Confidence-aware Levenberg-Marquardt Optimization for Joint Motion Estimation and Super-Resolution

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Introduction

Multiframe Super-Resolution: Basic Idea

- Given: multiple low-resolution images
- Idea: Exploit subpixel motion to reconstruct high-resolution image

26 low-resolution frames

3 x High-resolution image

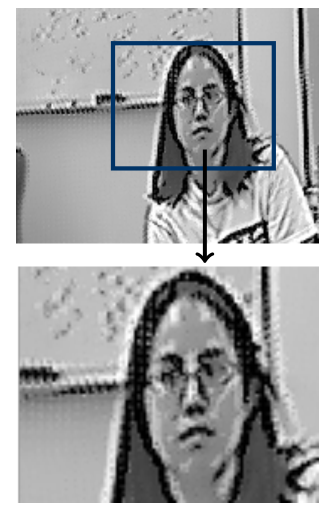
C. Bercea et. al: "*Confidence-aware Levenberg-Marquardt Optimization for Joint Motion Estimation and Super-Resolution*", 2016 IEEE ICIP

Robustness Issues

Super-resolution reconstruction is sensitive to:

- Motion estimation uncertainty

  Registration is error-prone



Superresolved image[1]

[1]Köhler et al., *"Robust Multiframe Super-Resolution Employing Iteratively Re-Weighted Minimization.,"* IEEE TCI, 2016.

Robustness Issues

Super-resolution reconstruction is sensitive to:

- Motion estimation uncertainty
  Registration is error-prone
- Outliers
  - Deviation of the real and assumed motion model
    $\rightarrow$ e.g.: non-rigid deformation assuming rigid motion
  - Invalid pixels
  - Space variant noise
  - …

Superresolved image[2]

[2] Yu He et al., *"A Nonlinear Least Square Technique for Simultaneous Image Registration and Super-Resolution.,"* IEEE TIP, 2007.

Proposed Method

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Modeling the Image Formation

- Given: sequence of low-resolution frames
  $\mathbf{y} = (\mathbf{y}^{(1)\top}, \dots, \mathbf{y}^{(K)\top})^\top$, $\mathbf{y}^{(k)} \in \mathbb{R}^M$
- $\mathbf{y}$ is assembled from the HR image $\mathbf{x} \in \mathbb{R}^N$ by:

$$\mathbf{y} = \mathbf{W}(\theta)\mathbf{x} + \epsilon \tag{1}$$

  - $\mathbf{W}(\theta) = \mathbf{DHM}(\theta)$ models subsampling, blur, and subpixel motion
  - ϵ is additive noise
- θ models a rigid transformation (3 degrees of freedom):
  $\rightarrow$ rotation angle φ and translation $t = (t_u, t_v)$

Energy Function

$$E(\mathbf{x}, \theta) = (\mathbf{y} - \mathbf{W}(\theta)\mathbf{x})^\top \mathbf{B}(\mathbf{y} - \mathbf{W}(\theta)\mathbf{x}) + \lambda R(\mathbf{x}) \quad (2)$$

- Weighted deviation between observation and model approximation

Energy Function

$$E(\mathbf{x}, \theta) = \mathbf{y} - \mathbf{W}(\theta)\mathbf{x})^\top \mathbf{B}(\mathbf{y} - \mathbf{W}(\theta)\mathbf{x}) + \boxed{\lambda R(\mathbf{x})}$$

- Weighted deviation between observation and model approximation
- Edge preserving WBTV[3]regularization given by:

$$R(\mathbf{x}) = ||\mathbf{ASx}||_1 = \sum_{l=-P}^{P} \sum_{m=-P}^{P} ||\mathbf{A}^{l,m}\mathbf{S}^{l,m}\mathbf{x}||_1$$

  - **S** models vertical and horizontal shifts around a local neighborhood P
  - **A** are weights to control influence of the prior

[3] Köhler et al., *"Robust Multiframe Super-Resolution Employing Iteratively Re-Weighted Minimization.,"* IEEE TCI, 2016.

Non-Linear Least-Squares Estimation

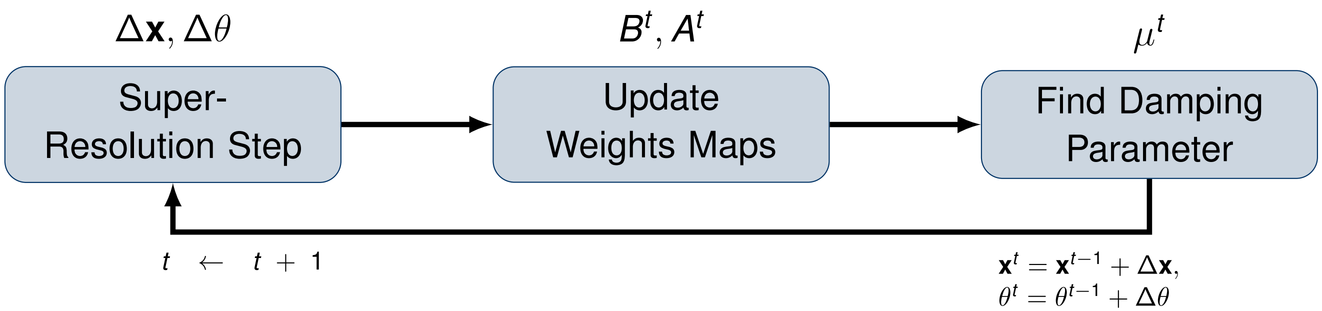
- Our energy function is non linear w.r.t θ

  $\rightarrow$ non-linear least-squares estimation of **x** and θ:

$$E(\mathbf{x}, \theta) = \left\| \begin{pmatrix} \mathbf{B}^{\frac{1}{2}}(\mathbf{y} - \mathbf{W}(\theta)\mathbf{x}) \\ \sqrt{\lambda}\mathbf{A}^{\frac{1}{2}} L^{\frac{1}{2}} \mathbf{x} \end{pmatrix} \right\|_2^2 \tag{3}$$

where L is a majorization of the WBTV term

Numerical Optimization

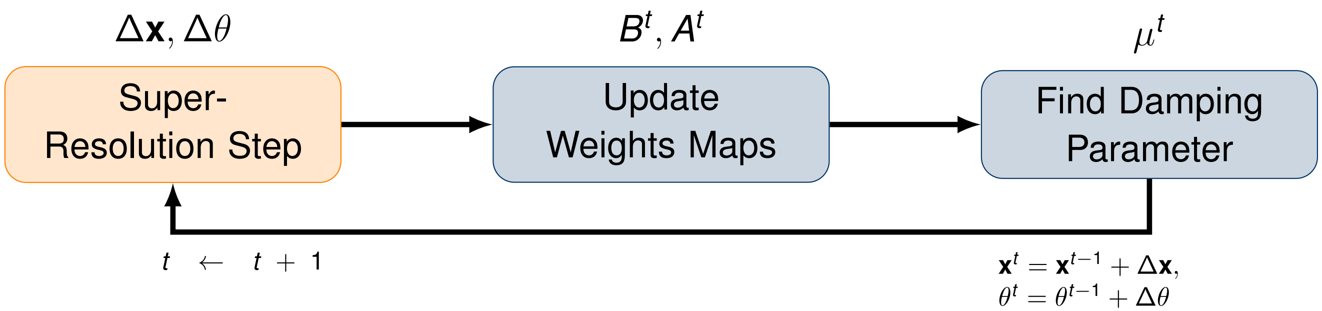


- Iterative confidence-aware optimization scheme
- The Taylor series expansion of our energy function in (3) yields small parameter updates according to:

$$\begin{pmatrix} \Delta\theta \\ \Delta\mathbf{x} \end{pmatrix} = \left[(\mathbf{P}^t)^\top \mathbf{P}^t \right]^{-1} (\mathbf{P}^t)^\top \mathbf{f}^t \tag{4}$$

- $\mathbf{P}, \mathbf{f}$ derived based on the Jacobian matrix

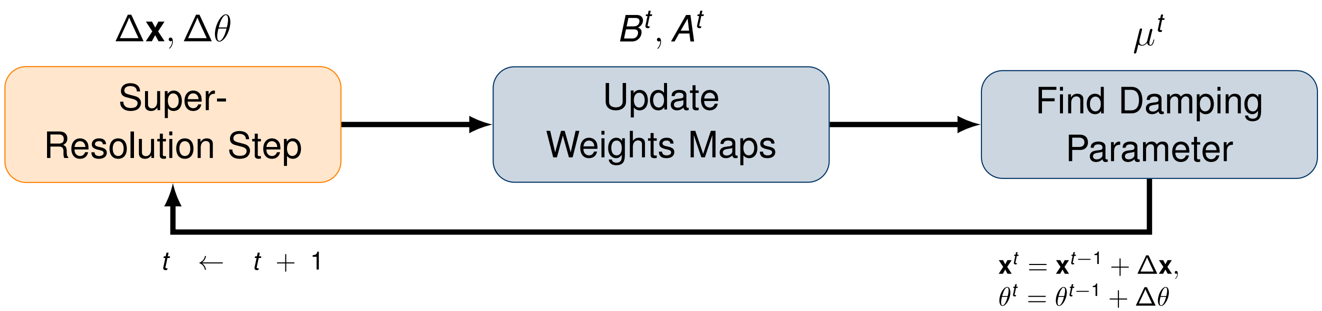
Numerical Optimization



Compute small changes $\Delta\mathbf{x}$ and $\Delta\theta$ for the high-resolution image $\mathbf{x}$ and the motion parameters θ

$$\begin{pmatrix} \Delta\theta \\ \Delta\mathbf{x} \end{pmatrix} = \left[(\mathbf{P}^t)^\top \mathbf{P}^t \right]^{-1} (\mathbf{P}^t)^\top \mathbf{f}^t \tag{5}$$

Numerical Optimization



Compute small changes $\Delta\mathbf{x}$ and $\Delta\theta$ for the high-resolution image $\mathbf{x}$ and the motion parameters θ using a Levenberg-Marquardt optimization:

$$\begin{pmatrix} \Delta\theta \\ \Delta\mathbf{x} \end{pmatrix} = \left[(\mathbf{P}^t)^\top \mathbf{P}^t + \mu \cdot \mathrm{diag}\left((\mathbf{P}^t)^\top \mathbf{P}^t \right) \right]^{-1} (\mathbf{P}^t)^\top \mathbf{f}^t \tag{6}$$

damping parameter μ: $\mu = 0 \rightarrow$ Gauss-Newton
$\mu \gg 0 \rightarrow$ gradient descent

Numerical Optimization

$\Delta\mathbf{x}, \Delta\theta$ → **Super-Resolution Step** → B^t, A^t **Update Weights Maps** → μ^t **Find Damping Parameter**

$t \leftarrow t + 1$

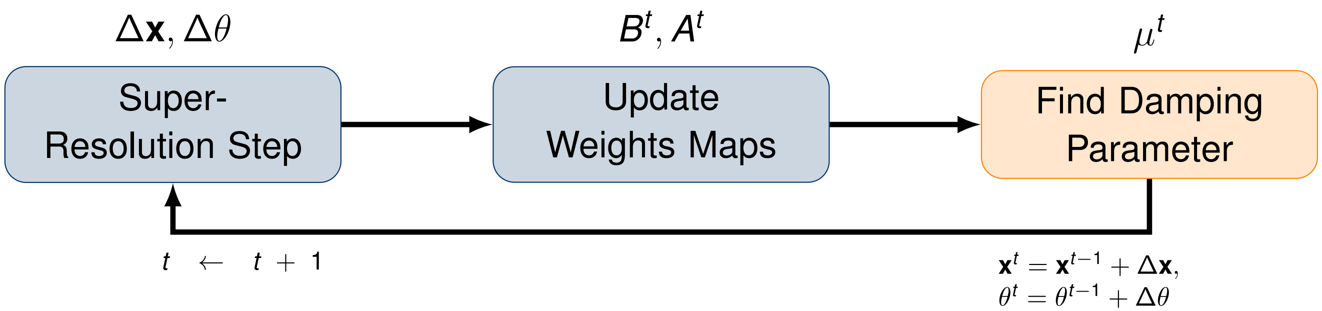
$\mathbf{x}^t = \mathbf{x}^{t-1} + \Delta\mathbf{x}$,
$\theta^t = \theta^{t-1} + \Delta\theta$

(a) Original (b) Data Weights **B** (c) Prior Weights **A**

Weights are computed proportional to the inverse of the residual erros[4]

[4]Köhler et al., *"Robust Multiframe Super-Resolution Employing Iteratively Re-Weighted Minimization.,"* IEEE TCI, 2016.

Numerical Optimization

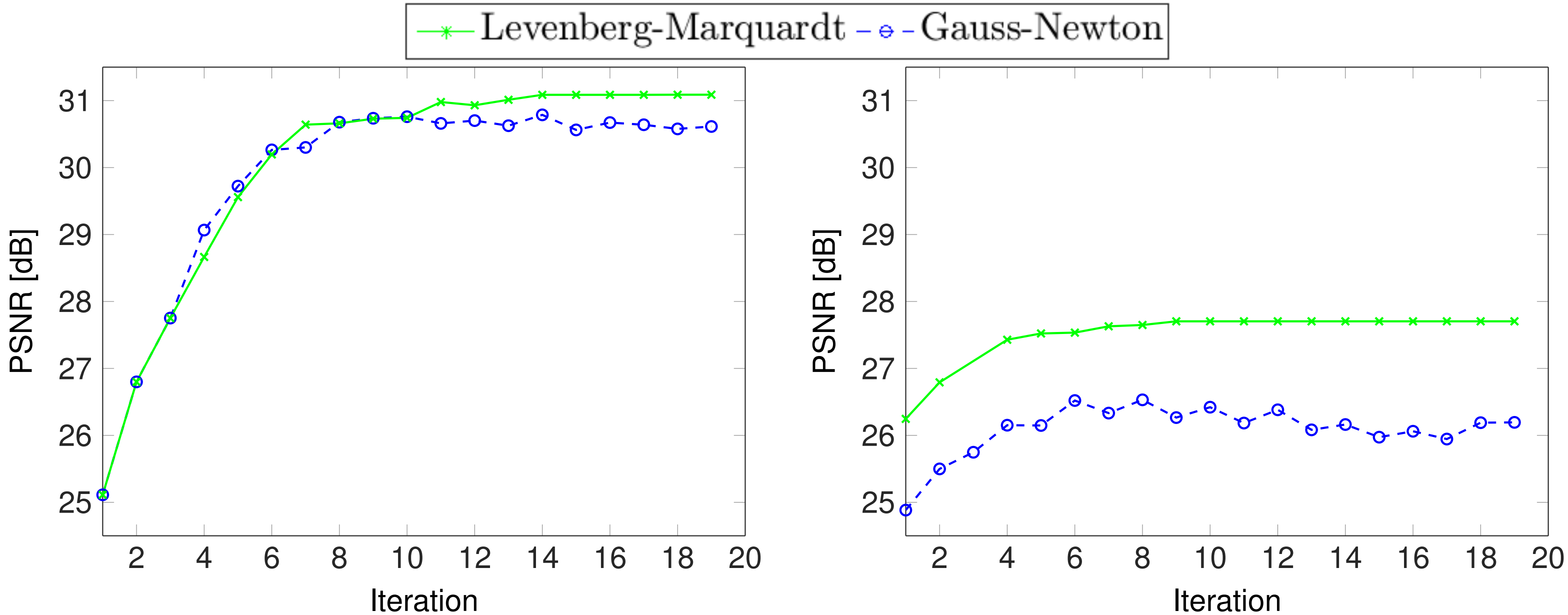


- A good damping parameter μ is crucial for a good performance of the Levenberg-Marquardt iterations
- Perform an one-dimensional search to minimize the confidence weighted residual error:

$$\mu^t = \arg\min_{\mu} \left|\left| (\mathbf{B}^t)^{\frac{1}{2}} \left[\mathbf{y} - \mathbf{W}\left(\theta(\mu)\right) \mathbf{x}(\mu) \right] \right|\right|_2^2, \tag{7}$$

Gauss-Newton vs. Levenberg-Marquardt

Gauss-Newton under practical conditions (e.g affected by outliers):
- converges to a worse local minima
- converges slowly



Left: Iterations without outliers. Right: Iterations in the presence of outliers due to invalid pixels.

Experiments and Results

Experimental Setup

Experiments:

- Real datasets[5]
- Simulated data with known ground truth[6]

Compared methods:

- **J**oint **M**otion Estimation And **S**uper-**R**esolution (JMSR)[7]
- **I**teratively **R**e-**W**eighted Minimization **S**uper-**R**esolution (IRWSR)[8]
- Proposed confidence-aware L.M. optimization

[5] https://users.soe.ucsc.edu/ milanfar/software/sr-datasets.html
[6] http://live.ece.utexas.edu/research/quality/subjective.htm
[7] Yu He et al., *"A Nonlinear Least Square Technique for Simultaneous Image Registration and Super-Resolution.,"* IEEE TIP, 2007.
[8] Köhler et al., *"Robust Multiframe Super-Resolution Employing Iteratively Re-Weighted Minimization.,"* IEEE TCI, 2016.

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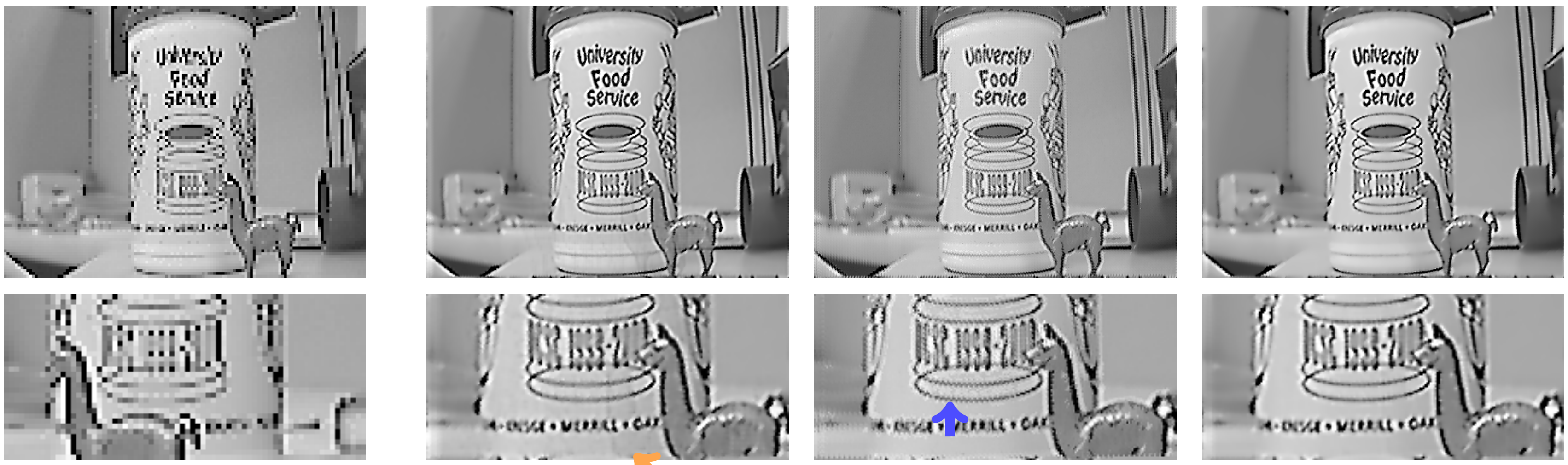
Real Data: Emily Sequence

(a) 2 original frames (b) JMSR (c) IRWSR (d) Proposed

- Head movements generate **outliers**
- Presence of **motion uncertainty**

Real Data: Alpaca Sequence



(a) 2 original frames (b) JMSR (c) IRWSR (d) Proposed

- Alpaca movement generates **outliers**
- Presence of **motion uncertainty**

Real Data: Results

(e) Original

(f) JMSR

(g) IRWSR

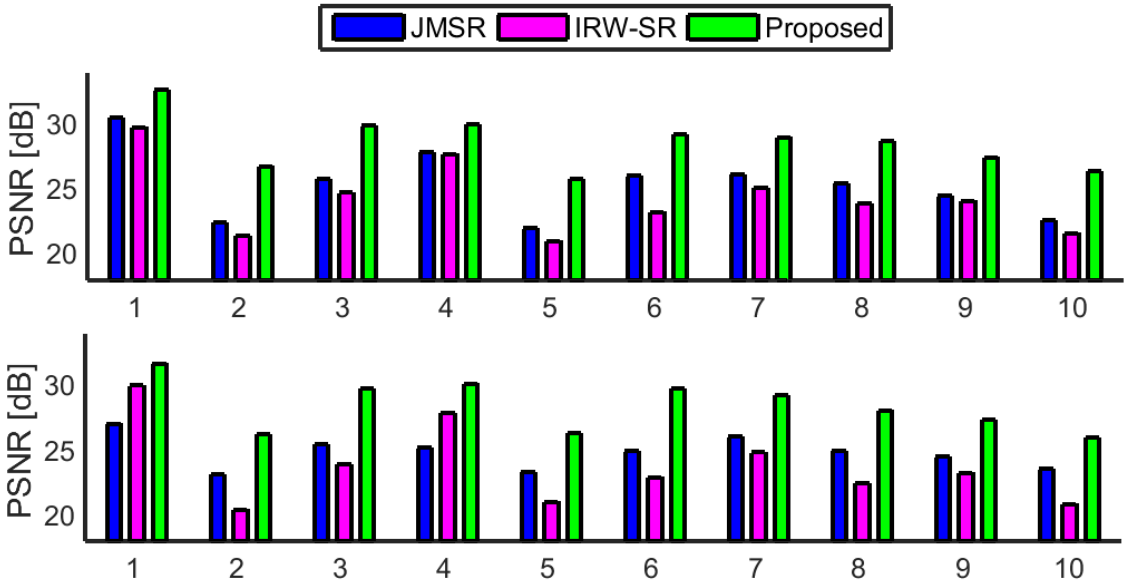
(h) Proposed

- Car drives away from the camera
  $\rightarrow$ cannot be modeled with a rigid transformation
- Our method is robust against mis-registered frames and refines motion estimate for the remaining frames

Simulated Data: Results

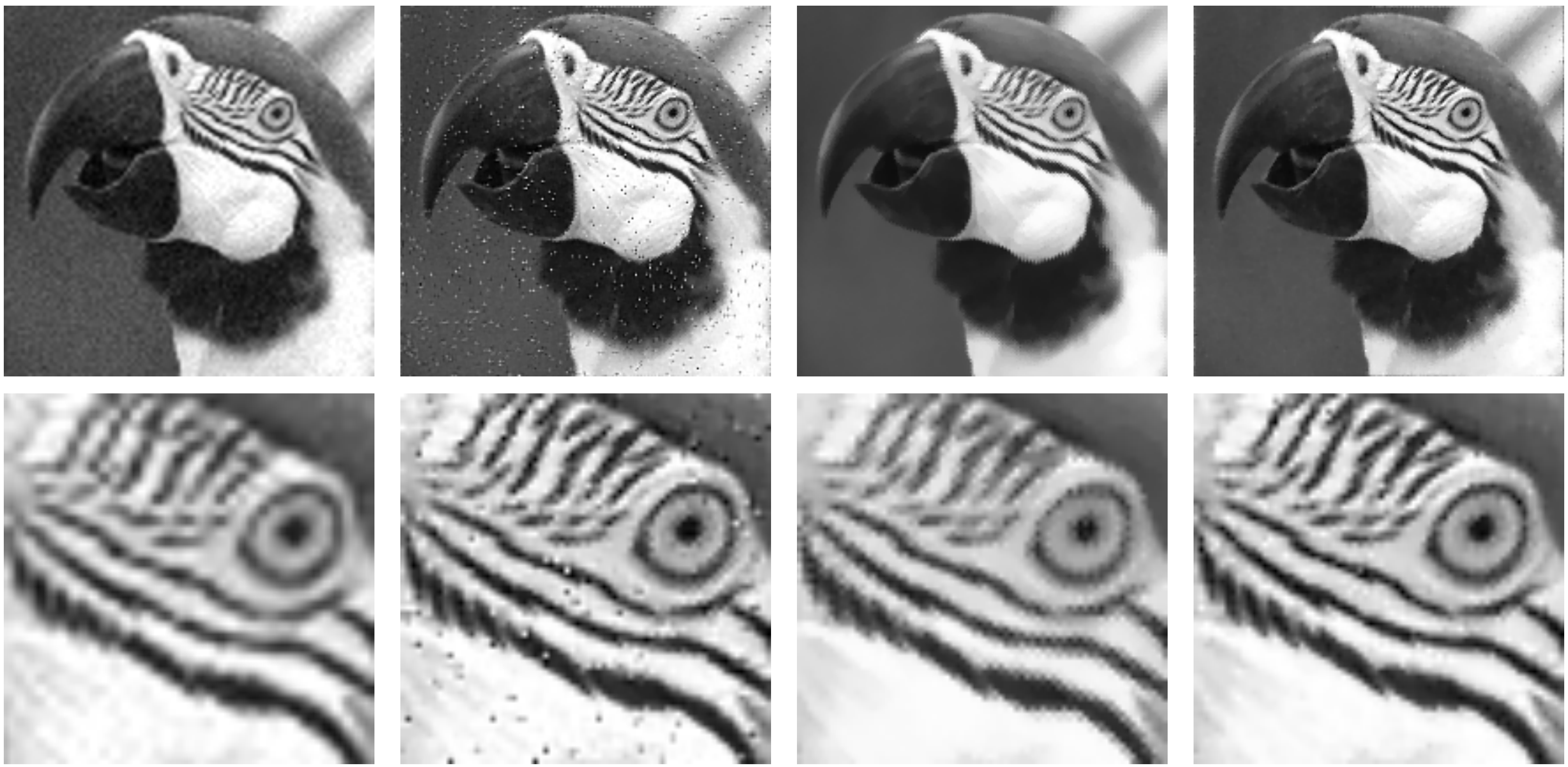
Setup:

- LR altered with salt and pepper noise
- Results averaged over $n = 10$ random test sequences



PSNR evaluation for sequences without outliers (top row) and sequences with outliers due to invalid pixels (bottom row):
$\rightarrow$ Increased PSNR by $\approx$ **3 dB**.

Simulated Data: Results



(a) Original (b) JMSR (c) IRWSR (d) Proposed

Summary and Conclusion

Summary and Conclusion

- Combine **robustness to outliers** in the formation process with the **refinement of the motion estimation**
- **Levenberg-Marquard** iteration scheme to boost convergence
- Outperform both two-stage and joint state of the art approaches.

Outlook: Extend the model to more general types of motion:
$\rightarrow$ e.g.: affine transformations

MATLAB code of this method is available on our webpage as part of our super-resolution toolbox:

www5.cs.fau.de/research/software/multi-frame-super-resolution-toolbox

Thank you very much for your attention!

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