Bayesian Sparse Representation for Hyperspectral Image Super Resolution

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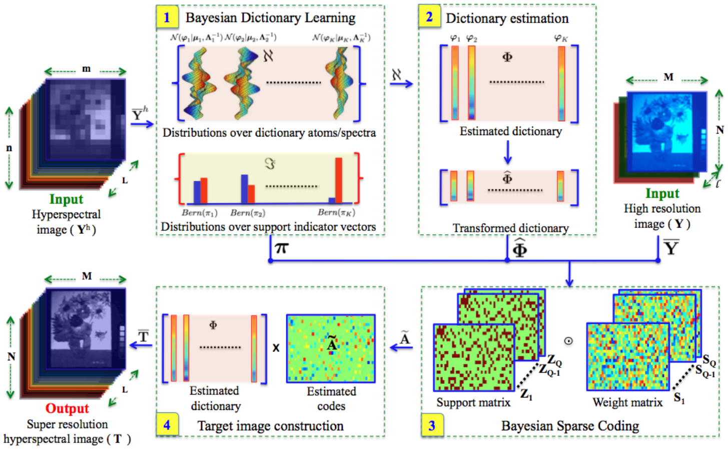

Figure 1: Schematics: (1) Sets of distributions over the dictionary atoms and the support indicator vectors are inferred non-parametrically. (2) A dictionary is estimated and transformed according to the spectral quantization of the high resolution image $\mathbf{Y}$. (3) The transformed dictionary and the distributions over the support indicator vectors are used for sparse coding $\mathbf{Y}$. This step is performed by the proposed Bayesian sparse coding strategy. (4) The codes are used with Φ to construct the target super resolution image.

Spectral characteristics of hyperspectral imaging have recently been reported to enhance performance in many computer vision tasks, including tracking, classification, segmentation and document analysis. They have also played a vital role in medical imaging and remote sensing. Hyperspectral imaging acquires a faithful spectral representation of the scene by integrating its radiance against several spectrally well-localized basis functions. However, contemporary hyperspectral systems lack in spatial resolution [1], [4]. This fact is impeding their widespread use. In this regard, a simple solution of using high resolution sensors is not viable as it further reduces the density of the photons reaching the sensors, which is already limited by the high spectral resolution of the instruments. Due to hardware limitations, software based approaches for hyperspectral image super resolution are highly attractive. At present, the spatial resolution of the systems acquiring images by a gross quantization of the scene radiance (e.g. RGB and RGB-NIR) is much higher than their hyperspectral counterparts. This work proposes to fuse the spatial information from the images acquired by these systems with the hyperspectral images of the same scenes using non-parametric Bayesian sparse representation.

The proposed approach fuses a hyperspectral image with the high resolution image in a four-stage process, as shown in Fig. 1. In the first stage, it infers probability distributions for the material reflectance spectra in the scene and a set of Bernoulli distributions, indicating their proportions in the image. Then, it estimates a dictionary and transforms it according to the spectral quantization of the high resolution image. In the third stage, the transformed dictionary and the Bernoulli distributions are used to compute the sparse codes of the high resolution image. To that end, we propose a generic Bayesian sparse coding strategy to be used with Bayesian dictionaries learned with the Beta process [5]. We also analyze the proposed strategy for its accurate performance. Finally, the computed codes are used with the estimated dictionary to construct the super resolution hyperspectral image. The proposed approach not only improves the state of the art results, which is verified by exhaustive experiments on three different public data sets, it also maintains the advantages of the non-parametric Bayesian framework over the typical optimization based approaches.

This is an extended abstract. The full paper is available at the Computer Vision Foundation webpage.

Table 1: Benchmarking of the proposed approach: The RMSE values are in the range of 8 bit images. The best results are shown in bold.

	CAVE database [6]						
Method	Beads	Spools	Painting	Balloons	Photos	CD	Cloth
MF [4]	8.2	8.4	4.4	3.0	3.3	8.2	6.1
SSFM [3]	9.2	6.1	4.3	-	3.7	-	10.2
GSOMP [1]	6.1	5.0	4.0	2.3	2.2	7.5	**4.0**
Proposed	**5.4**	**4.6**	**1.9**	**2.1**	**1.6**	**5.3**	**4.0**
	Harvard database [2]						
	Img 1	Img b5	Img b8	Img d4	Img d7	Img h2	Img h3
MF [4]	3.9	2.8	6.9	3.6	3.9	3.7	2.1
SSFM [3]	4.3	2.6	7.6	4.0	4.0	4.1	2.3
GSOMP [1]	1.2	**0.9**	5.9	2.4	2.1	1.0	**0.5**
Proposed	**1.1**	**0.9**	**4.3**	**0.5**	**0.8**	**0.7**	**0.5**

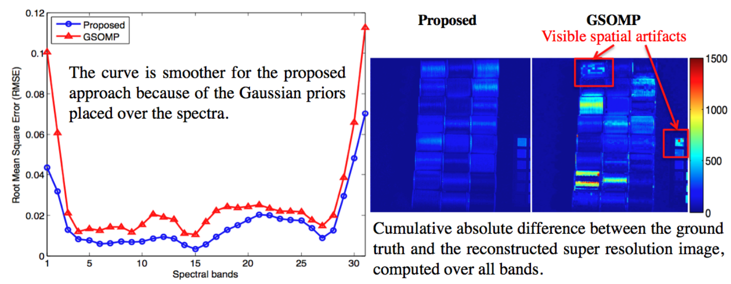

Figure 2: Comparison of the proposed approach with GSOMP [1] on image 'Spools' (CAVE database) [6].

Table 1 shows results on different images from the CAVE [6] and the Harvard [2] databases. The table shows the root mean square error (RMSE) of the reconstructed super resolution images. As can be seen, our approach outperforms most of the existing methods by a considerable margin on all the images. Only the results of GSOMP are comparable to the proposed method. However, an image reconstructed by GSOMP can suffer from spatial artifacts. For instance, these artifacts are visible for GSOMP in Fig. 2, whereas no such problem can be found for the approach proposed in this paper. The figure also compares the RMSE of the proposed approach with that of GSOMP as a function of the spectral bands of the image. The RMSE curve is lower and smoother for the approach proposed in this work.

Acknowledgement
This work is supported by ARC Grant DP110102399.

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