Exploiting Spectral and Spatial Correlations for Single Sensor Acquisition and Demosaicing of Multispectral Images

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Abstract—Multispectral images are successfully used in many applications, such as satellite imaging, remote sensing, and medical imaging. Capturing multispectral images is one of the main challenges in these applications. Among all possible techniques for multispectral imaging, our main focus is on the algorithms, which capture multispectral bands with only a single sensor. This method is similar to color imaging with a single sensor when a color filter array (CFA) is placed in front of the sensor to sample only one color at each spatial position. Therefore, similar to the single-sensor color imaging technique, a demosaicing algorithm should be applied to the image captured by the sensor to recover the full resolution multispectral image. Since multispectral and color imaging are analogous in this sense, we briefly review the general framework of most color demosaicing algorithms which has been discussed in [1]. We show that most color demosaicing algorithms exploit features of natural images especially intra and inter-channel correlations to estimate the full resolution image. An algorithm proposed in [2] for multispectral acquisition with a single sensor is then discussed. This technique exploits a preliminary model of multispectral images in the demosaicing step. Thus, one possibility to improve the performance of this method is to use more sophisticated statistical models for these images. However, statistical properties of multispectral images are largely unexplored. In this study, we present one of the few researches in this field, which investigates the statistics of far-infrared images [3]. Although this work addresses a special class of multispectral images, its approach to study the statistical properties and also the obtained results can be beneficial in other cases of multispectral characterization.

Index Terms—Multispectral imaging, demosaicing, spatial correlation, spectral correlation.

I. INTRODUCTION

MULTISPECTRAL imaging systems capture information at different wavelengths along the electromagnetic spectrum. In color imaging, three channels in the visible part of the spectrum are measured. Multispectral images, which contain more than three channels where some bands might represent the scene reflection outside the visible range, reveal much more information compared to color images. This information has been successfully used in many fields, including vegetation analysis in agriculture, medical imaging, home security, remote sensing, surveillance and satellite imaging [4]. In the current study, we mainly focus on capturing multispectral images in the range of 400-1100 nm, which covers visible and near-infrared (NIR) bands. The reason is that the sensors of most digital cameras are inherently sensitive to the NIR part of the spectrum. Thus, NIR acquisition with current cameras requires almost no additional cost in terms of the sensor. Besides, exploiting NIR information along with visible images has proven highly useful in some image processing and computer vision applications [5].

One approach for capturing scene information at different spectral bands is to use multiple sensors in the imaging device where each sensor measures one band [6], [7]. Another technique is to capture multispectral images with a single sensor and a multi-spectral filter array (MSFA) [2]. This technique is more cost-effective compared to the multi-sensor imaging system and can be implemented in a compact setup. The MSFA is an array of filters, which measures only one spectral band at each spatial position. Thus the output image of the MSFA, usually called the mosaiced image, is a down-sampled multispectral image. Consequently, a post processing named “demosaicing” needs to be applied to the mosaiced image, to reconstruct the full resolution multispectral image and estimate the missing spectral information at each pixel.

A demosaicing block is also essential in the color imaging pipeline, where a sensor samples one of three spectral bands
(red, green or blue) at each pixel. Color demosaicing is the process of reconstructing the full resolution color image from the output image of the sensor. The performance of the demosaicing algorithm can be improved by exploiting the specific features of natural images. Strong spectral and spatial correlations are important features of natural images in demosaicing. It has been shown that in these images different color planes are highly correlated (inter-channel correlation), and also strong correlation can be seen among neighboring pixels in the same plane (intra-channel correlation). Based on these observations, many color demosaicing algorithms try to use models describing inter-channel and intra-channel correlation in the reconstruction procedure (see [1] and references).

Among all possible techniques for multispectral imaging [4], we mainly focus on methods that use a single sensor to capture multiple bands of the light spectrum [2], [8]. In [8], Lu et al., proposed a novel algorithm for RGB/NIR joint acquisition using a single sensor. This method does not explicitly employ the prior knowledge about statistical properties of NIR and RGB images in the demosaicing step. In [2], Miao et al., addressed the more general case of multispectral imaging where any number of bands can be sampled using the MSFA. It has been shown in [2] that edge locations in images of different spectral bands are almost the same. It has been suggested in [2] to use this simple model in demosaicing of multispectral images.

One approach to improve the existing multispectral demosaicing algorithms ([2], [8]) is to use prior information about the statistical properties of multispectral images. However, a major challenge is that the statistics of multispectral images especially beyond the visible range have not been extensively explored. To the best of our knowledge, only one study investigates the statistics of images captured outside the visible range [3]. This paper characterizes far-infrared (IR) images by analyzing the distribution of wavelet coefficients and comparing them with visible distributions.

This proposal is organized as the following. We explain the general principles of color demosaicing algorithms by reviewing [1] written by Li et al., in Section II. The algorithm proposed by Miao et al., in [2] for MSFA design and multispectral demosaicing is described in Section III. We discuss the statistical properties of multispectral images in Section IV. In this section, the mathematical tools used in [3] by Morris et al., for studying the features of far-infrared images and their results are explained. We will conclude with a brief discussion on a preliminary study on characterizing the spectral correlation of natural RGB and NIR images. The obtained model has been used to design a NIR/RGB joint demosaicing algorithm [9]. We will also mention possible directions for addressing the multispectral acquisition by exploiting spectral and spatial correlations in these images in Section V.

II. COLOR DEMOSAICING ALGORITHMS

In single-sensor color imaging techniques the CFA is placed in front of the sensor to measure only one color at each pixel. The demosaicing is the process of estimating missing colors at each spatial position using the CFA samples.

In this section, we review the basic principles of most color demosaicing algorithms. In [1], Li et al., classified demosaicing algorithms into frequency-based and spatial-based methods and also deterministic and probabilistic algorithms. Since our focus in this proposal is on exploiting the correlation of natural images in image acquisition, we consider two classes of algorithms: the category which uses inter-channel correlation and the class which takes advantage of intra-channel correlation. In [1], more than seventy demosaicing algorithms have been cited and many of them can be categorized to algorithms which use intra-channel or inter-channel correlation to reconstruct the full resolution image. The general scheme of these algorithms is briefly discussed in the following sub-sections.

A. Intra-channel Correlation

In algorithms which only use intra-channel correlation, no prior knowledge about spectral correlation in natural images is exploited in the demosaicing process [10]. In these algorithms, each channel is interpolated separately using standard methods such as bilinear, bicubic and spline interpolation. However, strong correlation between different color planes in natural scenes can be effectively used to improve the performance of demosaicing algorithms.

B. Inter-channel Correlation

The basic assumption about the inter-channel correlation is that hue is locally constant in natural images [1]. Hue is usually defined by the ratio of color differences and can be written as the following:

\[ \text{hue} = \frac{R - G}{B - G} \]  

(1)

Constant hue assumption can be expressed as constant color difference in the following way:

\[ R(x, y) - G(x, y) = c_1, \]

\[ B(x, y) - G(x, y) = c_2, \]

(2)

where \( x \) and \( y \) belong to a local neighborhood in the image and \( c_1, c_2 \) are constant coefficients [11]. This assumption implies that the color differences are more lowpass than each color channel. Thus, interpolating color differences in the mosaiced image results in less aliasing error compared to direct interpolation of each color channel. Consequently a simple idea for using the constant hue assumption in color demosaicing, is to first interpolate color differences. Many demosaicing algorithms are designed based on the popular Bayer pattern [12], in which the sampling frequency of the green channel is twice the sampling rate of red and blue channels (see Fig. 1). As a result, the green channel is less aliased and can be used in recovering the red and blue channels. Thus, the next step after the color difference interpolation is to reconstruct the full resolution green channel. Finally, blue and red missing pixels are estimated using the full resolution green channel and demosaiced color differences [11].

To better explain the framework of algorithms which use inter-channel correlation, we describe the algorithm proposed by Lu and Tan in [13]. According to experimental results
of [1], this method outperforms the most state-of-the-art demosaicning algorithms, since it effectively uses spectral correlation in estimating missing pixels and also suppressing the demosaicning artifacts.

The demosaicning algorithm proposed in [13] consists of two main steps: missing pixels interpolation and a post-processing step applied to regions with high potential for demosaicning artifacts. We only explain the interpolation step to show how constant hue assumption can be used in the demosaicning.

Since the Bayer pattern is assumed as the CFA, first the green channel with the highest sampling rate is interpolated. In Fig. 2, the green value at the central pixel ($G_{44}$) is computed as the weighted average of four closest neighbors where the green values are known.

$$\hat{G}_{44} = \alpha_{34}\tilde{G}_{34} + \alpha_{43}\tilde{G}_{43} + \alpha_{45}\tilde{G}_{45} + \alpha_{54}\tilde{G}_{54}$$

In the above equation, $\alpha_{ij}$’s are weights of different spatial directions in interpolation. Interpolation across edges is not desirable, because it considerably smooth the edge. Thus, if one interpolation direction is across an edge, it should have less weight in (3). As a result, $\alpha_{ij}$ in each direction is inversely proportional to the magnitude of the gradient, which is a measure of the edge probability in that direction. Note that in (3), the exact green values are not used to estimate the missing pixel. Instead, the following adjusted values are used in estimating $G_{44}$.

$$\tilde{G}_{34} = G_{34} + \frac{B_{34} - B_{24}}{2}$$

$$\tilde{G}_{43} = G_{43} + \frac{B_{43} - B_{42}}{2}$$

$$\tilde{G}_{45} = G_{45} + \frac{B_{45} - B_{46}}{2}$$

$$\tilde{G}_{54} = G_{54} + \frac{B_{54} - B_{64}}{2}$$

where $\tilde{G}_{ij}$ is the adjusted value and $G_{ij}, B_{ij}$ are CFA samples of green and blue channels, respectively. To justify the above equations, assume that we use only $G_{34}$ (top direction information) to estimate $G_{44}$. The constant hue assumption (constant color difference) implies that:

$$G_{44} - B_{44} = G_{24} - B_{24}$$

Assuming the constant rate of change in one color plane in a small neighborhood, it is possible to write:

$$G_{44} - G_{34} = G_{44} - G_{24}$$

Combining (5) and (6), using only the green value in the top direction, $G_{44}$ can be computed as:

$$G_{44} = G_{34} + \frac{B_{44} - B_{24}}{2}$$

Thus the adjusted value of $G_{34}$ in estimating $G_{44}$ can be computed as (4). Other equations in (4) can be proved with the same argument.

After estimating the full resolution green plane, red and blue missing pixels are computed using the green channel and known red and blue values. Since interpolation processes for red and blue channels are exactly the same, we only describe the procedure for red pixels. In the first step, red values at blue pixels are estimated. For instance, $R_{33}$ (Fig. 3) is computed as follows:

$$\hat{R}_{33} = \alpha_{22}\tilde{R}_{22} + \alpha_{24}\tilde{R}_{24} + \alpha_{42}\tilde{R}_{42} + \alpha_{44}\tilde{R}_{44}$$

where $\tilde{R}_{ij}$ is the adjusted $R_{ij}$ value and $\alpha_{ij}$ is the weight of each direction in estimating the central pixel ($R_{33}$). Assuming constant color difference in a local neighborhood, adjusted red

1Note that in Fig. 3, at blue pixels where column and row of the pixel are even numbers (for example at the central pixel) only estimated green values are shown.
have about the input signal, the better it can be processed. To every other signal processing field, the more knowledge we designing multispectral acquisition techniques. In fact, similar algorithms. Data as accurately as possible in developing color demosaicing dB. These results emphasize the importance of modeling the dataset, when the average PSNR for Kodak dataset is about 40 these algorithms is decreased by about 5–10 dB in the IMAX peak signal to noise ratio (PSNR) of images demosaiced by reconstructed. Similar to green reconstruction, $\alpha_{ij}$ in (8) is inversely proportional to the gradient in the specific direction. The gradient in each direction for red reconstruction is computed only based on the green values. Since for red estimation in each direction only one known red value is present in a close neighborhood (see Fig. 3), it is not possible to compute the gradient based on the known values in the same color plane. However, the green plane is fully reconstructed in the previous step, thus using green values to estimate gradient leads to more accurate results. The red values at green pixels can be estimated using the procedure just described, with a small modification in computing gradients. By interpolating the blue channel similar to the red demosaicing, the full resolution color image is reconstructed.

As discussed in [1], the success of demosaicing algorithms to a large extent depends on the validity of the models assumed in the algorithm for natural images. In [1], the performance of eleven different demosaicing methods are compared. The Kodak PhotoCD which contains scanned images from film-based photos and IMAX high quality dataset have been used to test the performance of the demosaicing algorithms. Figure 4 illustrates one sample for each of these datasets. As discussed in [1], constant hue assumption is less valid for the IMAX dataset. In this case, the performance of algorithms which rely on this assumption is significantly degraded. The average peak signal to noise ratio (PSNR) of images demosaiced by these algorithms is decreased by about 5–10 dB in the IMAX dataset, when the average PSNR for Kodak dataset is about 40 dB. These results emphasize the importance of modeling the data as accurately as possible in developing color demosaicing algorithms.

Modeling the data also seems to be the first necessary step in designing multispectral acquisition techniques. In fact, similar to every other signal processing field, the more knowledge we have about the input signal, the better it can be processed.

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the example shown in Fig. 5, the highest POA corresponds to channels R, G, and B, thus the demosaicing process can start with each of these channels.

One of the difficulties in demosaicing multispectral images is that in each spectral band very few known pixels are available and they are insufficient to approximate missing pixels with acceptable accuracy. To handle this problem, it has been suggested in [2] to sequentially approximate the missing pixels for each band. In each iteration of the proposed algorithm, some missing pixels are estimated using the MSFA samples and pixels interpolated in previous iterations at the same channel. The process of pixel selection for interpolation can be explained using the example illustrated in Fig. 5. In this example, to reconstruct the full resolution M channel, first the M missing values at C pixels are estimated. In the next step, missing pixels at positions of the M channel parent’s sibling (G channel in this case) are interpolated. At the next iteration, the algorithm goes one level up and considers the sibling of node 1 (node 2). Since node 2 is an internal node, M values at the pixels of this node’s leaves, i.e., R and B bands, are computed. If the algorithm continues one more iteration, the root of the tree is reached which means the M channel is completely demosaiced. The procedure of demosaicing other bands is exactly the same as what is described here for the M channel.

At each iteration of demosaicing a channel, missing pixels are estimated as a weighted average of four closest neighbors. Similar to the color demosaicing, weights are computed as a function of the gradient in each direction. Since interpolation across edges would smooth the edge, the weight for each direction is inversely proportional to the magnitude of gradient in that specific direction.

It has been mentioned in [2] that the edge locations of different channels in a multispectral image are the same. Thus, using edge information of high-resolution bands with higher sampling rate, the gradient for low-resolution channels can be estimated more precisely. However, the authors of [2] did not use this information in the proposed algorithm. Therefore, incorporating the correlation between different bands in the interpolation phase is one possible direction to further extend this study.

Another issue which has not been addressed in [2] is the procedure of assigning the probability of appearance (sampling rate) for each spectral band. The POA assignment affects the MSFA design and also the band selection step in the demosaicing process. It is obvious that values of optimum POA’s depend on properties of the multispectral images we are interested in. To further explain this statement, consider the special case of Bayer pattern for color demosaicing where \( P_B = P_R = \frac{1}{4} \) and \( P_G = \frac{1}{2} \). The reason for this selection is that the human visual system (HVS) is more sensitive to high frequency distortions in luminance compared to chrominance distortions and the central wavelength of the green channel is close to the wavelength of the highest sensitivity point of the HVS to luminance. Thus, aliasing in the green channel is less tolerable and this channel needs to be sampled with a higher rate.

In contrast to the above argument, as discussed in [14] the performance of a frequency-based demosaicing algorithm may be improved by changing the Bayer pattern. Alleysson et al., proved that since the correlation of red and blue channels with the green band is stronger than the red and blue correlation, sampling the blue or red channel with a higher rate decreases the aliasing between luminance and chrominance. As a result, from the signal processing viewpoint the frequency-based algorithm proposed in [14] performs better with the modified Bayer pattern.

Based on this observation, one possible solution for the problem of POA assignment in the binary tree-based algorithm (\([2]\)) is to allocate higher POA to a spectral band that is less correlated to other channels. Applying this solution requires sufficient information about the correlation of different spectral bands. This again emphasizes the importance of studying features of natural multispectral images in designing sophisticated acquisition techniques.

IV. STATISTICS OF MULTISPECTRAL IMAGES

In this section, we review the few existing studies of the multispectral images’ statistics. As opposed to the statistical properties of visible images, which have been extensively studied (see references of \([3]\)), few researchers have considered the problem of characterizing the multispectral images especially beyond the visible range \([2], [3]\).

In \([2]\), a preliminary experiment was conducted to examine the constant hue assumption in multispectral images and determine the edge locations in these images. In this paper, hue is defined as the ratio of adjacent spectral bands. To investigate the constant hue assumption in multispectral images, Miao et al., computed the ratio of adjacent bands in a dataset of multispectral images. They also computed the hue in a color image database. The results of this study suggest that the constant hue assumption is less valid in multispectral images. Because the local variance of hue signals, which correspond to multispectral images, is higher than the variance of hue in color images.

However, their conclusion is not completely fair because in this experiment the multispectral and color images do not represent the same scenes. Besides, correlation between different channels of a color or a multispectral image extremely depends on the spectral sensitivity of sensors used in the imaging device. Since it is not possible to capture color and multispectral images with the same camera, it is not straightforward to compare the correlation of different channels in color and multispectral images.

It has been shown in \([2]\) that in a dataset of images for 7 visible bands, the edge locations of different channels are almost the same. Thus, the authors concluded that different channels of a multispectral image possess the same edge locations which can be used in the demosaicing process of these images.

The problem of characterizing multispectral images has also been addressed by Morris et al., in \([3]\). In this paper the marginal statistics of far-infrared (IR) images in the range of 4 to 12 microns are studied for a dataset of 400 images of indoor and outdoor scenes. Moreover they analyzed the joint statistics of IR and visible image pairs.
In the first set of experiments, they tried to validate the power law in far-infrared images. It is a well known fact that the power law matches the power spectrum of most visible images very well as shown here:

\[ P(f) \propto \frac{1}{f^{2-\eta}}, \]

where \( P(f) \) is the power spectrum, \( f \) is the spatial frequency, and \( \eta \) is different for each image but is generally small [15]. It has been shown in [3] that the power law is not valid for IR images and the generalized Laplacian distribution better fits the power spectrum of these images. The generalized Laplacian distribution can be written as:

\[ P(x) \propto \exp(-|x/s|^\alpha), \]

where \( s \) and \( \alpha \) are model parameters which can be computed using the least square estimation.

In the next step, they analyzed the wavelet coefficient statistics of far-infrared images and their joint distribution with the visible coefficients as a powerful tool to describe image features in different scales and orientations. The Haar wavelet has been used in [3] to study the statistics of IR and visible images. Lowpass and highpass basis functions of the Haar wavelet can be written as the following, respectively:

\[ h = \frac{[1 \ 1]}{\sqrt{2}} \quad g = \frac{[1 \ -1]}{\sqrt{2}} \]

Studying the marginal distribution of wavelet coefficients revealed that the general Laplacian model fits very well the statistics of four image categories studied in this paper (indoor/outdoor visible and indoor/outdoor far-infrared images).

Another important result reported in [3] is that wavelet distributions of IR images fall more rapidly than visible distribution. Figure 6 shows distributions of wavelet coefficients for indoor IR and visible images. Two plots in this figure illustrate the histogram of horizontal wavelet coefficients in three different scales. The fitted general Laplacian distributions are also shown in these plots. Note that vertical axes in Fig. 6 show histogram in the logarithmic scale. It is obvious in this figure that IR images have fewer wavelet coefficients with large magnitudes compared to visible counterparts. This observation can be explained considering the fact that reflectance in the far-infrared part of the spectrum is more temperature dependent. Thus, less texture and fewer fine details are present in far-infrared images, especially when the temperature of objects in the scene is somewhat homogenous, for example in indoor images (see Fig. 7 which shows IR and visible images of a same scene).

It has also been proved in [3] that visible and IR wavelet coefficients are highly correlated, which can be justified observing that object boundaries of the original scene are somewhat preserved in the IR image.

To summarize, the experimental results of [3] suggest that far-infrared images are more correlated spatially compared to visible images. Furthermore, it has been observed that visible and IR images are highly correlated (strong spectral correlation).

As already mentioned, our main focus is on multispectral acquisition in the interval of 400 to 1100 nm. Thus, we cannot directly exploit the results of [3] in developing demosaicing algorithms. Nevertheless, this study is interesting for us, since it provides useful tools for characterizing multispectral images and the obtained results can be used for comparison with NIR statistics. For instance, since reflection in the NIR is mostly material dependent, many fine details are not visible in the NIR image. Thus, based on the results of [3], we expect NIR wavelet distribution to decay more rapidly compared to visible.

V. DISCUSSION AND RESEARCH PROPOSAL

Extensive study of color and multispectral demosaicing and acquisition algorithms reveals that to design better techniques for multispectral acquisition, the first step is analyzing the statistics of multispectral images. As explained in Section IV, not many studies about the characteristics of multispectral images, especially those outside the visible range, are available. Thus, it is not possible for current multispectral acquisition methods ([2], [8]) to take advantage of sophisticated models for these images.

In [9], we briefly addressed the problem of characterizing multispectral images by studying the spectral correlation of NIR and visible images in different frequency bands. Our results show that the luminance channel (spatial information) of the visible image and the NIR representation of the same scene are strongly correlated in high frequency bands. The reason is...
that pixel intensities in visible and NIR representations of a scene can be too different. For instance, the sky in the NIR image usually appears dark, while it looks so much brighter in the visible image. However, the general shapes of objects are well preserved in the NIR image, so the edges which mostly contribute to high spatial frequencies are almost the same in NIR and visible images. Although these results have already been exploited in RGB and NIR joint demosaicing [9], the study can largely be extended. In this experiment only 4 bands have been examined (one band in the NIR and three bands in the visible part of the spectrum). One possible direction to extend the current study is to consider more bands in each part of the spectrum and compute the correlation. Since the closer spectral bands are more correlated, we may reach the conclusion that capturing a specific part of the NIR band results in better demosaicing performance compared to acquiring the whole NIR band.

Unlike multispectral images, the features of visible images have been broadly examined using different tools such as wavelet analysis, correlation computation, power spectrum analysis and so forth. It is possible to use the same methods for multispectral characterization. We are specifically interested in spectral and spatial correlations of natural images, which can be exploited in the demosaicing process. A popular characteristic of natural images largely used in designing color demosaicing methods is constant hue assumption. This property has been investigated for multispectral images in [2] and it has been shown that it is less valid in these images. However, as discussed in Section IV, this experiment can be expanded to obtain more solid results.

Another feature which has been effectively employed in the color demosaicing procedure is the sparseness of visible images in de-correlating spaces [16], [17]. In [16], Mairal et al., proposed a demosaicing method using the sparseness property of natural images, which outperforms the state-of-the-art demosaicing algorithms. Since this method performs remarkably well, we are interested in establishing similar methods for multispectral demosaicing. However, as already mentioned it is of significant importance to use models which fit the real data very well. Therefore, to develop multispectral demosaicing methods based on the sparse decomposition, we should carefully study the sparseness of these images. To this end, sparsifying transforms for color images such as curvelet, wavelet or DCT can be examined for multispectral images. It is also possible to build new transforms based on the specific multispectral dataset, as has been done for color images using dictionary learning algorithms [18].

To summarize, we propose two main directions for developing multispectral imaging with a single sensor. First, we will study the statistics of multispectral images in the range of 400 to 1100 nm in more detail. We can use the tools proposed in [3] for modeling statistics of multispectral images. We will specifically focus on studying constant hue assumption and sparsity of multispectral images, since these features have been exploited effectively in color demosaicing. It is worth mentioning that sparsity and constant hue, respectively, indicate the strong spatial and spectral correlation in natural images. The next step is to exploit the prior knowledge of multispectral natural images in designing imaging systems. We can start by improving the current methods. For instance, the problem of optimal POA assignment in [2] can be solved using the statistics of multispectral images.

REFERENCES