# Joint Demosaicing and Chromatic Aberration Correction of Images Using Neural Networks


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Typical colour digital cameras have a single sensor with a colour filter array (CFA), each pixel capturing a single channel (red, green or blue). A full RGB colour output image is generated by demosaicing (DM), i.e. interpolating to infer the two unobserved channels for each pixel. The DM approach used can have a significant effect on the quality of the output image, particularly in the presence of common imaging artifacts such as chromatic aberration (CA). Small differences in the focal length for each channel (lateral CA) and the inability of the lens to bring all three channels simultaneously into focus (longitudinal CA) can cause objectionable colour fringing artifacts in edge regions [3]. These artifacts can be particularly severe when using low-cost lenses.

Simple bilinear interpolation DM, while computationally efficient, tends to produce colour artifacts around edges. Edge-directed interpolation approaches, e.g. [2] are able to mitigate such artifacts to some extent while using learned demosaicing filters, e.g. using convolutional neural networks [4] can reduce artifacts further while preserving image detail. However, because these rely on the co-location of edges across colour channels, performance can degrade in the presence of strong CA. Given estimates of the CA parameters, lateral CA can be corrected by warping and red and blue channels (with the more densely sampled green channel unaltered), while per channel sharpening can be used to mitigate longitudinal CA. Performing CA correction after DM is suboptimal since artifacts from the demosaicing tend to be carried through to the final image. We propose to use a simple neural network to learn to jointly perform DM and CA correction, producing high quality colour images subject to severe CA as well as image noise.

Our approach is based on the demosaicing convolutional neural network (DMCNN) of [4], in which $33 \times 33$ patches of a CFA mosaiced input image are passed through a network with three convolutional layers to reconstruct RGB colour patches (Fig. 1). To account for the variation in lateral CA over the image, we train six such networks, each specialized to one 'effective CFA', where the effective CFA represents grid of colour channels active after displacing (to the nearest pixel) the red and blue channels of the CFA pattern so as to reverse the local displacement caused by lateral CA. After symmetries, there are six such effective CFAs (see Fig. 1).

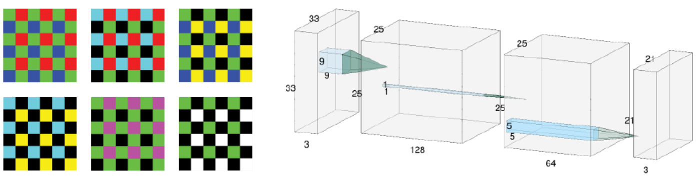
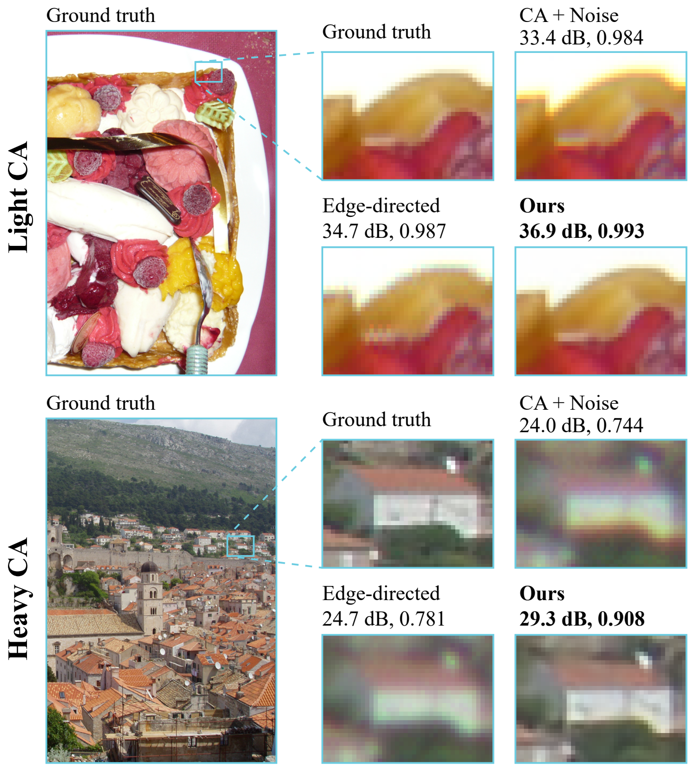


Figure 1: Left: The set of effective CFA patterns produced by pixel displacements of the red and blue channels. Right: DMCNN network architecture.

We generate pristine images (without JPEG compression artifacts and CA) by down-sampling consumer digital camera images by a factor of 2 using bicubic interpolation. We then model the corresponding captured mosaiced image for a given camera/lens (for which the CA and noise parameters have been estimated), applying scaling ($s_r$ and $s_b$, w.r.t. the centres) and Gaussian blurs ($\sigma_r$, $\sigma_g$, $\sigma_b$) to the respective channels. Zero-mean Gaussian noise ($\sigma_n$) is added to simulate sensor noise, and finally the standard Bayer pattern sampling mask is applied. The red and blue channels at each patch are displaced (to the nearest pixel) according to the known CA flow before the patch is fed to the corresponding network. We train the networks on 1 million image patches extracted from the first 1000 photos in the 'Holidays' dataset [1], augmenting by mirroring, rotating and colour balance shifting source patches. The network learns to perform DM while de-noising and mitigating the blur caused by longitudinal CA.

Fig. 2 shows results over the 490 test images, with two levels of CA and noise. The baseline approach is edge-directed linear interpolation [2] (Matlab's *demosaic* function) followed by CA correction. The neural network-based joint DM and CA correction produces a significant improvement in image quality metrics (PSNR and SSIM) compared the baseline approach. Qualitatively, there is a significant reduction in objectionable false colour and 'comb' artifacts around edges, while sharpness and noise levels are improved compared to the baseline approach. The proposed joint DM and CA correction approach could be applied in the production of high quality images and video from machine vision cameras with low cost lenses, thus extending the viability of such hardware to visual media production.




| | Mean (std) PSNR (dB) | | | Mean (std) SSIM | | |
|---|---|---|---|---|---|---|
| | CA+Noise | Edge-Dir | Ours | CA+Noise | Edge-Dir | Ours |
| Light CA | 31.5 (4.3) | 32.9 (4.2) | **35.8 (3.4)** | 0.9364 (0.045) | 0.9507 (0.034) | **0.9746 (0.015)** |
| Heavy CA | 27.4 (3.3) | 28.4 (3.4) | **32.5 (2.9)** | 0.8383 (0.085) | 0.8655 (0.076) | **0.9389 (0.031)** |

Figure 2: DM results on test images from the 'Holidays' dataset. 'CA + Noise' represents the input prior to Bayer mosaicing. PSNR and SSIM values are for the full images. Parameters: Light CA: $\sigma_{r,g,b} = (0.25, 0.125, 0.25)$, $s_{r,b} = (1.001, 0.999)$ and $\sigma_n = 0.001$, Heavy CA: $\sigma_{r,g,b} = (2.0, 1.0, 2.0)$, $s_{r,b} = (1.002, 0.9985)$ and $\sigma_n = 0.01$.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