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Using the dead leaves pattern for more than spatial frequency response measurements

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Abstract

The dead leaves pattern is very useful to obtain an SFR from a stochastic pattern and can be used to measure texture loss due to noise reduction or compression in images and video streams. In this paper, we present results from experiments that use the pattern and different analysis approaches to measure the dynamic range of a camera system as well as to describe the dependency of the SFR on object contrast and light intensity. The results can be used to improve the understanding of the performance of modern camera systems. These systems work adaptively and are scene aware but are not well described by standard image quality metrics.

Introduction

The DeadLeaves pattern itself was presented[5] in 2001 and was not used in the context of camera evaluation at that moment. The idea to use this pattern for this purpose was introduced much later. In following publications the use of the dead leaves pattern for evaluation of noise was presented [6]. In this paper different methods to analyse the dead leaves pattern are used to describe the dynamic range of an imaging system.

Three methods give a spatial frequency response (SFR) as a function of spatial frequencies and metrics are derived from these. Additionally also the histogram and color content is analysed.

DeadLeaves_core

The results of the first experiments for using the Dead Leaves pattern for texture loss analysis were presented by Cao et. al.[3]. The fundamental idea is to take advantage of a very nice feature of the dead leaves pattern: With the know probability function of gray value, position and radius, also the power spectrum distribution can be predicted. As we can easily measure the power spectrum in the image, the SFR can be obtained just from these two informations (Equation 1).

$$SFR_{DeadLeaves}(f) = \sqrt{\frac{PS_{image}(f)}{PS_{target}(f)}} \tag{1}$$

DeadLeaves_direct

The first approach clearly misses an important point: Camera do not only remove (high) spatial frequencies as part of the spatial frequency transfer, they also add noise to the image. This noise will therefore also add high spatial frequencies which will interfere with the measurement. McElvain et. al.[4] presented an approach that targets this problem with an additional noise measurement. The calculation extended by an correction by the noise power spectrum obtained from a flat, uniform patch in the image (see Equation 2).

$$SFR_{DeadLeaves}(f) = \sqrt{\frac{PS_{image}(f) - PS_{noise}(f)}{PS_{target}(f)}} \tag{2}$$

The weak point here is the fundamental assumption that is made for this approach: The noise that is added to the dead leaves pattern (where we measure the PS_{image}) is equal to the noise that is added to the flat uniform gray patch (PS_{noise}). We know that many noise reduction algorithms work adaptively, so they behave differently depending on the image content.

DeadLeaves_cross

A new intrinsic approach was presented by Kirk et. al.[2]. The transfer function $H(f)$ is calculated using the cross power density $\phi_{YX}(f)$ and the auto power density $\phi_{XX}(f)$.

$$H(f) = \frac{\phi_{YX}(f)}{\phi_{XX}(f)} \tag{3}$$

The final reported SFR is the 1-D representation of the real part of H(f). To go from 2D to 1D, the average of all spectral coefficients of the same frequency modulus $\|f\|$ is calculated. To be able to calculate the cross power density, reference data of the dead leaves pattern has to be aligned and matches to the image data, so that we basically have a full reference measurement approach. While the first two approaches only provide the amplitude response, in this approach we also have the full transfer function including the phase shift. All image content that is not in-phase with the chart content will have only a minor influence on the SFR, so also noise has only a very limited influence on the results.

Used metrics

Different metrics are used in the results section.

MTF10 and MTF50

Two simple metrics are the MTF10 and the MTF50 value. Basically these are the spatial frequency that leads to a specific SFR. So the MTF10 value is the spatial frequency that leads to an SFR of 10% and the MTF50 value is the spatial frequency that leads to an SFR of 50%.

Artefacts

One of the main differences between the different methods to analyse the dead leaves pattern is the sensitivity to noise. As shown in previous publications [6] DeadLeaves_core is very sensitive to noise, while DeadLeaves_cross is not. We make use of this properties and calculate an artefacts value as the ratio of the acutance based on DeadLeaves_core by the acutance based on DeadLeaves_cross. The acutance is the integral of the SFR over a frequency range from 0 cy/px to 0.5 cy/px.

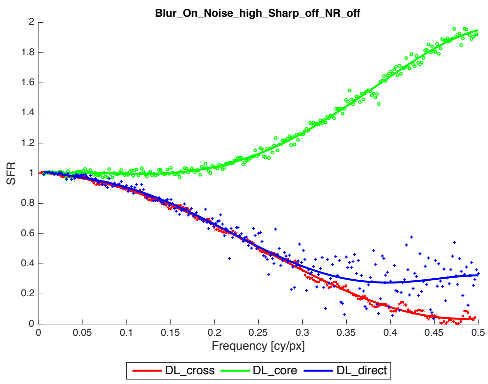

Figure 1. *Example of SFR based on three different methods. DeadLeaves_core is highly influenced by noise while DeadLeaves_cross is not. [6]*

Kurtosis

This value is not derived from the SFR, but from the histogram of the image itself.

To describe the shape of a distribution, the excess kurtosis is calculated. The value becomes 0 for a normal distribution and is increased for leptokurtic distributions. The kurtosis is calculated as the fourth moment devided by the square of the second moment of the distribution. The second moment is the variance. It has been used int he past as a metric to describe the influence of non-linear image processing like noise reduction[8].

$$kurtosis = \frac{m_4}{m_2^2} - 3 = \frac{m_4}{\sigma^4} - 3 = \left(\frac{1}{n} \sum_{i=1}^{n} \left(\frac{x_i - \mu}{\sigma} \right)^4 \right) - 3 \quad (4)$$

In this context, it is understood that the dead leaves pattern does not provide a normal distribution and that the exact distribution depends on the statistics of the specific dead leaves pattern. A generalisation still needs to be investigated. As an indicator, it showed good correlation with observations (see results for more details).

*CIE-C**

In this test setup, a coloured dead leaves target has been used[9]. A derived metric is the average CIE-C* value, so the mean CIE-C* value for the dead leaves pattern. The lower this value, the less saturated the image.

Dynamic Range Measurement

The dynamic range of a camera system defines the ratio of the brightest and the darkest area in a scene that can be captured. Equation 5 shows the definition as in ISO15739 [1]. A typical test system is shown in figure 2.

$$DynamicRange_{ISO} = \frac{L_{max}}{L_{min}} \quad (5)$$

The brightest part of a scene L_{max} is limited by saturation effects, so that a zone in the scene brighter than L_{max} will not lead to a higher digital value as the system has reached saturation. The darkest part of a scene L_{min} is, according to the definition, limited by noise. So if a signal to noise ratio (SNR) of 1 is reached, we have a loss of information and therefore L_{min} is the luminance that leads to SNR=1.

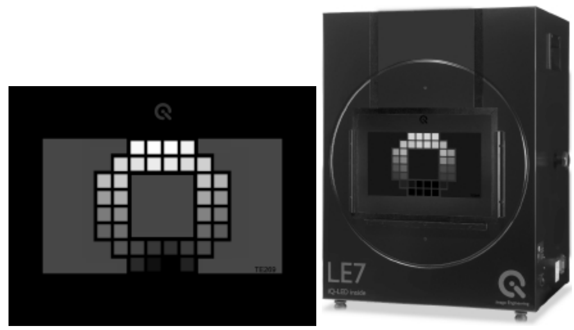

Figure 2. *Typical setup for chart based Dynamic Range measurement. Transparent test target with 36 patches and uniform back illumination.*

While this definition is well accepted, it is not without problems. One problem is shown in Figure 3. Due to sensor based multi-exposure for HDR imaging, the SNR curve shows significant "SNR drops" in the boundary regions between different exposures combined into an HDR image. So the assumption that every luminance between L_{min} and L_{max} is useful information is not always true.

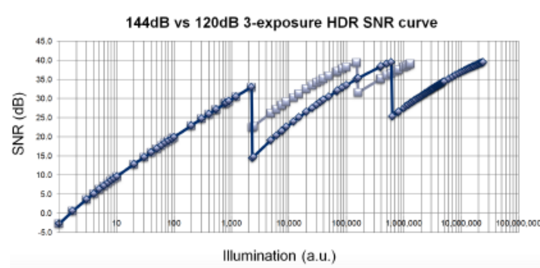

Figure 3. *Typical SNR drops for multi-exposure HDR technologies. Here: Comparison of 120bB vs. 144dB Dynamic Range configuration of same sensor.[7]*

Another key issue is non-linear image processing and image enhancement. As the dynamic range is purely based on noise, it means that a simple noise reduction algorithm can increase the measured dynamic range while it does not necessarily increase the information content of a scene.

One way this can be addressed is the use of contrast detection probability (CDP)[10]. This metric is currently under development within IEEE-P2020. Even though it does not directly address dynamic range, a CDP map as shown in figure 4 can be used to describe the combinations of contrast and luminance that lead to an acceptable CDP value. Therefore we can say that the CDP map can be used to define the dynamic range if we see dynamic range as the range of luminance that provides meaningful signal in the system under test.

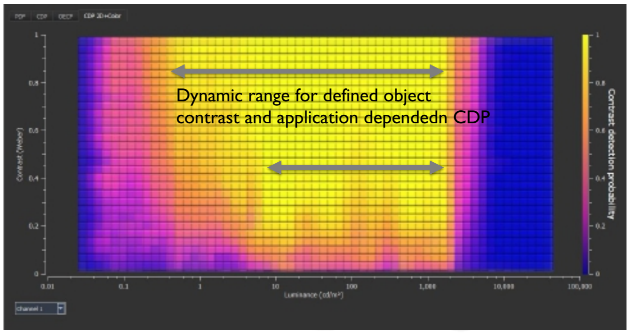

Figure 4. 2D- Contrast Detection Probability (CDP) map for an HDR sensor configuration. Luminance vs. Contrast with CDP color encoded. For the given use-case definition, the area with high CDP can be considered as useful and defines the dynamic range.

Measurement

We investigated two different approaches to measure the dynamic range of a camera system with the dead leaves pattern.

Exposure bracketing with fixed target

The first approach was to use a transparent dead leaves target, back illuminated with a light box. The camera reproduced this target as shown in figure 5 with varying exposure time. Each image was then analysed for different metrics.

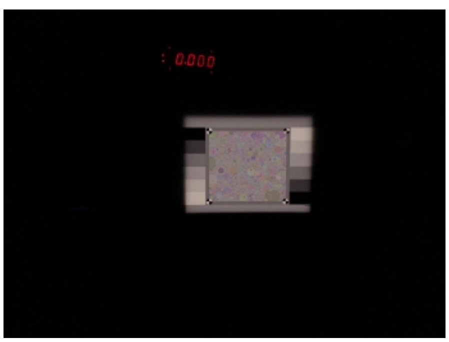

Figure 5. A back illuminated dead leaves target as used for exposure bracketing

With this setup a D-SLR camera and a mobile phone have been evaluated. The D-SLR camera (Canon 5DMkIII) captured JPEG and RAW images at the same time with a variation of the exposure time between 1s and 1/8000s. The mobile phone (Apple iPhone 11) was operated in a way that the exposure time could be manually selected and an HEIC image and DNG image where captured.[1]

Dynamic targets

For the dynamic target measurement, the test target for the camera under test consists of three dead leaves targets, each with dimmable back illumination. The setup (figure 6) was chosen that way, that a large dynamic range in the scene could be generated. Starting point was an equal illumination of all three targets. One light source was kept constant (upper left), another increase the illumination by 100% each step (lower left) and another decreased the illumination by 50%.

Figure 6. The used test setup for dynamic testing. Three light sources that back illuminate the dead leaves targets. Top: All light sources with similar illumination. Bottom: Setup with significant difference in illumination. Note the ghost in the upper right corner.

Results

Figure 7 shows MTF10 and MTF50 values for an exposure bracketing of direct JPEG images from a Canon 5DMkIII D-SLR camera. We can see that very bright and very dark images result also in a lower resolution value. We observe a plateau in which the values are quite stable.

Figure 8 shows the different metrics for images captured with an Apple iPhone 11 with DNGs captured. These DNGs have been converted to JPEG using dcraw[11] and then analysed. We can see that the MTF10 and MTF50 values are constant for a wide range and are only limited for very bright, overexposed images. The short exposure time images show very strong noise which can be observed in the artefacts value. The C* value increases with shorter exposure times. This can be explained with strong color noise, therefore the intention to describe the loss of color in the pattern can not be achieved by this metric.

Figure 9 shows a complete comparison of different metrics for an iPhone 11. The direct HEIC images from the phone have been analysed,. Based on the plots we can define a region of good image quality and one of acceptable image quality. So depending on the use case and user preference, a dynamic range can be defined.

[1] The 3rd party app "Camera+" was used, it has not been verified if the images are identical or different to the standard camera app. It was not the intention to make statements about the quality of device under test.

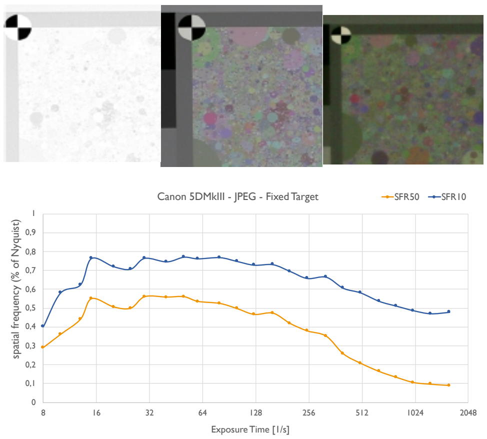

Figure 7. *Resolution metrics for an exposure bracketing with a Canon 5DMkIII D-SLR camera (JPEG). We see that the metrics decrease with significant under- and overexposure.*

Conclusion

The traditional dynamic range measurement is purely based on tonal curve and noise. In this paper we could show that also metrics derived from the dead leaves pattern can be used to describe dynamic range. It could be shown that a definition that is only based on an SFR is also not the solution. As shown, the dynbamicx range can be defined using different metrics that all cover different aspects of image quality and system performance. These include metrics derived from the measured SFR, but also new metrics like artefacts and kurtosis.

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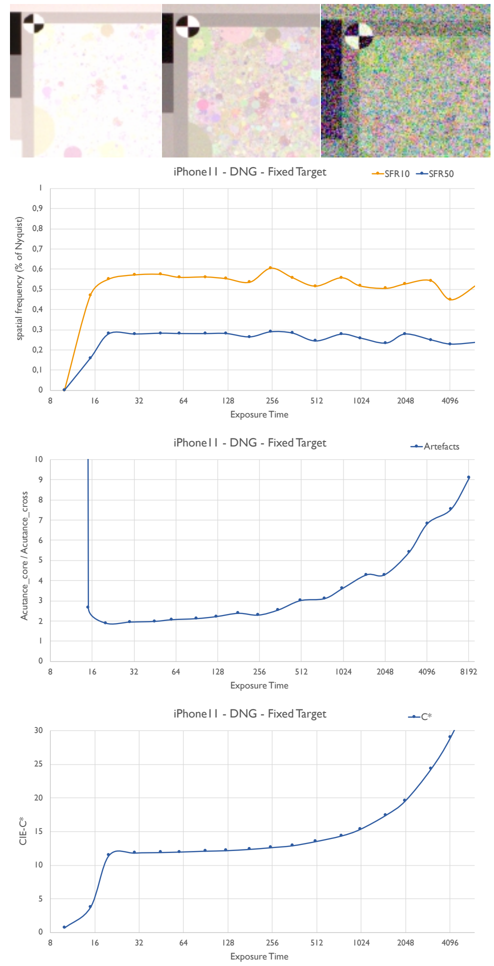

Figure 8. *Results for exposure bracketing with an iPhone 11 (DNG). The resolution metrics are not limited in the dark, but artefacts show the increase in noise. The ΔC value increases with lower light due to color noise.*

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Author Biography

Uwe Artmann studied Photo Technology at the University of Applied Sciences in Cologne following an apprenticeship as a photographer, and finished with the German 'Diploma Engineer'. He is now CTO at Image Engineering, an independent test lab for imaging devices and manufacturer of all kinds of test equipment for these devices. His special interest is the influence of noise reduction on image quality and MTF measurement in general.

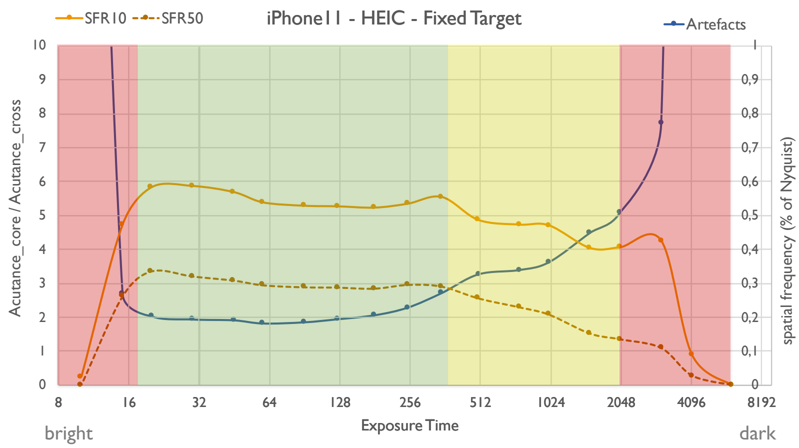

Figure 9. *Overview plot of different metrics for an iPhone11, direct HEIC images. SFR10, SFR50 and Artefacts values plotted over exposure time. The overlay can show useful data range and acceptable data range*

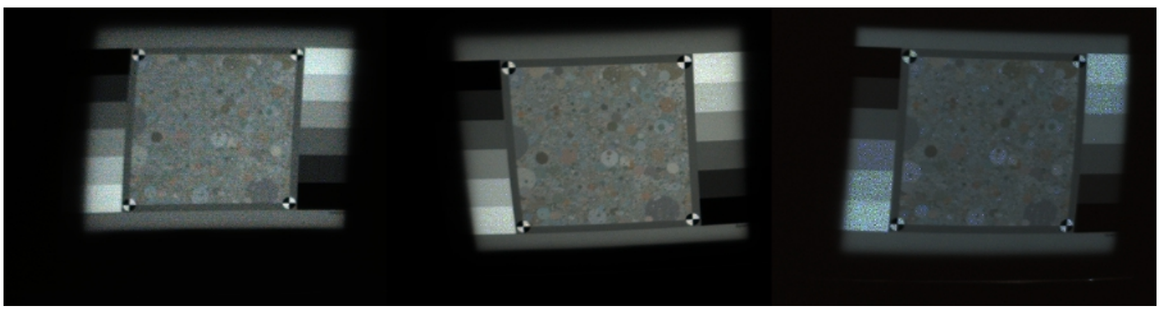

Figure 10. *Example for dynamic target test with an automotive sensor. The targets have been extracted from the image, scaled to 8bit (histogram based) and then mounted next to each other.*

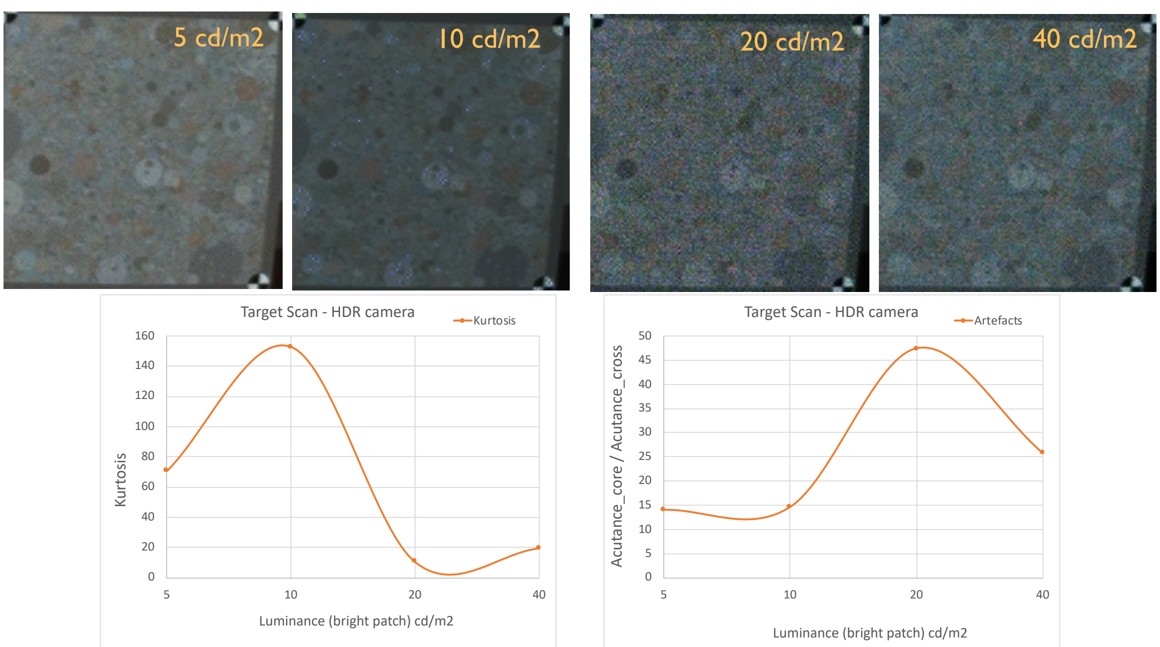

Figure 11. *The darkest dead leaves patch from a series of images. In yellow marked the luminance of the brightest patch. Below the corresponding artefacts and kurtosis values.*

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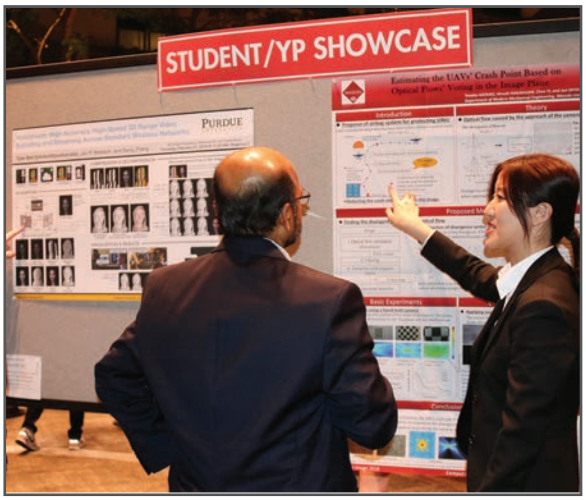

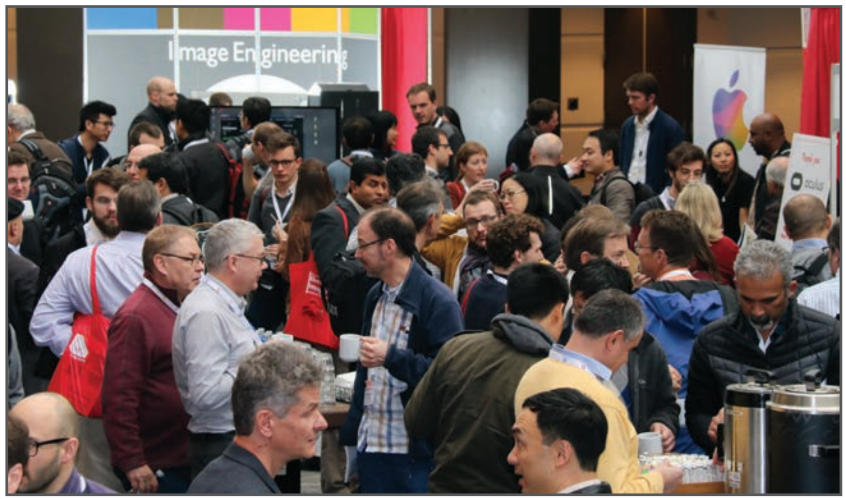

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