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

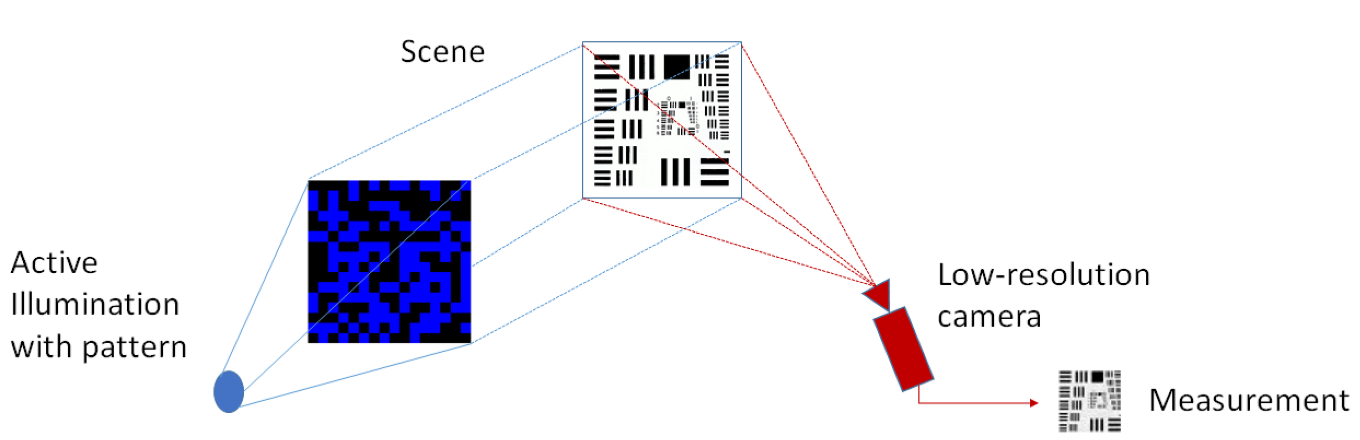

Figure 1: *Observation model, modulation using DMD*

- Linear Forward Model:

$$y = Ax + n \quad (1)$$

- A: Bernoulli type block-diagonal sensing matrix.

$$y_j = A_j x^{(j)} + n_j \quad (2)$$

- Full +1/0 sensing matrix
- x: scene, n: noise

Previous Approaches

$$\min_x TV(x) + \frac{\lambda}{2}\|Ax - y\|_2^2 \qquad (3)$$

- *Optional positivity constraint, other sparsity bases. TVAL3 [1]*
- *Exploit block-sparse structure*

Theory

- Approach:
    - Break block-sparse structure (reorder)
    - $A = [(D\Lambda_1)^T \quad \cdots \quad (D\Lambda_m)^T]^T$
    - D: Downsampling operator, Λ_i: Mask at snapshot i.

$$\min_x \alpha_1 TV(x) + \alpha_2 \|Fx\|_1 \qquad (4)$$
$$\text{subject to } \|D\Lambda_i x - y_i\|_2 \le \epsilon_i,$$
$$x[j] \ge 0, j \in 1, \cdots, N$$

- ϵ_i^2: noise energy in snapshot i

$$TV(x) = \sum_j \sqrt{(\nabla_1 |x[j]|)^2 + (\nabla_2 |x[j]|)^2},$$

$$\|x\|_p = \left(\sum_j (|x[j]|)^p\right)^{\frac{1}{p}}$$

- N:pixel #

Proposed Method

- An Alternating Direction Method of Multipliers (ADMM) was developed.

$$\min_{x,z} f_1(x) + f_2(z) \qquad (5)$$
$$\text{subject to } x = z^{(1)}, \dots, x = z^{(2+m)}$$

- Set $f_2(z) = \alpha_1 TV\left(z^{(1)}\right) + \alpha_2 \left\|Fz^{(2)}\right\|_1 + \sum_i \left(\left\|D\Lambda_i z^{(2+i)} - y_i\right\|_2 \le \epsilon_i,\right), f_1(x) = 0.$
- Solve 2 proximal mappings and m projections.
    - Total Variation → Chambolle Projection [2]
    - L1-norm → Soft Thresholding
    - Indicator Functions → **Derived in the Paper**

Advantages

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

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

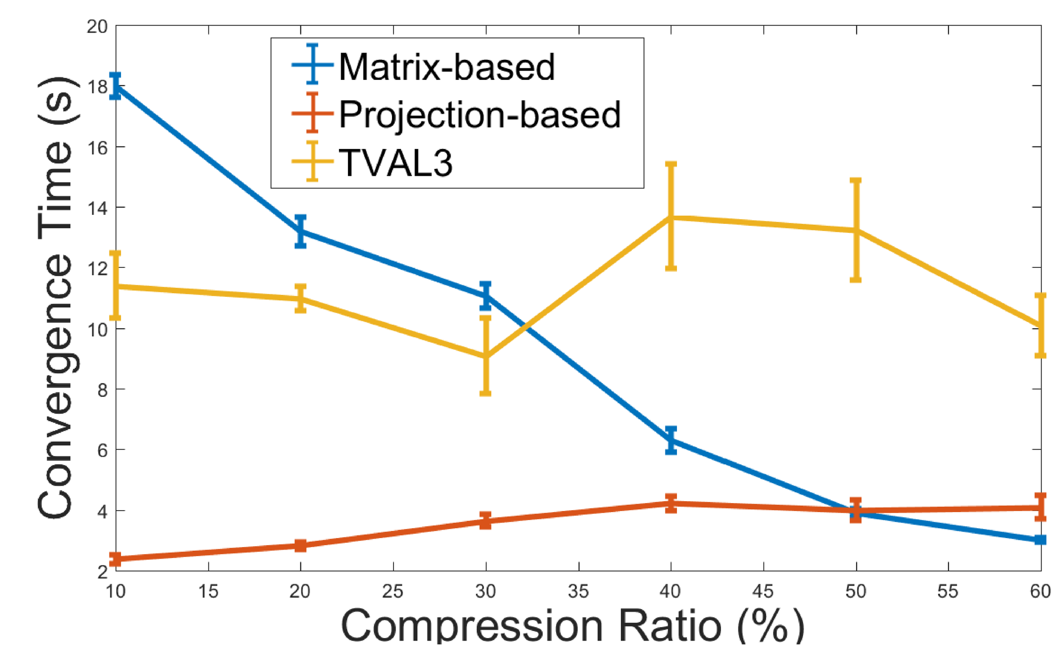

Figure 2: *Convergence times vs compression ratio*

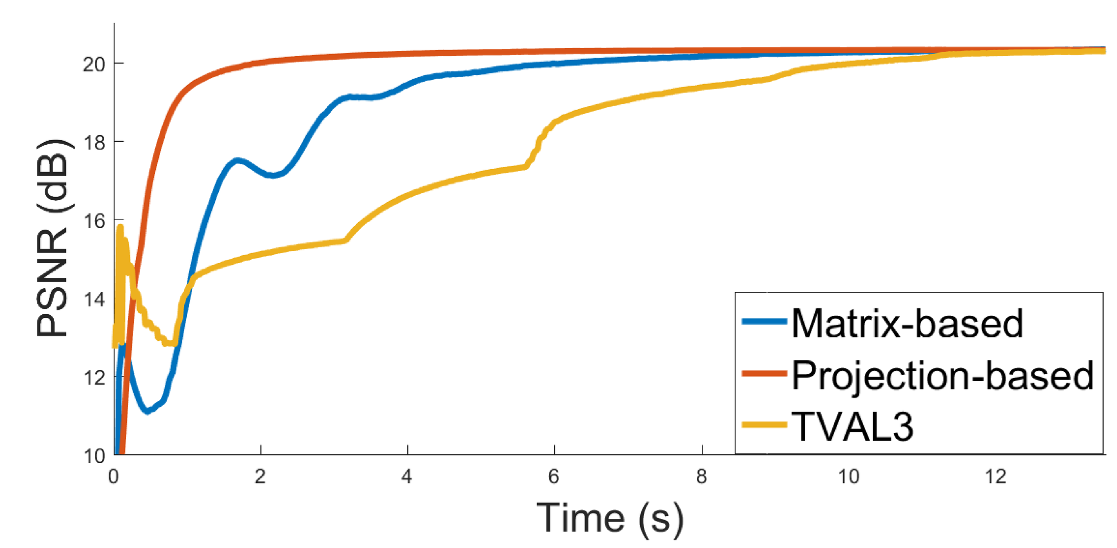

Figure 3: *Reconstruction PSNRs vs computation time (%20 compression)*

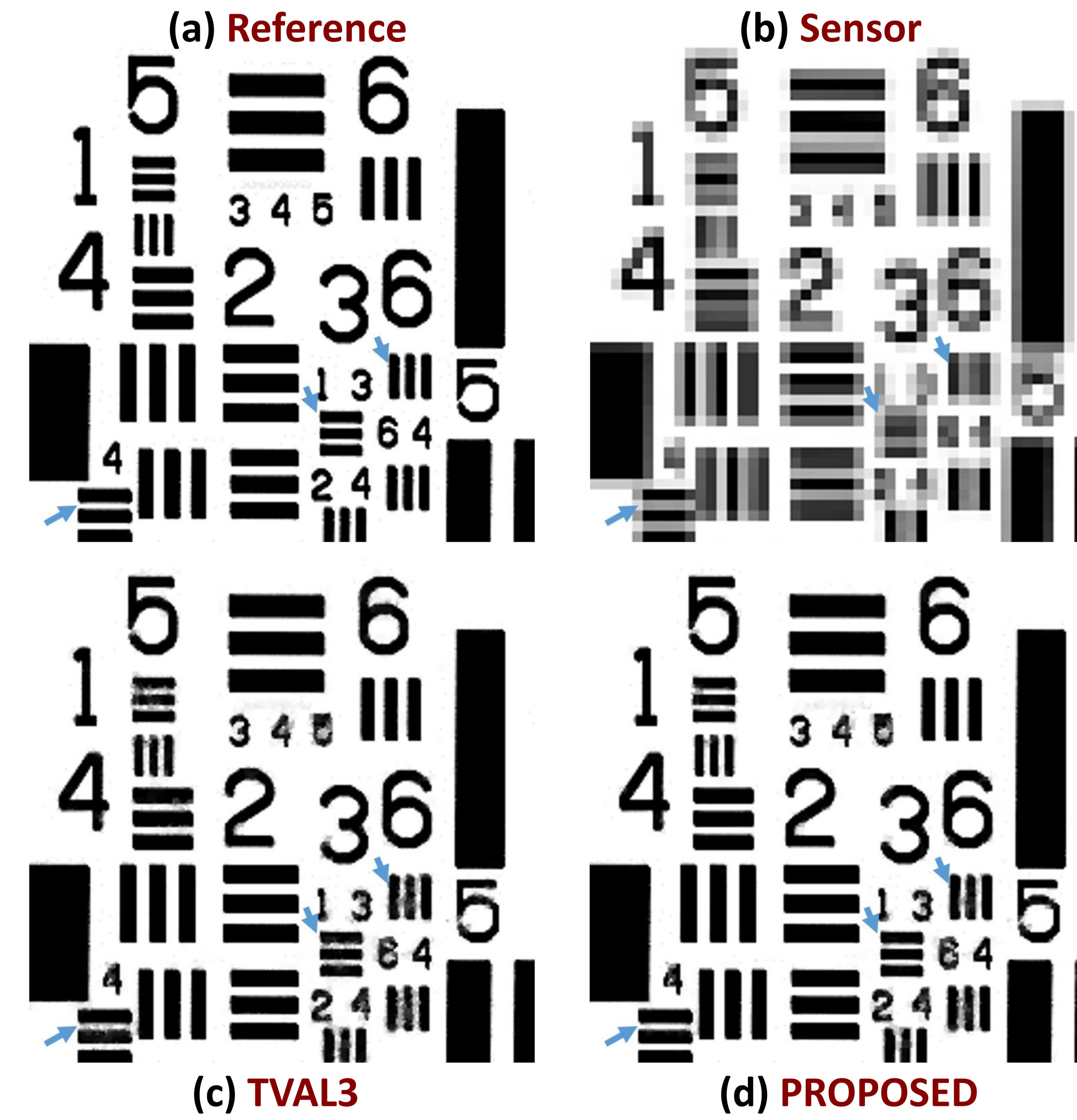

Figure 4: *Reconstruction from simulated data: (a) Reference image, (b) Low-resolution image obtained using the FPA sensor, (c) Reconstruction using TVAL3, (d) Reconstruction using the proposed algorithm*

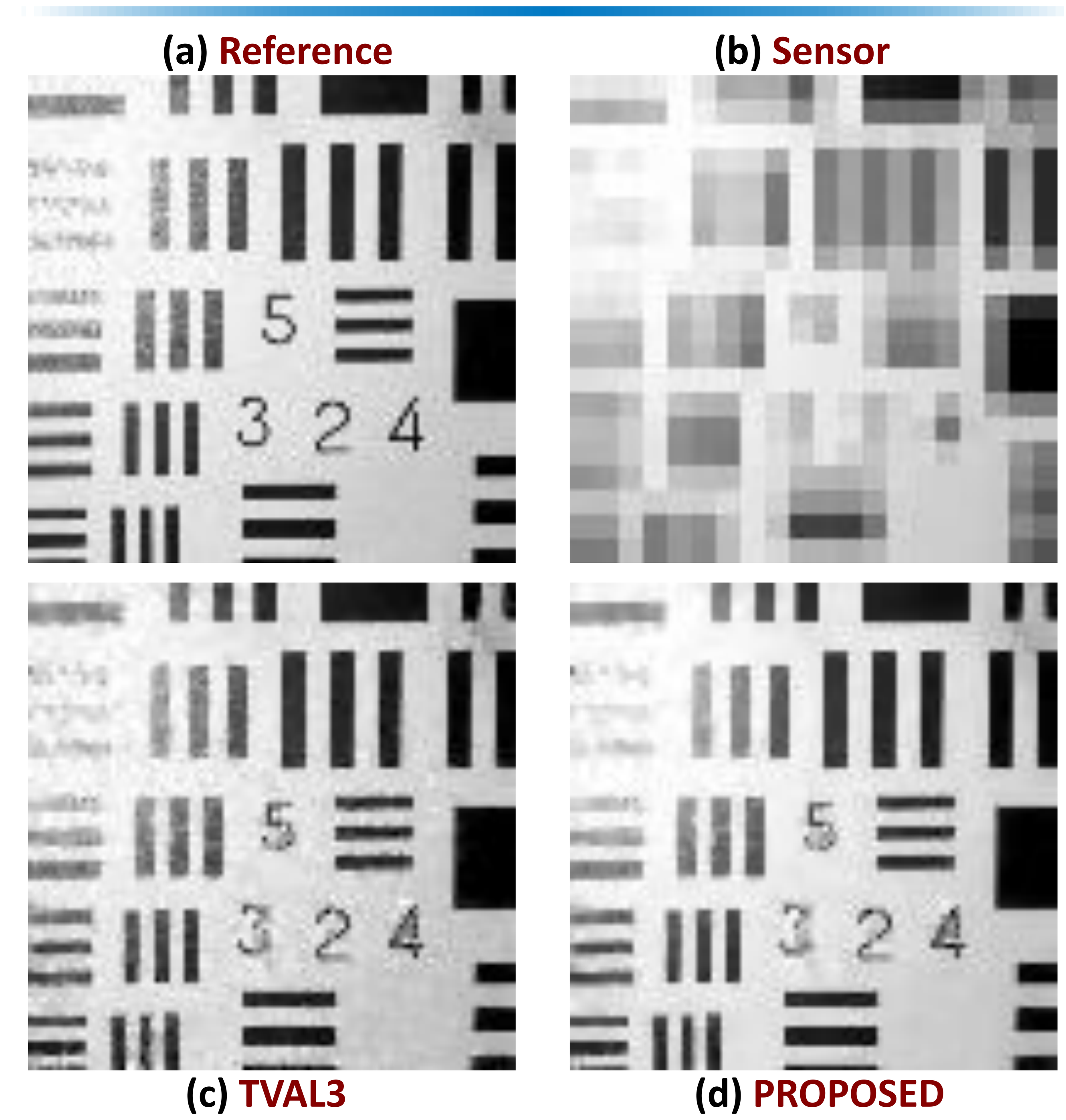

Figure 5: *Reconstruction from experimental data: (a) Reference image, (b) Low-resolution image obtained using the FPA sensor, (c) Reconstruction using TVAL3, (d) Reconstruction using the proposed algorithm*

References

- [1] Li et al, "Users guide for tval3: TV Minimization by augmented lagrangiand and alternating direction algorithms", CAAM report.
- [2] Chambolle, "An algorithm for total variation minimization and applications", J. Math. Imag. Vis.