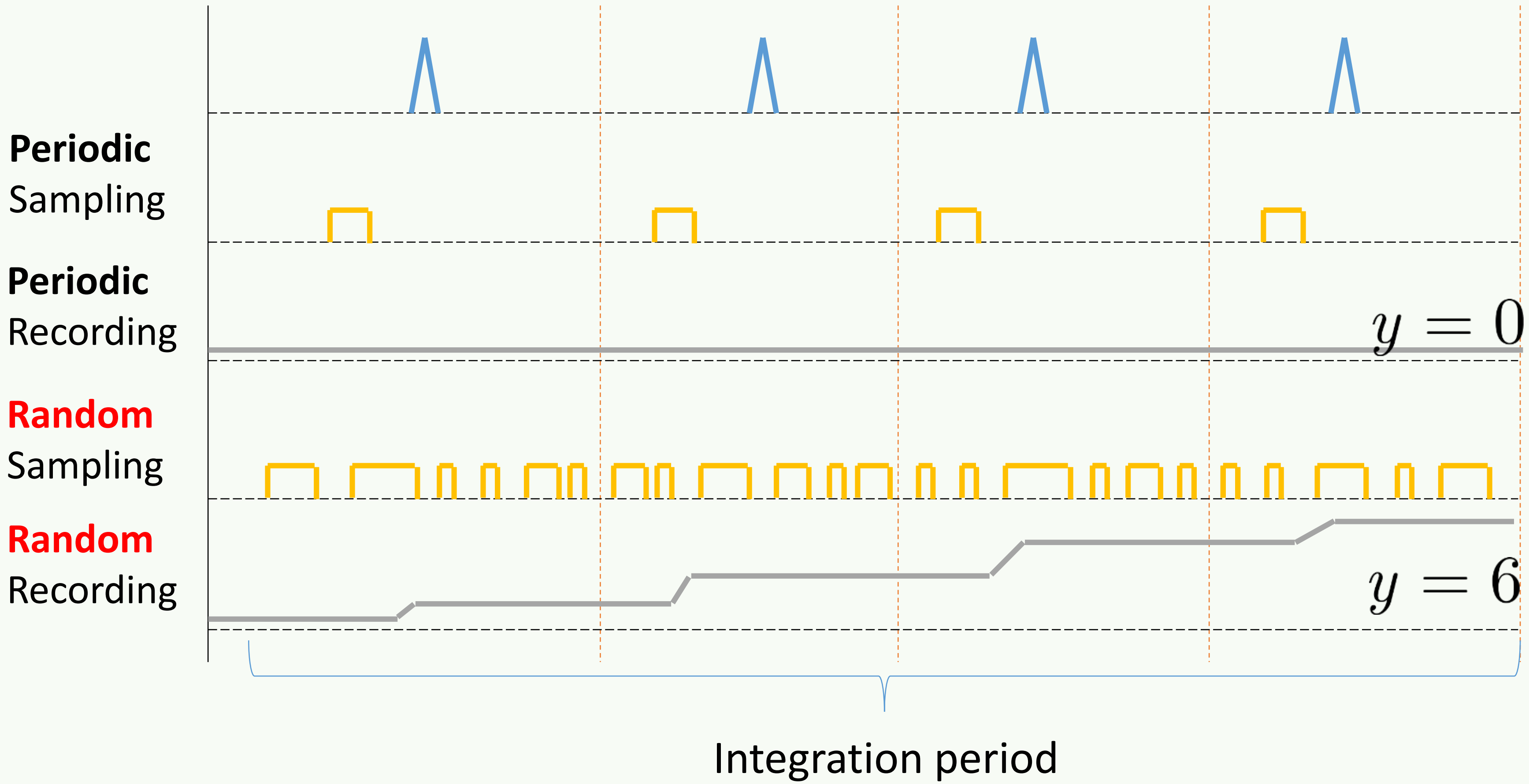
- At a specific time instance, a laser source transmits a pulse which propagates through the medium and is reflected back by objects in the scene, resulting in multiple reflected pulses, each one arriving at a different time instance (proportional to the traveled distance).
- An optical lens focuses the reflected pulses on a gating device which implements a coding mask for each pixel, corresponding to a random sampling of the reflected pulses.
- Knowledge of the projection sequences and prior knowledge in the form of a dictionary are exploited by CGRS to recover the depth signals.

- 1^{st} row: returning laser pulse after it has been reflected by the object.
- 2^{nd} & 4^{th} rows: periodic and random gating functions. Periodic sampling follows a canonical pattern of leaving the gate open, while the proposed random gating opens and closes the gate multiple times within the integration time.
- 3^{rd} & 5^{th} rows: captured signal.



- Target happens to be at a range where both the periodic and the random gating functions are able to record energy from the returning laser pulse.

- misalignment between the returning pulse and the periodic gating results in an all-zero captured signal by periodic sampling.
- the proposed random sampling is still able to record a valuable signal.
- the recorded energy by the random gating method can be used to infer the location of the target and to estimate its distance.



System model: Depth signal

- Depth signal is modeled as a delta at time=depth

$$\mathbf{S}_{init}(z) = \delta(t - \frac{2z}{c}) = \delta_\tau \quad \text{where} \quad \tau = \frac{2z}{c}$$

- Backscatter effect

$$\mathbf{S}(z) = \delta_\tau + c\mathbf{I}$$

- Atmospheric atten.

$$\mathbf{A}(z) = e^{\left(\frac{-2z}{\alpha}\right)}$$

- Divergence

$$\mathbf{d}(z) = \frac{1}{z^2}$$

- Ideal Gate/Pulse Modeling

$$\mathbf{G}_{ideal}(t) = \sum_{k=1}^{P} \Pi(t + t_k)$$

- Real Gate/Pulse Modeling

$$\mathbf{G}(t) = \mathbf{G}_{ideal}(t) * \mathbf{F}(t)$$

$$\mathbf{F}_G(t) = e^{\frac{t}{t_{gate}}} \cdot (t \geqslant 0)$$

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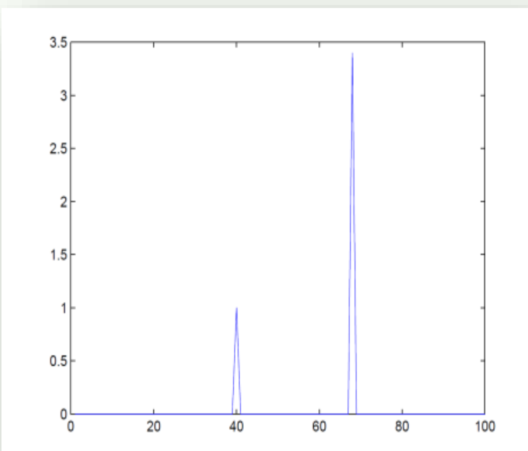
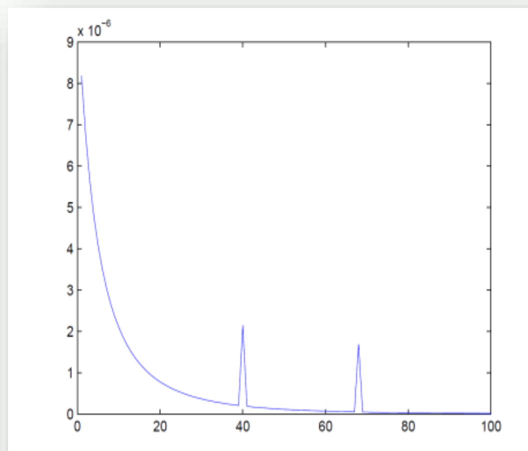
CGRS – Use of a Dictionary

- Due to the various effects of the imaging process, the natural sparsity of the signals can be lost.
- A <u>dictionary of elementary examples</u> is used as a sparsifying transform.
- We employ the fact that the signal can be sparsely represented in an appropriately designed dictionary.
- The use of prior knowledge regarding the physical process allows us to utilize the representational power of dictionaries to improve the depth signal recovery.

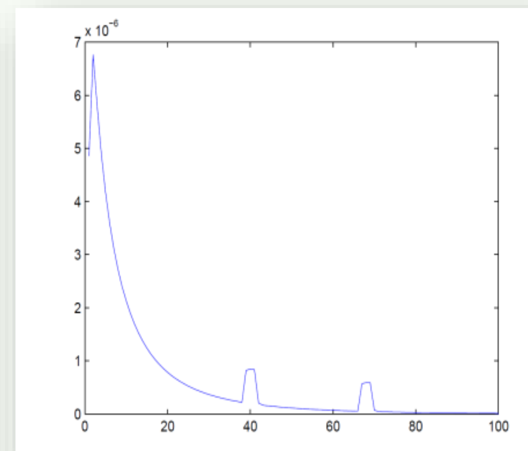
Ideal depth signal



Signal after propagation



Signal after gating



CGRS – Dictionary Construction

- **D** = [**I 1**] x A(z)d(z)
- Identity matrix, ***I***, is responsible for encoding the ideal depth signal.
- The unit vector, ***1***, encodes the effects of backscattering.
- A(z) & *d(z)* account for the effects of divergence and attenuation.

$$\begin{aligned} &\min \|\mathbf{s}\|_1 \\ &\text{s.t.} \quad \|\mathbf{y} - \mathbf{GDs}\|_2 \leq \epsilon \\ &\qquad\quad s \geq 0 \end{aligned}$$

Basis Pursuit Denoising

- The sensing matrix, ***G***, is composed of binary valued entries.
- The non-negativity constrain accounts for the fact that the signals in question have a direct physical interpretation as the acquired energy.

Simulation results

LIDAR data from Mt. St. Helens

Two scenarios

- Single surface mapping
- Two surfaces mapping (semi-transparent)

Methods

- Time Slicing
- Gate Coding
- CGRS

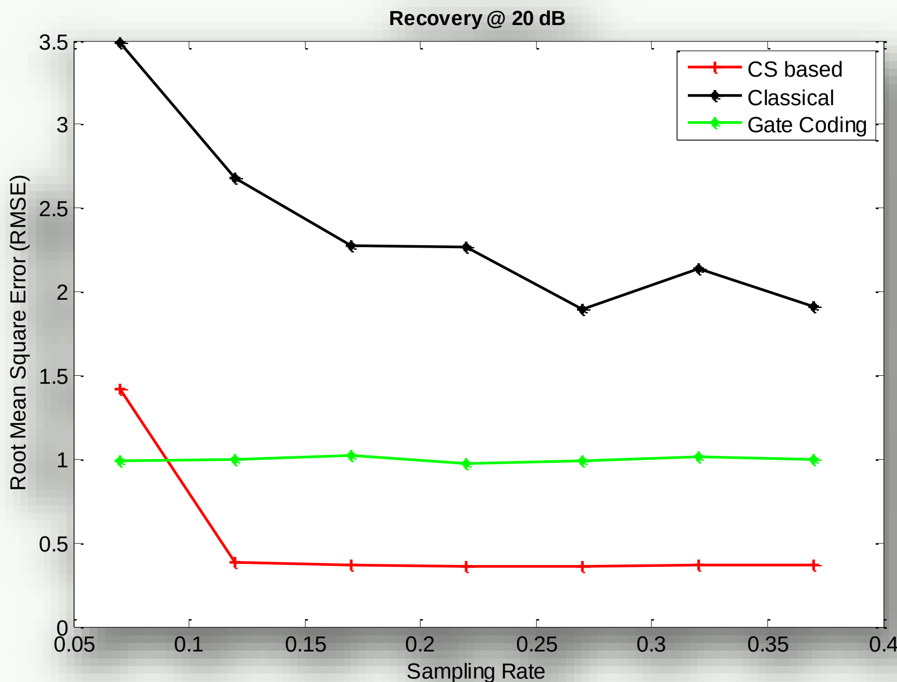
Evaluation

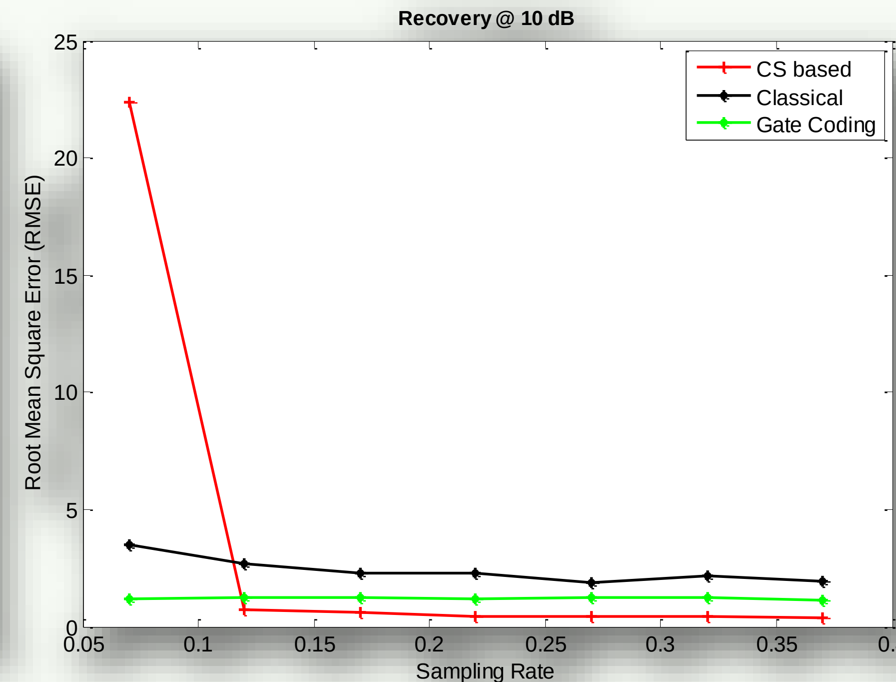
- Recovery w.r.t. #acquired frames
- Recovery in noisy conditions

Simulation results

- Depth information in the range from 500 m to 2.5 Km was captured with a depth resolution of 20 m/bin.
- The camera gating for the CGRS varied between 100 and 400 ns while the pulse duration was set to 100 ns.
- Varying noise conditions
- Varying sampling rate

Single Reflection Recovery





- CS exhibits "sharp phase transition," where recovery is impossible without sufficiently many measurements, while as soon as the number of measurements becomes adequate, error-free recovery can be achieved almost instantly.
- GC requires a very small number of frames for decoding the depth signals, but reconstruction is not improved by increasing the sampling rate.
- CGRS and GC show a robust behavior, in contrast to the classical TS approach.

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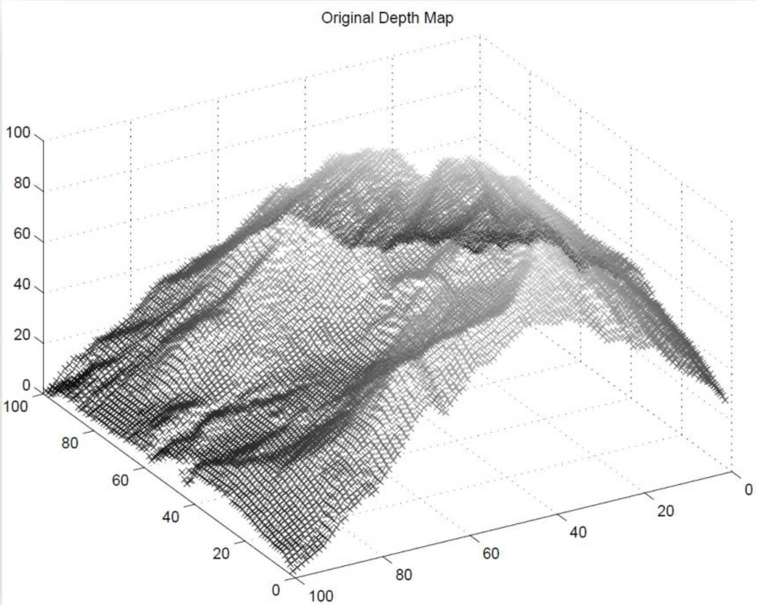
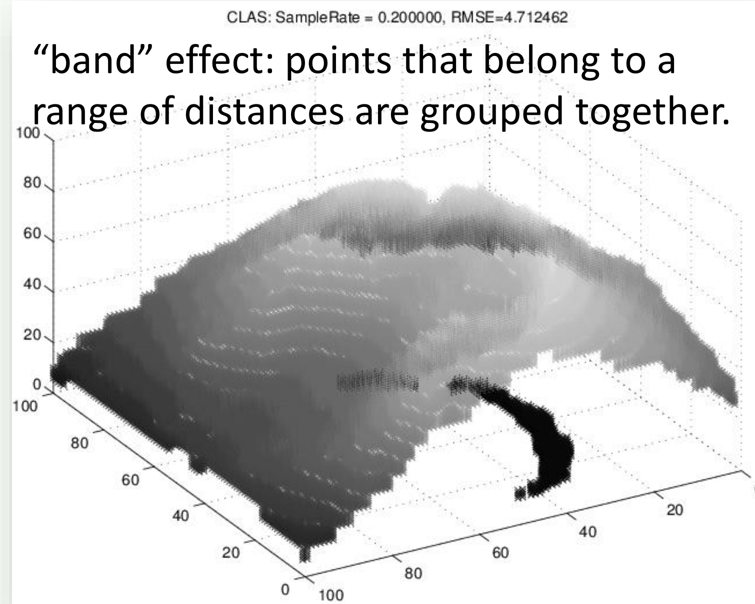
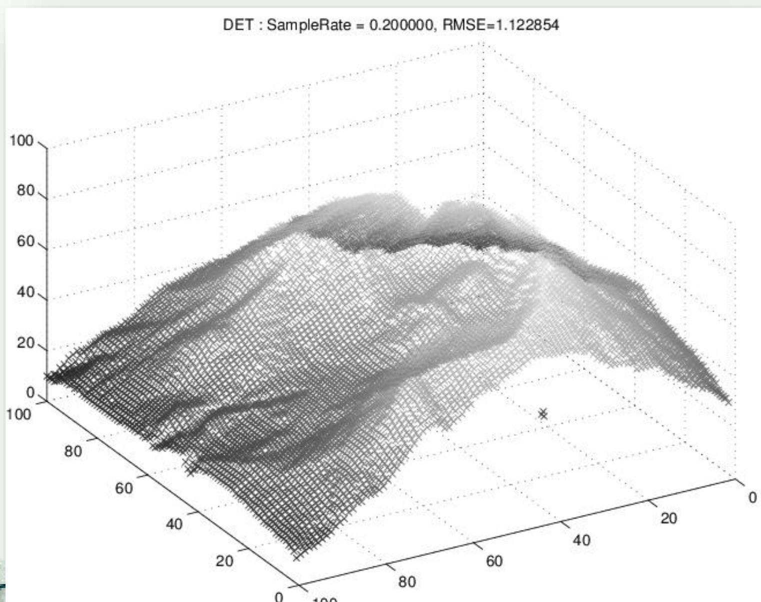


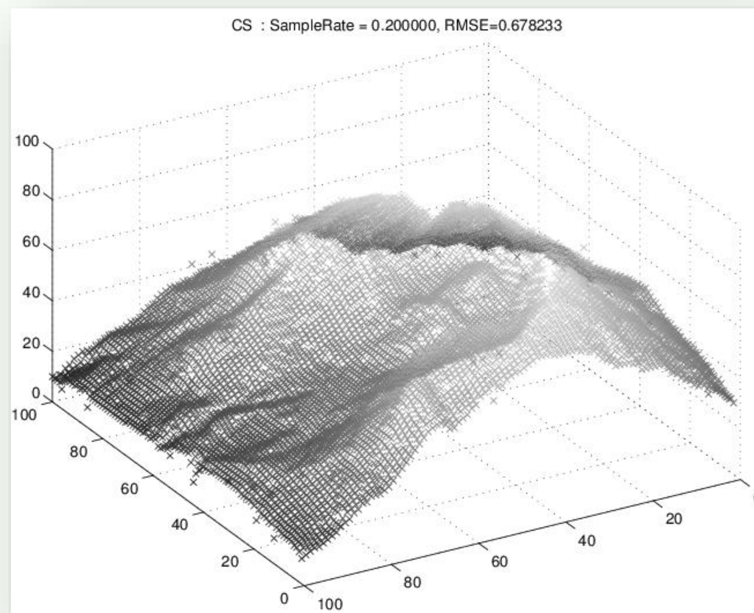
Original



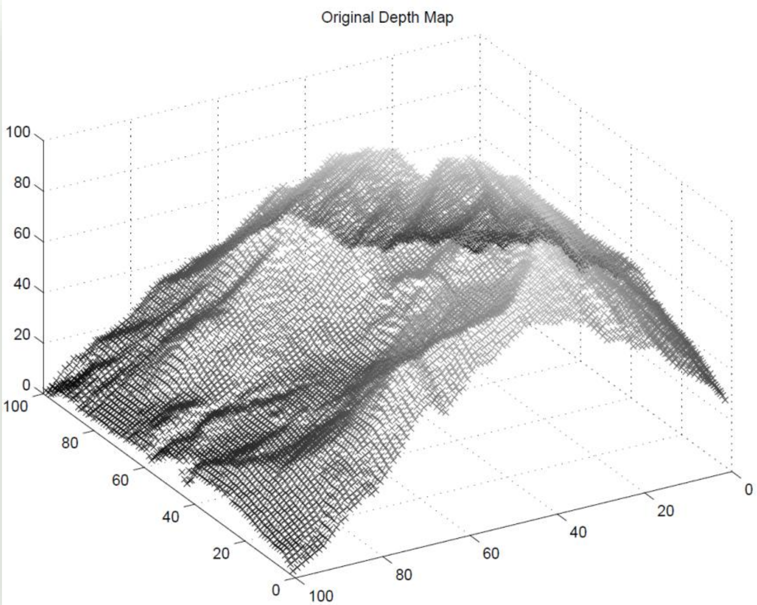
TS, RMSE=4,71



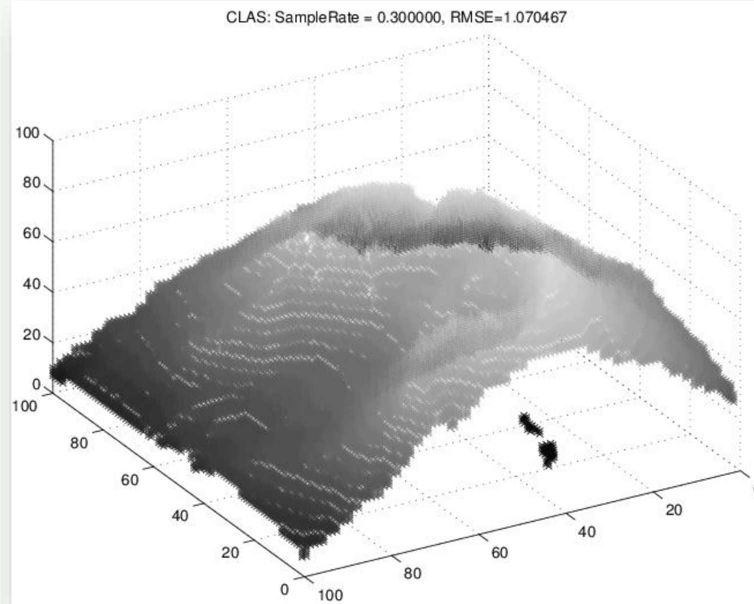
GC, RMSE=1,22



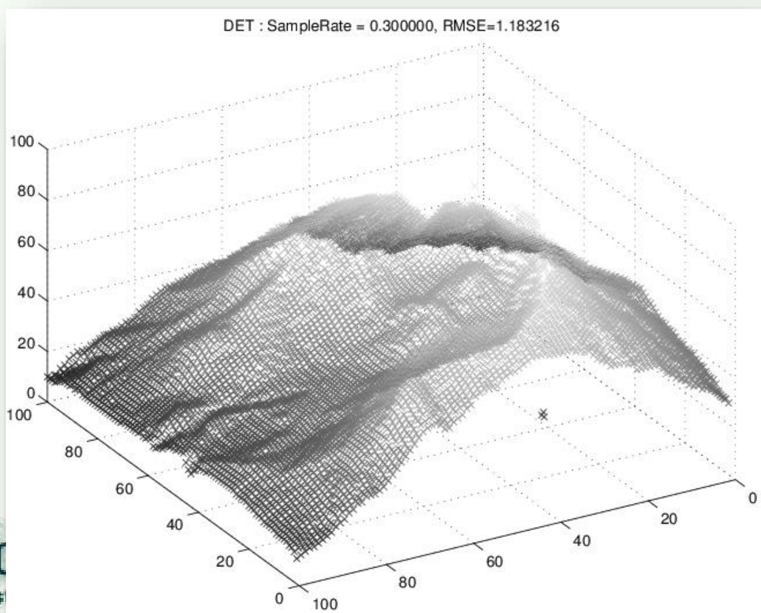
CGRS, RMSE=0,67



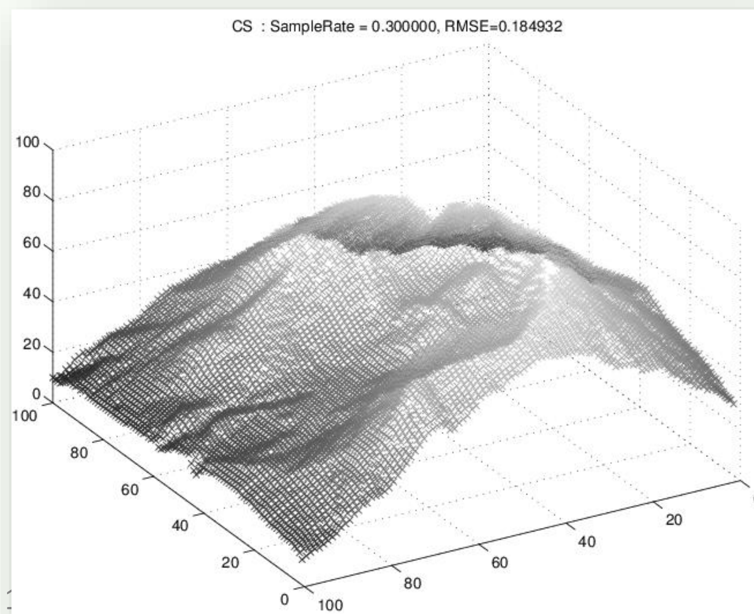
Original



TS, RMSE=1,07

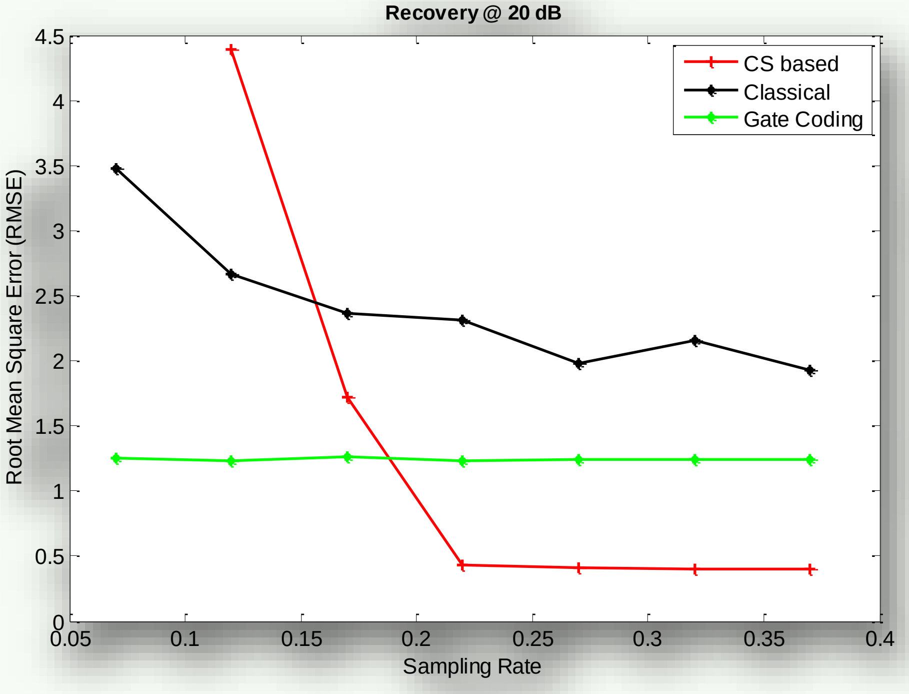


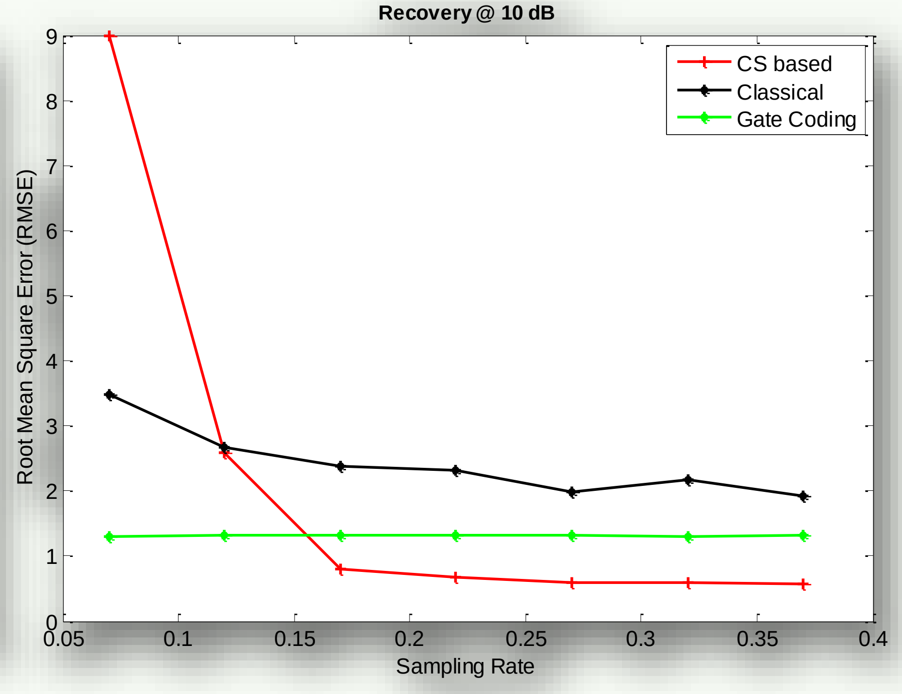
GC, RMSE=1,18



CGRS, RMSE=0.18

Multiple Reflection Recovery





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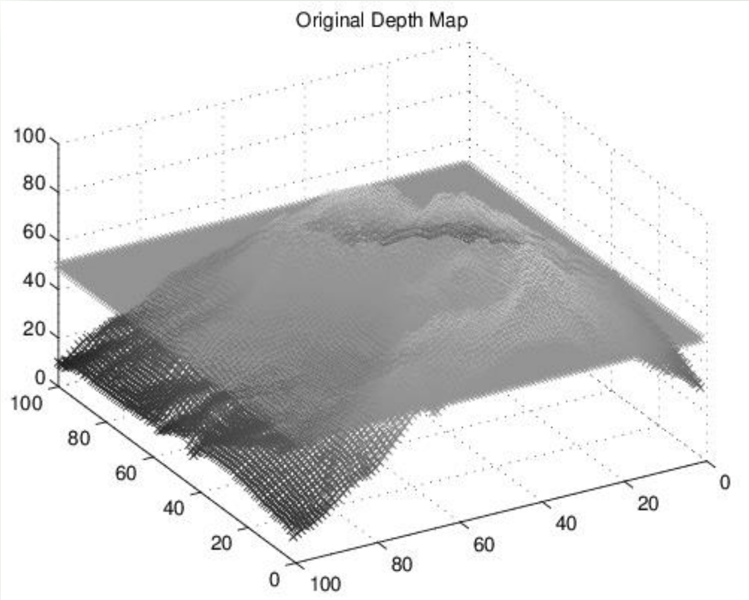
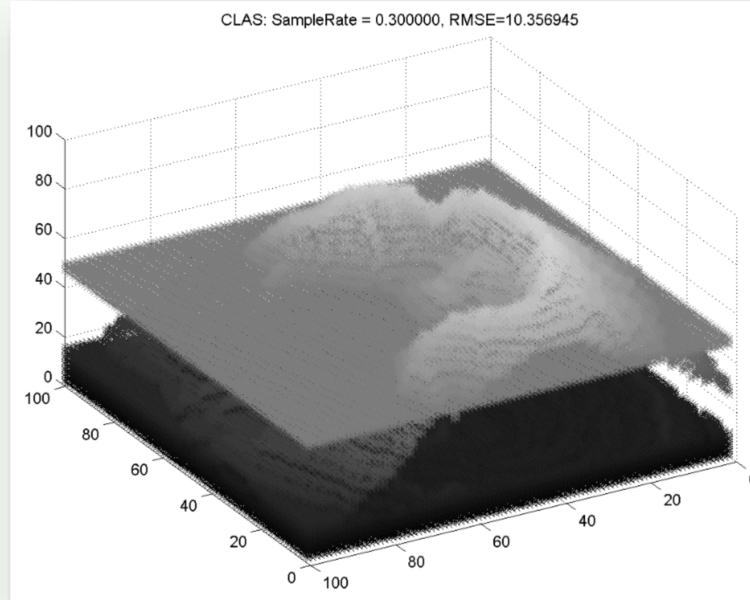
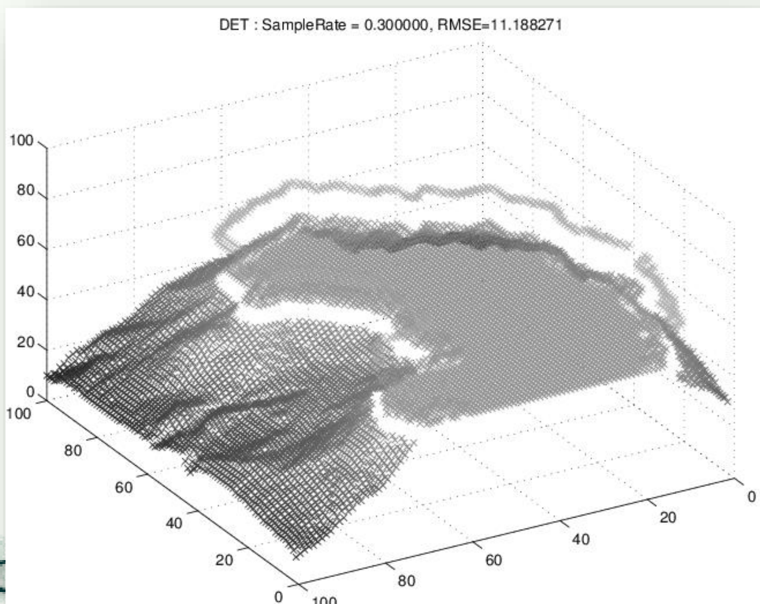


Original

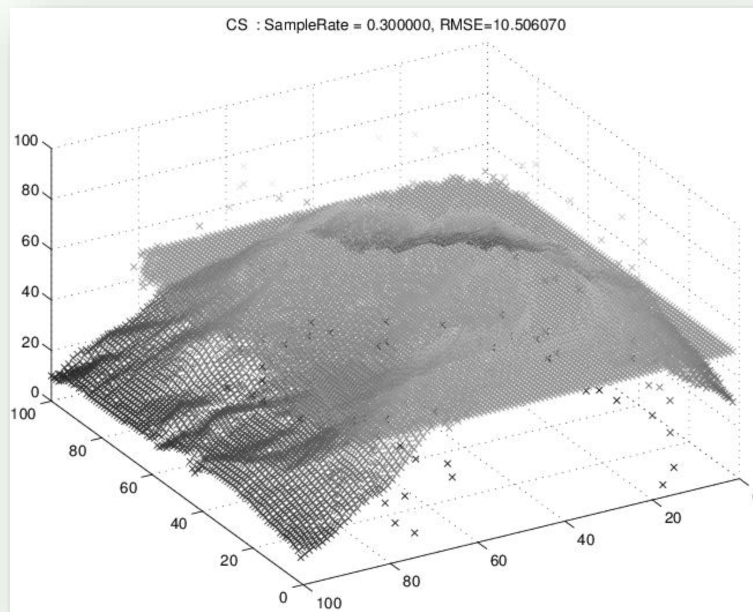


TS, RMSE=10,35

CGRS outperforms all methods by identifying both the semi-transparent layer, as well as the objects behind it.



GC, RMSE=11,18



CGRS, RMSE=10,18

Discussion

	Time Slicing	Gate Coding	GCRS
Resolution	Low	High	High
Speed	Low	High	High
Robustness	Low	Low	High
Multipulse	No	No	Yes

- Coding of Range Gates
  - Ideal: Super-resolution from 2 frames
  - Requires specific pattern (not generalizable)
- CS Range Imaging
  - Random sampling pattern
  - Multiple reflection decoding

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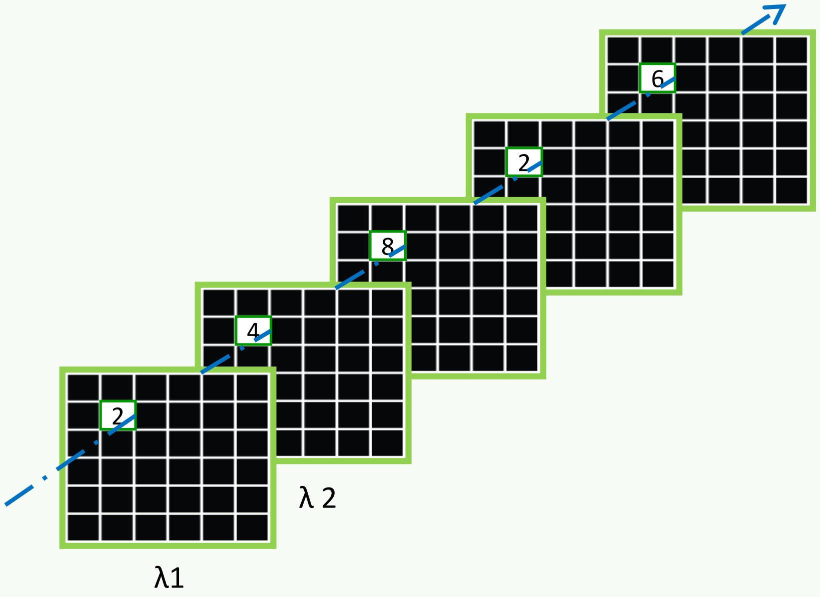
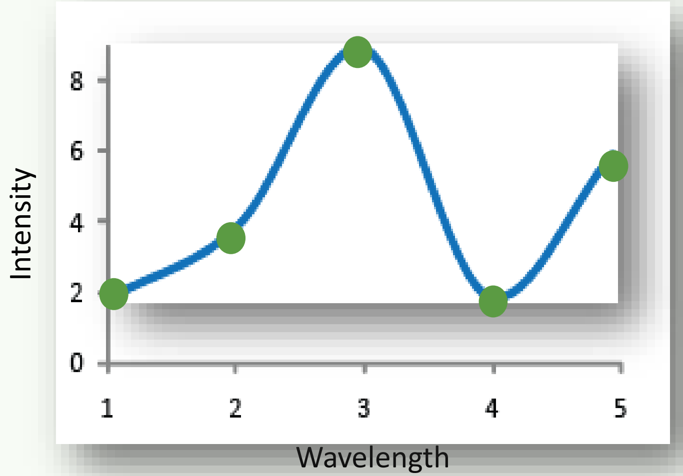
Hyperspectral Imaging

Application of CS in Range Imaging Data

- ➢ Complex & High Dimensional Signals
- ➢ Compressed ToF Sensing

Hyperspectral/Multispectral Imaging

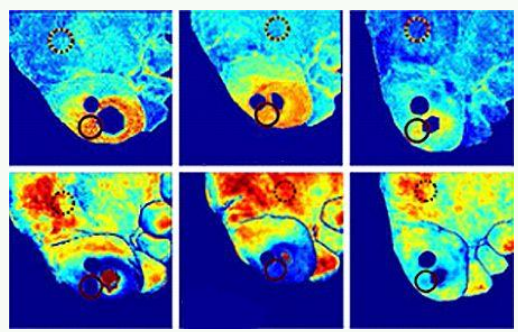




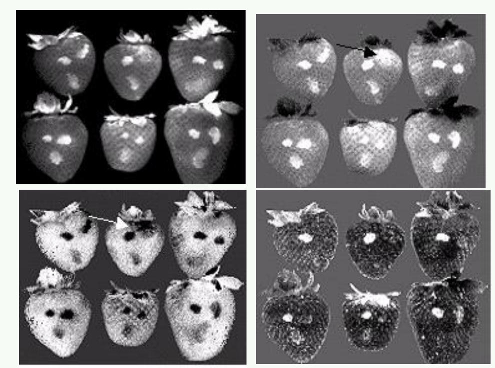
HSI technology & applications

Limitations	Properties
Spatial-Temporal-Spectral	Data redundancies
Equipment Cost/Size	Complexity shift enc./dec.
	Hardware-aware design

Environmental



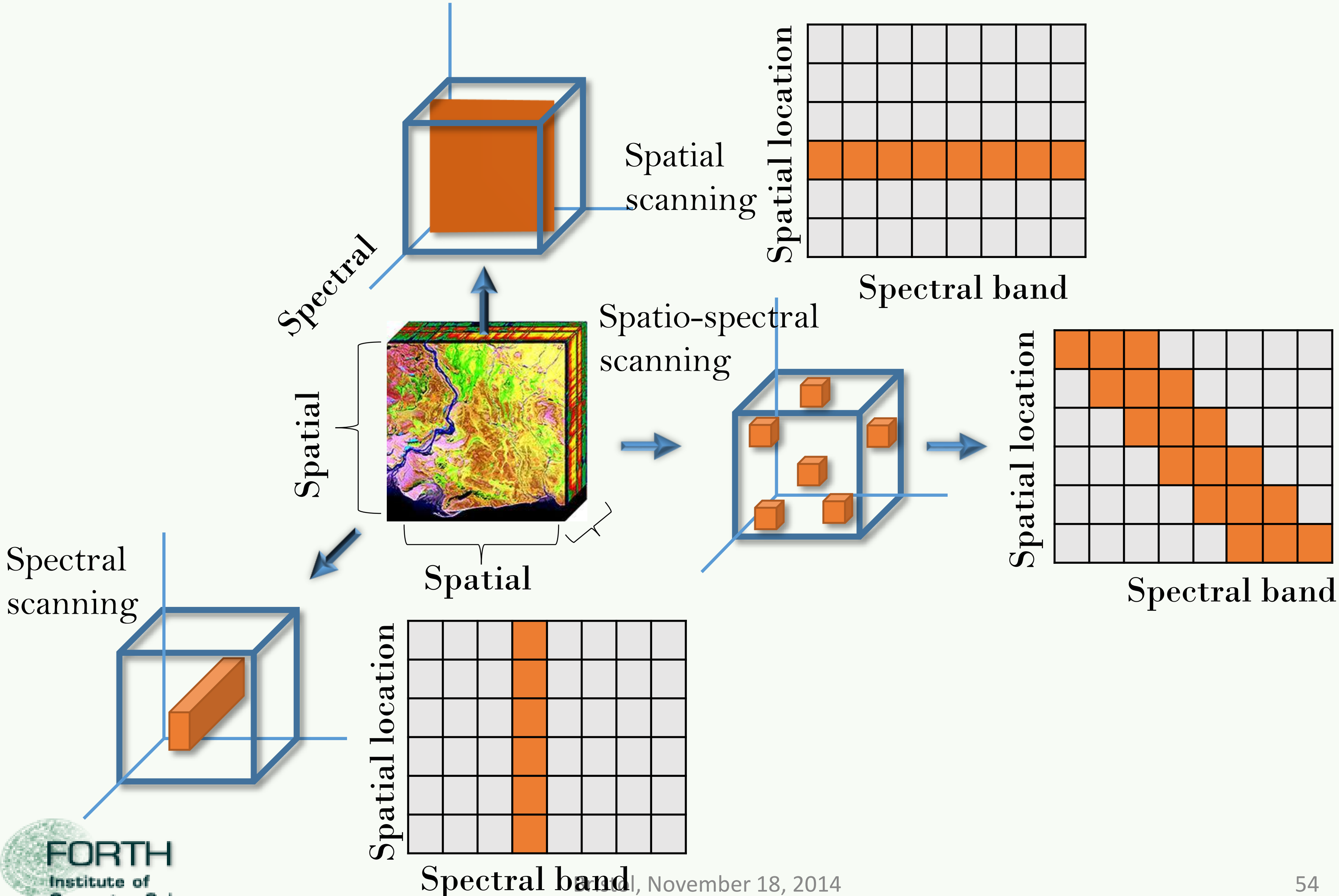
Medical



Food

An essential tool for distinguishing between physical phenomena with different spectral signatures.

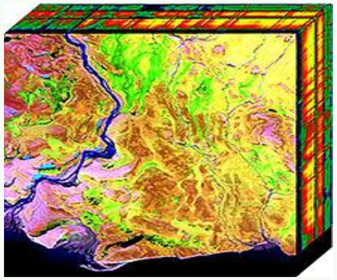
Hyperspectral Image Acquisition



CS-based HSI

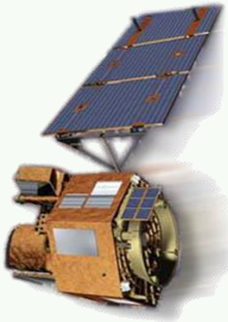
Video-rate Simultaneous Spectral Imaging

- Support portability
- Reduced cost
- Rigidness



Compressed Sensing

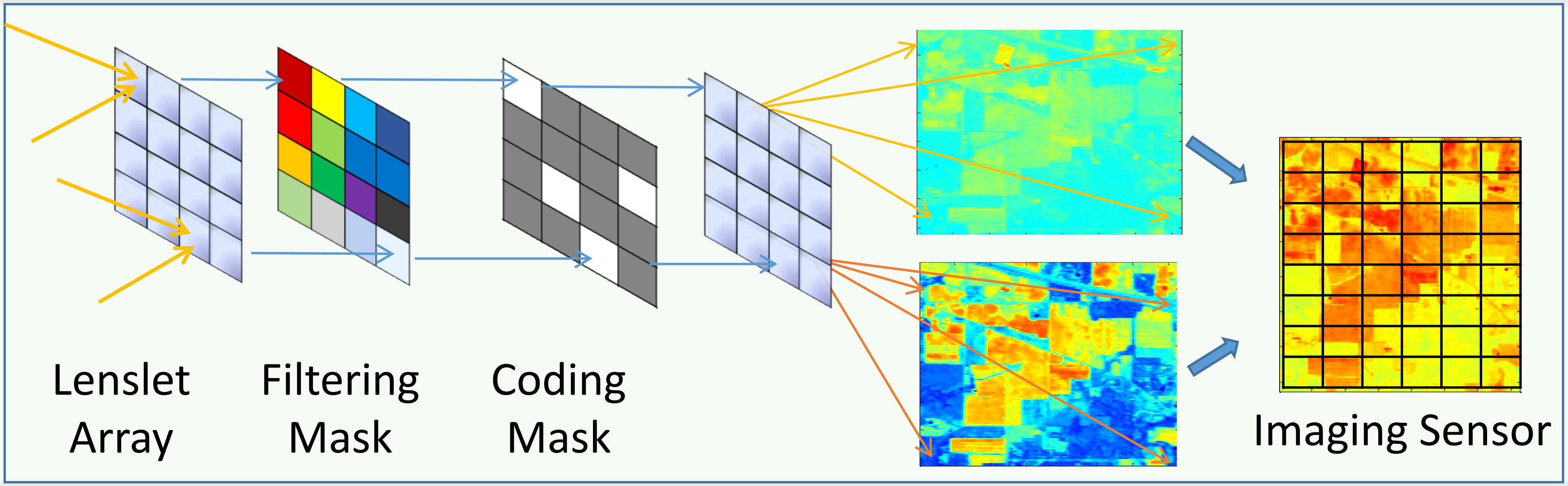
- Enhanced high quality data
- Analytical modeling
- Customizable applications



- Reduced payload
- Increased robustness
- Onboard processing
- Reduced bandwidth

Compressed Hyperspectral Sensing

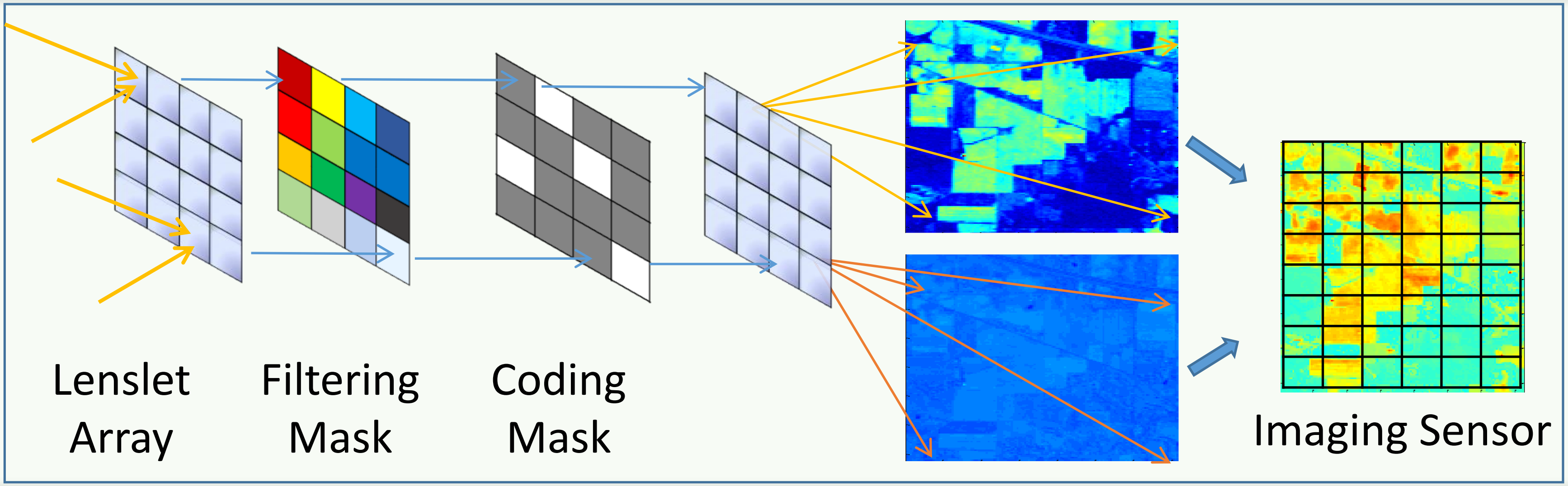
Time *T*



- Light from the scene enters each microlens (element of the lenslet array) and is focused on a single spectral filter.
- Depending on the state of the coding mask only a subset of filter images propagate through the mask.
- The selected filtered images are remapped to the imaging sensor (second array).

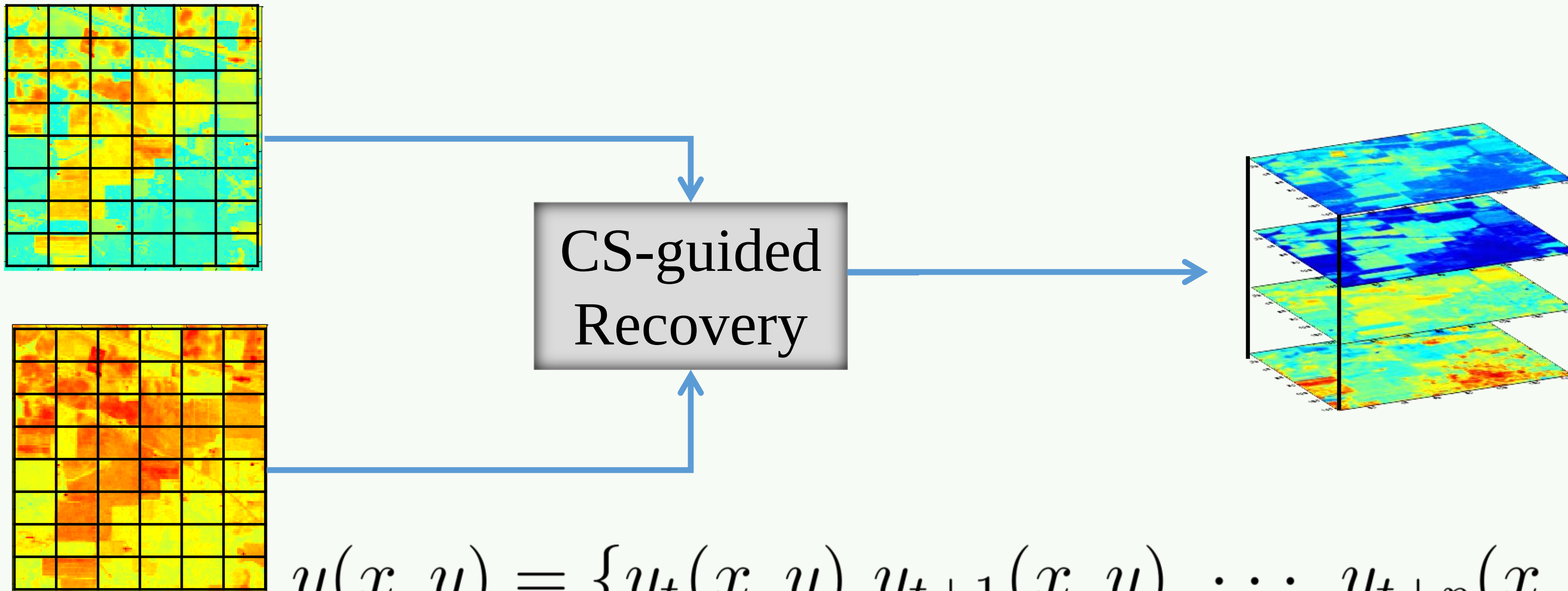
Compressed Hyperspectral Sensing

Time *T+1*



- In the next frame, by changing coding mask, different filters are selected and imaged.
- The coding mask can also be implemented by a Digital Micromirror Device (DMD) by placing two mirrors, one before the DMD and one after.

Compressed Hyperspectral Sensing

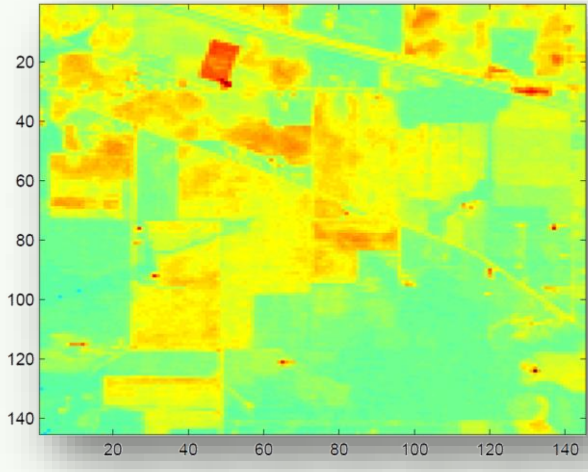


$$y(x,y) = \{y_t(x,y)\ y_{t+1}(x,y)\ \cdots\ y_{t+p}(x,y)\}$$

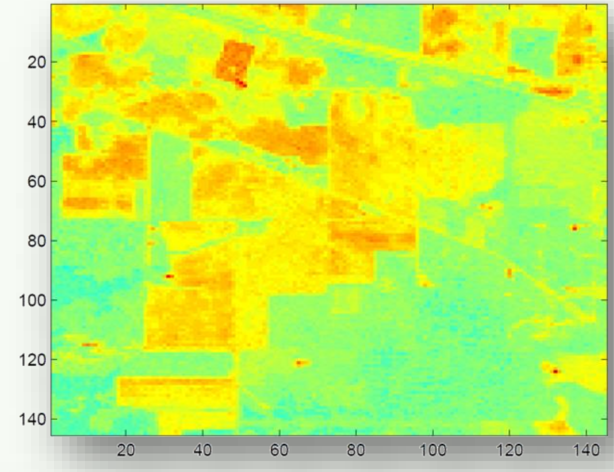
$$\min \|\mathbf{s}\|_1 \quad \text{subject to} \quad \|\mathbf{y} - \mathbf{\Phi}\mathbf{D}\mathbf{s}\|_2^2 < \epsilon$$

Simulation Results

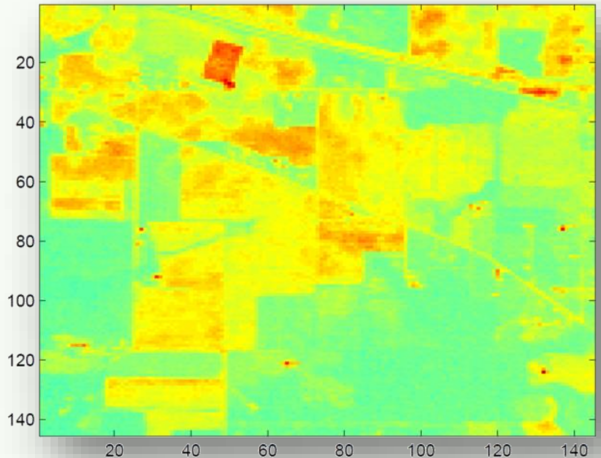
10th spectral band

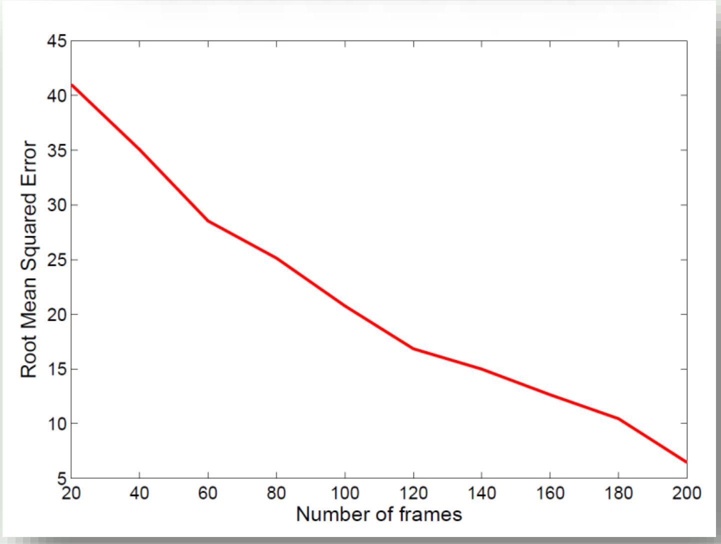


Reconstruction: 10 frames



Reconstruction: 20 frames





Potential of CS in HSI

- Increase spatial resolution
- Increase frame rate
- Support Image understanding

Requirements

- Integrated Computation & Sensing
- Reduce power/bandwidth requirements
- *Transmission?*

Thank you

http://www.ics.forth.gr/spl/

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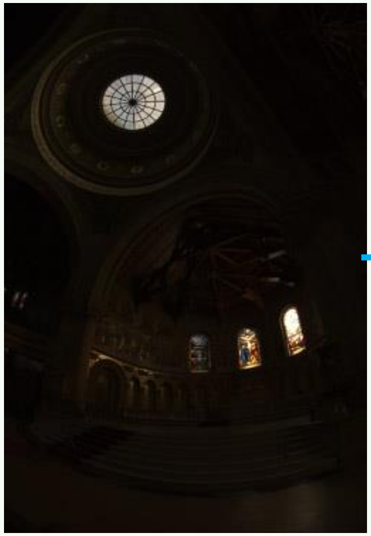
Low light Image Enhancement

Task: *Recover the high illumination version of a low illumination scene.*

Input



?

Output

Motivation: Multiple applications

- ❖ Astronomical
- ❖ Medical
- ❖ Smart phone devices

Benefits:

- ✓ Contrast and visual appearance
- ✓ Information details

Challenge: inverse problem

- ✓ exploit prior knowledge

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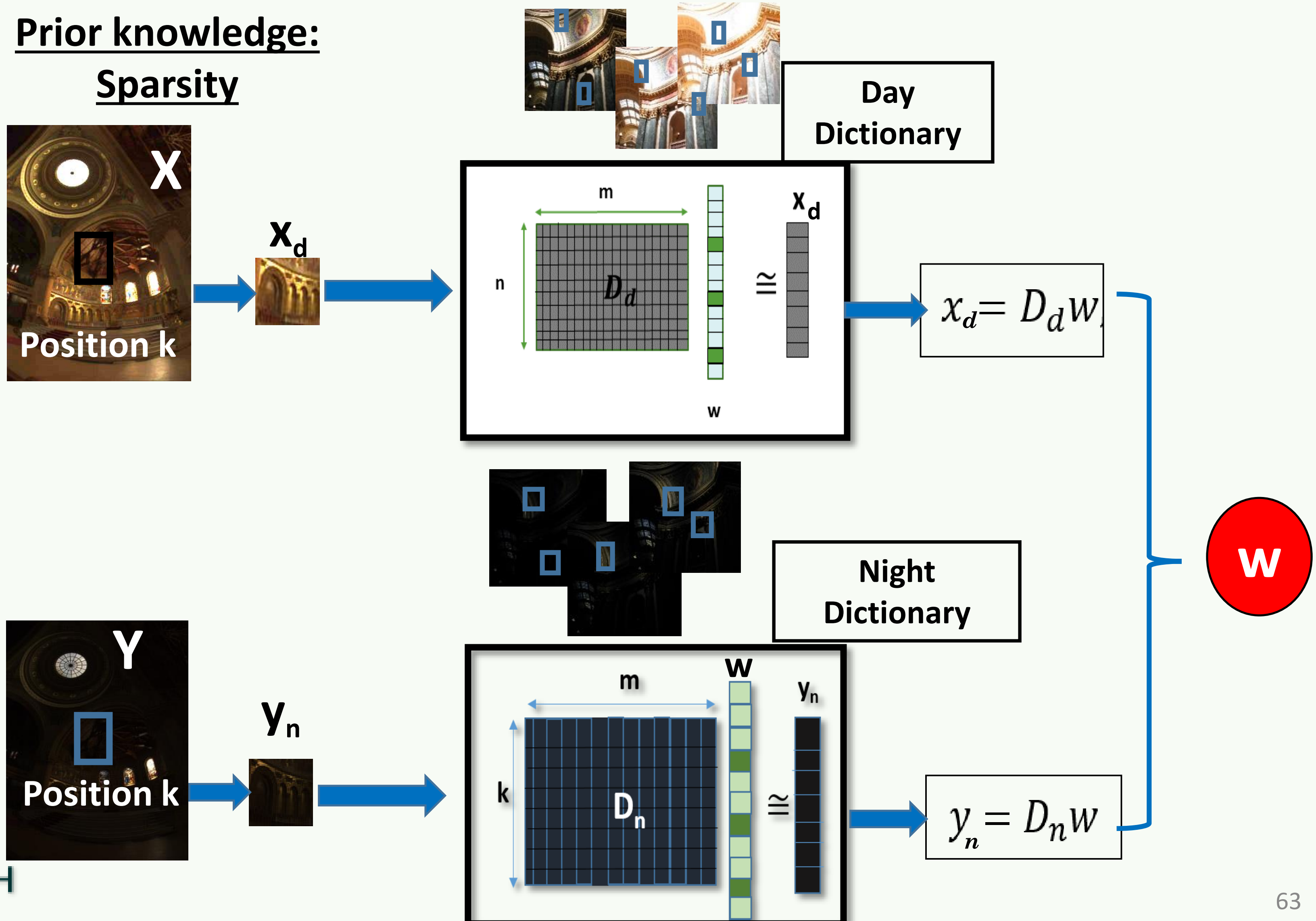
Learning for Image *De-nighting*

✓ **Prior knowledge:**
Sparsity



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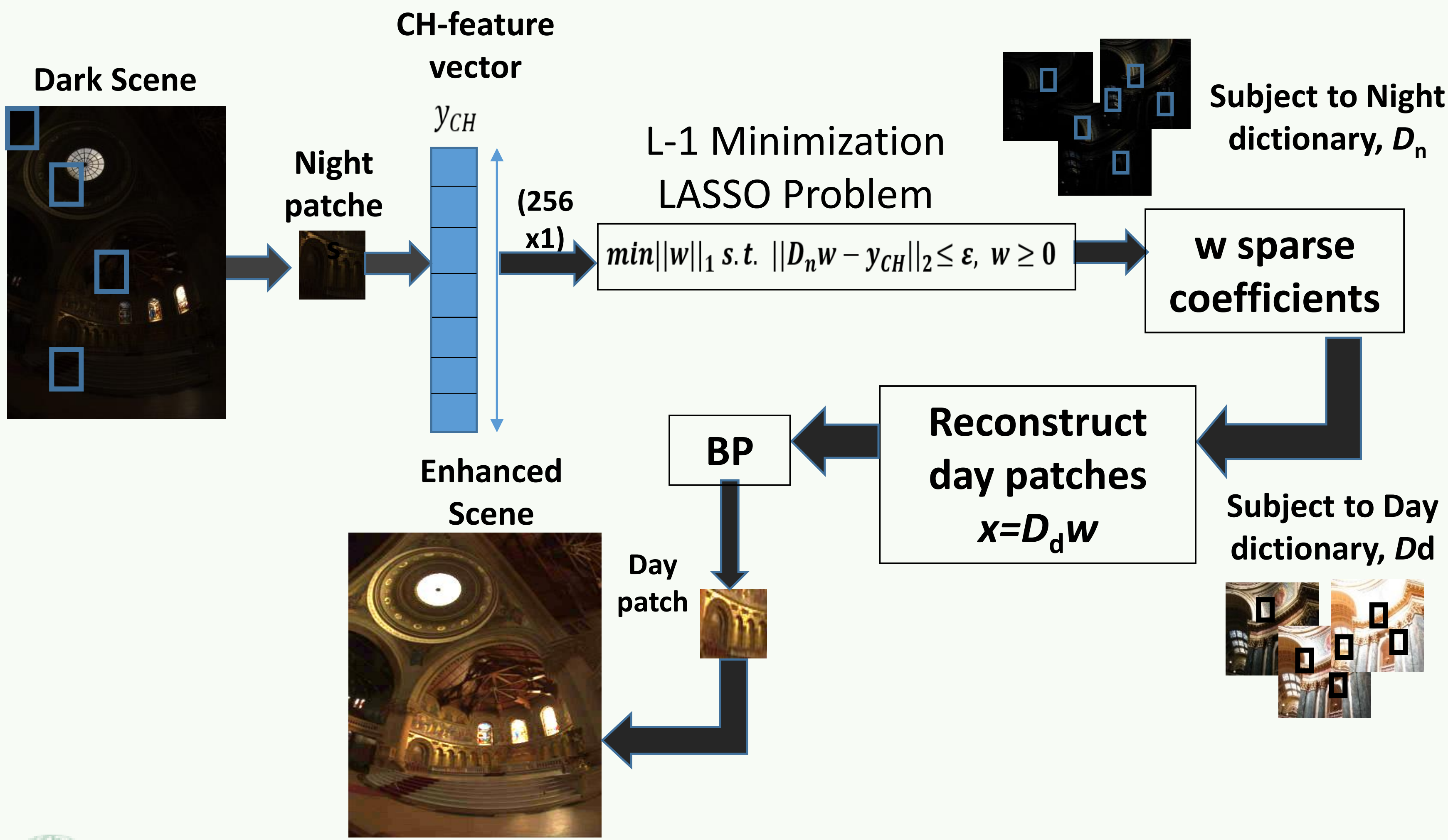
Overall Block Diagram



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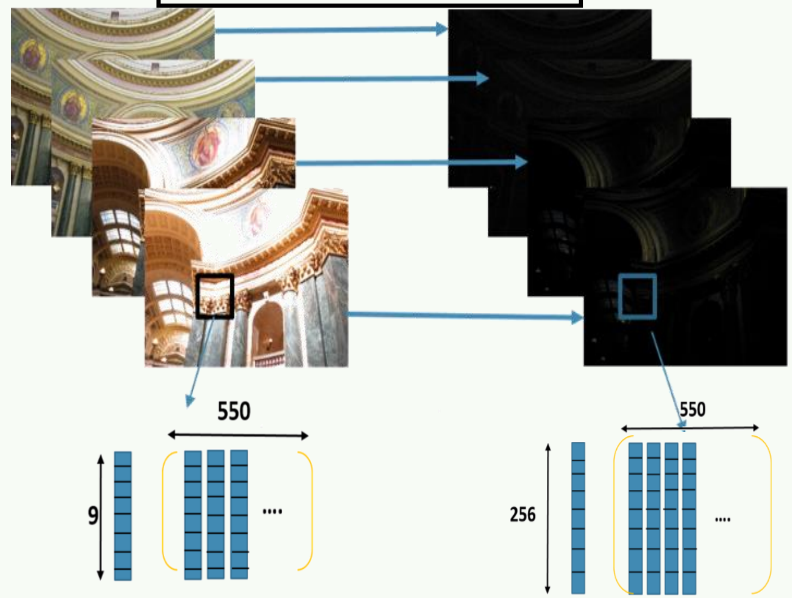
Experimental Setup

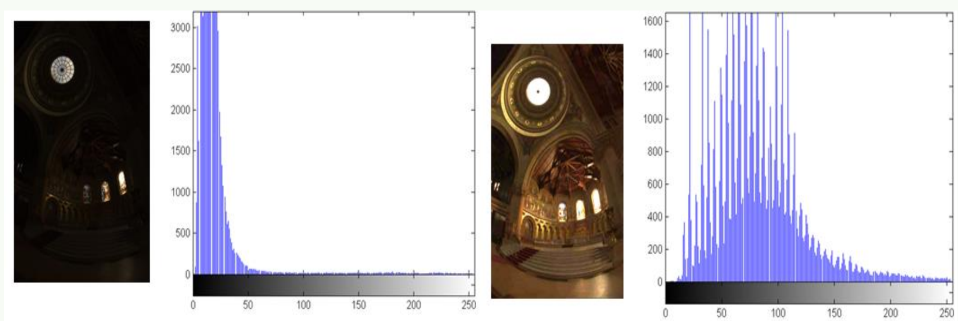
- ❑ Dictionaries : **HDR** registered images
- ❑ **HSV** color space → **Value (V)**

RGB | **HSV (V)** | **Reconstruction**

HDR Dataset



- ❑ Comparison
  - **Dong's et al.**
  - **Histogram Equalization (HE)**
  - **Color Estimation Model (CEM)**



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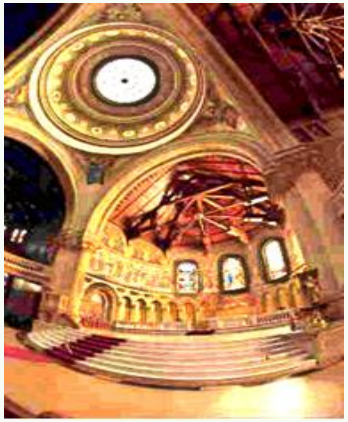
Experimental Results - Memorial

Input Image

Reference Image



Dong's method
SSIM: 0.5354

HE
SSIM: 0.5830

CEM
SSIM: 0.7497

Proposed
SSIM: *0.8579*

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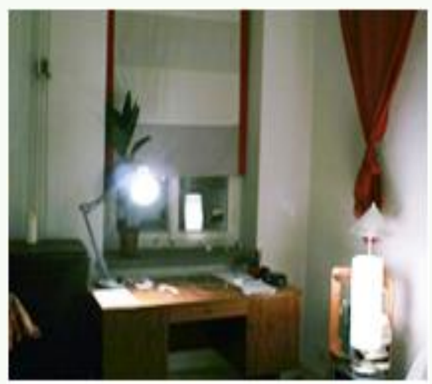
Experimental Results - Office

Input Image

Reference Image

Dong's
SSIM: 0.4116

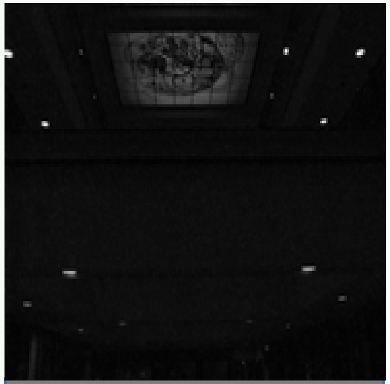
HE
SSIM: 0.5654



CEM
SSIM:0.7676

Proposed
SSIM: *0.9498*

Experimental Results - UWMech



Input Image

Reference Image

Dong’s method
SSIM: 0.2922

HE
SSIM: 0.2182

CEM
SSIM: 0.4156

Proposed
SSIM*: 0.6212*

Discussion

✓High Performance Enhancement.
✓Robust to low light noisy conditions.
✓Sophisticated image prior knowledge.
✓Flexibility in dictionary learning.

Sparsity of Singular Values

➢ Matrix Completion in High Dynamic Range Imaging

High Dynamic Range Imaging

Under – exposed
- Noisy like signal
- Loss of information

Over – exposed
- Saturated values
- Loss of information

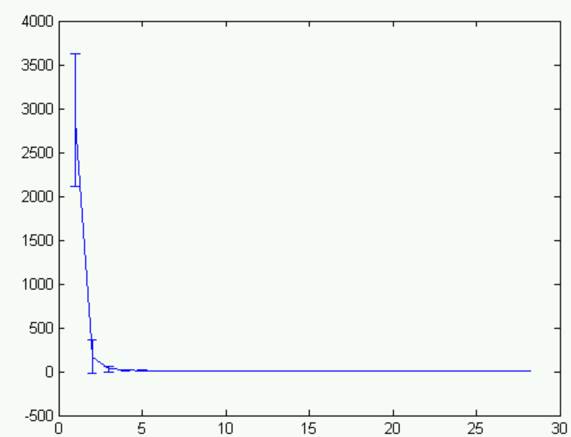
Example of tone mapped image

Observation

Matrices of stacked patches are low rank

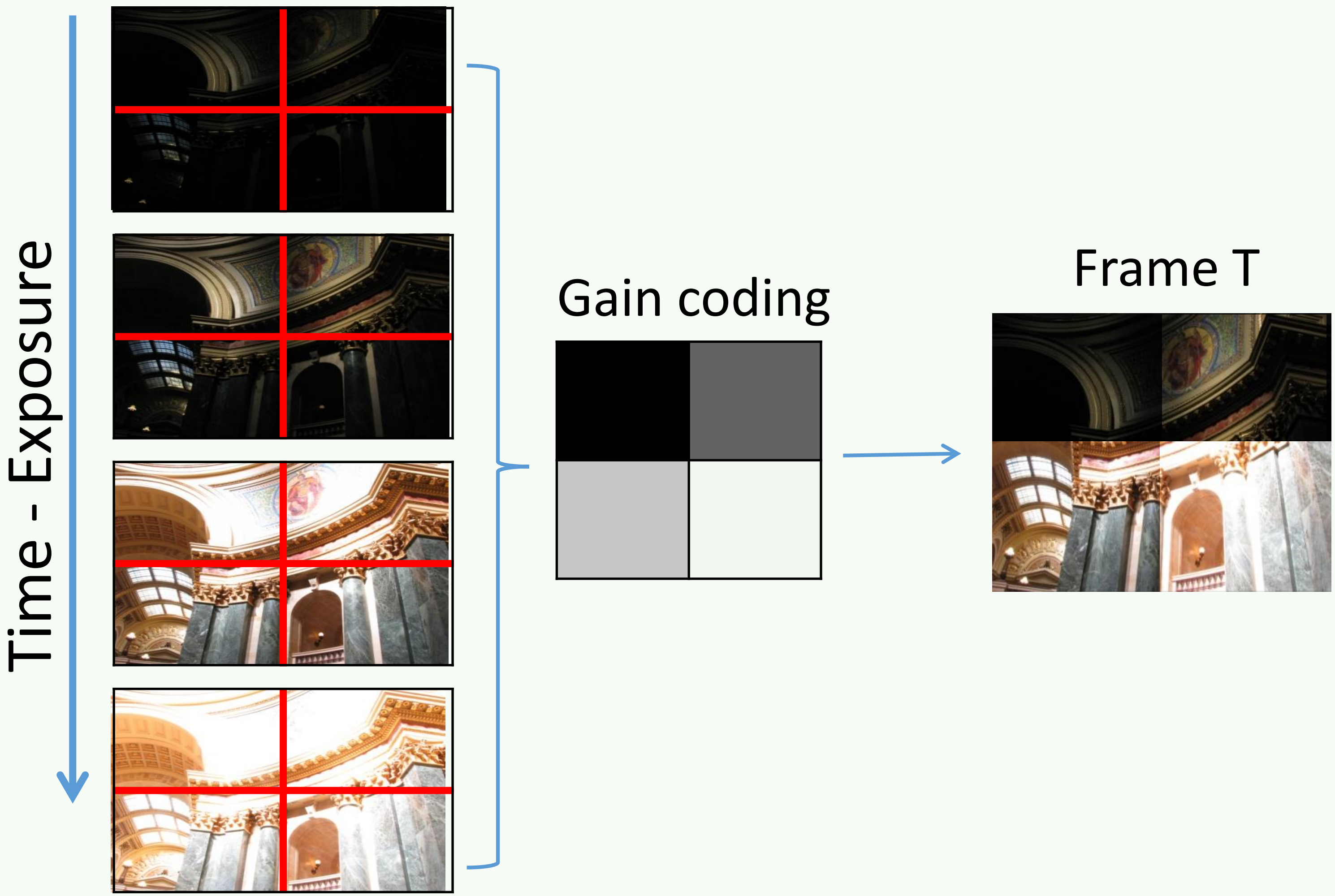
Objective

Reduce number of frames

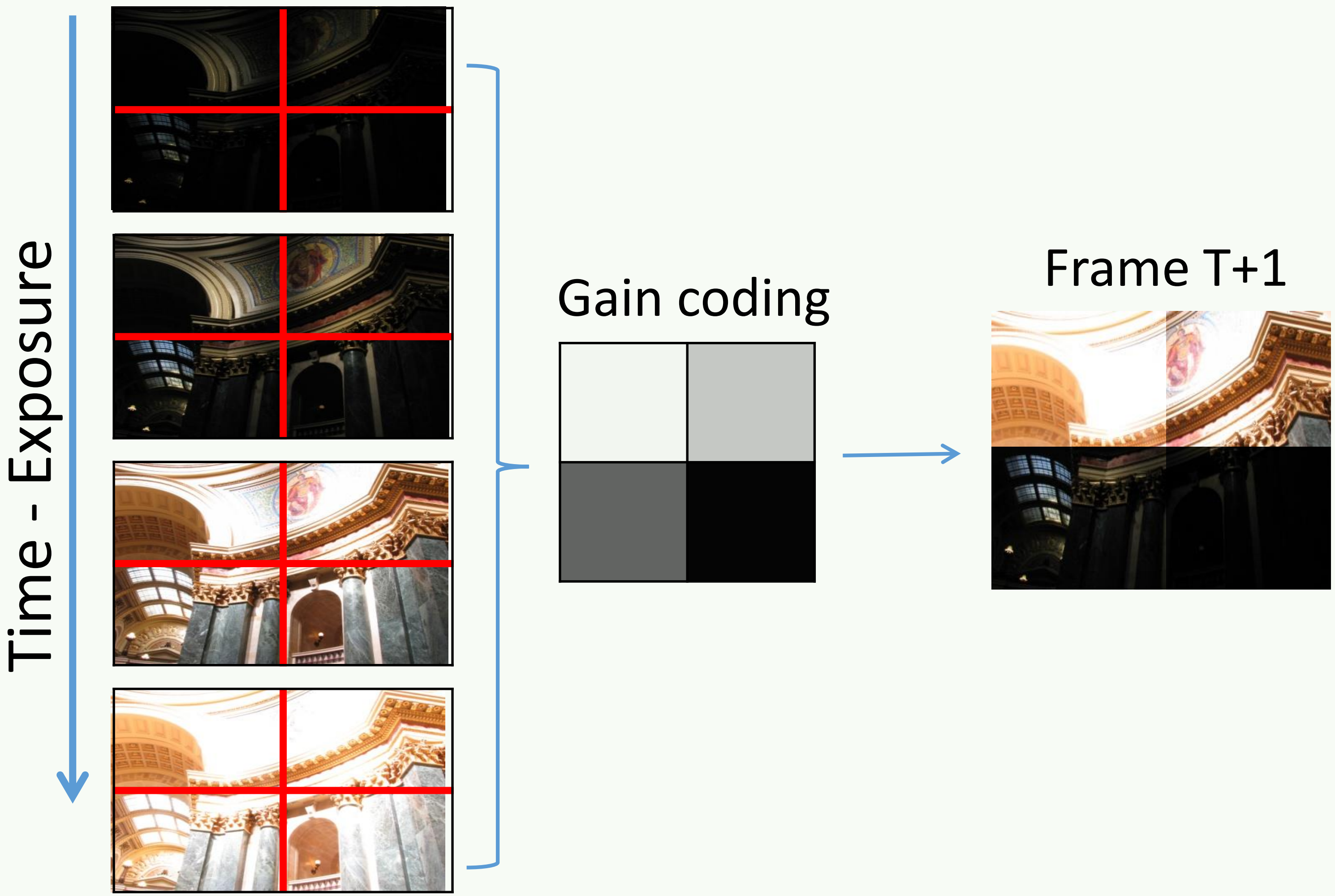


Singular Values

HDR imaging encoding



HDR imaging encoding

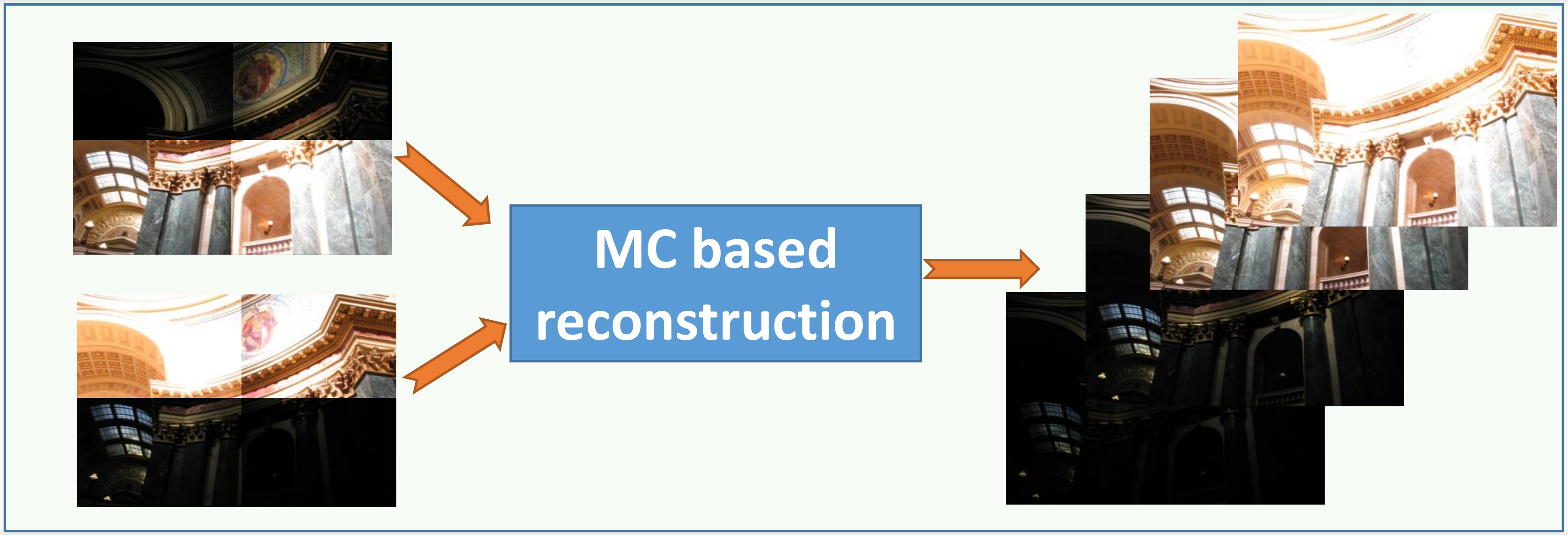


MC based HDR recovery

Let $\boldsymbol{I} = \{ \boldsymbol{I}^1, \ \boldsymbol{I}^2 \ldots \ \boldsymbol{I}^T \}$ be a set of LDR images.

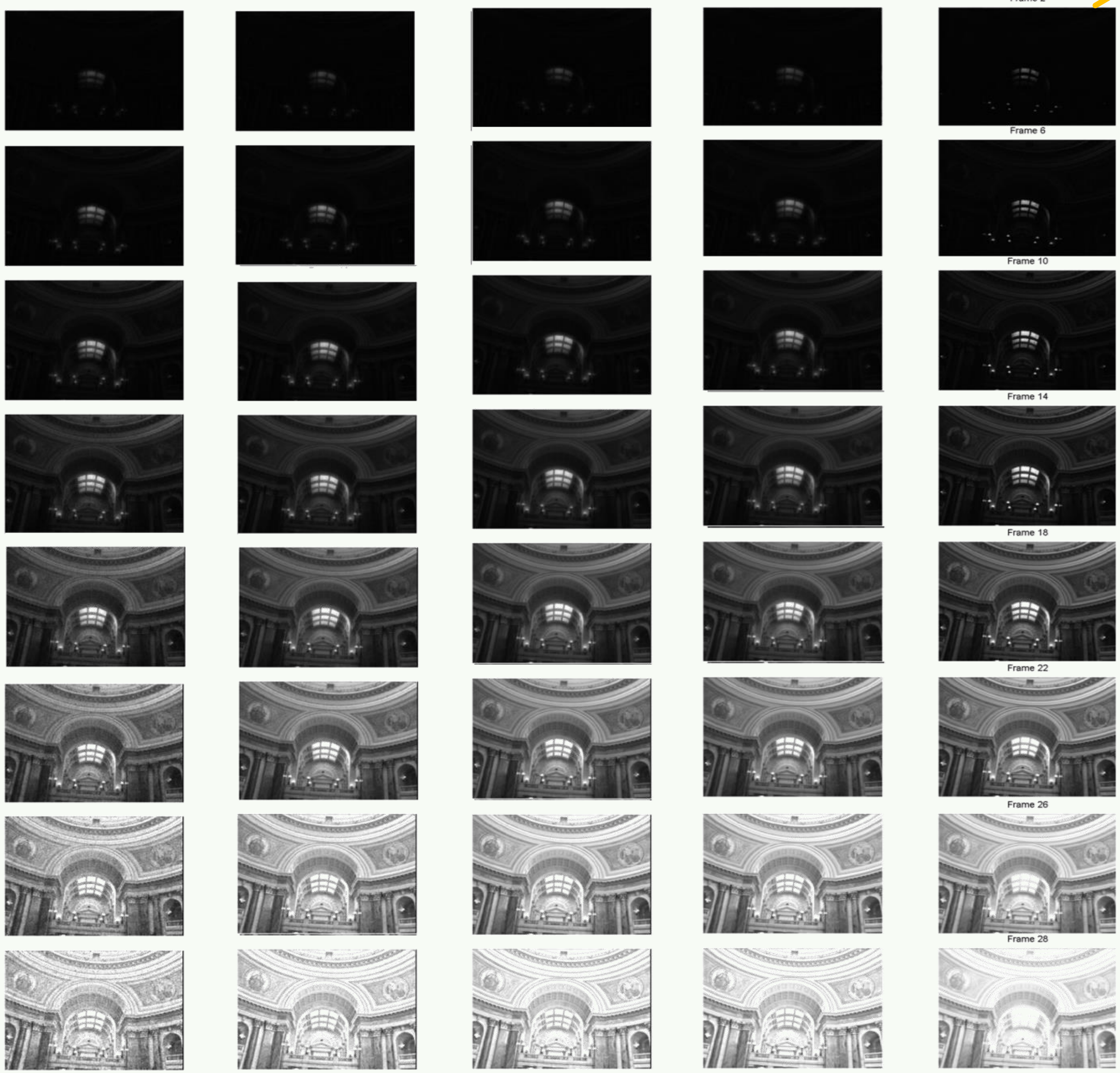
$\boldsymbol{I}^t = \{B_1, B_2, \ldots B_K\}$ overlapping spatial blocks.

<u>Estimation</u> $\boxed{\min\{ \ \|\mathbf{X}\|_* \ : \ \ \|\mathcal{A}(\mathbf{X}) - \mathcal{A}(\mathbf{B}_i^j)\|_F^2 \leq \epsilon\}}$



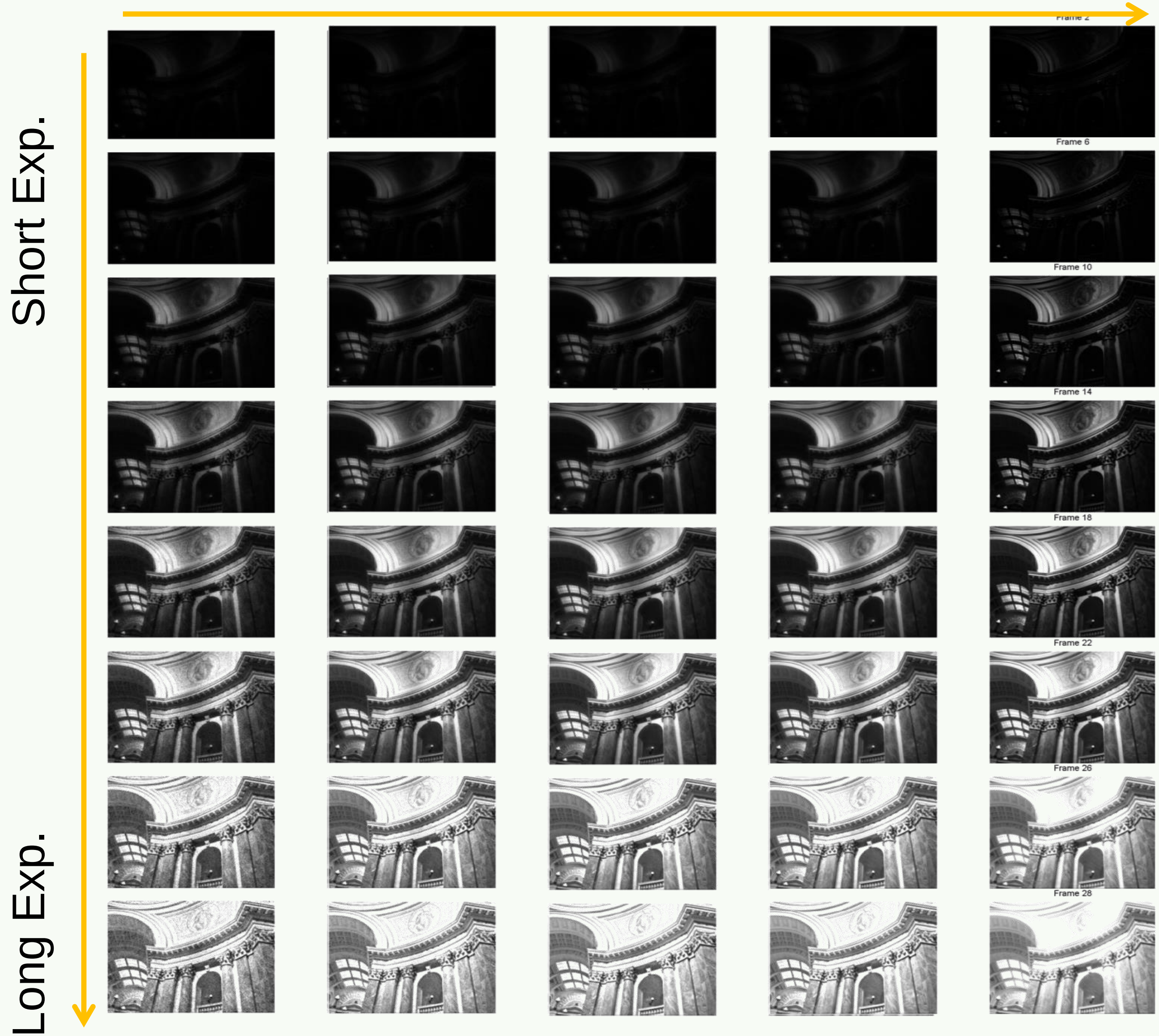
Sampling rate (20%, 30%, 40%, 50% and 100%)

Short Exp.



Long Exp.

Sampling rate (20%, 30%, 40%, 50% and 100%)



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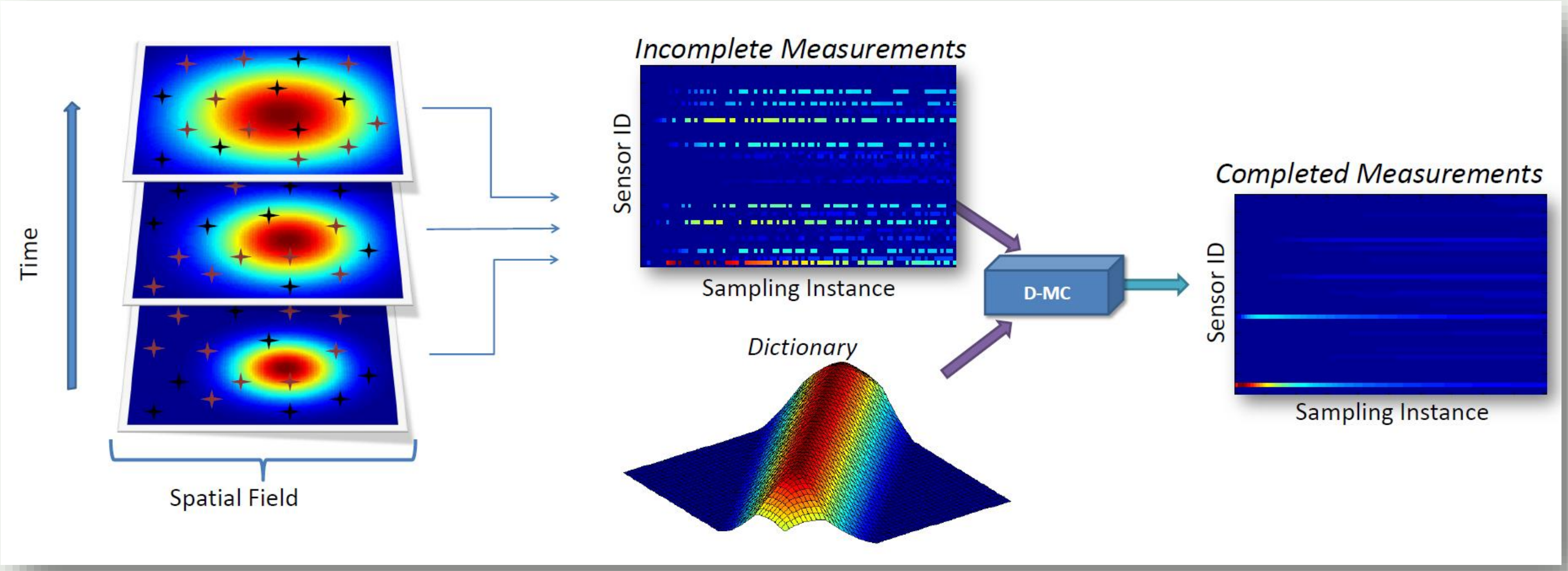
MC in Wireless Sensor Networks

Limitations
- Battery
- Bandwidth
- Storage

Benefits
- Robustness
- Lifetime
- Flexibility



Discussion

- Potential of CS and MC in imaging
  - Reduce size & cost
  - Increase performance
  - Robustness (noise, failures)
- Other applications
  - Radar, Ultrasound, Ultrawide band, Ground penetrating radar, SAR
- Joint design of acquisition hardware + image recovery
- Non-linear modeling & recovery

Understanding Complex data

Challenges

- High temporal-spectral data acquisition/processing
- Single source of data
- Fusion with alternative sources e.g. EPA
- Distributed storage & processing

➢ Volume + Velocity + Variety = Big Data

➢ Scientific Big Data Learning

Related Publications

- G. Tsagkatakis and P. Tsakalides, "Recovery of Quantized Compressed Sensing Measurements," in Proc. SPIE Electronic Imaging Symposium, Computational Imaging XIII, San Francisco, CA, February 8-12, 2015.
- G. Tsagkatakis and P. Tsakalides, "Compressed Hyperspectral Sensing," in Proc. 2015 SPIE Electronic Imaging Symposium, Image Sensors and Imaging Systems, San Francisco, CA, February 8-12, 2015.
- K. Fotiadou, G. Tsagkatakis, and P. Tsakalides, "Low Light Image Enhancement via Sparse Representation," in Proc. International Conference on Image Analysis and Recognition (ICIAR2014), Portugal, October 22-24, 2014.
- G. Tsagkatakis, G. Tzagkarakis, A. Woiselle, M. Bousquet, JL Starck, and P. Tsakalides, "Compressed Sensing Reconstruction of Convolved Sparse Signals," in Proc. 39th International Conference on Acoustics, Speech, and Signal Processing (ICASSP '14), Florence, Italy, May 4-9, 2014.
- S. Nikitaki, G. Tsagkatakis, and P. Tsakalides, "Efficient recalibration via Dynamic Matrix Completion," in Proc. IEEE Machine Learning for Signal Processing Workshop (MLSP '13), Southampton, UK, September 22-25, 2013.
- G. Tsagkatakis, A. Woiselle, G. Tzagkarakis, M. Bousquet, J. L. Starck, and P. Tsakalides, "Compressed Gated Range Sensing," in Proc. 2013 SPIE Optics + Photonics Symposium, Wavelets and Sparsity XV, San Diego, CA, August 25-29, 2013.
- S. Poularakis, G. Tsagkatakis, P. Tsakalides, and I. Katsavounidis, "Sparse Representations for Hand Gesture Recognition," in Proc. 38th International Conference on Acoustics, Speech, and Signal Processing (ICASSP '13), Vancouver, Canada, May 26-31, 2013.
- G. Tsagkatakis, A. Woiselle, G. Tzagkarakis, M. Bousquet, J. L. Starck, and P. Tsakalides, "Active Range Imaging via Random Gating," in Proc. SPIE Security and Defense, Edinburgh, United Kingdom, September 24-27, 2012.
- G. Tsagkatakis and P. Tsakalides, "Efficient High Dynamic Range Imaging Via Matrix Completion," in Proc. 22nd IEEE Machine Learning for Signal Processing Workshop (MLSP '12), Santander, Spain, September 23-26, 2012.
- G. Tzagkarakis, G. Tsagkatakis, J. L. Starck, and P. Tsakalides, "Compressive Video Classification in a Low-Dimensional Manifold with Learned Distance Metric," in Proc. 20th European Signal Processing Conference (EUSIPCO '12), Boucharest, Romania, August 27-31, 2012.