Super-Resolution in Compressive Coded Imaging Systems via l2 – l1 – l2 Minimization Under a Deep Learning Approach

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Introduction

High-resolution image

- High-resolution Sensor → A huge amount of data; No post-processing
- Low-resolution Sensor + Up-sampling with AI → A lower amount of data; Data-depend results; High post-processing charge
- Compressive sensing → A lower amount of data; High post-processing charge

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Compressive sensing

CS imaging

$\boldsymbol{y} = \mathbf{Hf}$

Reconstruction

Post-processing

- Sensing matrix $\mathbf{H}$ depends on the optical architecture.
- Inverse ill posed problem

$$\hat{\mathbf{f}} = argmin_{\mathbf{x}} ||\mathbf{Hx} - \mathbf{y}||_2^2 + \tau||\mathbf{\Phi x}||_1$$

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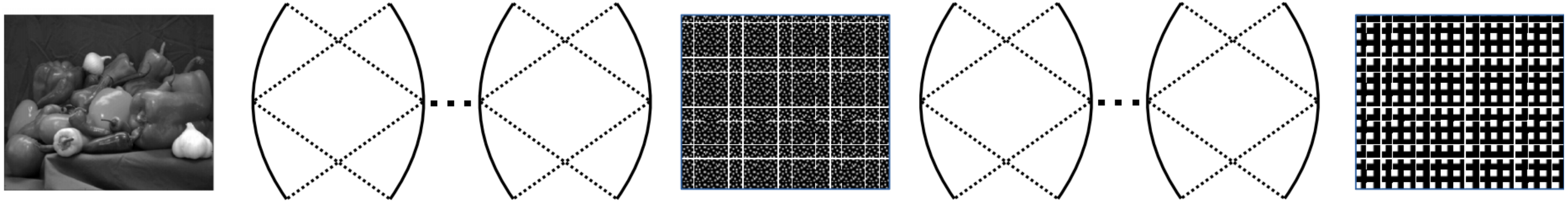
Sensing model – General scheme



$$(\mathbf{y})^i = \mathbf{D}\mathbf{H}_1(\mathbf{H}_2)^i\mathbf{H}_3\mathbf{f}$$

$$y = \begin{bmatrix} (\mathbf{y})^1 \\ (\mathbf{y})^2 \\ \vdots \\ (\mathbf{y})^k \end{bmatrix} = \begin{bmatrix} \mathbf{D}\mathbf{H}_1(\mathbf{H}_2)^1\mathbf{H}_3 \\ \mathbf{D}\mathbf{H}_1(\mathbf{H}_2)^2\mathbf{H}_3 \\ \vdots \\ \mathbf{D}\mathbf{H}_1(\mathbf{H}_2)^k\mathbf{H}_3 \end{bmatrix}\mathbf{f} = \overline{\mathbf{H}}\mathbf{f}$$

$\mathbf{F} \in \mathbb{R}^{M\times \boldsymbol{N}}$	$\mathbf{h_2} \in \{0,1\}^Q$
$\mathbf{H_3} \in \mathbb{R}^{Q\times MN}$	$\mathbf{H_1} \in \{0,1\}^{P\times Q}$
$\mathbf{H_2} = diag(\mathbf{h_2})$	$\mathbf{D} \in \{0,1\}^{S\times P}$

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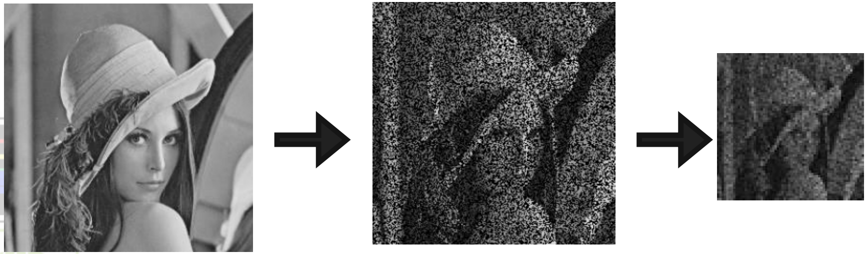
Sensing model – Super-resolution systems

Grayscale imaging

$$\mathbf{H_1} = \mathbf{H_3} = \mathbf{I}_Q \qquad \mathbf{D} \in \{0,1\}^{Q/16\times Q}$$

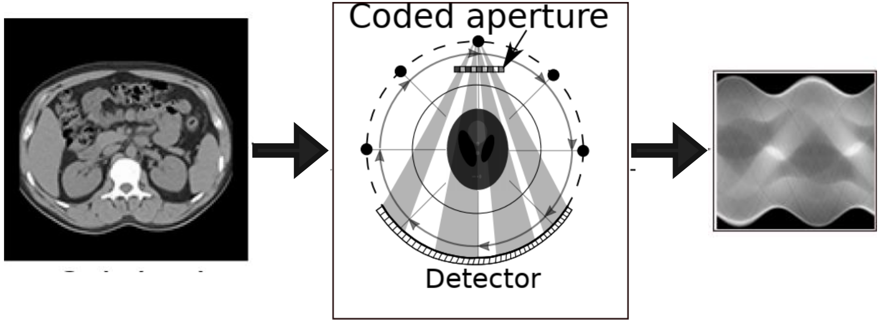
$$Q = P = MN \qquad \boldsymbol{h}_2 \in \{0,1\}^{Q}$$



Fan beam computed tomography

$$\mathbf{H_1} = \mathbf{I}_{\theta d} \qquad \mathbf{D} \in \{0,1\}^{(1/4)\theta d\times \theta d}$$

$$S = (1/4)\theta d \qquad \boldsymbol{h}_2 \in \{0,1\}^{\theta d}$$



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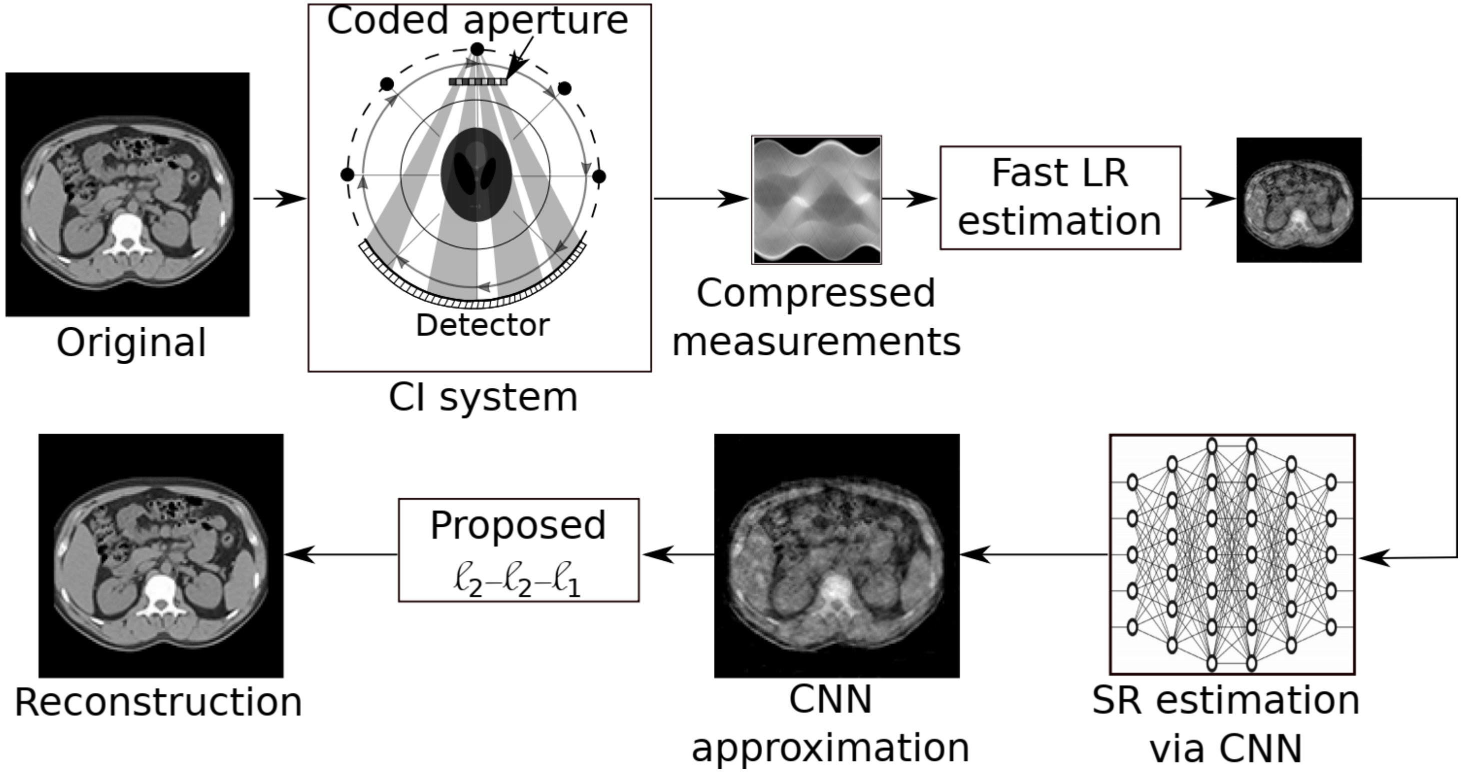
Proposed reconstruction model



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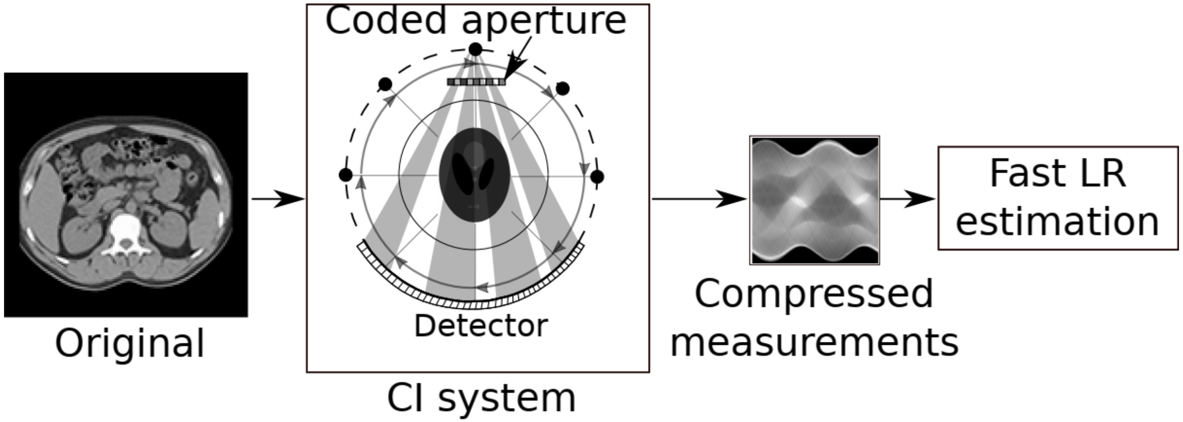
Proposed reconstruction model



$$\tilde{\mathbf{f}} = argmin_x \left|\left|\bar{\mathbf{H}}\tilde{\mathbf{D}}^T\mathbf{x} - \mathbf{y}\right|\right|_2^2 + \tau \left|\left|\boldsymbol{\Phi}\tilde{\mathbf{D}}^{\mathrm{T}}\mathbf{x}\right|\right|_1$$

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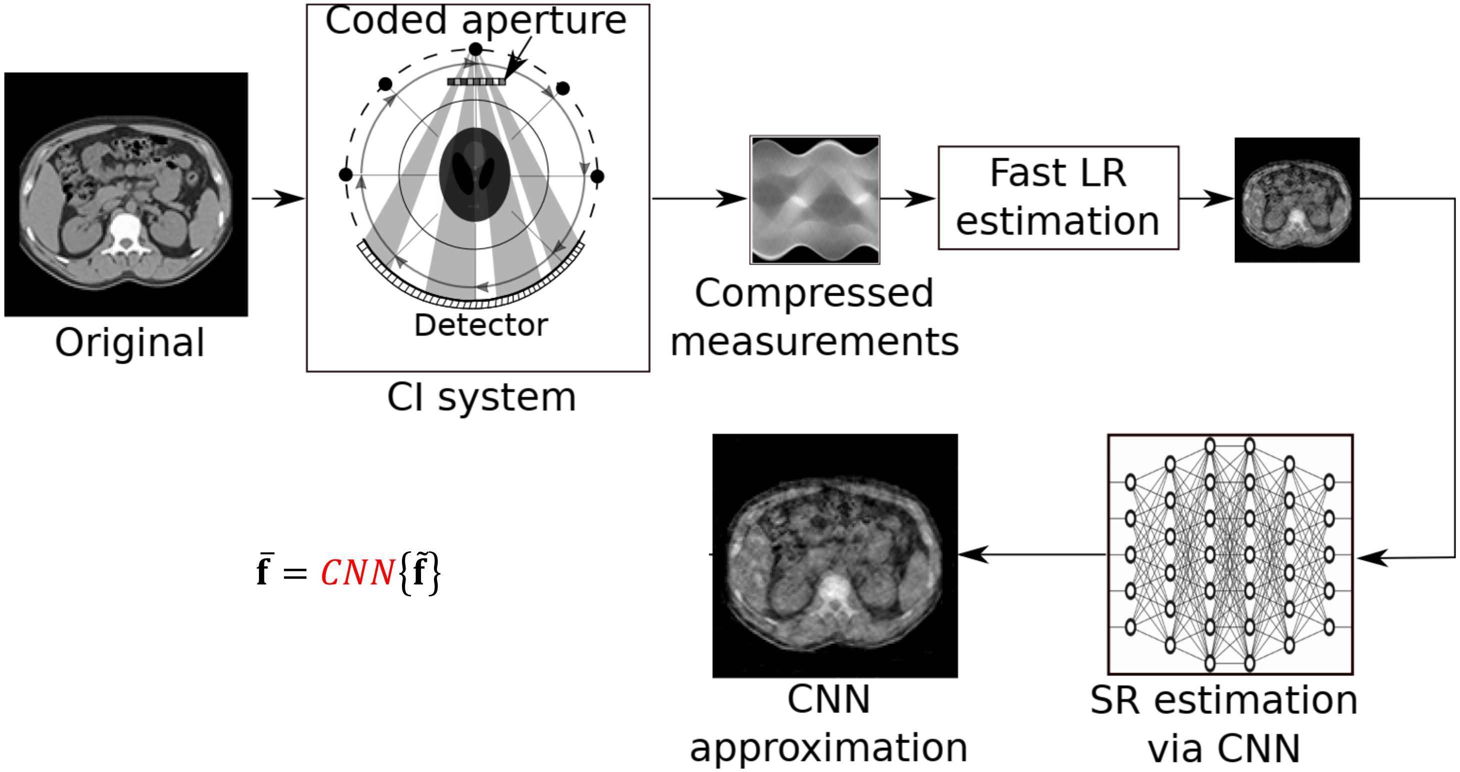
Proposed reconstruction model



$$\bar{\mathbf{f}} = \color{red}{CNN}\{\tilde{\mathbf{f}}\}$$

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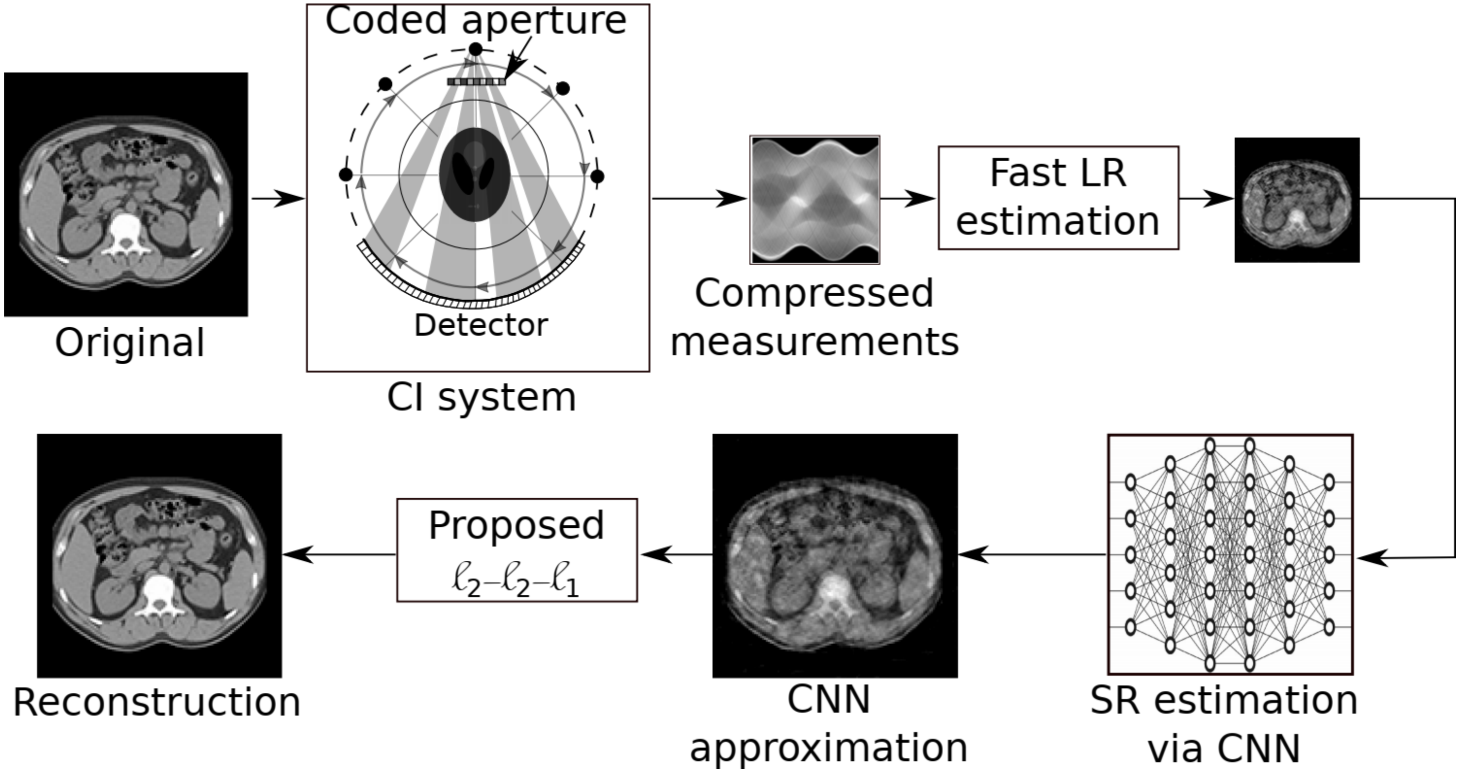
Proposed reconstruction model



$$\hat{\mathbf{f}} = argmin_x \left|\left|\bar{\mathbf{H}}\mathbf{x} - \mathbf{y}\right|\right|_2^2 + \tau_1 \left|\left|\mathbf{\Phi x}\right|\right|_1 + \tau_2 \left|\left|\bar{\mathbf{f}} - \mathbf{x}\right|\right|_2$$

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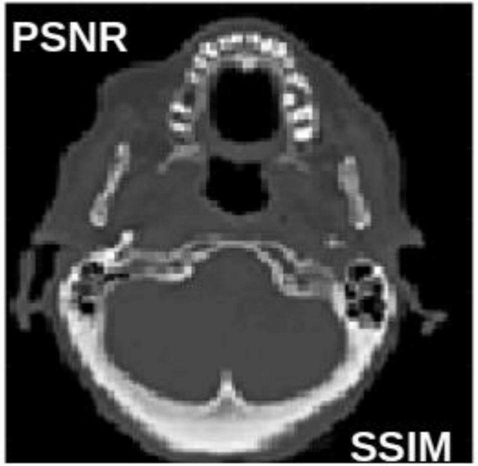
Simulation and Results

- $\mathbf{F} \in \mathbb{R}^{256\times\mathbf{256}}$ For the grayscale scheme
- $\mathbf{F} \in \mathbb{R}^{128\times 128}$ For the CT scheme.
- $K = \{2,4,6,8\}$
- Error metrics: PSNR and SSIM
- Solved using Gradient projection for sparse reconstruction (GPSR)



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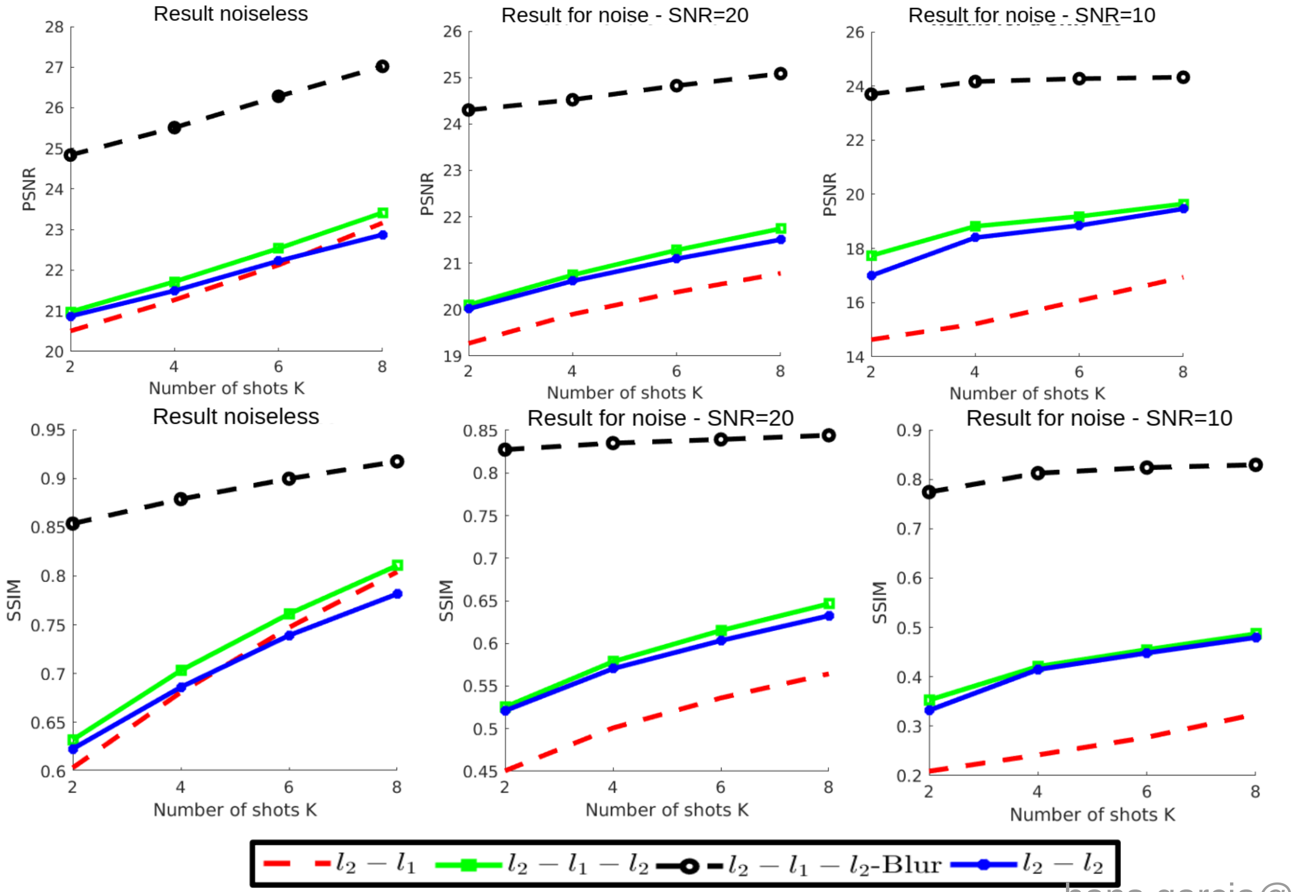
Results Grayscale imaging



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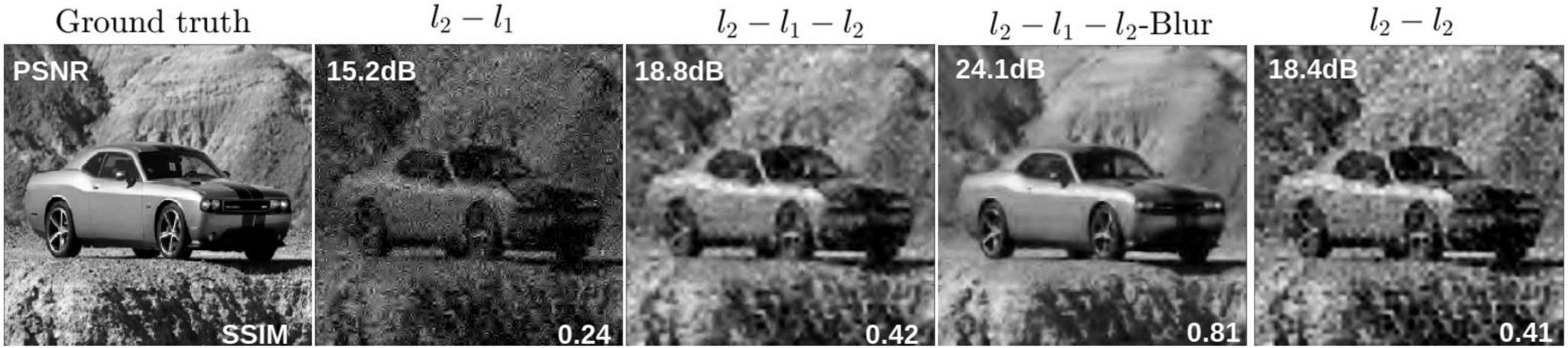
Results Grayscale imaging



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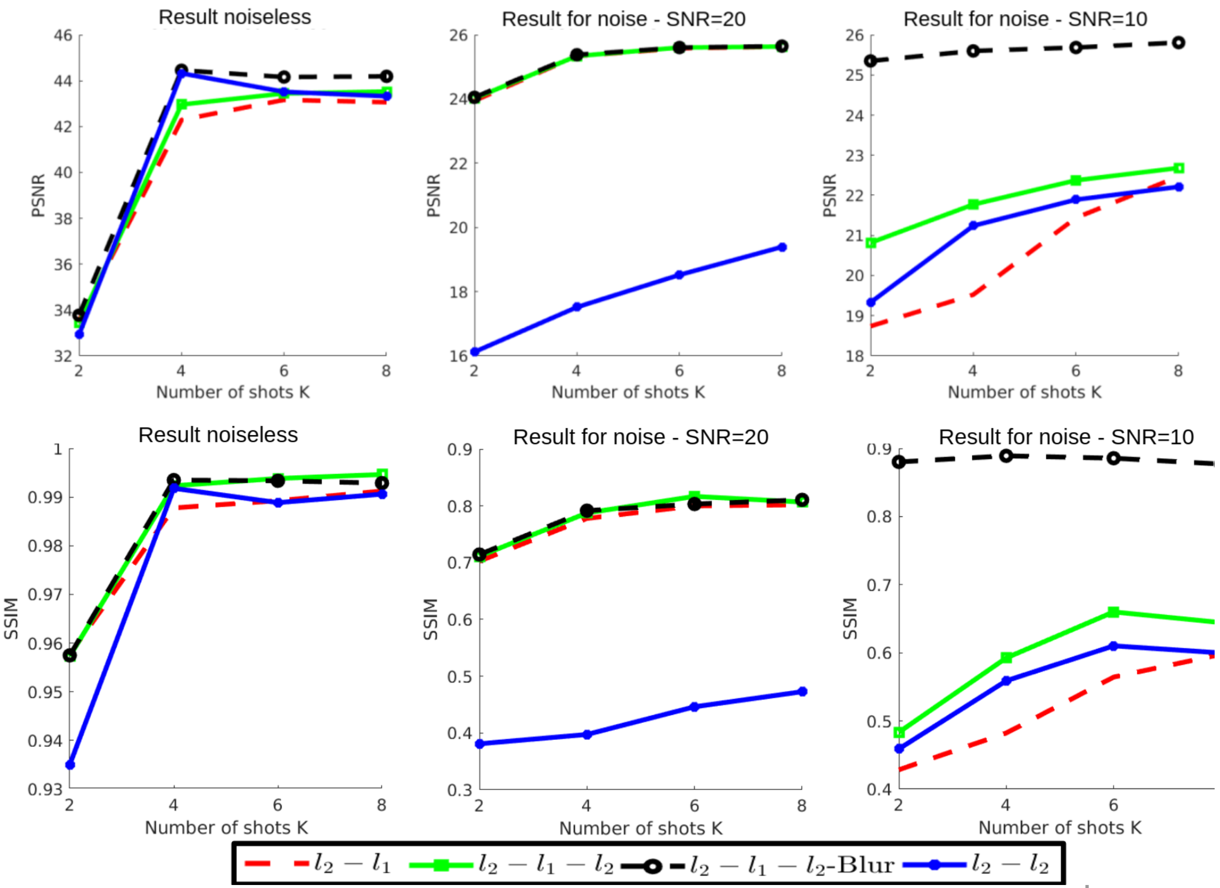
Results Fan beam computed tomography



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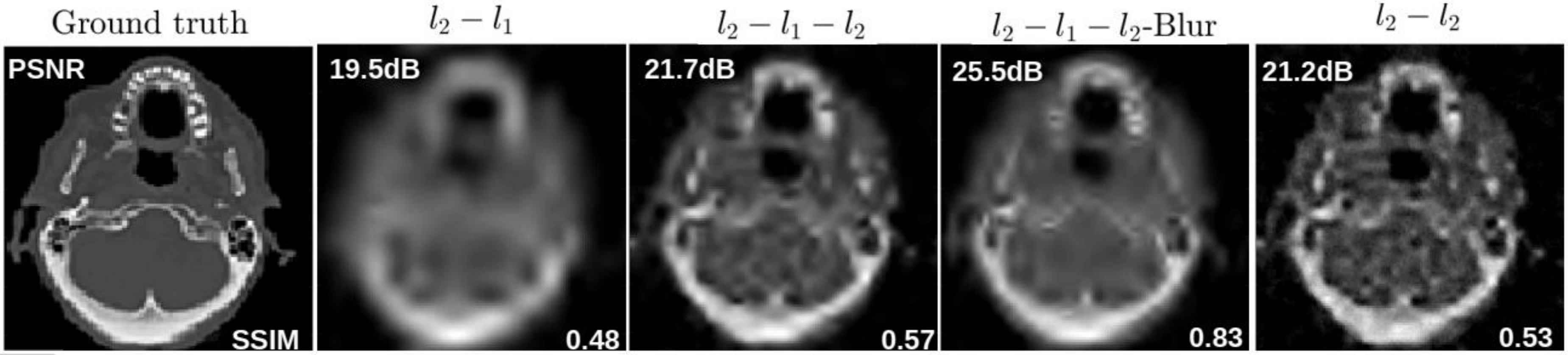
Results Fan beam computed tomography



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Conclusions

- This paper proposed a mathematical sensing model for the systems that acquire low-resolution compressive measurements from a high-resolution codification.

- In this work was proposed to include this reconstruction into an l2 fidelity regularizer in the traditional $l2 - l1$ optimization problem

- The proposed mathematical model gains up to 3.7dB in averaged PSNR against the use of the traditional $l2 - l1$ approach

- In the case that use a blur version of the input scene, the proposed approach gains up to 9dB in averaged PSNR against the use of the traditional $l2 - l1$ approach.

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