CS Applications in Graphics & Vision

27 Colóquio Brasileiro de Matemática

Outline

- Overview of Applications
  - How & Where to Use CS
- Hardware
  - Single-Pixel Camera
- Software
  - Light Transport Sensing

The Good and Bad of CS

- Good:
  - Simultaneous Sensing & Compression
  - Minimal Non-Adaptive Measurements
  - Stable / Robust to Noise
- Bad:
  - Global Probing ~ *Special Devices*
  - Non-Linear Estimation ~ *Expensive Recovery*

Where to Use CS?

- Massive (Sparse) Raw Data
- Hardware Options
  - Existing Suitable Devices (i.e., MRI, CT, etc..)
  - Data Parallel Acquisition (i.e., Sensor Networks)
  - New Analog-Digital Converters

✳ *Break Technological Limits*

How to Use CS?

- Asymmetrical
  - Low Rate Sampling + Large Scale Optimization
- Universality
  - Representation Independent Sensing
- Model-Based Estimation
  - Dimensionality Reduction
- Operator Sparseness
  - Statistical Analysis / Processing

Application Areas

- Biomedical Imaging
- Geophysics / Radar
- Astronomy
- Analog-Digital Converters
- Machine Learning
- Vision and Graphics

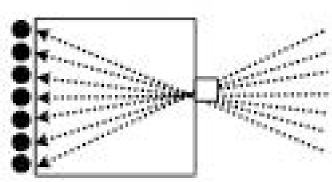
Single-Pixel Camera

- Early Example of Dedicated CS Device

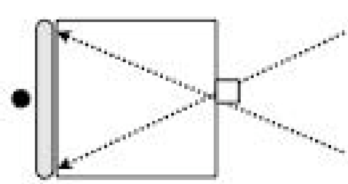
- http://dsp.rice.edu/cscamera (data)
- Rice University / DSP Group (2006)
- MIT Technology Review:
  Top 10 emerging technologies for 2007

Comparison

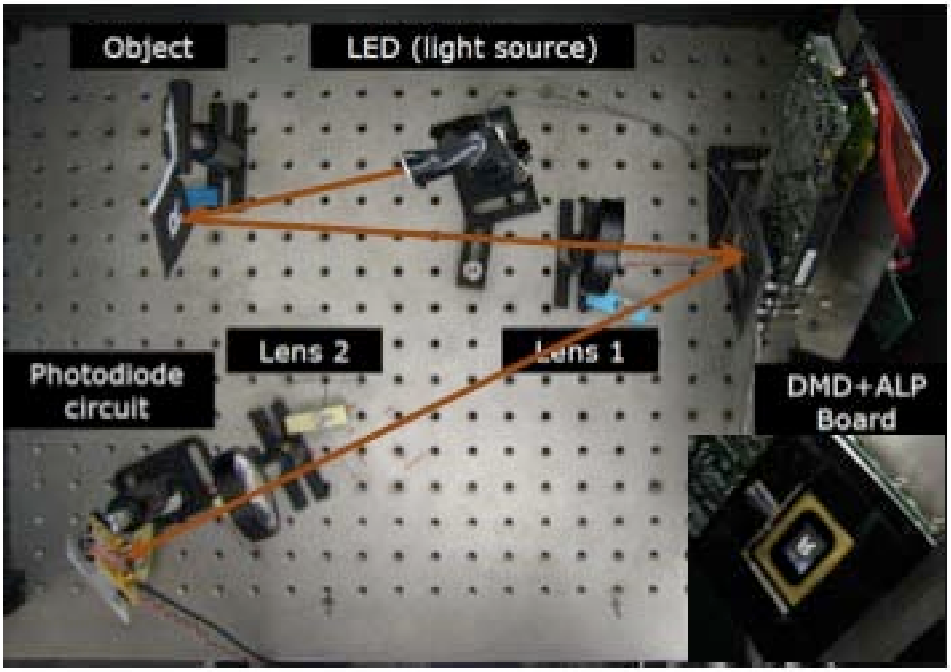
- Conventional Camera (CCD/CMOS array)
  - Millions of Sensors (ray bundle per pixel)
  - Space Multiplexed



- CS Camera (CS integrator)
  - One Sensor (all rays)
  - Time Multiplexed



Experimental Setup



CS Integrator

- DLP Technology

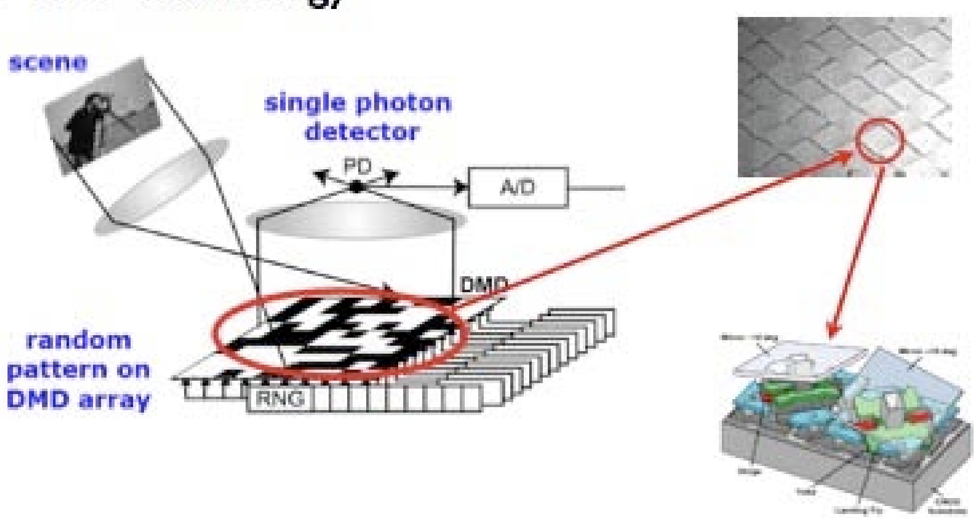


Image Sensing

- Measurements in Time
  - Flip Mirrors *M* Times

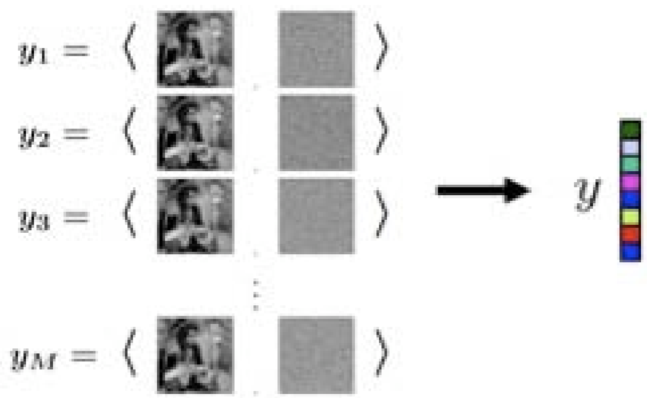
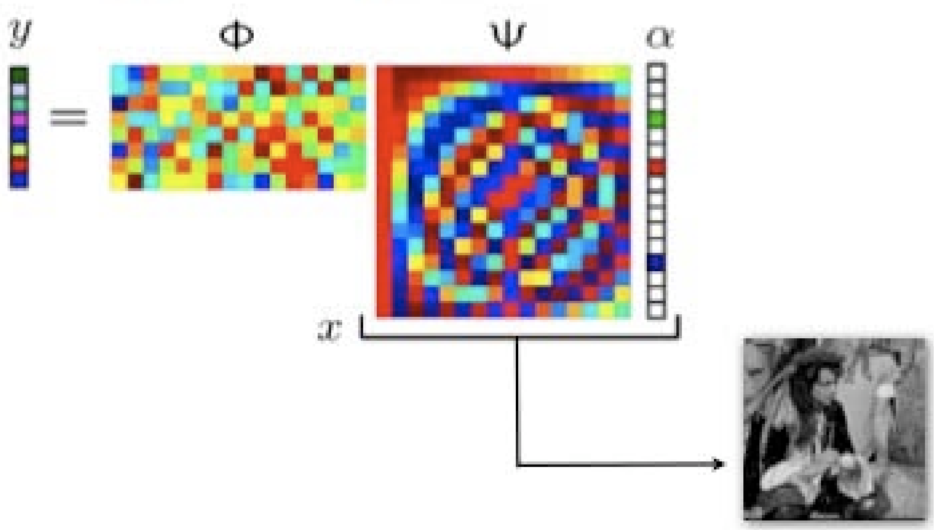


Image Recovery

- CS Optimization (TV)



Example 1

- First Image Acquisition

target
65536 pixels

11000 measurements
(16%)

1300 measurements
(2%)

Example 2

4096
pixels

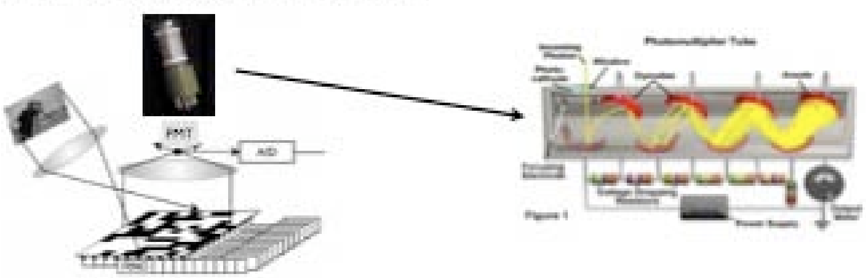
500
random measurements

Advantages

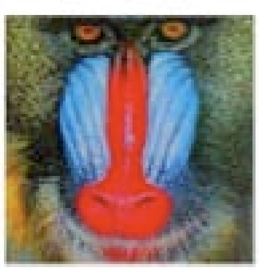
- When the sensor is expensive:
  - Low Light Imaging
  - High Dynamic Range
  - Hyperspectral Imaging
  - Shutterless Video
  - etc...

Low-Light Imaging

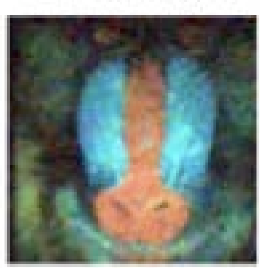
- Photomultiplier Tube



Mandrill 256x256

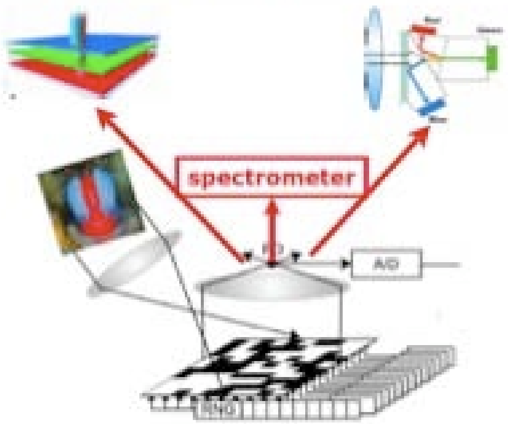


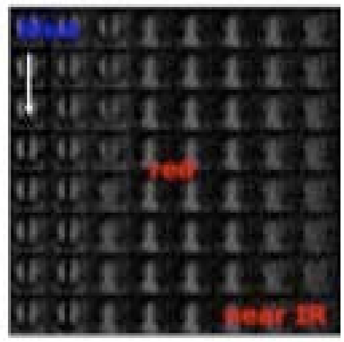
Mandrill 10x sub-Nyquist



Hyperspectral Imaging

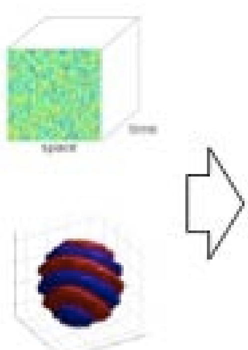
- Layer Sensors (Multi-Photodiodes, etc)
- Prism Assembly

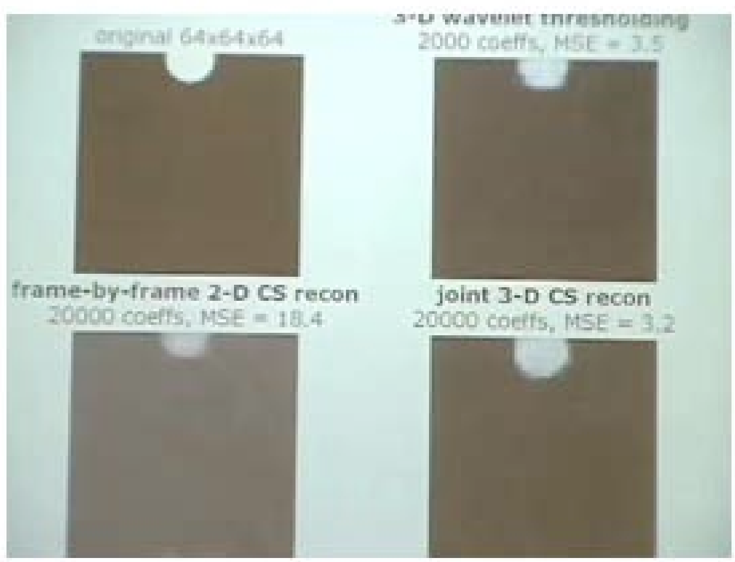




Shutterless Video

- Space-Time Reconstruction (3D Wavelets)





Dual Photography

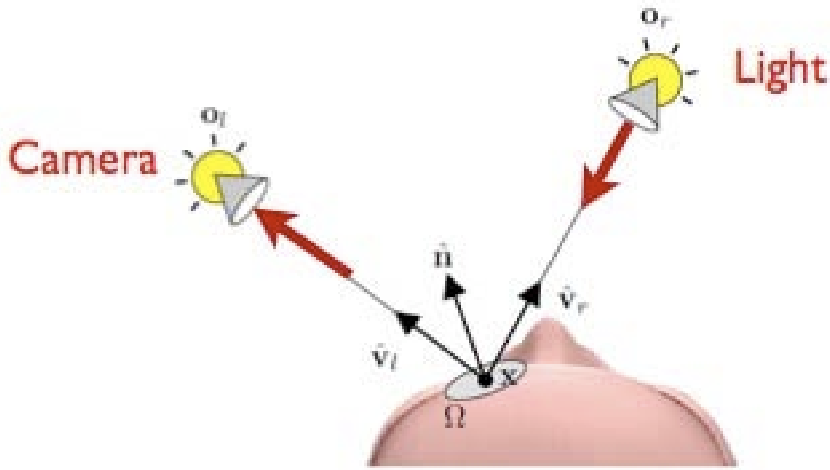
- The Reciprocity Principle
- Single Pixel Dual Camera
- Compressive Light Transport Sensing
- Relighting
- CS Dual Camera

First Application in Graphics

- *Compressive Dual Photography*
  - Sen, P. and Darabi, S. - EUROGRAPHICS 2009
- *Compressive Light Transport Sensing*
  - Peers et al. - SIGGRAPH 2009
- *Compressive Structured Light for Recovering Inhomogeneous Participating Media*
  - Gu et al. - ECCV 2008

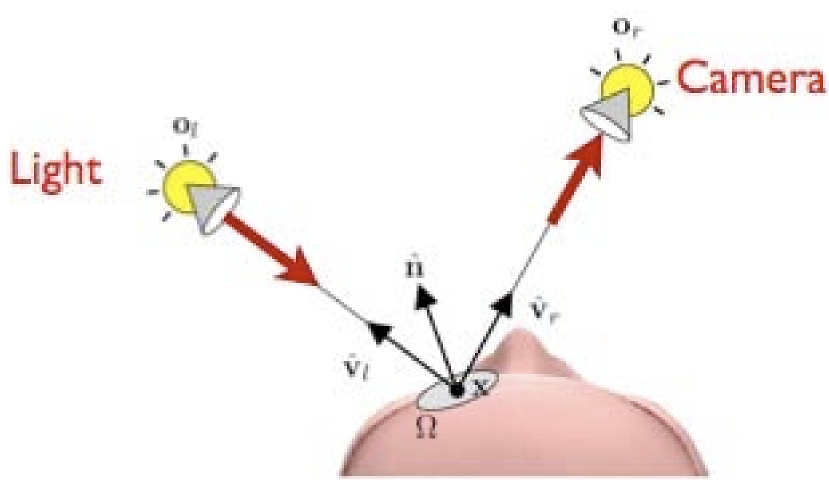
The Reciprocity Principle

- Interchange Camera and Light (*Helmholtz, 1856*)



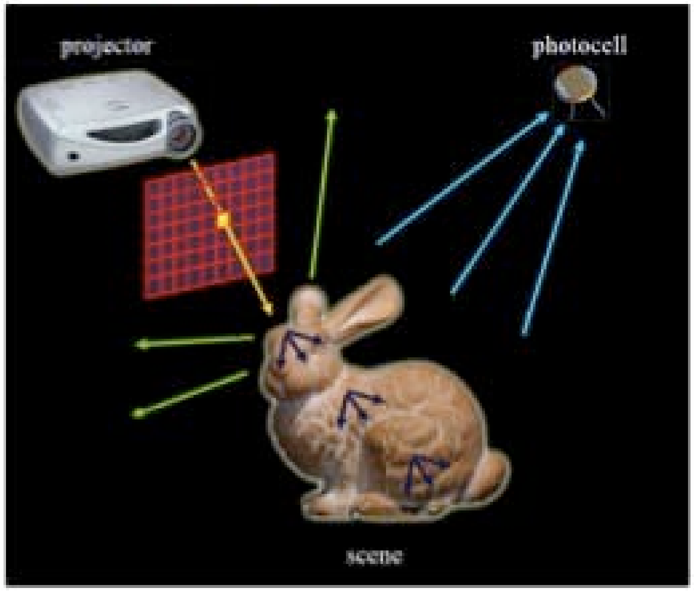
The Reciprocity Principle

- Interchange Camera and Light (*Helmholtz, 1856*)



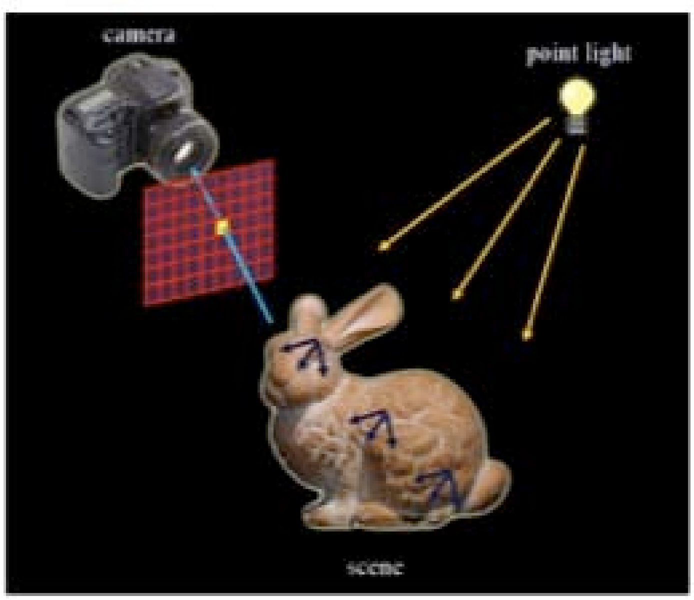
Dual Single Pixel Camera

- Primal Configuration

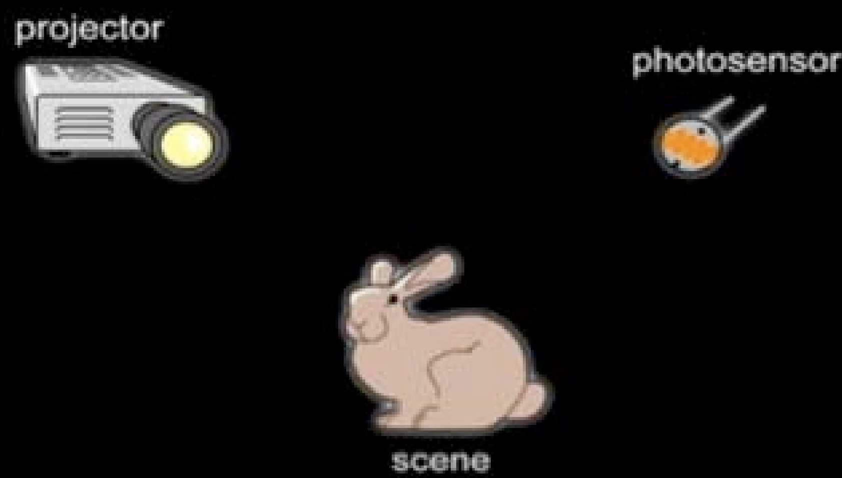


Dual Single Pixel Camera

- Dual Configuration

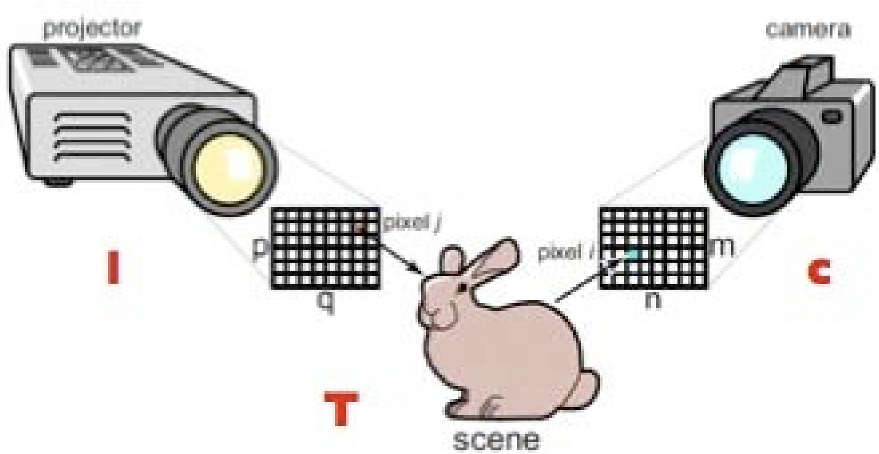


Brute Force Acquistion



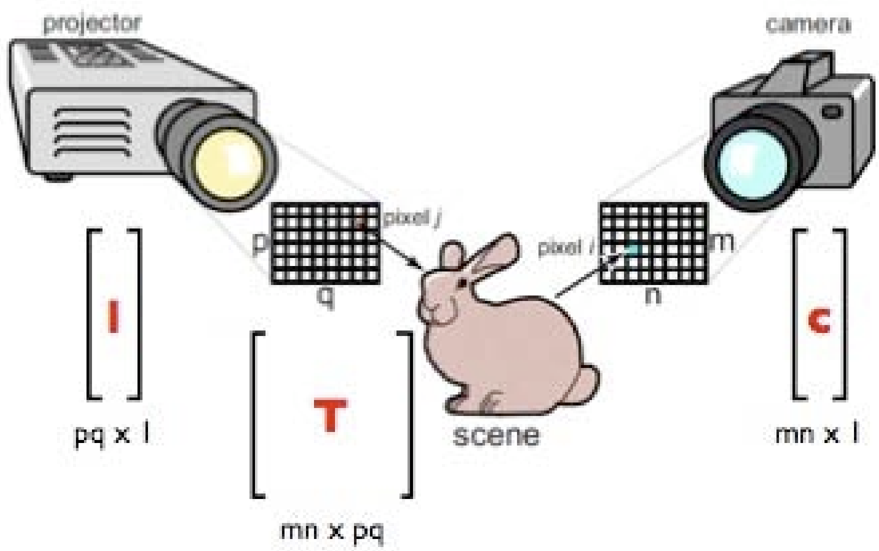
4D Light Transport

- Replace Photocell with a Camera



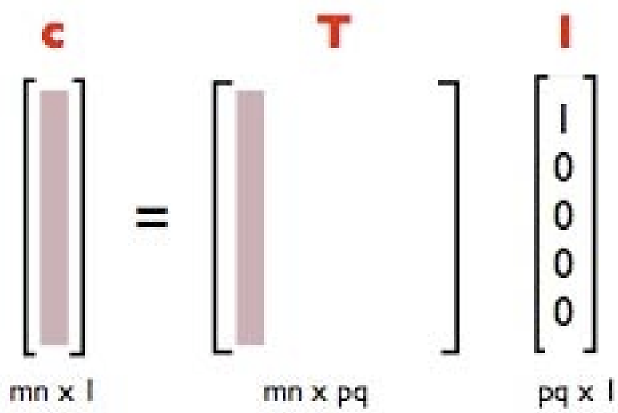
4D Light Transport Matrix

- Replace Photocell with a Camera



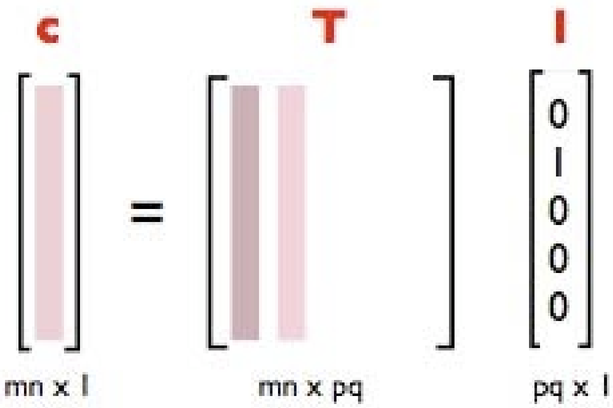
The 4D Transport Matrix

- Primal Configuration



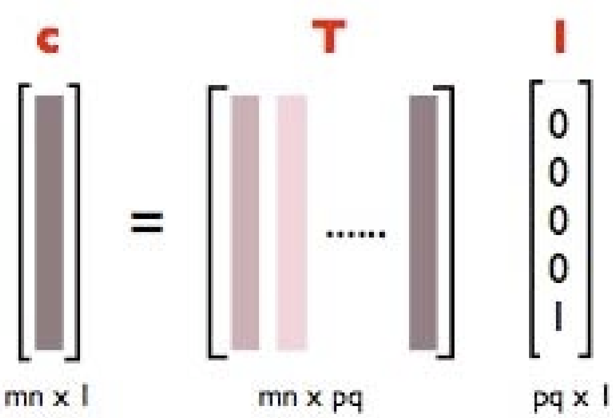
The 4D Transport Matrix

- Primal Configuration



The 4D Transport Matrix

- Primal Configuration

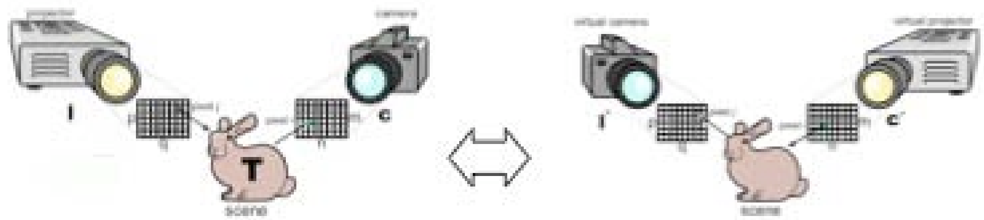


Helmholtz Reciprocity

$$\mathbf{c} = \mathbf{T}\mathbf{l} \quad \Leftrightarrow \quad \mathbf{l}' = \mathbf{T}^{t}\mathbf{c}'$$

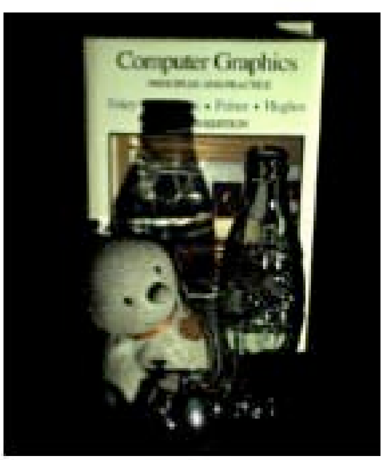
Primal Dual

- Dual Photography

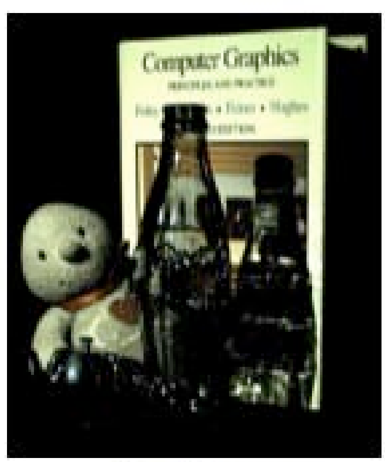


Example 1

- (Sen et al., SIGGRAPH 2005)



Primal Photograph
(*projector is the light source*)

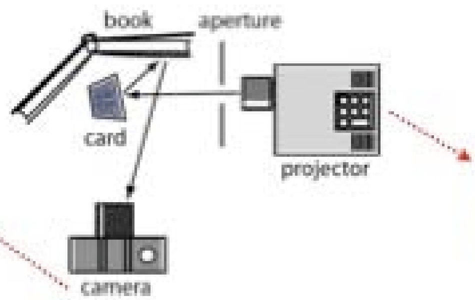


Dual Image
(*as seen from projector*)

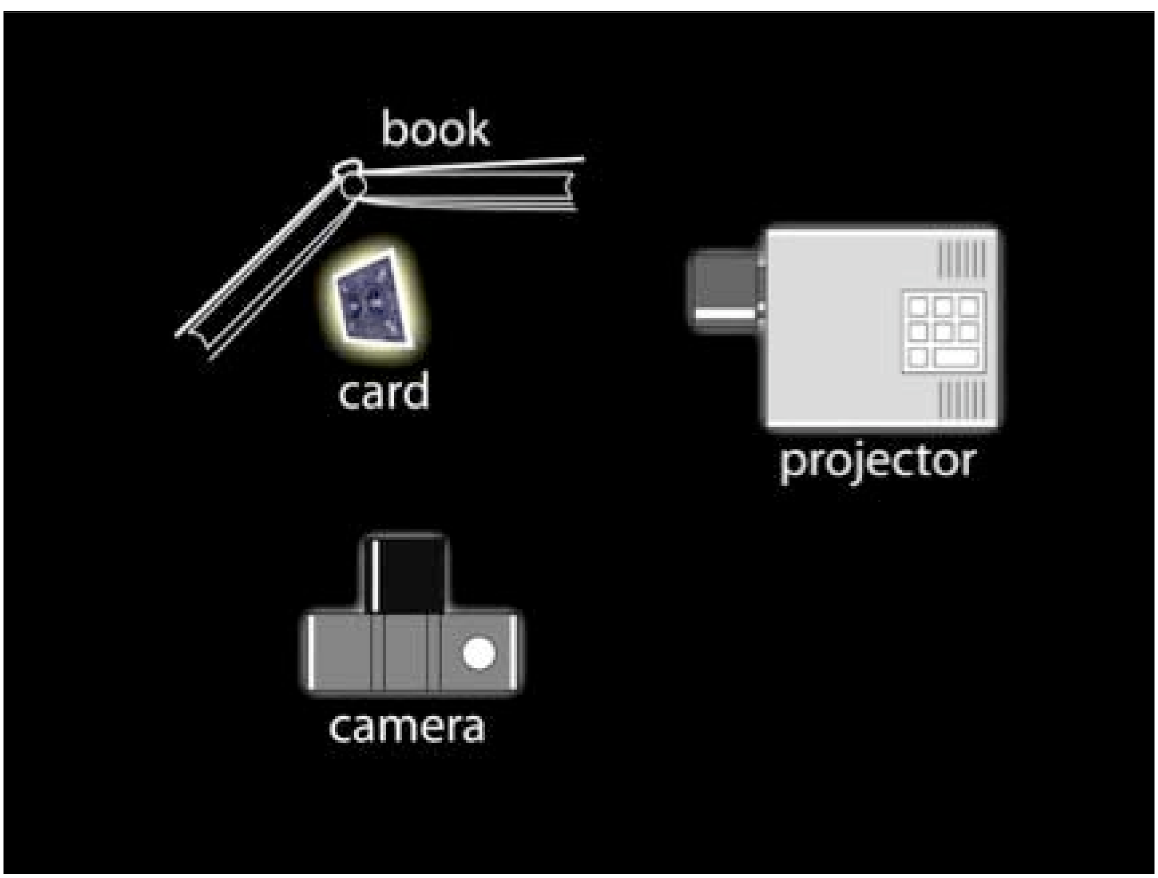
Example 2

- Dual Photography from Diffuse Reflections

Camera's View



Projector's View



Analysis

- Properties of the 4D Light Transport Matrix
  - little inter-reflection → sparse matrix
  - many inter-reflections → dense matrix
  - convex object → diagonal matrix
  - concave object → full matrix

▶ *How to Compute the Transport Matrix ?*

Brute Force Approach

1. Project "Canonical Basis"
2. Capture Each Column of the Matrix

- <u>Acquisition Costs</u>
  - Image / Projector Resolution:
    - ▸ 800 x 600 pixels = 480000 images
    - ▸ ~ 30 seg. / image = 4000 hours (167 days!)

✳ *Not Feasible in Practice... (CS to the Rescue!)*

CS Dual Photography

- *Compressive Light Transport Sensing*
  - Few Non-Adaptive Measurements
- Sparsity Properties
  - Simple Scene and Lighting
    - Matrix ***T*** Directly Sparse
  - Complex Scene and Lighting (columns of ***T*** are images)
    - Sparse in the Wavelet Domain

Sensing

- Light Transport Equation

$$\mathbf{C} = \mathbf{T}\mathbf{L}$$

- Brute Force (*N* images)

$$\begin{bmatrix} c_0 & \cdots & c_k \end{bmatrix} = \begin{bmatrix} & \mathbf{T}_{n\times n} & \end{bmatrix} \begin{bmatrix} 1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 1 \end{bmatrix}$$

- Compressive Sensing (*K* images, i.e, *K* << *N*)

$$\begin{bmatrix} c_0 & \cdots & c_k \end{bmatrix} = \begin{bmatrix} & \mathbf{T}_{n\times k} & \end{bmatrix} \begin{bmatrix} l_0 & \cdots & l_k \end{bmatrix}$$

The Recovery Trick

- Must Relate
  - Light Transport Equation

$$\mathbf{C} = \mathbf{T}\mathbf{L}$$

- to
  - Compressive Sensing Equation

$$\min ||x||_{\ell_1} \qquad y = \mathbf{A}x$$

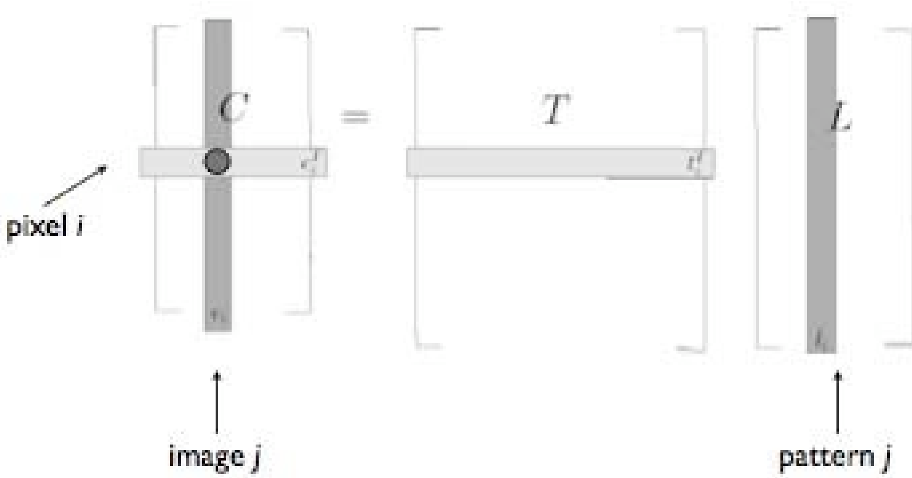
matrix

unknowns

vector

Recovery: Step 1

- Single Pixel through Time



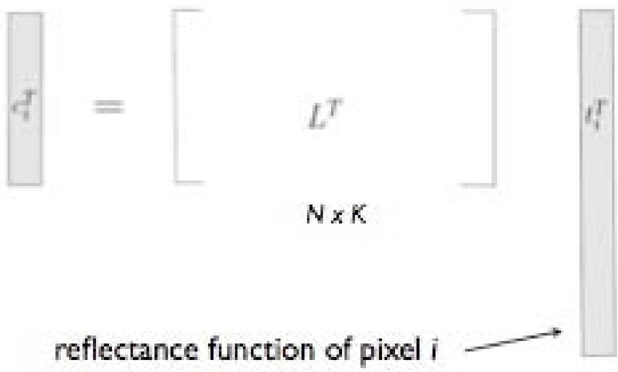
Recovery: Step II

- Transpose Equation

$$\mathbf{C}^t = \mathbf{L}^t\mathbf{T}^t$$

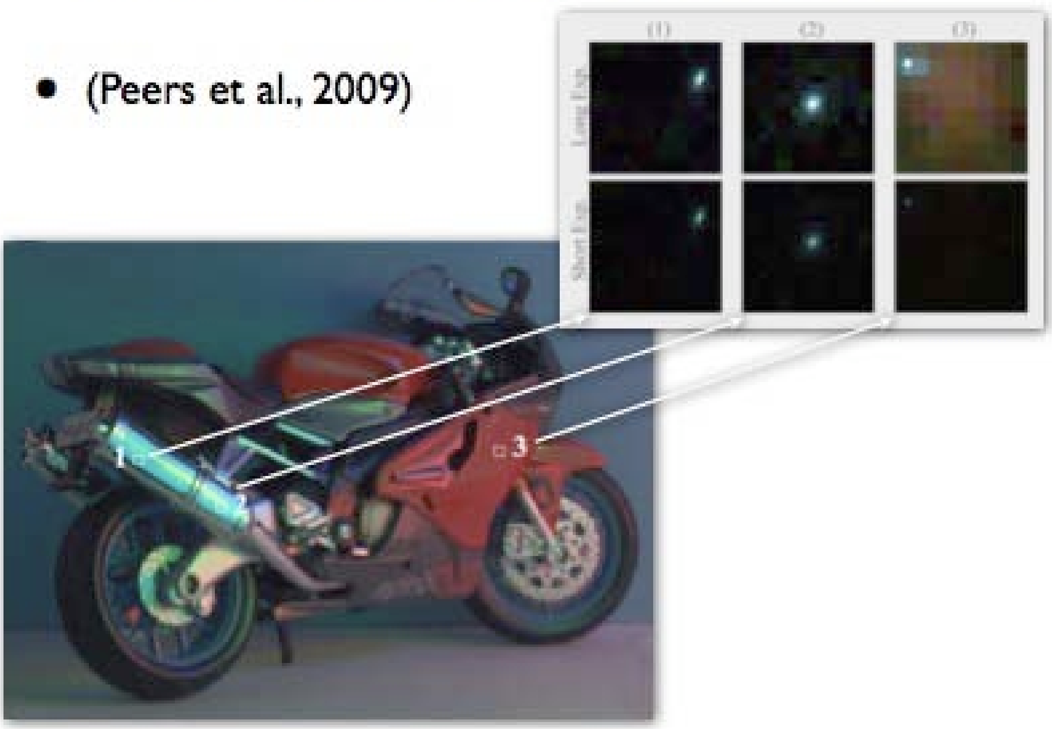
- Solve for each pixel

$$c_i^t = \mathbf{L}^t t_i^t \quad \text{for } i = 1, \ldots, K$$



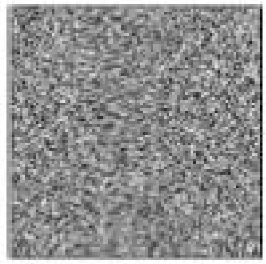
Reflectance Functions

- (Peers et al., 2009)



Implementation Details

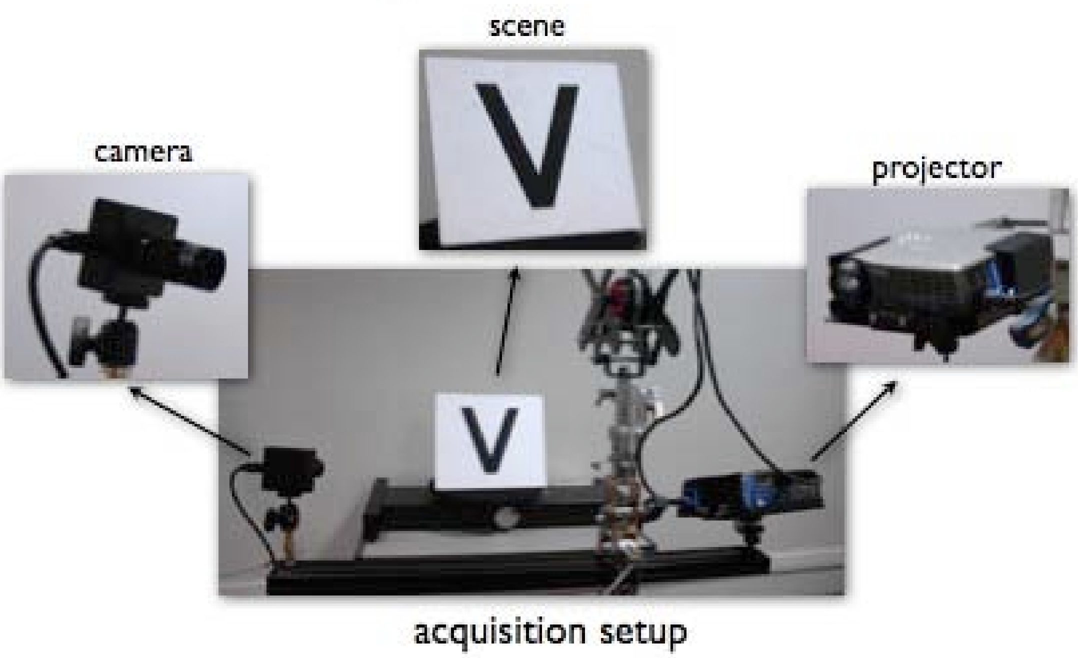
- Matrix L
  - Sparse $T \rightarrow L = \Phi$ (i.e., Bernoulli Matrix)
  - Dense $T \rightarrow L = \Phi\Psi$ (i.e., Daubechies Wavelets)



- Optimization Algorithm
  - ROMP (Regularized Orthogonal Matching Pursuit)

▶ *OBS: Solve in Parallel for each pixel !!!*

Experiments



camera, lights, .. action!

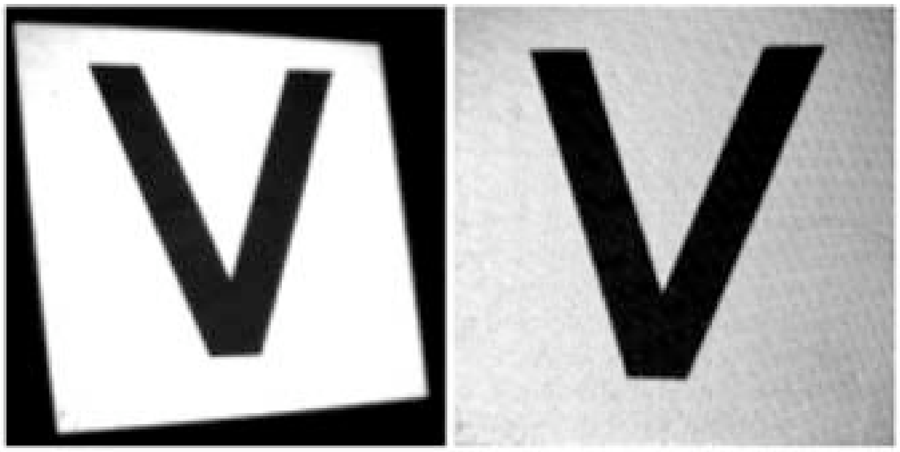
Images

- Projected Pattern

from the camera

from the projector

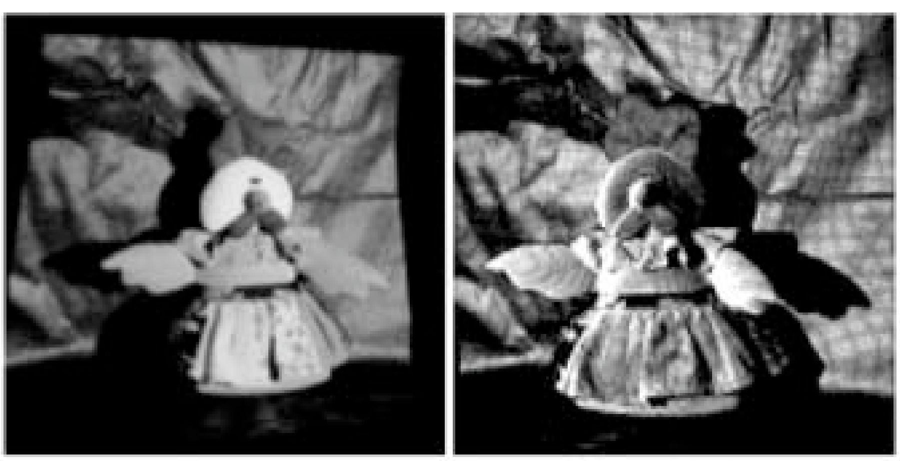
Results I



(a) Primal image. (b) Dual image.

Figure: Image of size 128 × 128, captured with 1500 patterns.

Results II



(a) Primal Image (b) Dual Image

Figure: Image of size 128 × 128, captured with 1000 patterns.

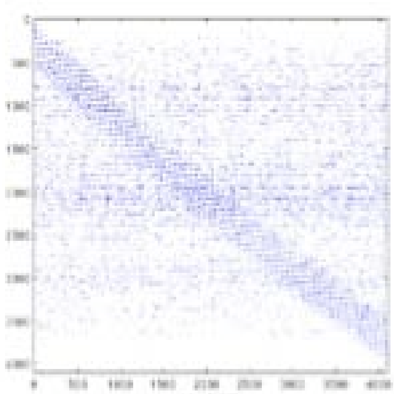
Results III-a

(a) 800 patterns

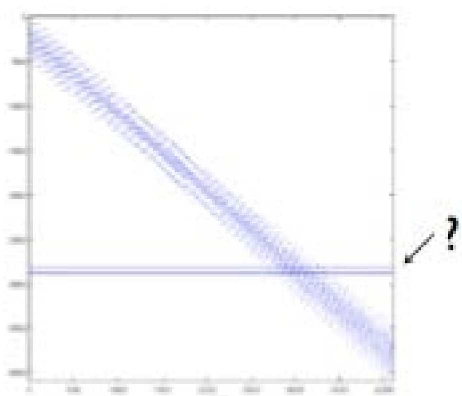
(b) canonic base

Figure: Image of size 64 × 64.

Results III-b



(a) 800 patterns



(b) canonic base

Figure: Image of size 64 × 64.

Image-Based Relighting

- Pipeline:

1. Measure 4D Light Transport Matrix ***T***

$$\mathbf{C}^t = \mathbf{L}^t \mathbf{T}^t$$

2. Synthesize Incident Light Field *l'*

$$l' = f(p)$$

3. Relight Scene with Transport Matrix

$$c' = \mathbf{T} l'$$

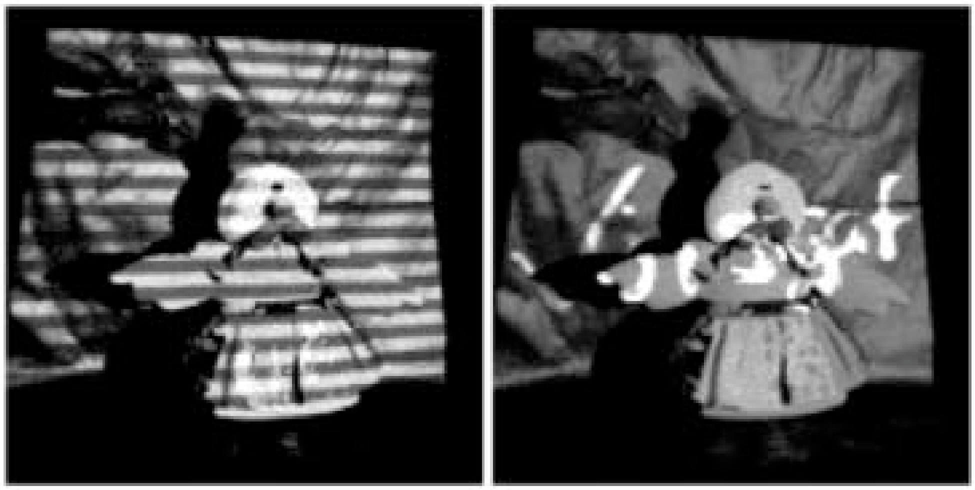
Relighting I

- (Schulz, et al., 2009)

(a) Image Relighting (b) Image Relighting (c) Image Relighting

Figure: Image of size 128 × 128, captured with 1500 patterns.

Relighting II



(a) Image Relighting (b) Image Relighting

Figure: Image of size 128 × 128, captured with 100 patterns.

Dual CS Single Pixel Camera

- Use Camera as a Photocell
  - Integrate over All Image Pixels

$$c = \sum_j c_j$$

- Solve using Wavelet basis

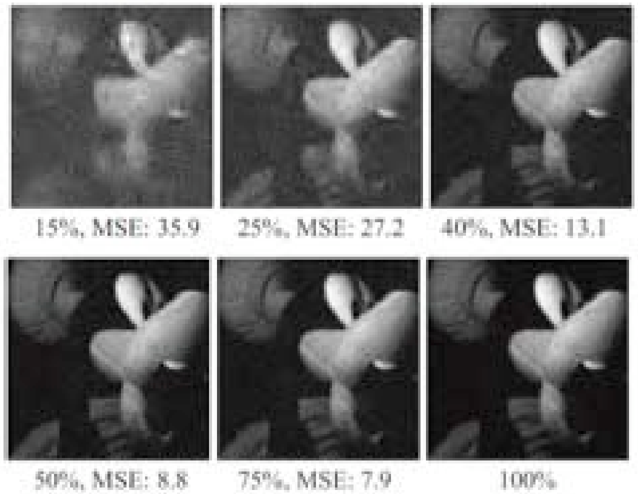
$$c = \mathbf{L}^t \Psi^t \hat{t}$$

- Reconstruct

$$t = \Psi^t \hat{t}$$

Example

- Comparison: Dual Single Pixel x Full DLT



MSE: 7.3

Full DLT
(512 patterns)

Image Resolution: 128 x 128 (16.384)

Conclusions

- to be continued...