Sparse Reconstruction of Compressed Sensing Multi-spectral Data using Cross-Spectral Multi-layered Conditional Random Field Model

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ABSTRACT

The broadband spectrum contains more information than what the human eye can detect. Spectral information from different wavelengths can provide unique information about the intrinsic properties of an object. Recently compressed sensing imaging systems with low acquisition time have been introduced. To utilize compressed sensing strategies, strong reconstruction algorithms that can reconstruct a signal from sparse observations are required. This work proposes a cross-spectral multi-layerd conditional random field(CS-MCRF) approach for sparse reconstruction of multi-spectral compressive sensing data in multi-spectral stereoscopic vision imaging systems. The CS-MCRF will use information between neighboring spectral bands to better utilize available information for reconstruction. This method was evaluated using simulated compressed sensing multi-spectral imaging data. Results show improvement over existing techniques in preserving spectral fidelity while effectively inferring missing information from sparsely available observations.

Keywords: Sparse Reconstruction, Compressive Sensing, Multi-spectral Imaging, Computer vision, Graphical Models

1. INTRODUCTION

Having access to information that is available from other wavelengths other than the visible can provide intrinsic properties of the object. Current multispectral (MS) cameras usually utilize filter wheels, liquid-crystal tunable filters or acousto-optical tunable filters. These instruments are expensive, bulky and require very long acquisition time to capture images at multiple wavelengths. Reducing acquisition time and instrument complexity is highly desired for MS imaging.

Advances in multi-spectral imaging techniques allow wavelength filtering on the imaging detector at a pixel level.[1–3] This approach can greatly improve acquisition time and ease of use at a cost in spatial resolution as pixels on the detector are assigned to different spectral bands of information. In order to utilize this acquisition strategy, compressed sensing techniques have been proposed. Compressed sensing techniques allow the reconstruction of an entire signal using sparsely yet sufficiently sampled observations.[4] Compressed sensing systems require advanced sparse reconstruction algorithms to infer state information given the observations that are made.[4–6] Reconstruction algorithms that can effectively infer missing information while maintaining spectral fidelity and preserving spatial resolution are strongly desired.

Previous work by Kazemzadeh et al. has proposed a multi-layered conditional random field (MCRF) approach for compressively sensed multispectral data.[7] This approach extends CRFs first proposed by Lafferty et al.,[8] and models each information band as a MCRF to use spatial and intensity prior information to enhance and infer high spatial resolution states. The MCRF also incorporates an additional layer of abstraction to enforce the quality of the observations into the optimization. One limitation of the MCRF is that additional information from multiple neighboring spectral bands is not utilized. This additional information can be utilized to improve on the reconstruction result. This paper will propose a cross-spectral multi-layered CRF (CS-MCRF) approach for sparse reconstruction of compressed sensing multispectral data.

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Information between spectral bands with similar wavelengths can improve the reconstruction quality of compressive sensed multispectral data. Images taken from spectral bands with similar wavelengths contain spatial characteristics that can be taken into account in the reconstruction process such as fundamental relationships between neighboring pixels in an image. Channels with similar wavelengths would share similar characteristics such as intensity differences in a neighborhood, and similar edge structure; this allow the utilization of these cross spectral relationships in conjunction with spatial relationships in a CRF model. The CS-MCRF will use neighboring bands that share similar characteristics to guide the inference of our focused band. A multilayered CRF approach is still incorporated to validate the quality of ovservations at each iteration. CRF uses a concept of unary and pairwise potentials, where the unary enforces original observations performing data fidelity and the pairwise enforces spatial and inter-modal relationships filling in missing data. The novelty of the CS-MCRF approach is the enforcement of the intra-spectral consistencies between neighboring spectral bands.

2. METHODOLOGY

The CS-MCRF is an extension of the MCRF[7] incorporating the provided information in neighboring spectral band to estimate the interseting band. The proposed CS-MCRF models the conditional probability of $P(Y|\underline{X})$ as:

$$P(Y|\underline{X}) = \frac{1}{Z(\underline{X})} \exp(-\psi(Y, Cr|\underline{X})) \tag{1}$$

where $Z(\underline{X})$ is the normalization function, Cr is the abstraction level that validates the reliability of observations, and $\psi(.)$ represents the combination of unary and pairwise potential functions:

$$\psi(Y, Cr|\underline{X}) = \sum_{i=1}^{n} \psi_u(y_i, \underline{X}) + \sum_{\varphi \in C} \psi_p(y_\varphi, \underline{X}) \tag{2}$$

here $y_i \in Y$ is a random variable in the set $Y = \{y_i\}_{i=1}^n$, $y_\varphi \in Y$ is the subset of random varibales constructed based on the clique structure φ in the set of C, and $\underline{X} = \{\{x_j\}_{j=1}^n\}_{k=1}^m$ is the set of multi-spectral (MS) observations which $x_{j,k}$ encodes the observation corresponding to the random variable j in the spectral band k. Each node i has a set of neighbors allowing the formation of multiple clique structures. The pairwise clique structure is used in our method following the clique formulation presented in.[9]

A Gaussian distribution is used to determine the inter-spectral weights W_k used in the cross-spectral reconstruction. The motivation behind this procedure is to control the affect of each spectral band to the being reconstructed band based on the difference in their bandwidths and overlapping where k indicates the neighboring spectral band. However the summation of all the inter-spectral weights for each currently reconstructed spectral band must be 1:

$$W_k = f(\bar{k}, \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{(\bar{k}-\mu)^2}{2\sigma^2}} \tag{3}$$

$$W = \sum_{k=1}^{m} W_k = 1 \tag{4}$$

where μ is the central wavelength of each band and σ is a controlling factor that determines the effects of neighboring spectral bands on the reconstructed one.

The unary potential $\psi_u(.)$ enforces original observations while the pairwise potential $\psi_p(.)$ enforces spatial information into the model to smooth the reconstructed result regarding intra-band neighboring pixels and inter-band ones as well in Eq. 2. The unary feature function utilizes original measurements with high confidence. This enforces original observations. The pairwise feature function utilizes a combination of euclidean distances between nodes based on spatial and data differences.

The proposed CS-MCRF utilizes an additional abstraction layer, Cr in the framework as like as[7] where represents the uncertainty layer in the model which more detail can be found in.[7]

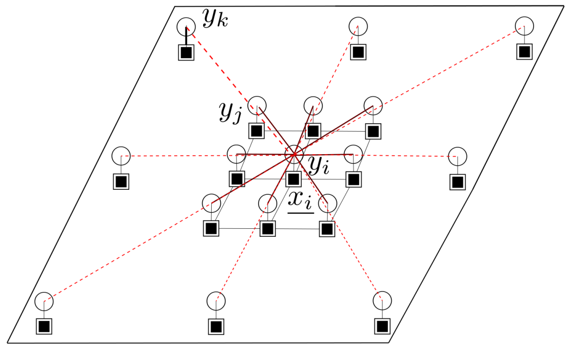


Figure 1: Realization of CS-MCRF graph. $\underline{\mathrm{x}}_i$ represents the set of sparse MS observations captured by the MS camera and y_i represent states. Nodes with higher probability of connectivity have solid black edges while lower probable connections are represented as dashed red lines. Connectivity can be calculated using different models.

Using the pairwise clique, the pairwise potential can be modeled as the combination of spatial $P^s_{i,j}$ and data $Q^d_{i,j}$ relationship between two pixels at locations i and j for each MS bands $k \in K$. The neighborhood pairwise potential has no effect if the uncertainty is less than a predetermined threshold Th_1.

To summarize the CS-MCRF into a graphical model, let $G = (V; E)$ be an undirected graph such that V is the set of nodes of the graph representing states $Y = \{y_i\}^n_{i=1}$, E is the set of edges in the graph. Corresponding to each vertex on the graph $G(.)$ there is an observation $\underline{\mathrm{x}}_i \in \underline{\mathrm{X}}$ which is a set of MS observations containing information from multiple bands of information at the pixel location i. Furthermore the order of E is dependent on the number of neighborhood connections considered in the pairwise interpolation. A higher order pairwise neighborhood promotes higher data and spatial driven consistencies at the cost of computational complexity. In our method a higher order pairwise connectivity is used as the sparsity of available information limits the amount of information available in a small neighborhood. For better reconstruction a higher order pairwise connectivity is implemented.

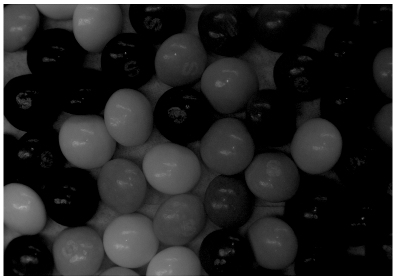
3. EXPERIMENTAL SETUP

The data used for this project were captured using a interchangeable filter-based imaging system at full resolution and subsampled using a subsampling mask. This is to simulate a new imaging camera proposed by Kazemzadeh et al. for multispectral stereoscopic vision.[10]

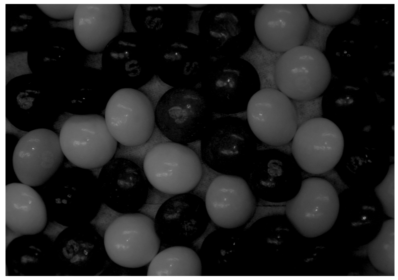
Table 1: Bandwidth information for each spectral band

Channel	λ (nm)
1	553
2	608
3	650
4	800
5	880
6	1000

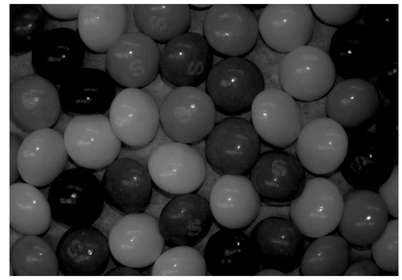
The experimental setup follows the setup presented by.[10] In order to test for the effectiveness of the new reconstruction algorithm it is important to perform testing on sparse sampled full sized MS data. This allows testing on a controlled and quantitatively verifiable environment. To collect the MS data, a camera system augmented with a bandpass filter wheel is used. The camera used is the IDS U-EYE detector with a detector resolution of 1200x1600, pixel pitch of 4.5 μm, and a 12 mm format. The detector was equipped with a Pontax 6mm f/1.4 zoom lens with a 9 mm format. There is a mismatch between the detector and the lens, therefore



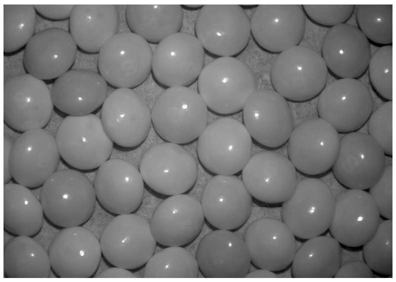
(a) Channel 1 (553nm)



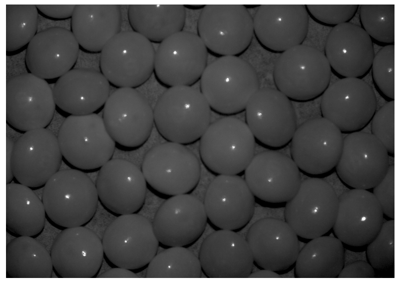
(b) Channel 2 (608nm)



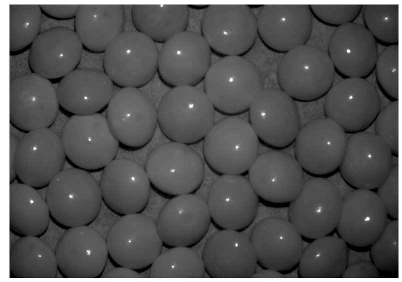
(c) Channel 3 (650nm)



(d) Channel 4 (800nm)



(e) Channel 5 (880nm)



(f) Channel 6 (1000nm)

Figure 2: Fully sampled original images. Images are from six different wavelengths

some Seidel aberrations were observed at full resolution, and were cropped to a 896x1280 resolution to avoid the aberrations.

Images from different spectral bands in the visible and near infrared (NIR) wavelengths were captured. Table 1 denotes the central wavelength of each channel. In order to image the NIR region, a Tungsten-Halogen light source is used to illuminate the scene. The exposure time was controlled for each of the six images to avoid saturation, shown in figure 2.

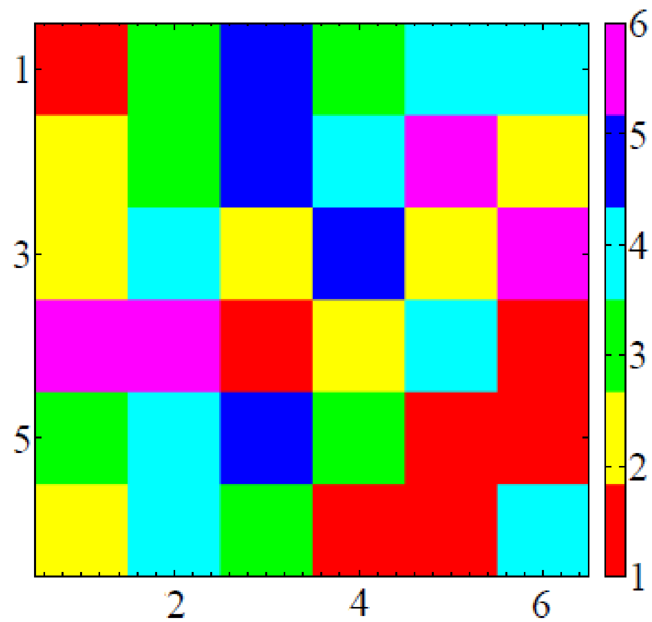


Figure 3: Simulated MS detector (sampling mask) in a 6x6 region. The color code represents the different spectral bands imaged

Table 2: Calculated PSNR for different methods

Channel	$PSNR_G(dB)$	$PSNR_{MCRF}(dB)$	$PSNR_{CS-MCRF}(dB)$
1	24.87	33.96	**38.18**
2	25.10	33.37	**37.76**
3	22.77	31.30	**36.11**
4	17.62	30.37	**36.09**
5	22.72	31.50	**36.89**
6	20.92	30.65	**36.32**

Table 3: Calculated SSIM for different methods

Channel	$SSIM_G(\%)$	$SSIM_{MCRF}(\%)$	$SSIM_{CS-MCRF}(\%)$
1	86.72	91.07	**98.23**
2	86.69	89.88	**97.92**
3	81.96	89.67	**97.85**
4	75.74	91.46	**98.22**
5	82.92	92.58	**98.45**
6	80.44	91.94	**98.38**

Using the available set of six high resolution fully sampled MS images, it is possible to apply a sampling mask across each image. For each band a sampling mask samples roughly $\approx 17\%$ of the original image. This is to simulate the pixel level bandpass filtering on the camera proposed by.[10] Figure 3 shows a portion of the sampling mask that simulates the MS detector. The sampling mask for each spectral band is applied to simulate the compressed sensing of MS data. It is important to note that the sampling rate for each spectral band is well below the Nyquist rate.[11]

4. RESULTS

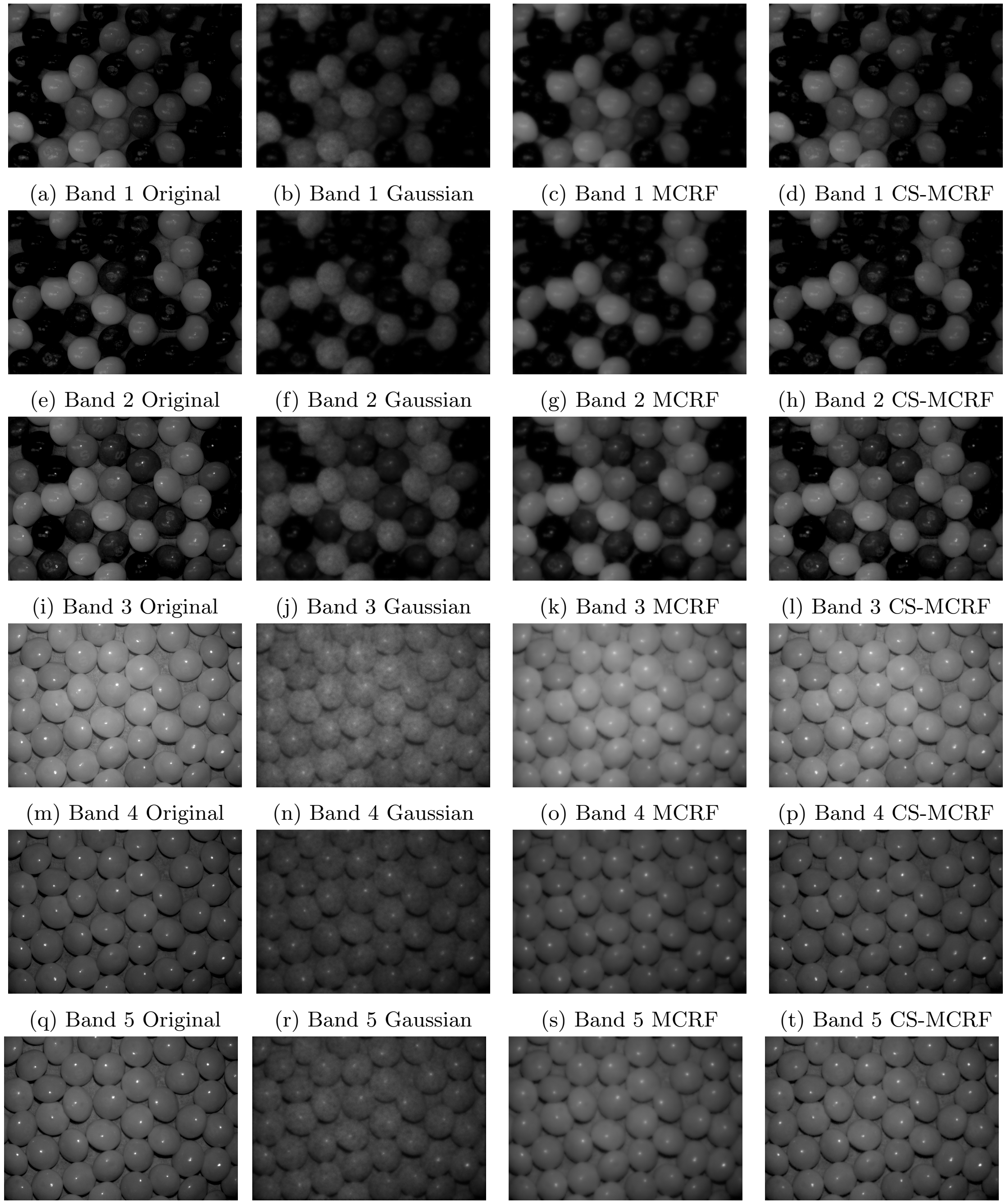
To evaluate the quality of reconstruction from the proposed CS-MCRF method, comparisons are made between a Gaussian interpolation and the original MCRF.[7] These methods are compared both visually as well as quantitatively through Peak Signal-to-noise (PSNR) analysis as well as structured similarity index (SSIM).[12]

Table 2 shows the PSNR calculated for the different methods. The PSNR values are evaluated according to the original fully sampled high-resolution MS data. Comparisons of different methods demonstrate an improvement over existing methods. The CS-MCRF showed improvements of as much as 6 dB over the MCRF and improvements of as much as 17 dB over Gaussian interpolation in certain spectral channels.

Table 3 shows the structured similarity measures calculated for the different methods. Structured similarity is compared with the original fully sampled high-resolution MS data. Comparisons of the different methods demonstrate an improvement over the existing methods. The CS-MCRF showed improvements of around $7-8\%$ structure similarity over the MCRF and improvements of as much as 22% structure similarity over Gaussian interpolation in certain spectral channels.

From the two quantitative measures, it is evident that the CS-MCRF performed quality reconstruction and provided significant improvements over the existing methods.Visually Figure 4 shows the improvement of the CS-MCRF over the MCRF and Gaussian interpolation. The CS-MCRF produced sharper edges and preserved original details while smoothing and filling in missing information. Due to sparsity of the original measurements, the reconstruction process is very challenging. It is a balance between inferring state information as well as the preservation of original observations. Visually, Gaussian interpolation produced significant artifacts in the reconstruction process while MCRF produced better interpolation. The results are very smooth and fine details are blurred out. The CS-MCRF was able to produce quality reconstruction without sacrificing edge and details preservation.

Furthermore, from Figure 5, it is noticeable that Gaussian interpolation produced reconstruction artifacts as seen in Figure 5b while blurring the image. Gaussian interpolation only takes advantage of spatial consistencies



(a) Band 1 Original (b) Band 1 Gaussian (c) Band 1 MCRF (d) Band 1 CS-MCRF

(e) Band 2 Original (f) Band 2 Gaussian (g) Band 2 MCRF (h) Band 2 CS-MCRF

(i) Band 3 Original (j) Band 3 Gaussian (k) Band 3 MCRF (l) Band 3 CS-MCRF

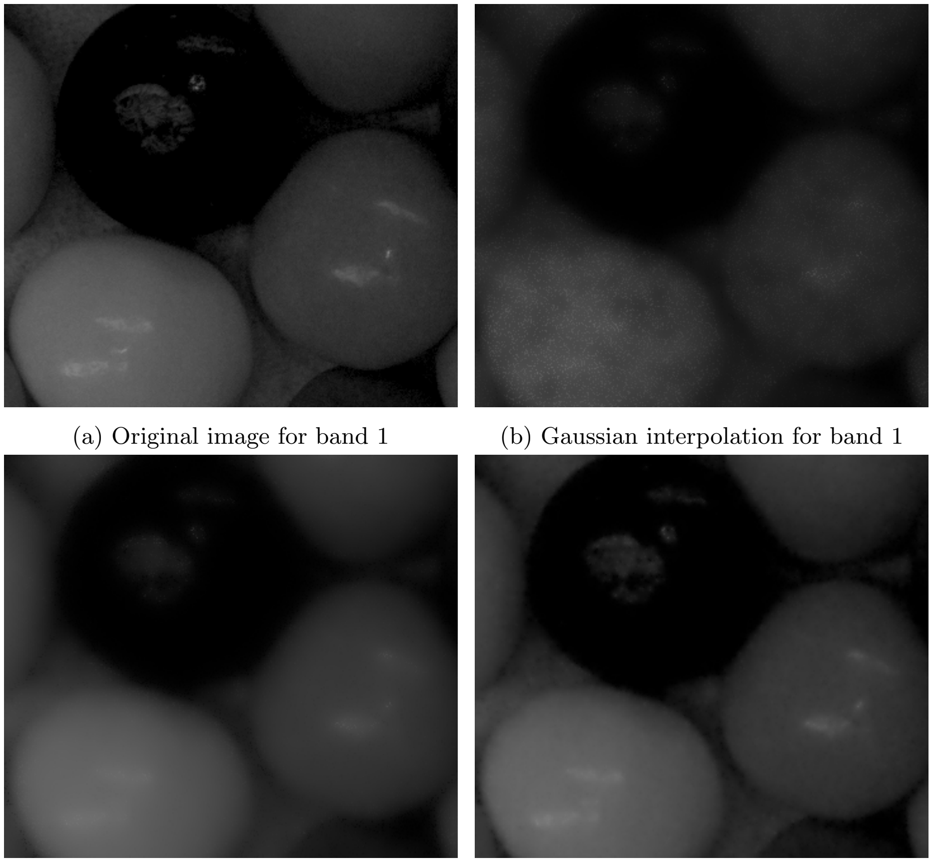
(m) Band 4 Original (n) Band 4 Gaussian (o) Band 4 MCRF (p) Band 4 CS-MCRF

(q) Band 5 Original (r) Band 5 Gaussian (s) Band 5 MCRF (t) Band 5 CS-MCRF

(u) Band 6 Original (v) Band 6 Gaussian (w) Band 6 MCRF (x) Band 6 CS-MCRF

Figure 4: Visual result of proposed reconstruction method (CS-MCRF) compared to existing methodology (Gaussian, MCRF)

and simple data consistencies. The MCRF performed better than Gaussian interpolation in its ability to preserve original observations while enforcing spatial consistencies. Limited by the amount of information used, the MCRF utilizes increased enforcement of neighborhood consistencies resulting in increased blurring as evident in Figure 5c. Using additional information available through cross-spectral consistencies, the CS-MCRF produced improved edge and detail enhancement evident in Figure 5d. Using additional information from multiple spectral bands, higher unary enforcement can enhance the edge and texture details from the original observa-



(a) Original image for band 1 (b) Gaussian interpolation for band 1

(c) MCRF reconstruction for band 1 (d) CS-MCRF interpolation for band 1

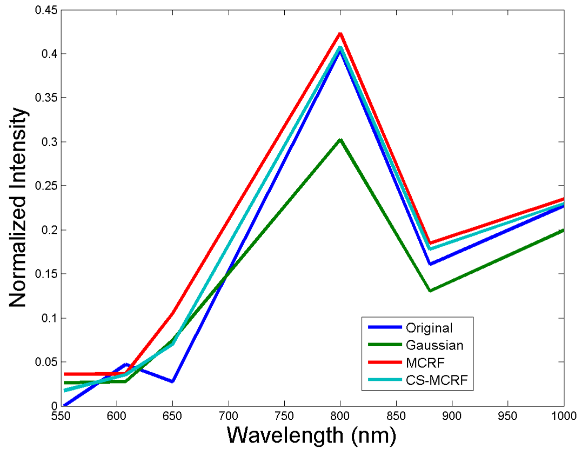
Figure 5: Comparison of results in a zoomed-in region, notice the sharpness and enhanced edge details compared with other methods

tions. Blurring is still evident as pairwise constraints are still required for inferring pixel locations with missing observations. Overall results demonstrate improvements over existing methods through the use of additional cross-spectral consistencies from neighboring MS bands.

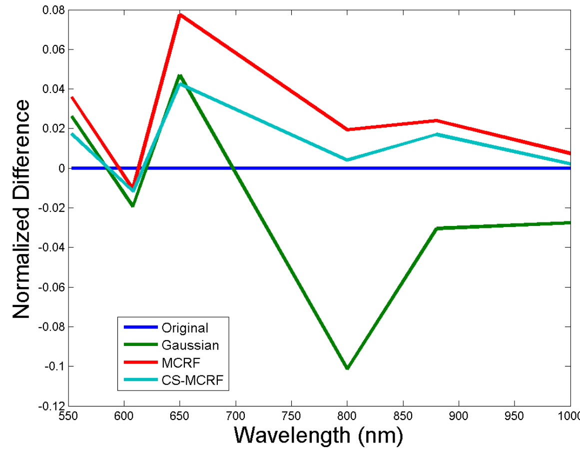
Additionally, spectral fidelity is an important measure of MS imaging and the reconstruction algorithm should be able to achieve good preservation of spectral fidelity. The six-channel spectrum of a specific pixel are plotted in Figure 6. It is observed that the CS-MCRF has the highest spectral fidelity in comparison with other methods. Gaussian interpolation demonstrated high variability from the original spectrum while the MCRF was closer to the original spectrum. Finally the CS-MCRF produced the best results, closest to the original spectrum. This demonstrates the CS-MCRF's ability to successfully estimate the spectral response accurately across multiple MS bands. Spectral fidelity is an important quality measure of the reconstruction algorithm for compressive sensed MS imaging.

5. CONCLUSIONS

Compressive sensing for multi-spectral data can greatly increase imaging efficiency, compactness and ease of use for multi-spectral imaging systems. Strong reconstruction algorithms are required to accompany such sensing devices. A cross spectral multi-layered conditional random field reconstruction approach is presented. Which attempts to utilize additional spectral information from neighboring spectral bands to improve the sparse reconstruction quality. To test the qualitative and quantitative efficacy of the CS-MCRF, simulated wavelength sub-sampling was performed on fully sampled multi-spectral data from a six channel multi-spectral imaging system. Peak signal-to-noise and Structured similarity analysis was performed. Results show a great improvement



(a) Spectral Intensity at different wavelengths



(b) Spectral Intensity deviation at different wavelengths

Figure 6: Six-channel spectrum of a specific pixel in the image. Intensities are plotted in (a). Intensity differences are plotted in (b). For each plot, blue is the ground truth spectrum; Green represents the Gaussian spectrum; Red represents the MCRF spectrum and cyan represents the CS-MCRF spectrum

over existing MCRF as well as Gaussian interpolation. Additionally, visual improvements can be observed from the CS-MCRF over existing methodology. There are less reconstruction artifacts and better preservation of spectral fidelity, which is very important to multi-spectral imaging.

REFERENCES

[1] Care, H.-b. H., Yi, D., Wang, C., Qi, H., Kong, L., Wang, F., and Adibi, A., "Real-Time Multispectral Imager for Home-Based Health Care," *IEEE Transactions on Biomedical Engineering* **58**(3), 736–740 (2011).

[2] Park, H., Dan, Y., Seo, K., Yu, Y. J., Duane, P. K., Wober, M., and Crozier, K. B., "Filter-free image sensor pixels comprising silicon nanowires with selective color absorption.," *Nano letters* **14**, 1804–9 (Apr. 2014).

[3] Park, H. and Crozier, K. B., "Multispectral imaging with vertical silicon nanowires.," *Scientific reports* **3**, 2460 (Jan. 2013).

[4] Donoho, D., "Compressed sensing," *IEEE Transactions on Information Theory* **52**, 1289–1306 (Apr. 2006).

[5] Baraniuk, R., "Compressive Sensing," *IEEE Signal Processing Magazine* **24**(July), 1–9 (2007).

[6] Candès, E. J., "Compressive sampling," *Int. Congress of Mathematics,* **3**, 1433–1452 (2006).

[7] Kazemzadeh, F., Shafiee, M. J., Wong, A., and Clausi, D. a., "Reconstruction of compressive multispectral sensing data using a multilayered conditional random field approach," 921712 (Sept. 2014).

[8] Lafferty, J. and Mccallum, A., "Conditional Random Fields : Probabilistic Models for Segmenting and Labeling Sequence Data Conditional Random Fields : Probabilistic Models for Segmenting and," **2001**(Icml), 282–289 (2001).

[9] M. J. Shafiee, A. Wong, P. Siva, P. F., "Efficient Bayesian Inference using Fully Connected Conditional Random Fields with Stochastic Cliques," in [*IEEE ICIP*], 5 (204).

[10] Kazemzadeh, F., Member, S., Haider, S. A., Scharfenberger, C., Wong, A., Clausi, D. A., and Member, S., "Multispectral Stereoscopic Imaging Device : Simultaneous Multiview Imaging from the Visible to the Near-Infrared," *IEEE transactions on Instrumentation and Measurements* **63**(7), 1871–1873 (2014).

[11] Nyquist, H., "Certain topics in telegraph transmission theory," *American Institute of Electrical Engineers, Transactions of the* **47**(2), 617–644 (1928).

[12] Wang, Z., Bovik, A. C., Sheikh, H. R., and Simoncelli, E. P., "Image quality assessment: from error visibility to structural similarity," *Image Processing, IEEE Transactions on* **13**(4), 600–612 (2004).