https://doi.org/10.2352/issn.2694-118X.2020.LIM-17

A practical approach on non-regular sampling and universal demosaicing of raw image sensor data

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Abstract

Non-regular sampling is a well-known method to avoid aliasing in digital images. However, the vast majority of single sensor cameras use regular organized color filter arrays (CFAs), that require an optical-lowpass filter (OLPF) and sophisticated demosaicing algorithms to suppress sampling errors. In this paper a variety of non-regular sampling patterns are evaluated, and a new universal demosaicing algorithm based on the frequency selective reconstruction is presented. By simulating such sensors it is shown that images acquired with non-regular CFAs and no OLPF can lead to a similar image quality compared to their filtered and regular sampled counterparts.
The MATLAB source code and results are available at: http://github.com/PhilippBackes/dFSR

Introduction

To be able to capture coloured images, digital single sensor cameras mostly rely on an array of colour filters (CFA) in front of the panchromatic sensor elements. The most common is the Bayer CFA, a regular matrix with two green and one red and blue filter each (Figure 1(i)). Colour is represented by at least three values, therefore the missing values must be interpolated in the subsequent image processing steps. This process is called demosaicing and has been subject to extensive research [1].
Image capture by means of a regular pattern is prone to aliasing. Due to subsampling by the CFA the highest reproducible frequency is even lower and consequently the question about effective resolution of these sensor types arises. Camera manufacturers rely on limiting the incoming signal by an optical lowpass filter (OLPF) and highly optimized demosaicing algorithms to avoid aliasing. However, it is known that non-regular sampling is an effective method to prevent visually disturbing impairments due to aliasing. The compromised areas appear as less annoying high frequency noise rather than apparent moiré artefacts [2]. Although there is research on alternative CFAs and universal demosaicing for arbitrary CFAs, most commercial effort is concentrated on improving demosaicing algorithms for Bayer CFAs.
This paper is divided into three topics. At first a simulation for evaluating arbitrary sampling structures is presented. The second part provides a small insight into the design aspects of non-regular CFAs. Finally a new universal demosaicing method is presented.

Related Work

Most of the existing work on the design of CFAs and demosaicing use image databases such as the Kodak PhotoCD [3], the IMAX Collection (also known as McMaster Dataset) [4] or the TECNICK image set [5], which either consist of scanned film or multi-exposure images. Even though there have been concerns about the applicability of those image sets regarding contrast and saturation [6], only a few questioned whether these sets can be taken into serious account at all. For example, demosaicing is usually applied to linear encoded and raw sensor data of high tonal resolution, yet all of the databases above provide display encoded, somehow colour-processed and, in case of Kodak and IMAX, 8-bit quantized images. The ARRI-ImageSet [7] introduced a new set consisting of twelve high-quality raw 16-bit sensor data sequences. With one exception this dataset consists of regular Bayer CFA sampled images and thus cannot be directly used in testing different CFAs. In order to test arbitrary sampling structures with raw sensor data a new approach is needed.

CFA Design and Universal Demosaicing

Since Bryce E. Bayer presented the Bayer colour sampling matrix in 1976 [8], there has been a lot of effort in researching alternative layouts and filter colours [9]. The challenge in designing a new CFA is that every improvement in one quality aspect entails a downside in others. In terms of CFA layout e.g., a balance must be found between efficient image reconstruction, immunity to aliasing, optical or electrical crosstalk, and sensor imperfections. While e.g. a cost-effective demosaicing process can be more easily implemented for periodic CFAs, regular sampling is vulnerable to aliasing and colour moiré [10].
Hence, a significant number of random or pseudo-random sampling structures and universal demosaicing algorithms for arbitrary CFAs has been presented and shown worthwhile results [11]. The main challenge in designing non-regular sampling structures is to create a random yet uniform pattern. Random to avoid aliasing and uniform to yield a good location-invariant reconstruction [12].

Frequency Selective Reconstruction

Originally presented to conceal local connected losses of image information, e.g. due to transmission errors, the Frequency Selective Reconstruction (FSR) has proven useful

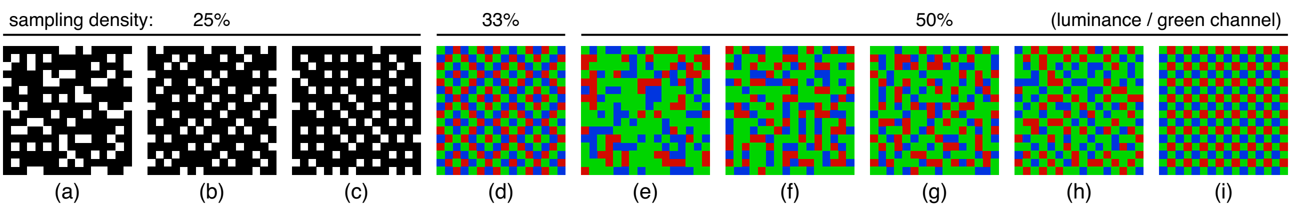

Figure 1. *sampling patterns: (a) randomQuarter, (b) randomICIP, (c) gauss25, (d) condat, (e) random, (f) randomQrgb, (g) randomICIPrgb, (h) gauss50, (i) Bayer grbg*

in reconstructing non-regular sampled images as well [13, 14]. The basic idea behind the FSR is to iteratively generate a model

$$g[m,n] = \sum_{(k,l)\in K} \hat{c}_{k,l}\,\varphi_{k,l}[m,n] \tag{1}$$

of the unknown signal (size $M \times N$) by superimposing weighted basis functions on the known samples. With $\varphi_{k,l}[m,n]$ being two-dimensional Fourier basis functions and $\hat{c}_{k,l}$ the expansion coefficients to be determined. The set K holds all chosen basis functions. In every iteration the weighted residual energy is calculated, a suitable basis function to maximally decrease the residual is selected, and the coefficient is updated. The characteristic of the local weighting is determined by the decay factor $\hat{\rho}$, the coefficient update is controlled by the orthogonality deficiency factor γ, and the selection of the basis functions is influenced by a frequency weighting in favour of lower frequencies. The parameters and their impact are explained in detail in [13, 14].
The FSR usually reconstructs an image block-wise, whereas a difference is made between the area to reconstruct (reconstruction size) and the area around used to generate the signal model (block size). Lastly the size of the FFT employed and thereby number of basis functions, is of importance.

Methods

Sensor Simulation

To simulate different types of CFAs and evaluate demosaicing algorithms a reference image with true, full RGB colour samples at every pixel is usually masked by the CFA in question, reconstructed and compared to the reference. Because of the concerns about existing image sets and their image acquisition, a method is proposed to simulate an ideal single sensor capturing full RGB samples at every pixel. Therefore the raw sensor data of a high resolution camera is resampled to a smaller grid of pixels with full RGB values. In short: the loss of spatial resolution is used to gain colour depth. To reduce complexity, sensor characteristics such as fill factor and micro-lenses are left aside in this basic version of the sensor simulation. Mimicking an OLPF and generating different CFAs is considered more important. A simple Gaussian-blur filter is used to limit the spatial frequencies of the input image, even though real OLPFs are more complex. In order to further improve the simulation the input image is demosaiced before resampling.

Verification

To validate this approach an experiment was set up, wherein a low resolution camera (Canon D30, 3.2 MP) with and without OLPF was mounted on a tripod, and several reference images were shot. Subsequently the reference camera was replaced with a high resolution camera (Canon 77D, 24MP) of same sensor size and optic. The high resolution images were then processed as described above, and the reference images were simulated. The input for the OLPF-simulated images were filtered by a Gaussian-blur with a standard-deviation of 1.6. The resulting raw images of both cameras were then demosaiced using the same debayering algorithm and compared.

Evaluation of CFAs and Demosaicing

The image set to evaluate the different sampling structures and demosaicing algorithms presented in this paper consists of 15 images. The first eleven images are from the ARRI-ImageSet but resampled with the sensor simulation by 2/3 to 1920x1080 px. The 12th image is an unaltered full RGB image from the 12th sequence of the ARRI-ImageSet. The last three images were made during the sensor simulation experiments with a Canon 77D, and, like the first eleven images, resampled with the sensor simulation by 2/3. The image set is created with (Gaussian-blur, std. = 1) and without OLPF.

Different Sampling Structures

Overall, nine sampling structures with different characteristics and sampling densities were implemented and tested. To reduce complexity and focus on the different spatial layouts, only CFAs consisting of red, green, and blue filters were used.
The first structure is built by sampling from a uniform discrete pseudorandom distribution without any constraints other than the ratio of 50% green and 25% red and blue pixels each. This pattern will be referred to as *random*. In [15] a non-regular sampling approach is described randomly masking 3/4 of every 2x2 pixel area. This approach yields only a pattern for one colour channel or luminance. As a result it is extended and every 2x2 pixel area is filled randomly with two green and one red and blue filter each. They will be referred to as *randomQuarter* and *randomQrgb*. An improvement of randomQuarter is presented in [16]. An iterative process reduces predefined structures such as large voids or areas with regular sampling. In order to build RGB patterns the algorithm is extended by assigning the optimized structure to the green channel, whereas the other three quarters are randomly filled with one red, green and blue pixel each (*randomICIP* and *randomICIPrgb*). In [12] successively new pixels are added to a sampling mask. Each location is determined by a constantly updated non-uniform discrete probability distribution. This way a non-regular pattern is created without large voids or sampling clusters. This strategy is again enhanced to generate RGB patterns by firstly adding green pixels as described and then alternating red and blue sampling points (*gauss25* and *gauss50*). Lastly a pattern presented by L. Condat in [9] is implemented. Condat suggests that CFAs with blue noise chromatic spectra are ideal to avoid aliasing. The main objective is to avoid same colour pixel neighbours, which in this case is achieved by systematically tiling three-pixel blocks of various RGB combinations together. The sampling pattern used can be seen in Figure 1.

Demosaicing with FSR - dFSR

The FSR has not been primarily used to demosaic images and nore has been tested on linear encoded image data. Therefore a few changes have been made in terms of parameters and the overall procedure the FSR is embedded in. The parameters used were determined in pre-experiment testing and can be seen in Table 1.

Table 1. FSR parameters

Reconstruction Size	2 x 2
Block Size	8 x 8
FFT Size	32 x 32
iMin, iMax	32, 512
decay factor $\hat{\rho}$	0.5
orthogonality deficiency compensation γ	0.25

They differ from the commonly used settings [13, 14] by a smaller reconstruction and block size but less sharp decay factor, which were found to result in more noisy but visually more pleasing images – especially in small areas with high frequencies.
Another difference is that only the original sampling values are taken into account. The dFSR computes the image block-wise and in scan-line order.
The dFSR is implemented in three different versions. The obvi-

ous option is to just apply the reconstruction on each channel seperately (independent - dFSR). However many demosaicing strategies exploit the feature of natural images to show a certain amount of correlation between colour channels [1]. As a result a constant difference demosaicing version has been implemented. This first reconstructs the green channel and interpolates the calculated colour difference R-G and B-G afterwards (diff - dFSR). The last solution presented is based on the assumption that colour hue of natural images changes very slowly and therefore can be interpolated much more smoothly (diffLowC - dFSR). Again, the green channel is reconstructed by the parameters specified in Table 1, but the colour difference interpolation is done with modified FSR parameters. The reconstruction and block size are enlarged to 4x4 px and 28x28 px, the decay factor is slightly higher with 0.6, and the frequency weights for selecting the basis function are altered even more in favour of lower frequencies.

Demosaicing Domain

The dFSR has been tested working with three different types of encoded data. First with linear encoded images. Secondly with pseudo-logarithmic encoded data. In the case when images by ARRI are used, ARRI-LogC as described in [7] is used, whereas the images originating from the Canon 77D are transformed by the logarithmic-like function

$$I_{log} = \begin{cases} 99.0256 \times I_{lin}, & I_{lin} < 0.0039 \\ \frac{log2((65535 \times I_{lin}+4))-3}{13}, & I_{lin} >= 0.0039 \end{cases} \quad (2)$$

Lastly, the dFSR is tested with display referred gamma-corrected images, specified in ITU-R BT. 709-4 [18].

Results

The sensor simulation and dFSR is implemented in MATLAB (2019b). Specifically, four metrics are used to measure the reconstruction or demosaicing performance, the Peak-Signal-to-Noise ratio PSNR, a value based on the mean squared error, and the structural similarity measure SSIM [19] as a more perceptual based quality index. Additionally the images are assessed with FSIMc [20], a metric based on features such as the phase congruency and gradient magnitude, and the HDR-VDP-2.2 [21], a visual difference predictor. In terms of evaluating the different domains, all images are evaluated in display-referred ITU-R. BT. 709 domain. As colour encoding parameter for the HDR-VDP 2.2 'sRGB-display' respectively 'luma-display' is used.

Sensor Simulation

As can be seen in Figure 3, the simulation generates a realistic and similar image of the lower resolution camera. Even

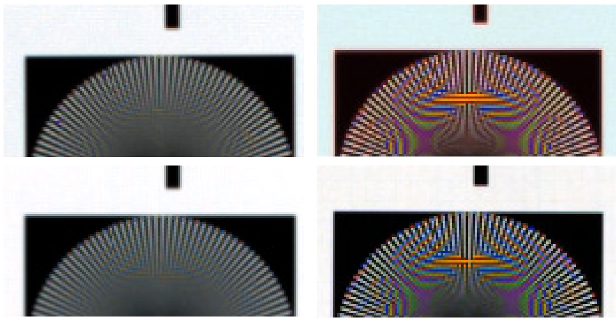

Figure 3. *Sensor simulation results: reference image on top, simulation below. With OLPF on the left, without on the right.*

though the OLPF simulation may not be as realistic, the resulting images look very similar. Yet the comparison of the simulated and reference images without OLPF is of bigger interest. They both show almost exactly the same aliasing artefacts at the same locations with the same colouring. The red tint in the reference image without OLPF is due to the missing infrared-blocking filter which was removed with the OLPF.

Pattern and dFSR Domain

First, only the green channel or different luminance pattern and the various encoding domains are tested (Figure 2). As expected, the sampling density is a key influence for the reconstruction quality [14]. The improvement in all metrics between more random patterns (*random*, *randomQuarter*) and more structured patterns (*randomICIP*, *gauss*) can be noticed. The Bayer CFA seems to be superior by a noticeable margin in all metrics, yet the visual impression is different. Particularly in image areas compromised by aliasing, the non-regular sampling patterns lead to far less visible impairments. This is even true for small areas where a non-regular sampling mask shows regular structures.

The second conclusion drawn from Figure 2 concerns the encoding of the image data. The difference between linear encoded and more perceptual encoded data is sizeable with respect to all metrics. This is due to an effect widely known to occur while working with linear image data. The FSR overestimates the values on either side of small highlights and sharp edges. As the image processing proceeds this results in holes without information because values below zero and above the maximum are clipped. Whether logarithmic or gamma encoded data is more suitable however, cannot be conclusively determined. It seems that a logarithmic domain leads to better results with the PSNR metric in particular and low sampling densities overall.

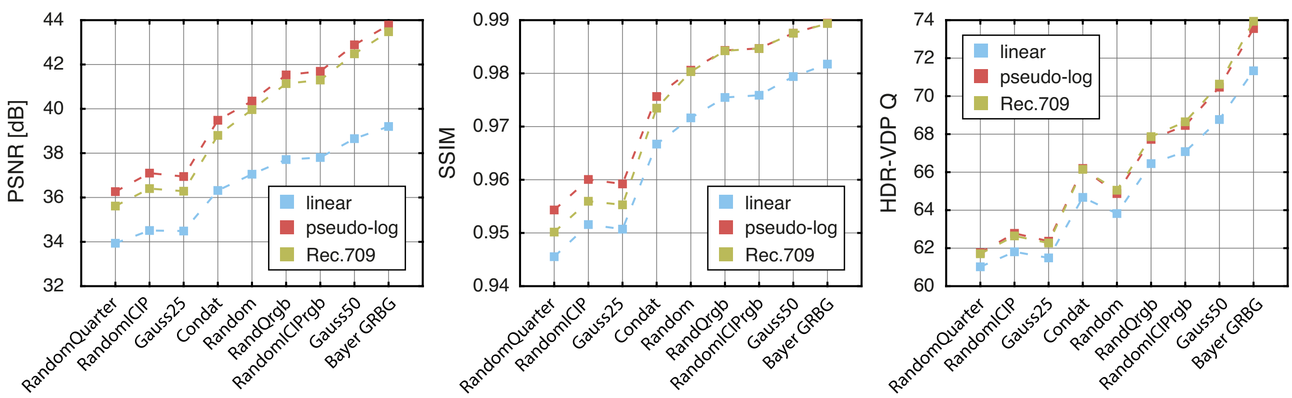

Figure 2. *Reconstruction quality of green/luminance channel FSR for different patterns and different domains*

Considering the demosaicing process overall (Table 2), it seems as if the display-referred encoding is superior. Interestingly, the Condat CFA with an even split sampling density between all channels performs better in PSNR and SSIM but the HDR-VDP and FSIMc is closest to the visual impression, the Condat sampled images being less sharp and showing more chromatic noise.

Table 2. Demosaicing performance (diff-dFSR)

Domain	CFA	PSNR	SSIM	FSIMc	hdrvdp Q
Logarithmic	Condat	37.77	0.983	0.986	68.57
	Gauss50	37.67	0.981	0.987	70.35
Rec. 709	Condat	**38.43**	**0.985**	0.986	68.85
	Gauss50	38.35	0.984	**0.987**	**70.40**

dFSR-Versions

The different versions of processing the colour channels are shown in Table 3. A clear advantage of using inter-channel correlation can be observed, thus both difference-based variants are clearly an improvement to the independent dFSR. The margin between the two difference-based methods is relatively small, but considering that the dFSR parameters used to reconstruct the colour-difference channel are not yet finally optimized, there may be room for future improvement.

Table 3. Demosaicing performance dFSR versions (CFA: gauss50, encoding domain: Rec. 709) and Bayer-Demosaicing algorithms

Algorithm	PSNR	SSIM	FSIMc	HDR-VDP Q
independent	34.91	0.964	0.981	69.06
diff	38.35	0.983	0.987	70.41
diffLowC	**38.61**	**0.984**	**0.987**	**70.49**
HQLin	34.87	0.973	0.982	72.28
AHD	37.48	0.982	0.989	72.95
ARI	**39.71**	**0.987**	**0.991**	**74.42**
HQLin OLPF	35.47	0.974	0.982	70.02
AHD OLPF	35.79	0.975	0.980	68.39
ARI OLPF	36.01	0.975	0.979	68.81

dFSR vs. Bayer-Demosaicing

The newly proposed demosaicing method and the best performing non-regular CFA are compared with the current status of Bayer CFA and specialized demosaicing algorithms. Three different algorithms are tested: a high quality linear demosaicer (MATLAB built-in function), the adaptive homogeneity directed demosaicing (AHD) [22], and a state of the art demosaicing algorithm referred to as adaptive residual interpolation (ARI) [23]. Even if non-regular sampling and dFSR do not show the best measured results, it has to be emphasized that this combination performed better than any OLPF simulated images and superior in PSNR and SSIM to two of three tested regular demosaicing methods (Table 3). However the visual difference in sharpness is clearly visible. The regular sampled and demosaiced images appear clean with overly sharpened edges, whereas the non-regular sampled seem to be smoother and more noisy. However, the image areas with possible aliasing are masked and visually less disturbing than the aliasing artefacts shown by *all* regular sampled images.

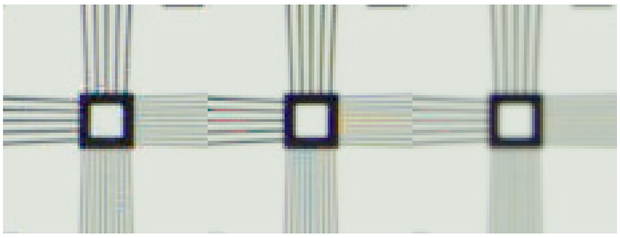

Figure 4. *Left to right: dFSR, ARI, ARI with OLPF*

To support the calculated image quality metrics, a simple user study was conducted. The participants could toggle between two versions of an image and were asked to select the qualitatively better one. A third option was given in case they were unable to detect any visual difference. Four different versions of the 15 images were compared: the reference image without sampling and demosaicing simulation, a version of regular sampling with and without OLPF and ARI demosaicing and the non-regular sampled and dFSR demosaiced image. Overall 28 participants evaluated 1140 image pairs. The images and versions were displayed in random order on a Dolby PRM-4200 monitor [24].
The result of the study is consistent with the image quality metrics. Most participants chose the reference or the version without OLPF. This suggests that in direct comparison the perceived sharpness is a key feature. In case of non-regular vs. regular sampled images the result is much more evenly split with a slight advantage towards the regular-sampled version.

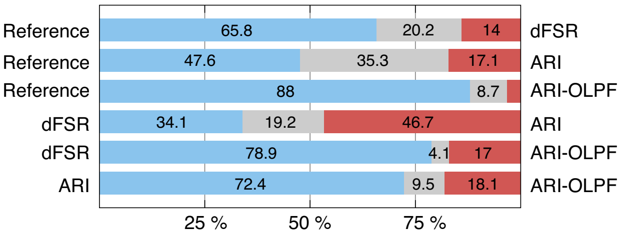

Figure 5. *Study results in percent (blue = preference for left algorithm, red = pref. for right algorithm, grey = no visible difference)*

Conclusion and Prospect

Non-regular sampling is an effective strategy to avoid aliasing in digital image capture without physically limiting the incoming signal. To simulate different sampling structures and CFAs, a sensor simulation has been presented and verified. In terms of CFA design, the balance between different sampling characteristics from random to uniform, their advantages and drawbacks is shown. Lastly a new universal demosaicking algorithm based on the FSR is presented. It is found that the FSR performs better on non-linear encoded image data.
In future, every aspect presented in this paper can and should be subject to further research and improvement. Especially the dFSR can be optimized in terms of parameters and overall processing. The combination of FSR and other interpolation techniques is thinkable as well as an enhancement of the dFSR by additional post-processing steps. Further it is desirable to investigate the impact of different image encoding domains for the dFSR and how to better exploit the correlation between the RGB colour channels.

Acknowledgments

Thanks are due to Michael Felten as advisor and Ingmar Rieger for providing the AHD as MATLAB code. Additional thanks to the Chair of Multimedia Communication and Signal Processing at the Friedrich-Alexander University Nürnberg, Germany for providing us with the FSR as Matlab code and fruitful discussions.

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