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Learning based demosaicing and color correction for RGB-IR patterned image sensors

Navinprashath R R, Radhesh Bhat; PathPartner Technology Pvt. Ltd., Bangalore, India

Abstract

RGB-IR sensor combines the capabilities of RGB sensor and IR sensor in one single sensor. However, the additional IR pixel in the RGBIR sensor reduces the effective number of pixels allocated to visible region introducing aliasing artifacts due to demosaicing. Also, the presence of IR content in R, G and B channels poses new challenges in accurate color reproduction. Sharpness and color reproduction are very important image quality factors for visual aesthetic as well as computer vision algorithms. Demosaicing and color correction module are integral part of any color image processing pipeline and responsible for sharpness and color reproduction respectively. The image processing pipeline has not been fully explored for RGB-IR sensors. We propose a neural network-based approach for demosaicing and color correction for RGB-IR patterned image sensors. In our experimental results, we show that our learning-based approach performs better than the existing demosaicing and color correction methods.

Keywords *RGB-IR, demosaic, color correction, convolutional neural network*

Introduction

Color image sensors based on RGB color filter arrays (CFAs) are now a robust, cost−effective and widely available solution for visible−light imaging. The Bayer sensors restricts only a certain portion of visible spectrum to pass through it and capture either of the three primary channels (R, G or B). The alternating rows contain Green-Red and Blue-Green pattern. Certain applications, such as security, machine vision, ADAS etc. needs imaging of objects in wavelengths outside of the visible band (400−700 nm) e.g. 700-900nm. Single sensor RGB-IR sensors provides the power of both Bayer and IR sensors without the need of two separate cameras. In case of RGB-IR sensor depending on the pattern (2x2 or 4x4), for every 2x2 block either B, R or G is replaced by IR(Infrared) pixel (Figure 1). Due to this pixel reduction, color resolution of the B and R is reduced by a factor of 2 in case 4x4 pattern and color resolution of G is reduced by a factor of 2 in case of 2x2 pattern with respect to Bayer sensors. Since there is no exclusive IR-cut filter, each of the R, G and B pixels collect a portion of IR light. Figure 2 shows difference when IR-cut filter is not used versus the one being used. While reduced number of B and R pixels affects details at high resolution, the presence of IR content in R, G and B pixels makes it harder for color reproduction. Since usage of RGB-IR cameras lies in safety critical applications such as ADAS, surveillance and biometric authentication, every aspect of image quality is important. We propose a machine learning based approach for demosaicing and color correction that greatly reduces artifacts in visible channel introduced due to the addition of IR pixel.

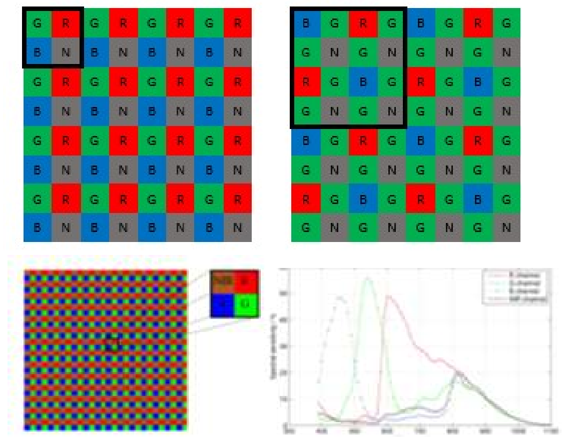


Figure 1. RGB-IR sensor patterns and their typical spectrum [6]

Figure 2. Image captured without IR-cut filter (L) and with IR-cut filter(R) [1]

Proposed Approach

Demosaicing

The demosaicing is performed to reconstruct full RGB and NIR images from the mosaiced sensor output, where only one spectral band is measured at each pixel location according to the filter array pattern. We use light weight CNN based approach to perform demosaicing. The motivation in using CNN is based on the fact that the problem does not have one absolute mathematical solution. The missing values cannot be reconstructed using only mathematical analysis because the problem is under-constrained. To train the model, McMaster (McM) [9] dataset is used. Figure 3 shows the flow for performing CNN based demosaicing.

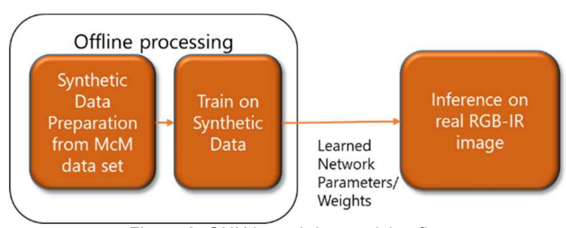


Figure 3. CNN based demosaicing flow

Synthetic Data Preparation

As discussed, McM dataset is used for training the network. For interpolation at each pixel location, the pixel's visibility is limited to only 3 channels. E.g. if we are interpolating red channel, then only red, green and IR will be considered. Blue will be set to zero. Similarly, for interpolating green channel, either B or R can be set to zero and work with other 3 channels. The synthetic dataset is created from the McM dataset by considering R or B as IR channel and adding this IR content to green channel representing contaminated green due to addition of IR as in real RGB-IR.

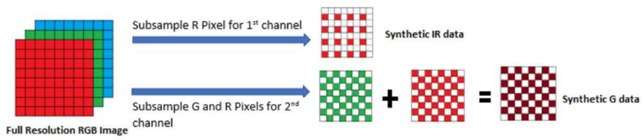


Figure 4. Synthetic data preparation

The Network

Once the dataset is ready, the CNN network is built to generate missing color channel at every location. Figure 5 shows the network for interpolating red channel at green pixel location. Feature extractor is used for reordering of each of 7x7 masked patch in grouped manner. Similar to the network represented for interpolating R channel at G location, six other networks need to be learned for channels at different pixel locations. The learned network parameters output the kernel weights required for demosaicing adaptively for each pixel location. Relu is used for activation. No data augmentation is done for training.

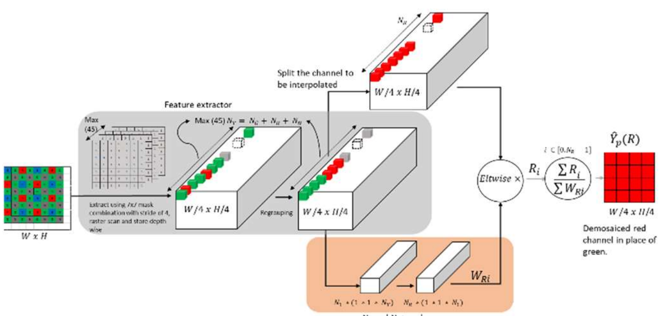


Figure 5. CNN model for demosaicing

The training loss target is to minimize the Euclidean loss:

$$EL(C) = \sqrt{(\widehat{Y_p}(C) - Y_{GT}(C))^2} \quad where\ C \in \{R,G,B,N\}$$

Where $\hat{Y}_p(C)$ is predicted color channel output from the network and $Y_{GT}(C)$ is the ground truth color channel output from the synthetic dataset.

Color Correction

The objective of color correction is to restore the accurate color RGB image from RGB-IR which is influenced by IR content. We propose a light weight neural network for color correction. The network is optimized to remove IR content from R, G and B channel. Two set of demosaiced images: a) one without IR illumination and b) one with IR illumination both taken at same capture controls (exposure and gain) will be used to find the color correction network parameters (Figure 6).

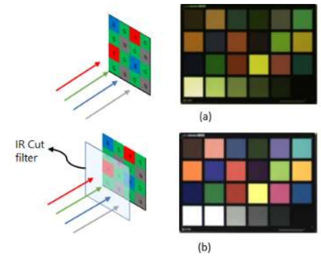


Figure 6. (a) without IR-cut filter (b) with IR-cut filter

The optimization objective of the color correction is to remove the IR content from the images with IR illumination and to match the output images to the images taken at same capture settings without IR illumination, while the images taken without IR illumination remains unaffected by color correction module as shown in Figure 6. Idea is to formulate removal of IR information from R_{RGBI}, G_{RGBI}, B_{RGBI} of RGB-IR image as a regression problem. To find optimal parameters for the color correction network, standard Macbeth color chart can be used. The learned network will be used for color correction. After color correction, both the images results in color accuracy comparable to the image before color correction without IR content. The resulting RGB image can then be passed to the conventional RGB image pipeline for further processing such as white balance, CCM(3x3), gamma, denoising etc. Figure 7 shows the light weight network used for correcting the color. For training, input images are Macbeth color chart images captured with IR illumination or without IR-cut filter enabled. Ground truth images are the ones without IR illumination or with IR-cut filter enabled. Training objective is to minimize two Euclidean losses (L1 and L2).

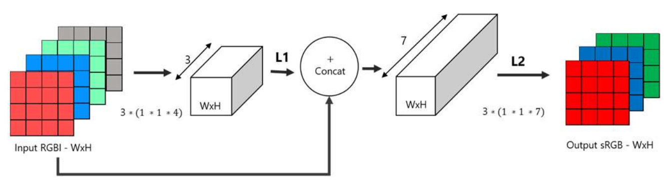
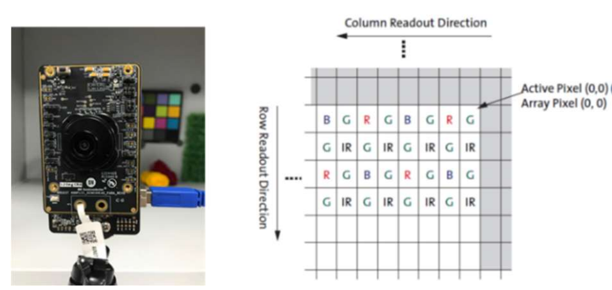


Figure 7. CNN model color correction flow

Experimental Results

We used ON Semiconductor's AR0237CS [10] camera kit with 4x4 RGB-IR Bayer pattern. The camera kit is connected to PC via USB interface. The video output from the camera is fed to the demosaic and color correction algorithm running on PC. The AR0237CS outputs video at 1920x1080 resolution.



(a) (b)

Figure 8. (a) AR0237CS Camera kit (b) 4x4 RGB-IR Bayer pattern

Demosaicing

For evaluating demosaicing network performance, we used McMaster (McM) [9] data set. This dataset was established in a project of developing new CDM (color demosacing) methods by McMaster University, Canada, in collaboration with some industry partners. It has 8 high resolution (size: 2310×1814) color images that were originally captured by Kodak film and then digitized.

Figure 9. McM Dataset images

The performance of proposed demosaic algorithm is compared with traditional gradient based demosaicing method using Peak Signal to Noise Ratio (PSNR).

$$PSNR = 10\log\frac{255^2}{\frac{1}{3M}\sum_{i=1}^{3}\sum_{j=1}^{M}\left\|\widehat{x}_{ij} - x_{ij}\right\|^2}$$

Where:

- M is total number of pixels in one channel
- $\widehat{x}_{ij}$ is the estimated pixel at j-th pixel in i-th color channel
- x_{ij} is the corresponding ground truth pixel value

Table 1 summarizes the PSNR comparison between the two approaches. The McM dataset is mosaiced to RGB-IR pattern with IR = 0 for the benchmarking purpose. So, the PSNR is only for RGB, not for IR since there is no ground truth available for IR.

Table 1: PSNR comparison for demosaicing

Image Sequence in McM dataset	PSNR (dB) Gradient based demosaicing	PSNR (dB) Proposed CNN based demosaicing
1	29.479	32.465
2	29.978	34.433
3	30.243	33.154
4	32.467	34.493
5	29.657	34.795
6	30.749	35.855
7	31.075	33.491
8	33.311	36.368
9	29.805	35.897
10	29.492	35.983
11	29.713	37.299
12	28.945	37.054
13	28.928	38.800
14	29.897	36.989
15	29.557	37.143
16	29.670	33.966
17	29.870	33.877
18	29.516	34.484
Average	**30.131**	**35.364**

Table 2 summarizes total no. of learned parameters and total MACs required. Note that the MACs (multiply and accumulate) computed are not with optimal implementation and has huge scope for further reduction.

Table 2: Demosaicing model performance

Total no. of learned parameters	Total MACs for 1920x1080 image
9598	7.9GMACs

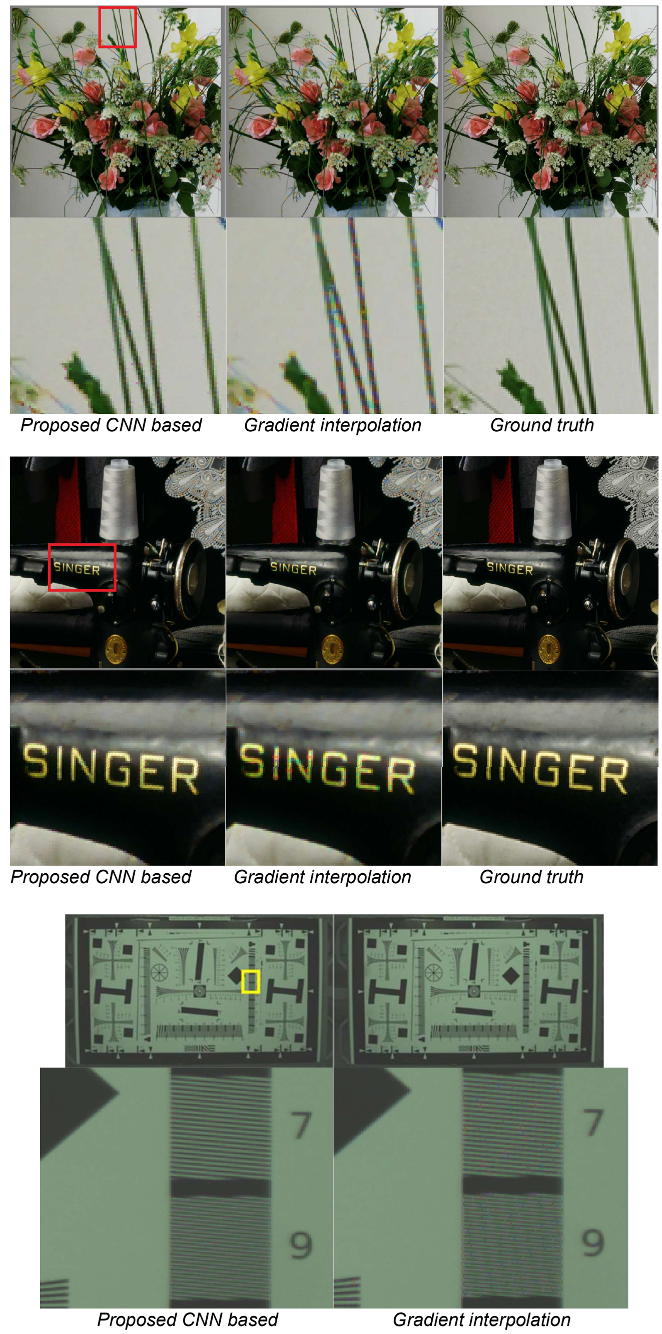


Figure 10. Visual comparison of demosaicing performance

Color Correction

The proposed color correction implementation is compared against the standard 4x3 based matrix approach [3] w.r.t. image with IR cut filter (ground truth or reference) under different lighting conditions. To evaluate both the approaches, chroma difference [11,12] is calculated as follows:

$$\Delta C_{ab} = \sqrt{(\Delta a^*)^2 + (\Delta b^*)^2}$$

Where $\Delta a^* = a_1^* - a_2^*$ & $\Delta a^* = b_1^* - b_2^*$.

a_1^* and a_2^* represents color on green-red scale for target and reference image respectively. Similarly, b_1^*& b_2^* represent color on blue-yellow scale.

Table 3 summarizes ΔC_{ab} results comparing between 4x3 matrix based traditional approach and proposed CNN based approach. Lesser the value of ΔC_{ab} corresponds to better color correction accuracy performance.

Table 3: Chroma difference comparison

Scene (same learned parameters for all the scenes)	ΔC_{ab} **4x3 CCM**	ΔC_{ab} **Proposed Approach**
Vegetation	3.68	3.01
Outdoor	3.49	3.27
Indoor under D65	3.61	2.86
Indoor under CWF	7.09	6.93
Indoor under A	5.61	5.06

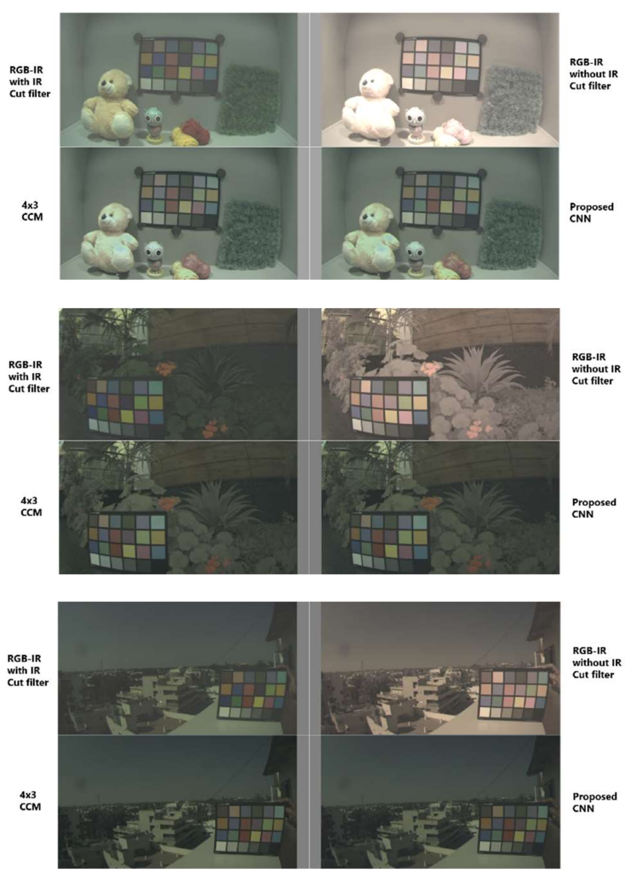


Figure 11. Visual comparison of color correction method

Conclusion

In this paper, we proposed a novel neural network-based approach for RGB-IR demosaicing and color correction. As ground truth for IR channel is not available, we created a synthetic dataset for IR reconstruction training using McM dataset. We are able to achieve significant improvements over existing methods in terms of resolution and color accuracy. The proposed demosaicing algorithm can also be extended to other non-Bayer sensors like RCCC, RCCB and RGBW. The color correction calibration does not strictly require a calibrated color chart and hence the process of color calibration. The proposed approach can further be enhanced or improved by combining demosaicing and denoising, using more datasets, exploiting sparsity in model for further improvement in inference run time and optimize for real time performance on camera based embedded platforms.

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Author Biography

Navinprashath R *holds a Bachelors from College of Engineering, Guindy, Chennai (2015). His interest lies in image signal processing pipelines and computational photography. He is currently with the camera team of Google. Previously Navinprashath was with digital imaging division at PathPartner Technology Pvt Ltd working on image signal pipelines and image enhancement (2015 - 2019).*

Radhesh Bhat *received his BE degree in Electronics and Communication from Visvesvaraya Technological University in 2004. Currently he is heading digital imaging division at PathPartner Technology Pvt. Ltd. His research interests include camera image signal processing pipeline, image quality, computer vision and deep learning.*

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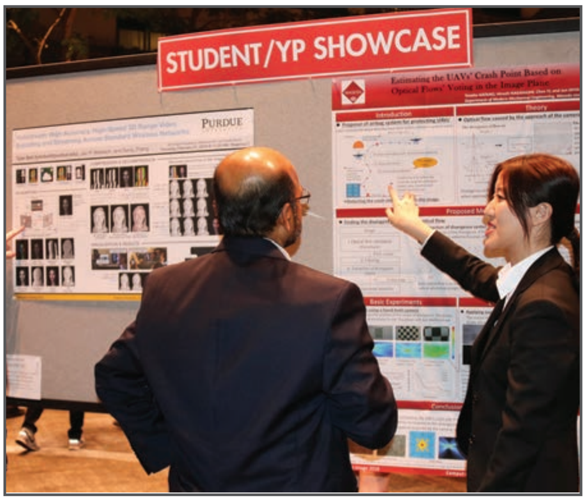

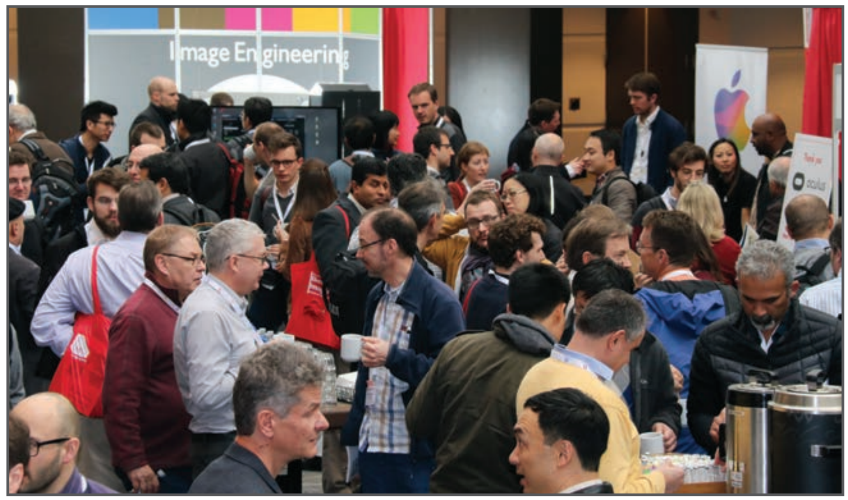

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