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DePhaseNet: a deep convolutional network using Phase Differentiated Layers and Frequency based Custom Loss for RGBW Image Sensor Demosaicing

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Abstract

Panchromatic Color Filter Arrays with white signal were introduced a while ago, e. g. RGBW Color Filter Array (CFA), assuming to have better resolution in lowlight due to panchromatic signal. However, there is no successful RGBW image sensor in the industry targeting mobile cameras until now. In this work, we introduce a novel Samsung RGBW image sensor and we study its performance in a popular remosaic scenario. We propose a DePhaseNet - a deep fully convolutional network to solve RGBW remosaicing or demosaicing problem. We propose to have 3 layers of phase differentiated inputs and custom frequency-based loss function for each layer. Proposed method successfully suppresses False Colors inherent to RGBW sensor due to heavily under-sampled colors. By using this method, we were able not only to increase details preservation, but also increased color reproduction. We found that RGBW sensor is beneficial not only in low light scenarios, but also in widely spread remosaic scenarios. Experiments show improvement in image quality, yielding CPSNR of 42dB for Kodak dataset, reaching the bar of Bayer CFA demosaicing result. Proposed method advances state-of-the-art in RGBW demosaic by 6dB in CPSNR.

Introduction

Nowadays, mobile camera resolutions reach 100MP and often use non-Bayer Color Filter Arrays (CFAs) [1][2][13][14]. For example, to enhance light sensitivity, Quad Bayer CFA, shown in Fig. 1, is adopted. Such sensors have better performance under challenging lowlight image capture conditions or preview modes which is achieved using pixel binning. However, when it comes to full image resolution imaging, the performance degrades. Irregularly subsampling induce a lot of aliasing, therefore more sophisticated algorithms are needed to cover various aliasing and zippering artifacts. Panchromatic CFAs, such as RGBW can provide better performance than Bayer CFA, however due to heavily subsampled color channels, it usually shows loss in color resolution and has color artifacts, e.g., False colors.

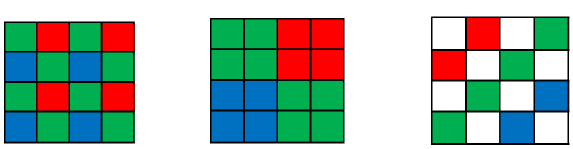


Fig 1. Bayer, Quad Bayer and RGBW- Kodak Color Filter Array (CFA)

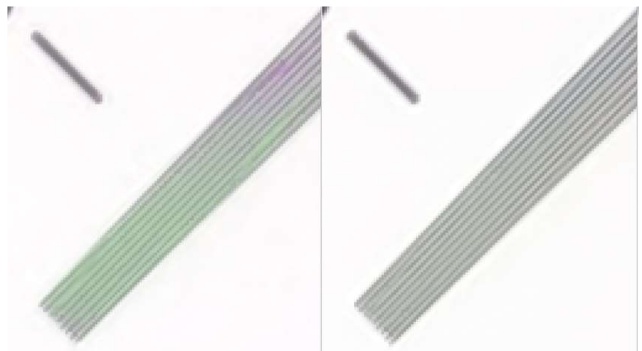


Fig 2. Reduction of False Colors of conventional algorithm (left) and proposed (right) in RGBW demosaic

To reuse existing Image Signal Processor (ISP) pipeline, modern cameras often require remosaicing block that rearranges non-Bayer to Bayer CFA, followed by Bayer ISP processing, to achieve full resolution imaging

In this work, we propose an **end-to-end RGBW remosaic imaging solution,** that can reconstruct raw image from RGBW sensor using one convolutional neural network – dePhaseNet. We proposed a novel hierarchical network structure with phase modulated inputs and carefully designed attention modules that allow to handle color related artifacts. We also proposed to use custom multi-level loss including frequency domain component. Proposed network has a large receptive field allowing to extract more features from source image. Experiments show that proposed method outperforms conventional algorithms by a large margin – by 6dB in PSNR on Kodak dataset. Visual inspection show that it can reconstruct details perfectly and does not produce visually disturbing color artifacts inherent to RGBW sensor – see example in Fig. 2.

Contributions. In this work we proposed an end-to-end method to perform RGBW demosaicing. Due to irregular and sparse subsampling RGBW sensor image quality is prone to various color artifacts. Proposed solution achieves better image quality, outperforming conventional methods by 6dB in CPSNR on widely used Kodak dataset with less False Colors and better color resolution.

Related works

Demosaicing of Bayer Color Filter Array (CFA) has been extensively studied for several decades [6][7][8][9][10][11][12][13][3]. Various demosaicing approaches are studied, including color difference interpolation [17], edge directional interpolation [18], frequency domain filtering [8], [4], [5], and reconstruction methods [19], [20]. However, when it comes to rarely used patterns, such as Quad Bayer, Nonacell or RGBW, there are only a few works addressing demosaicing of those CFAs [2][12][13][14].

Unfortunately, hand-crafted algorithms are mainly designed for most commonly used until recently Bayer CFA, so they have to be redesigned to support any other CFA pattern. Universal demosaicing algorithm, that can be easily extended to new type of CFA pattern, was proposed in Zhang [8] .

Deep learning approach to image demosaicing has been applied in 2016 - see [9], [10], [11], [12]. Early works were also designed for Bayer CFA, however recently there are two works addressing Quad Bayer CFA - Kim [13] and Stojkovic [14]. Compared to hand-crafted algorithms, deep learning methods do not need to be completely redesigned and can be adopted to support various CFA patterns. For example, for Quad Bayer CFA, a new efficient network was proposed to reconstruct Quad Bayer CFA with significantly reduced visual artifacts. However, if we apply previous works to reconstruct RGBW sensor, we can observe visually disturbing False colors and loss of details.

Recently, there are works targeting RGBW image sensor image, see [21][22]. In [21], authors proposed to reconstructed white channel first and binned Bayer image from color channels and then applied pan-sharpening approach to reconstruct full resolution image. In [22] authors use an iterative three stages demosaicing inspired by conventional algorithms. Both methods are complex and not suitable for mobile deployment. Despite of complexity, deep methods fail to provide high image quality required for commercial image sensors.

Problem formulation

In this work we aim to reconstruct subsampled RGBW raw images to full color RGB – this process is called demosaicing, see Fig. 4. We also solve the problem of remosaicing – the process of converting RGBW raw image to Bayer raw image, depicted in the Fig. 5. Remosaicing is widely used in modern camera SoC, to reuse existing Bayer ISP pipelines.

Demosaicing of each color channel can be treated as an interpolation problem of each channel, however due to phase shift during color subsampling and inter-channel dependency, demosaicing normally comes with various visually disturbing artifacts: color moiré, false colors or zippering along edges. For irregularly subsampled FFA patterns, such as Quad Bayer or RGBW, aliasing increases and cause severe artifacts compared to Bayer – see [13] for more detailed analysis.

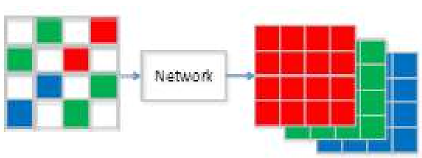


Fig 3. RGBW-Kodak demosaic using neural network.

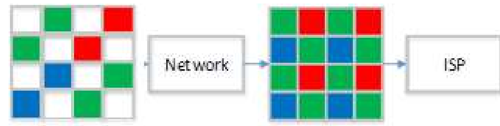


Fig 4. RGBW-Kodak remosaic using neural network.

Proposed method

In this work we propose to remosaic RGBW sensor to standard Bayer CFA by using deep convolutional network – dePhaseNet. Inspired by success of Quad Bayer deep remosaicing in [13], we tried to remosaic RGBW sensor suffering from loss of resolution and various color artifacts due to heavily undersampled color components. Unfortunately, directly applying Bayer or Quad Bayer network working well for Bayer or Quad Bayer, could not solve false color artifacts problem. Therefore, we proposed several improvements to reconstruct RGBW CFA.

Unlike prior art, when pan-sharpening approach was used to reconstruct white signal, we directly reconstruct color channels, without using white signal. Indeed, we found it does not benefit to reconstruct white signal first. The block diagram of the proposed method is depicted in the Fig. 5.

Fig 5. RGBW remosaic solution with dePhaseNet

Furthermore, we propose to reconstruct various phase of the image using phase detector. We actually aim to reconstruct each phase of the image to reduce color sparsity and irregularity. We use specific phase differentiated inputs for that purpose, as shown in Fig. 6.

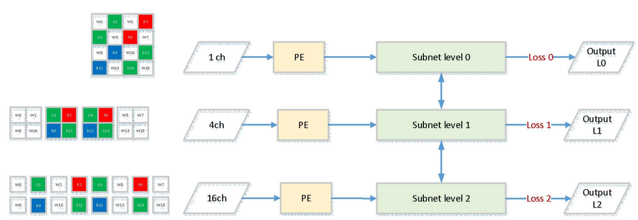


Fig 6. dePhaseNet block diagram

Proposed network has 3 levels, at each level we propose to use phase modulated input and we calculate loss function at each modulated input, as shown in the Eq. 1. We suggest to use specific frequency-based loss function for this purpose.

$$Loss_{final} = \sum_{i=0}^{L} Loss_i + a\sum_{i=0}^{L} FT(Loss_i), \qquad (1)$$

where $Loss_i$ is custom loss at the level i, L – number of levels, FT is a frequency transform. In this work we used Haar wavelet transform and Fourier Transform.

We learn end-to-end mapping function F from training samples pairs and phase modulated pairs by taking RGB images as ground truth and mosaicked images as observed images. We estimate model parameters Ω by minimizing following loss function at each level:

$$Loss_i(\Omega) = L_2\left(F\left(X^i(\Omega)\right), Y^i\right) \quad (2)$$

where L_2 is an Euclidean distance, shown in the Eq. 3.

$$L_2 = \frac{1}{n}\sum_{k=1}^{n}\left\|F(X_k, \Omega) - Y_k\right\|_2 . \quad (3)$$

In addition to this, we propose to use a new Distribution Attention Module (DAM) when we inject new modulated signal, see Fig. 7. It allows better color recovery and better false color reconstruction, a weak point of RGBW sensor.

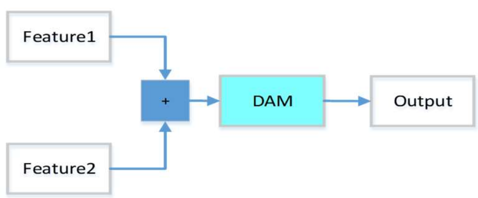


Fig 7. Block diagram of the Distributed Attention Module (DAM)

Detailed DAM block diagram is depicted in the Fig. 8. As you can see,

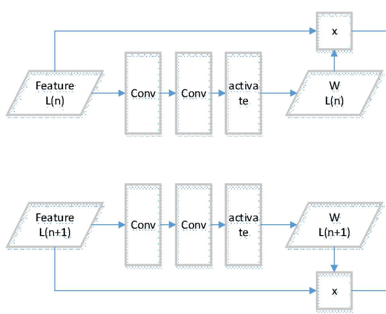


Fig 8. Detailed block diagram of the DAM block.

Final dePhaseNet detailed block diagram is depicted in Fig. 9. It shows that we have different number of channels at each level and 3 outputs that allows us to calculate multi-level loss using Eq. (1).

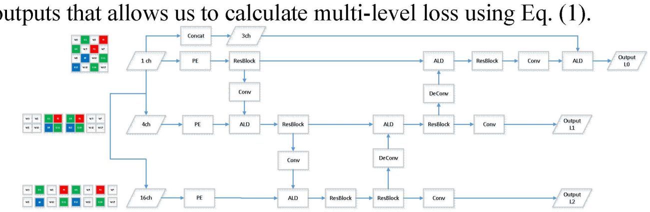


Fig 9. Block diagram of the dePhaseNet (detailed).

Experimental results

We conduct experiments by preparing pairs of distorted inputs and ground truth images. The network was trained on MIT dataset [9] on patches of size 128x128. We augmented input data with random flip and rotation.

We trained our model with ADAM optimizer [15] with the following settings: $\beta_1 = 0.9$, $\beta_2 = 0.999$, $\varepsilon = 10^{-8}$, weight decay = 10^{-8}. We set initial learning rate as 10^{-4} and schedule learning rate decrease at milestones [5, 10, 20], with decay = 0.1. The model was implemented using Pytorch and trained on NVIDIA Volta GPUs.

We tested our algorithm on Kodak dataset [16] and used Color PSNR (CPSNR), defined in Eq. 4, as an objective image quality metric.

$$CPSNR = \frac{1}{3}\sum_{i=1}^{3} PSNR(C_i), where \quad (4)$$

$$PSNR(C_i) = 10log_{10}\frac{2^{2b}}{\sum_{i=1}^{n}\|X_i - Y_i\|_2} \quad (5)$$

where C – color components, b – image bitwidth, n - number of pixels, X – ground truth image, Y – reconstructed image.

Objective image quality evaluation results are provided in the Table 1. For reference, we used state-of-the-art RGBW demosaicing algorithm in [21] and [22]. We can see that our algorithm outperforms state-of-the-art algorithms by a large margin – over 6dB in CPSNR.

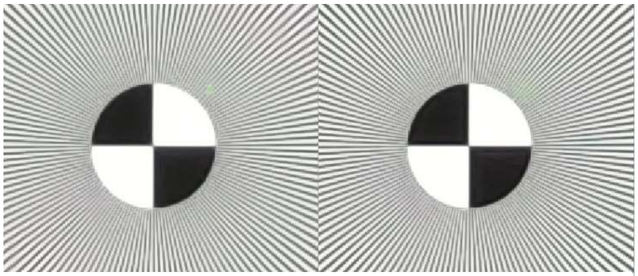
Table 1. Objective image quality evaluation results, CPSNR [dB]

Metric	Reference 1 [21]	Reference 2 [22]	Proposed method
CPSNR on Kodak dataset [dB]	34.4dB	36.4dB	42.7dB

Subjective image quality evaluation shows that proposed method can significantly reduce color artifacts and improve color resolution. For instance, Fig. 10 and 11 show examples of the reduced False Colors in real RGBW sensor images in challenging Fuziki and Resolution chart images.

a) Conventional method *b) Proposed method*

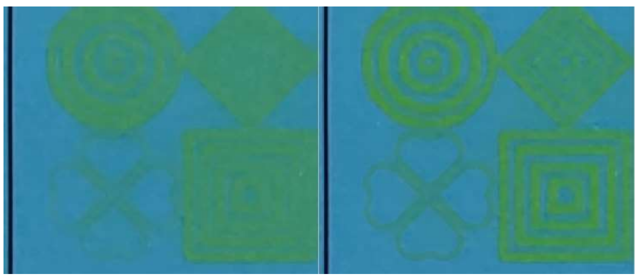
Fig 10. Subjective image quality evaluation results: illustration of False Colors reduction



a) Conventional method *b) Proposed method*

Fig 13. Illustration of False Colors reduction

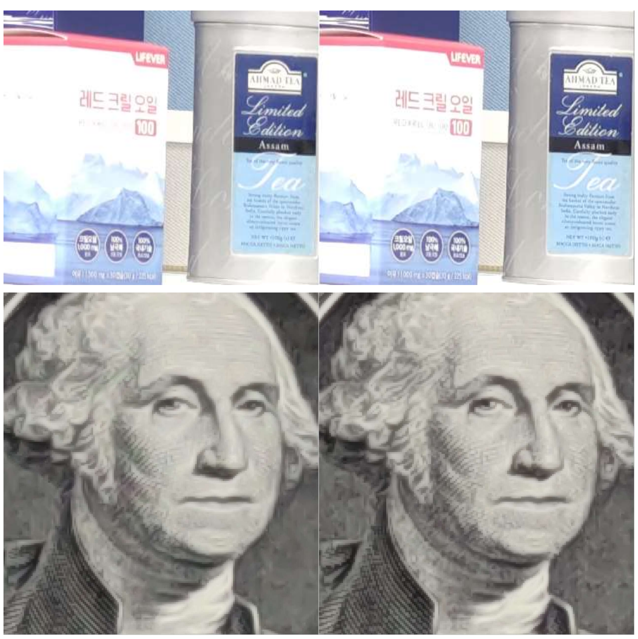
Subjective evaluation of experimental results also show that we can reconstruct RGBW image with more details and less artifacts as compared to conventional approach. As illustrated in the Fig. 11, color resolution is improved significantly with the proposed method.



a) Conventional method *b) Proposed method*

Fig 11. Illustration of color resolution improvement

We also observed improvement in detail preservation using proposed approach as shown in the Fig. 13.



a) Conventional method *b) Proposed method*

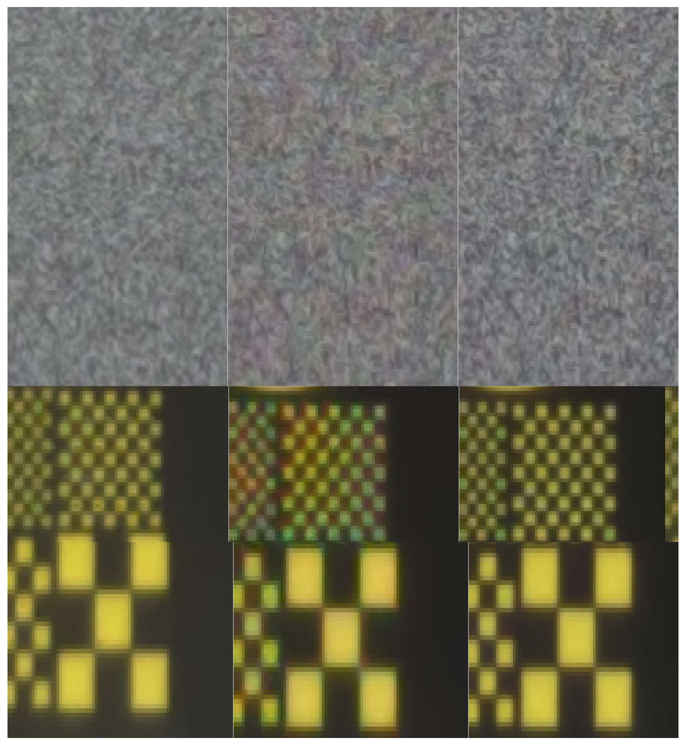
Fig 12. Subjective image quality evaluation results: illustration of better detail and texture preservation

Furthermore, we measured objective image quality of RGBW, Bayer and Quad Bayer demosaicing in the Table 2. Results show that reconstruction of RGBW-Kodak using proposed method can outperform Quad Bayer demosaicing and achieve similar results to Bayer CFA demosaic which was our target.

Table 2. Image quality comparison results, CPSNR [dB].

Metric	Bayer	Quad Bayer	RGBW-Kodak
CPSNR on Kodak dataset [dB]	42.62dB	40.6dB	42.68dB

Subjective image quality evaluation on real captured images demonstrates that RGBW can outperform even Bayer CFA image quality in terms of detail and texture preservation and reduce False colors significantly.



a) Bayer *b) RGBW conventional* *c) RGBW proposed*

Fig 14. Subjective image quality evaluation: illustration of better image quality vs Bayer CFA demosaicing

Conclusion

In this work, we proposed an efficient end-to-end demosaicing solution for RGBW-Kodak sensor (CFA2.0) for mobile phones at full resolution. Experiments show that it achieves superior image quality, outperforming state-of-the-art deep learning solutions and conventional solution for RGBW-Kodak image sensor both in terms of objective and subjective image quality greatly reducing artifacts. Proposed solution can be adopted to any RGBW image sensor remosaicing IP or RGBW ISP, e. g. for RGBW-Canon.

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