A Unified Bayesian Approach to Multi-Frame Super-Resolution and Single-Image Upsampling in Multi-Sensor Imaging

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Background

Many **multi-sensor imaging systems** that acquire **multi-channel images** require software-based resolution enhancement due to economical or technological constraints.

Contribution: Novel approach to multi-sensor resolution enhancement

- Unified framework for multi-frame super-resolution and single-image upsampling using a spatially adaptive Bayesian model
- General-purpose approach without limitation to a fixed number of channels compared to prior work [1]
- Does not rely on guidance data as used, e. g. in RGB-D imaging [2]

Bayesian Modeling of Multi-Channel Images

Formulation of multi-frame super-resolution and single-image upsampling as **maximum a-posteriori (MAP)** estimation problem:

$$\hat{\boldsymbol{x}} = \arg\max_{\boldsymbol{x}_1,\ldots,\boldsymbol{x}_n} \left\{ p(\boldsymbol{y}_1,\ldots,\boldsymbol{y}_n \,|\, \boldsymbol{x}_1,\ldots,\boldsymbol{x}_n) p(\boldsymbol{x}) \right\}$$

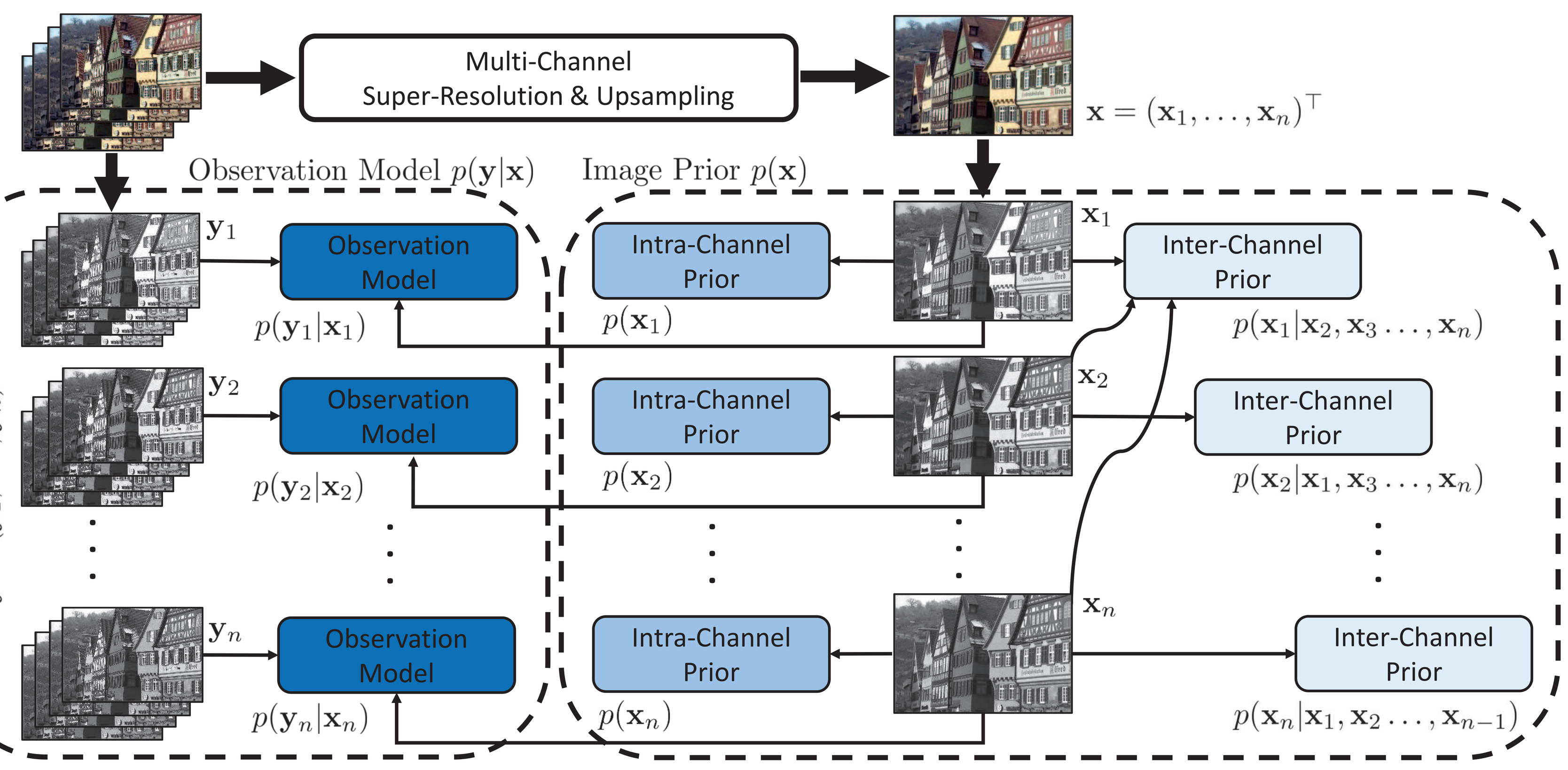


Figure 1: Basic outline of the proposed Bayesian multi-channel model

Multi-channel observation model: Formation of channel $\boldsymbol{y}_i$ from $\boldsymbol{x}_i$ modeled by system matrix $\boldsymbol{W}_i$ under Gaussian noise for each channel

$$p(\boldsymbol{y}_i \,|\, \boldsymbol{x}) \propto \exp\left\{ -\sum_{i=1}^{n} \frac{1}{2\sigma_i^2} ||\boldsymbol{y}_i - \boldsymbol{W}_i \boldsymbol{x}_i||_2^2 \right\}$$

Multi-channel image prior modeling two complementary aspects:

$$p(\boldsymbol{x}_i) \propto \exp\left\{ -\left(\underbrace{\lambda_i R_{\text{intra}}(\boldsymbol{x}_i)}_{\text{intra-channel prior}} + \sum_{j=1,j\neq i}^{n} \underbrace{\mu_{ij} R_{\text{inter}}(\boldsymbol{x}_i, \boldsymbol{x}_j; \Phi_{ij})}_{\text{inter-channel prior}} \right) \right\}$$

- **Intra-channel prior:** Exploits sparsity of individual channels in the gradient domain using total variation like regularization
- **Inter-channel prior:**
  - Modeling of statistical dependencies across channels
  - Definition of locally linear regression (LLR):

$$R_{\text{inter}}(\boldsymbol{x}_i, \boldsymbol{x}_j; \Phi_{ij}) = ||\kappa(\boldsymbol{x}_i, \boldsymbol{x}_j) \odot (\boldsymbol{A}_{ij}\boldsymbol{x}_i + \boldsymbol{b}_{ij} - \boldsymbol{x}_j)||_2^2$$

  - LLR defined by filter coefficients (hyperparameters) $\Phi_{ij} = (\boldsymbol{A}_{ij}, \boldsymbol{b}_{ij})$ and spatially adaptive confidence weighting $\kappa(\boldsymbol{x}_i, \boldsymbol{x}_j)$

Numerical Optimization

Energy minimization problem: Joint estimation of all high-resolution channels $\boldsymbol{x}$ and unknown LLR filter coefficients Φ

$$\arg\min_{\boldsymbol{x},\Phi} \sum_{i=1}^{n} ||\boldsymbol{y}_i - \boldsymbol{W}_i \boldsymbol{x}_i||_2^2 + \epsilon\Gamma(\Phi) + \lambda_i R_{\text{intra}}(\boldsymbol{x}_i) + \sum_{j=1,j\neq i}^{n} \mu_{ij} R_{\text{inter}}(\boldsymbol{x}_i, \boldsymbol{x}_j; \Phi_{ij})$$

LLR filter coefficients described by prior $\Gamma(\Phi)$ with weight ϵ

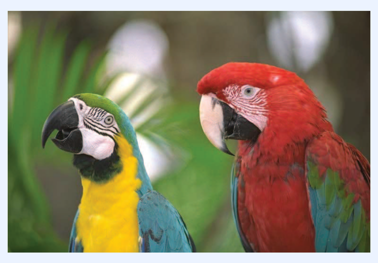
Alternating minimization scheme:

1. Estimate filter coefficients $\boldsymbol{A}_{ij}$ and $\boldsymbol{b}_{ij}$ by pair-wise guided filtering [3] of $\boldsymbol{x}_i$ and $\boldsymbol{x}_j$ exploited as input and guidance image
2. Estimate confidence weights $\kappa(\boldsymbol{x}_i, \boldsymbol{x}_j)$ from $\boldsymbol{A}_{ij}$ and $\boldsymbol{b}_{ij}$
3. Update high-resolution multi-channel image $\boldsymbol{x}$

Applications and Experimental Evaluation

Evaluation of our method in several multi-sensor imaging setups:

1. **Application to color imaging:** Color upsampling/super-resolution
   - Channel-wise vs. multi-channel reconstruction using the prior in [4] and the proposed model
   - Color super-resolution on simulated images (LIVE database):



	Channel-wise	Inter-channel	
		Farsiu [4]	Proposed
Mean ± Std	26.9 ± 1.67	28.0 ± 1.88	**28.2 ± 1.93**
Median	26.8	28.2	**28.3**

Figure 2: PSNR of color super-resolution on 29 simulated sequences (LIVE database)

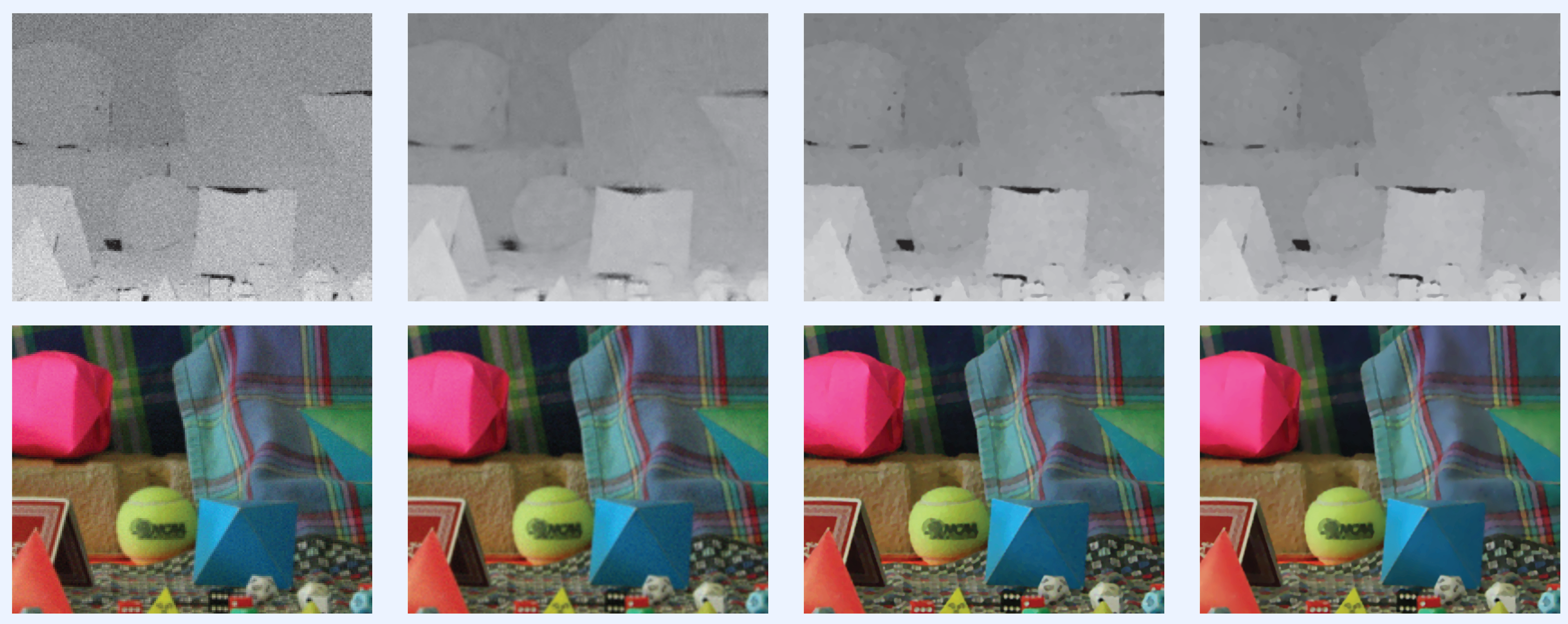
   - Experiments with real RGB and multispectral image data:

(a) Original (b) Channel-wise (c) Multi-channel ([4]) (d) Multi-channel (ours)

Figure 3: Top row: multi-frame super-resolution for color images (MDSP dataset). Bottom row: single-image upsampling for multispectral data (Harvard dataset).

   Avoidance of color artifacts in channel-wise reconstruction (jagged edges) and avoidance of erroneously copied structures (in multispectral data) compared to the prior in [4]

2. **Application to RGB-D imaging:** Joint color & range upsampling
   - Comparison of channel-wise upsampling, guided upsampling [3] (color image guides range upsampling) and our approach
   - Experiments on simulated RGB-D data (Middlebury dataset):



(a) Original (b) Guided ([3]) (c) Channel-wise (d) Multi-channel (ours)

Figure 4: Guided upsampling [3], channel-wise upsampling and proposed multi-channel upsampling on RGB-D images (Middlebury dataset)

   Improved reconstruction of smooth surfaces and edges without texture copying artifacts compared to guided upsampling [3]

Conclusion

Unified framework for multi-channel super-resolution and upsampling:

- **Applicable to various imaging setups:** no limitations regarding the number of channels or the existence of guidance data
- **Outperforms tailor-made approaches** in different domains
- **Matlab code** available on our webpage to facilitate future research

References

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[3] K. He, J. Sun, and X. Tang. Guided image filtering. *IEEE Trans Pattern Anal Mach Intell*, 35(6):1397–409, 2013.

[4] S. Farsiu, M. Elad, and P. Milanfar. Multiframe demosaicing and super-resolution of color images. *IEEE Trans Image Process*, 15(1):141–159, 2006.