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

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Multi-sensor imaging has become an emerging field of research with a vast number of applications including color and multispectral cameras or 3-D range imaging to capture RGB-D data. One common property of these systems is that they provide *multi-channel* images that are, unfortunately, often limited in terms of their spatial resolution. However, channel-wise resolution enhancement might not be optimal as it ignores dependencies across the channels. This is obvious if structures are visible in multiple channels. For this reason, tailor-made approaches for single-image upsampling and multi-frame super-resolution have been investigated in different domains. Super-resolution of color images exploits the correlation of color channels as a prior to super-resolve them [2]. In multispectral imaging, super-resolution can be guided by panchromatic data [1]. A similar concept has been established in range imaging, where high-quality color images guide single-image upsampling [3, 5] or multi-frame super-resolution [6] of range images. To avoid the need of reliable guidance data, joint resolution enhancement of all channels has been proposed [4]. However, this formulation does only consider simplified setups with two image channels.

Bayesian Multi-Sensor Model. This work introduces multi-frame super-resolution and single-image upsampling that exploit correlations across complementary channels in a unified way. Unlike prior work, this framework is neither limited to a certain setup nor a fixed number of channels and does not require guidance data. Our framework is derived from a Bayesian model to infer a high-resolution multi-channel image $\boldsymbol{x}$ assembled from n channels $\boldsymbol{x}_1, \ldots, \boldsymbol{x}_n$ from multiple low-resolution multi-channel images $\boldsymbol{y}_1, \ldots, \boldsymbol{y}_K$. As a key idea, we formulate an image prior according to:

$$p(\boldsymbol{x}_i \,|\, \mathcal{X}_i) \propto \exp\Big\{ -\big(\lambda_i R_{\text{intra}}(\boldsymbol{x}_i) + \sum_{j=1, j \neq i}^{n} \mu_{ij} R_{\text{inter}}(\boldsymbol{x}_i, \boldsymbol{x}_j; \boldsymbol{\Phi}_{ij})\big)\Big\}, \quad (1)$$

where $\mathcal{X}_i = \{\boldsymbol{x}_1, \ldots, \boldsymbol{x}_{i-1}, \boldsymbol{x}_{i+1}, \ldots, \boldsymbol{x}_n\}$ and consider two aspects: 1) Each channel $\boldsymbol{x}_i$ is described by an intra-channel prior defined by the regularization term $R_{\text{intra}}(\boldsymbol{x}_i)$ with the regularization weight $\lambda_i \geq 0$. 2) Dependencies across channels $\boldsymbol{x}_i$ and $\boldsymbol{x}_j$ are modeled by an inter-channel prior $R_{\text{inter}}(\boldsymbol{x}_i, \boldsymbol{x}_j; \boldsymbol{\Phi}_{ij})$ with pair-wise weights $\mu_{ij} \geq 0$ and hyperparameters $\boldsymbol{\Phi}_{ij}$.

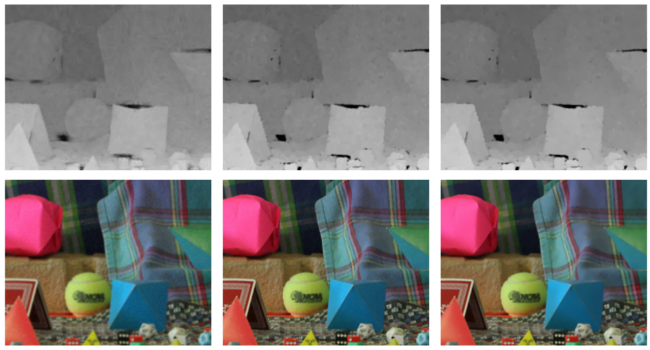
Locally Linear Regression. The inter-channel prior is defined by *locally linear regression* (LLR) that explains dependencies across channels by:

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

where the hyperparameters $\boldsymbol{\Phi}_{ij}$ are given by filter coefficients $\boldsymbol{A}_{ij}$ and $\boldsymbol{b}_{ij}$ for each channel pair $(\boldsymbol{x}_i, \boldsymbol{x}_j)$ and associated confidence weights $\kappa(\boldsymbol{x}_i, \boldsymbol{x}_j)$.

(a) Channel-wise (b) Multi-channel [2] (c) Multi-channel proposed

Figure 1: Comparison of multi-frame color super-resolution (top row) and single-image upsampling of multispectral data (bottom row).



(a) Guided upsampling [5] (b) Channel-wise (c) Multi-channel proposed

Figure 2: Single-image upsampling of RGB-D data.

This prior is spatially adaptive and tolerates outliers due to image regions that violate the LLR assumption. The inference of the hyperparameters $\boldsymbol{\Phi}_{ij}$ that are treated as latent variables as well as the multi-channel image $\boldsymbol{x}$ are formulated as *maximum a-posteriori* (MAP) estimation. For this purpose, our paper presents an efficient alternating minimization scheme.

Applications. We evaluated our unified approach for color-, multispectral and range imaging. In color and multispectral imaging, we compared the proposed inter-channel prior to conventional channel-wise processing as well as the color channel regularization of Farsiu et al. [2], see Fig. 1. Our multi-channel method got rid of color artifacts present in channel-wise super-resolution, e. g. jagged edges highlighted in Fig. 1 (top). Unlike [2] that erroneously copied structure from other, original channels to the reconstructed channel, this issue was avoided by our adaptive confidence weighting as highlighted for multispectral data in Fig. 1 (bottom). In range imaging, our method was evaluated for single-image upsampling, where we compared channel-wise and guided upsampling [5], see Fig. 2. Unlike [5], our multi-channel approach does not rely on high-quality color images as guidance. In particular, it achieved better reconstructions of surfaces and edges in range images compared to channel-wise and guided upsampling.

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