A Matrix-Free Reconstruction Method for Compressive Focal Plane Array Imaging

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Introduction

- High Resolution & Contrast imaging requirement
- Large FPA sensors are expensive
- Effect of noise & bad pixel
- Compressive Sensing → Compressive Focal Plane Array Imaging
- Digital Micromirror Devices (DMD)
- Compressive Sensing reconstruction algorithms are slow
  - Real-time application
  - Large matrix multiplication

Motivation

- Real-time applicable algorithms needed for reconstruction.
- Alternating Direction Method of Multipliers (ADMM) for fast convergence
- Requires large matrix inversion with ADMM
- Robustness against bad pixels.
- Fast implementation

Observation Model

- Multiple snapshots, each modulated using a DMD mask
- Linear Forward Model:
  - \( y = Ax + n \) (1)
  - \( A \): Bernoulli type block-diagonal sensing matrix.
  - \( y_j = A x_j + n_j \) (2)
    - Full +1/-1 sensing matrix
  - \( x \): scene, \( n \): noise

Previous Approaches

- Main advantage:
  - Lower computational complexity \((O(mN + Nlg(N) + kN))\)
  - \( m \to s lg(N) \)
  - Faster convergence, complexity of OMP

Theory

- Approach:
  - Break block-sparse structure (reorder)
  - \( A = [(D \Lambda_1)^T \cdots (D \Lambda_m)^T]^T \)
  - \( D \): Downsampling operator, \( \Lambda_i \): Mask at snapshot \( i \).
- \[ \min_{\alpha_1, \alpha_2} TV(x) + \alpha_1 \|Fx\|_1 \] subject to \[ \|D \Lambda_i x - y_i\|_2 \leq \varepsilon_i \]
- \( \varepsilon_i^2 \): noise energy in snapshot \( i \)

Advantages

- Faster than state-of-the-art (TVAL3)
- Better image quality using linear combination of two sparsifying bases

Proposed Method

- An Alternating Direction Method of Multipliers (ADMM) was developed.
- \[ \min_{x,z} f_1(x) + f_2(z) \] subject to \( x = z^{(1)}, \ldots, z = z^{(2+m)} \)
- Set \( f_2(z) = \alpha_1 TV(z^{(1)}) + \alpha_2 \|Fz^{(2)}\|_1 + \sum_i (|D \Lambda_i x^{(2+i)} - y_i|_2 \leq \varepsilon_i)_1 f_i(x) = 0 \).
- Solve 2 proximal mappings and \( m \) projections.
  - Total Variation → Chambolle Projection [2]
  - L1-norm → Soft Thresholding
  - Indicator Functions → Derived in the Paper

Results

- Comparison to literature
  - TVAL3
  - Matrix-based ADMM
  - Projection-based ADMM (Proposed)
- Faster than state-of-the-art (TVAL3)
- Better image quality using linear combination of two sparsifying bases

References


Figure 1: Observation model, modulation using DMD

Figure 2: Convergence Ratio (%)

Figure 3: Reconstruction PSNRs vs computation time (%20 compression)

Figure 4: Reconstruction from simulated data: (a) Reference image. (b) Low-resolution image obtained using the FPA sensor. (c) Reconstruction using TVAL3. (d) Reconstruction using the proposed algorithm

Figure 5: Reconstruction from experimental data: (a) Reference image. (b) Low-resolution image obtained using the FPA sensor. (c) Reconstruction using TVAL3. (d) Reconstruction using the proposed algorithm