Summary of Work at IITB: Ajit Rajwade

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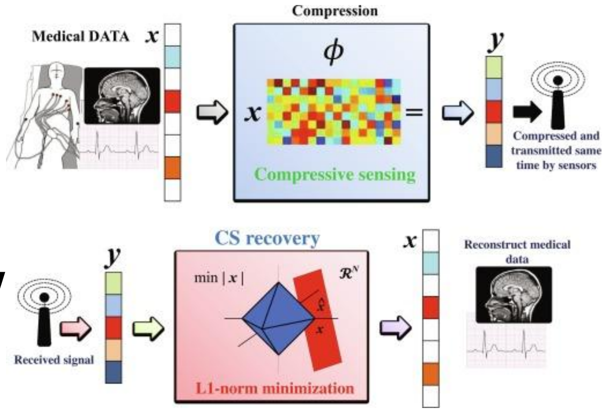
Research Summary: Area Overview

- **Broad Area:** Image Processing, Computer Vision
- **Sub-areas of focus:**
  ✓ Image Restoration
  ✓ Compressed Sensing
  ✓ Tomography
- **Research Theme:** Use of principles from following disciplines to solve afore-mentioned computational problems:
  ✓ Statistics
  ✓ Signal processing
  ✓ Physics (Optics/Geometry)

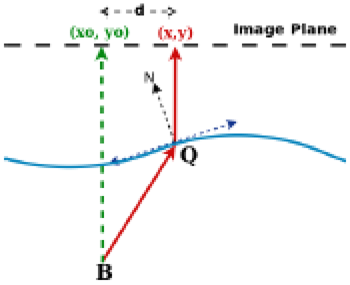
Research Philosophy

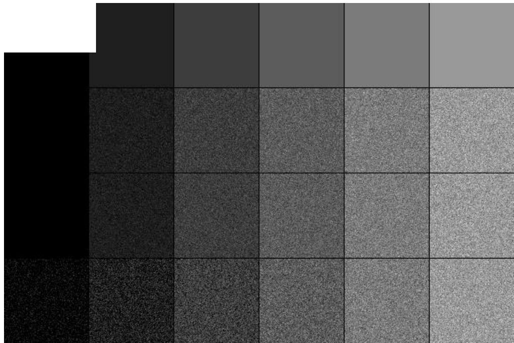
- Aim: Bringing in (artificial) intelligence in data acquisition
- Era of BIG data – but you should acquire data **smartly** and measure only what is **really** needed
- Compressed sensing: acquisition of data directly in **compressed format**
- Improves acquisition **speed** and **reduces resources** for acquisition
- Resources: Time, radiation, battery power, electricity, etc.



Application Areas

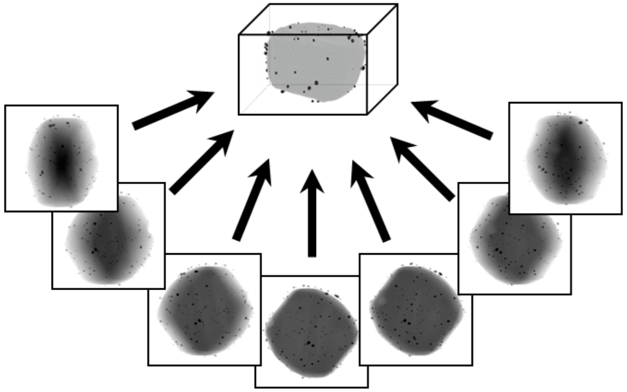
- Low dosage computed tomography (CT)
- Algorithms to deal with errors in acquisition of MRI (magnetic resonance imagery)
- Underwater image restoration
- Compressed sensing with realistic noise models: theoretical analysis





(1) Low Dosage Computed Tomography

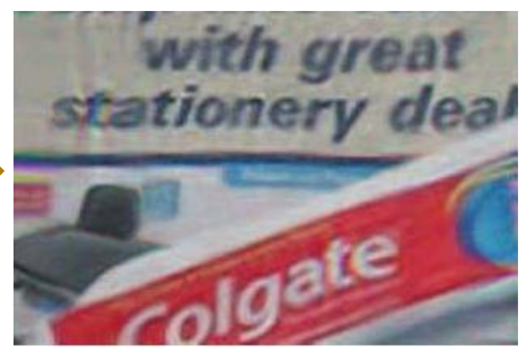
- Potential Social Impact of Research:
- ✓ Designing algorithms to enable reduction of radiation dosage administered to patients undergoing repeated CT Scans
- ✓ More angles of radiation = better reconstruction quality = higher radiation dosage
- ✓ But past scans can act as guiding templates for good reconstruction with reduced number of radiation angles
- ✓ Work with Sharat, Imants Svalbe, Preeti Gopal (PhD student), Dr. Akshay Baheti (Tata Memorial Hospital)



- P. Gopal, S. Chandran, I. Svalbe and A. Rajwade, "Low radiation tomographic reconstruction with and without template information", submitted to Elsevier Signal Processing
- * P. Gopal, S. Chandran, I. Svalbe and A. Rajwade, "Learning from past scans: Tomographic reconstruction to detect new and evolving structures", submitted to Elsevier Signal Processing

(2) Underwater imaging: restoration

- Static scene submerged in clear shallow water at constant depth
- Imaged by orthographic camera
- Distortion due to dynamic refraction at wavy surface
- Special case of non-rigid motion estimation
- End-goal: Image Restoration
- Applications: underwater or submarine surveillance



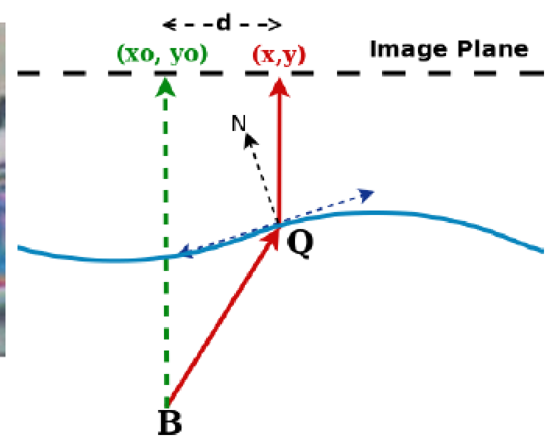


Figure 1. Refractive image formation at a wavy water surface

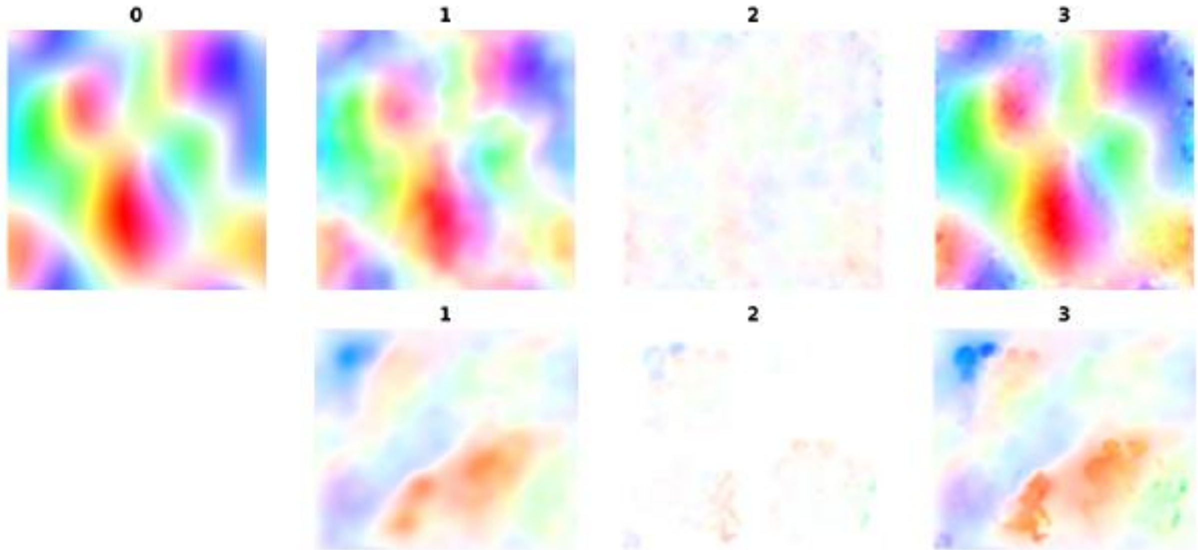
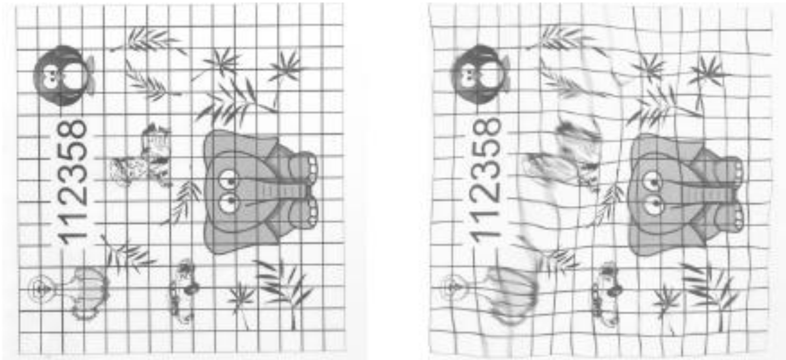
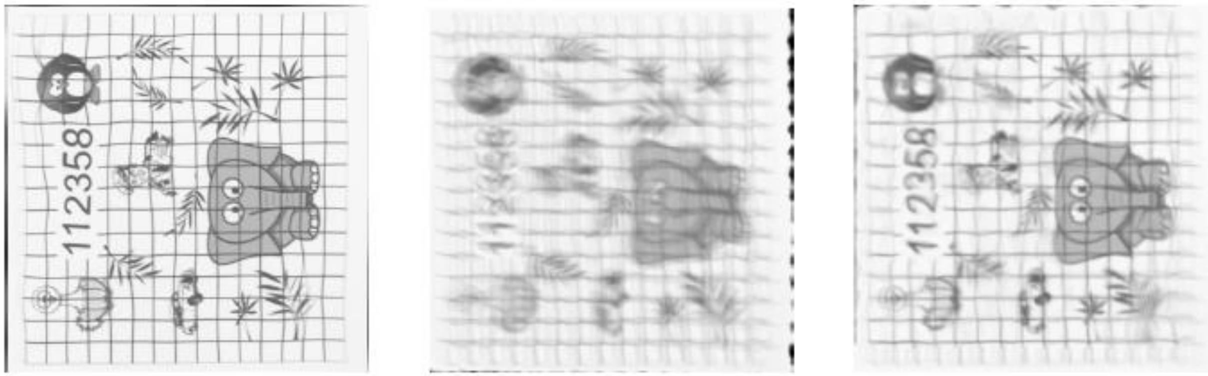


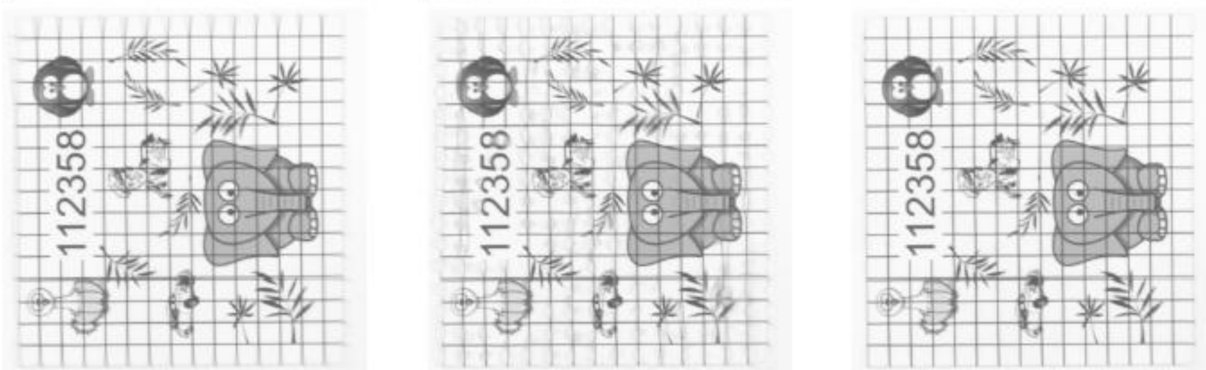
Figure 1. Two stage estimation of MVF. Top row: from a synthetic video; bottom row: from a real video (Cartoon). (0) Ground truth flow for a randomly selected frame (only for synthetic video) (1) MVF estimated by CS Stage (2) The residual MVF estimated by PEOF (3) Final estimate of the MVF: CS+PEOF. One can observe that CS initially estimates a good approximation to the original flow (*Motion reduction*: $\approx 89\%$ for synthetic and $\approx 94\%$ for real). PEOF improves the approximation to the original flow. Flow visualization uses known convention from 'Baker et al, *A Database and Evaluation Methodology for Optical Flow*, IJCV 2011'.



Distorted data



Three SOTA techniques

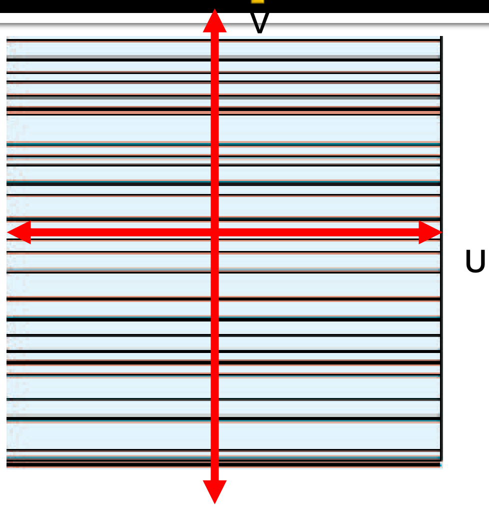


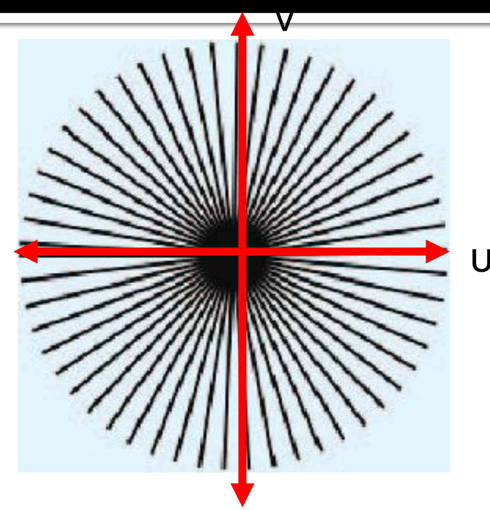
Results with our algorithms

*J. G. James and A. Rajwade, "*Restoration of Non-rigidly Distorted Underwater Images using a Combination of Compressive Sensing and Local Polynomial Image Representations*", ICCV 2019 (oral), WACV 2020

*Qualcomm India Innovation Fellowship, 2018 for Jerin

(3) Error-resilient MR image acquisition





- Errors in MR hardware (gradient delays *)
- Specified frequencies ≠ measured frequencies, i.e. error in specification of sensing matrix **F**.
- Now we have a problem where **θ** and the $\{\delta_i\}$ values are both unknown.

$$\mathbf{y} = \mathbf{F}_\delta \mathbf{x} + \eta = \mathbf{F}_\delta \mathbf{\Psi} \theta + \eta$$

$$\mathbf{y} \in C^m, \mathbf{F}_\delta \in C^{m \times n}, \mathbf{x} \in C^n, \boldsymbol{\theta} \in C^n, \eta \in C^m$$

$$m << n$$

- Each row – measurement at frequency u_i (known) + δ_i (**unknown**)
- $|\delta_i| \leq r$, r known

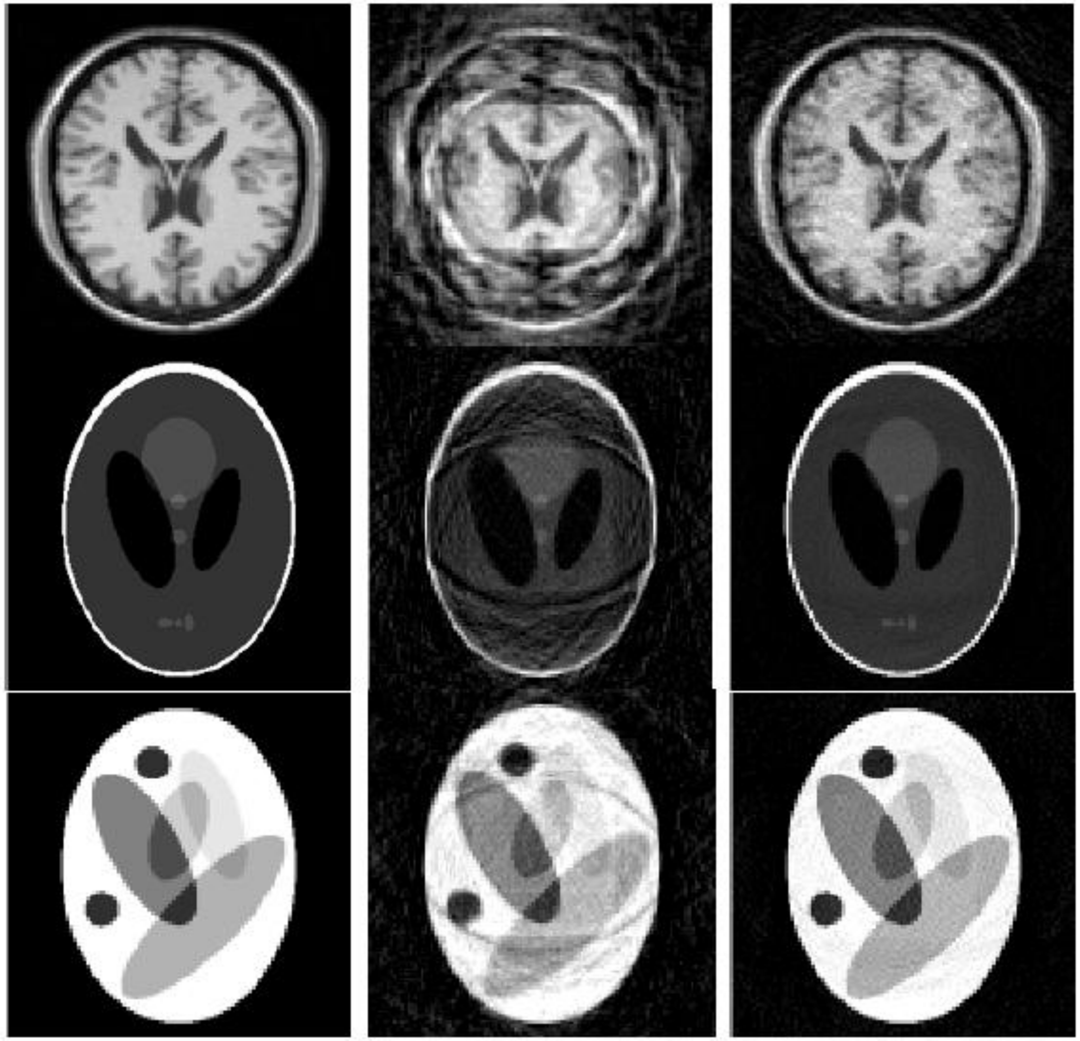
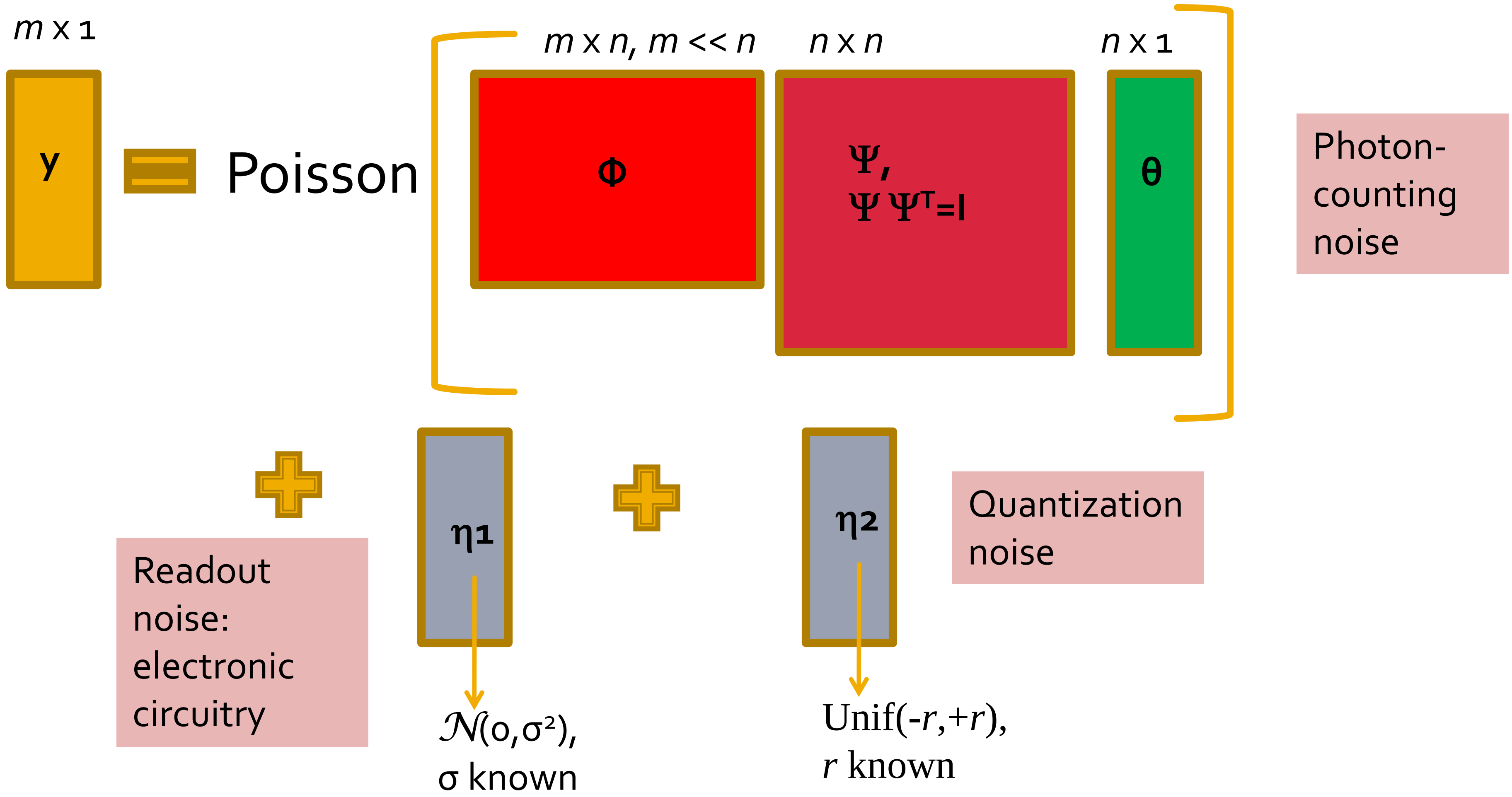


Figure 11. Reconstruction for 200×200 images with 5% zero mean Gaussian measurement noise, 70% compressive measurements, angle error from Uniform$[-3°, +3°]$. In each row, left: original image, middle: reconstruction using Baseline 1 (RRMSE 38.75%, 35.48%, 14.59%), right: reconstruction using modified version of Algorithm 1 (RRMSE 13.15%, 5.29%, 5.85%).

Himanshu Pandotra, Eeshan Malhotra, *Ajit Rajwade* and Karthik S. Gurumoorthy, "Dealing with Frequency Perturbations in Compressive Reconstructions with Fourier Sensing Matrices", Signal Processing (Elsevier), 2019

(4) Compressed sensing with realistic noise models: Poisson-Gaussian-quantization noise



Our contributions

- Theoretical error bounds for a tractable estimator for Poisson CS
- Principled parameter tuning
- Easily extensible to Poisson-Gaussian-quantization noise
- ✓ Novel usage of the Variance Stabilization Transforms
- ✓ A case of *non-linear* compressed sensing!

- Pakshal Bohra, Deepak Garg, Karthik S. Gurumoorthy and *Ajit Rajwade*, "Variance Stabilization Based Compressive Inversion under Poisson or Poisson-Gaussian Noise with Analytical Bounds", Inverse Problems (IOP), 2019
- Sukanya Patil, Karthik S. Gurumoorthy and *Ajit Rajwade*, "Using an Information Theoretic Metric for Compressive Recovery under Poisson Noise", Signal Processing (Elsevier), 2019
- Rudrajit Das and Ajit Rajwade, "Nonlinear blind compressed sensing under signal dependent noise", ICIP 2019