Measurement of Noise using the dead leaves pattern

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Abstract

When evaluating camera systems for their noise performance, uniform patches in the object space are used. This is required as the measurement is based on the assumption that any variation of the digital values can be considered as noise. In presence of adaptive noise removal, this method can lead to misleading results as it is relatively easy for algorithms to smooth uniform areas of an image. In this paper, we evaluate the possibilities to measure noise on the so called dead leaves pattern, a random pattern of circles with varying diameter and color. As we measure the noise on a non-uniform pattern, we have a better description of the true noise performance and a potentially better correlation to the user experience.

Introduction

Noise reduction is an image enhancement option all image signal processors used in todays cameras provide. This option will apply algorithms to the image rendering process that shall reduce the noise in the image while preserving texture. Texture loss is the loss of low contrast fine details in an image due to noise reduction and/or compression and is a very important part of camera benchmarking and testing. The so called DeadLeaves pattern has been used in the industry already for a while to describe texture loss.

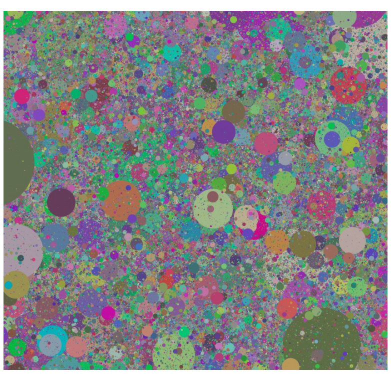

Figure 1. *The so called DeadLeaves pattern. A structure formed by circles stacked on top of each other with a know propability function of gray value, diameter and position. Here a colored version.*

The measurement of texture loss had a significant improvement by using the so called "DeadLeaves_cross" method introduced by Kirk et al[**?**] (the author of this paper was co-author).

The noise reduction algorithms will try to distinguish between image noise and image content and try to apply filter to the noise part only, while preserving the image content. That means that if a camera applies noise reduction filter, the image content will define how much noise remains in the image. Parts of the image with a lot of details are more likely to contain the noise content before the noise filtering, while flat uniform areas show only the filtered noise. So the noise reduction algorithms are adaptive and make the description of noise dependent on the image content.

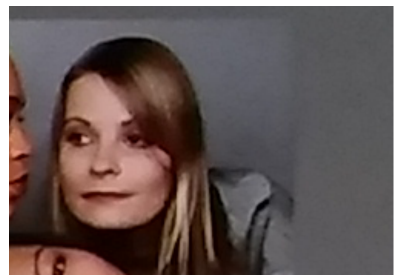

Figure 2. *Detail of an image captured with a mobile phone camera. The noise is low on uniform areas, but increased noise is visible on structuted areas and close to edges.*

Current standardized methods to measure and describe the image noise are based on the reproduction of uniform patches in the image (See Fig. 3). Significant improvements in the correlation between measured noise metrics and perceived noise have been made by using the Visual Noise metric[1] rather than Signal to Noise ratio. But the used test targets are still all based on gray, uniform patches which implies, that it is very likely that the measured noise on theses patches does not provide the information about the noise on non-uniform patches containing image details.

Figure 3. *Test target used for noise measurement according to ISO15739:2013 (TE264)- the chart consists of 20 uniform gray patches.*

In this paper, we evaluate the possibilities to use the Dead Leaves pattern (see Fig.1) for noise measurement. We check for the influence of noise on the different methods to obtain a spatial frequency response (SFR) from an image of the dead leaves pattern and use the differences as a measurement of the noise.

Texture loss methods

The DeadLeaves pattern itself was presented[7] 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 all cases, the pattern was used for the texture loss analysis, not for the evaluation of noise in the image.

DeadLeaves_core

The results of the first experiments for using the Dead Leaves pattern for texture loss analysis were presented by Cao et. al.[5]. 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).

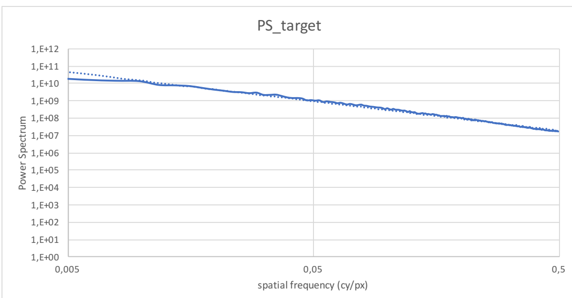

Figure 4. The power spectrum of the used dead leaves target. The dotted line is a fitted line to show how close the power spectrum follows a power law.

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

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.[6] 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). This approach is also described in the IEEE-P1858 standard[8].

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

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.

Simulation

The idea is to use the differences in the three mentioned approaches to analyze the dead leaves pattern as a description or indicator for the amount of noise that is present on the dead leaves pattern. For this purpose the three methods have been implemented into a simple environment using Mathworks Matlab.

Starting point is an image as shown in Figure 1 in the size of $512px \times 512px$. The RGB image has been reduced to a single channel intensity image.

For the DeadLeaves_core and DeadLeaves_direct approach, the power spectrum of the dead leaves target $PS_{target}(f)$ has been calculated directly from the used original image data. Other than in a non-simulated setup, a potential error from a mismatch of the calculated power spectrum (from the target properties) and the real power spectrum (in the printed target) is eliminated.

All modifications and other processing steps have been applied to the dead leaves image and to a noise reference image. This image has the same size as the dead leaves image and shows a gray value equal to the mean value of the dead leaves image.

Figure 5 shows the results depending on different noise level. As expected, all three methods show a perfect SFR in case no noise was added. The other graphs show the different SFR curves for low, medium and high noise level added. Noise was added in form of gaussian white noise with a standard deviation of 4, 8 and 16 (digital values on a 8bit scale range). The direct output data is plotted with dots, while each data set is fitted with a 3rd order polynomial fitted solid line. We see that with increasing noise, the DeadLeaves_core approach is more and more influenced by noise. The two other remain stable, while the DeadLeaves_direct results show a higher variation, as seen by the high fluctuations in the dots. The fitted line remains stable.

These results are as expected.

For the data as shown in Figure 6, the procedure was the same, just that a blur filter has been applied to the image before noise has been added. The blur filter is shown in Equation 4.

$$blurfilter = \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix} /16 \tag{4}$$

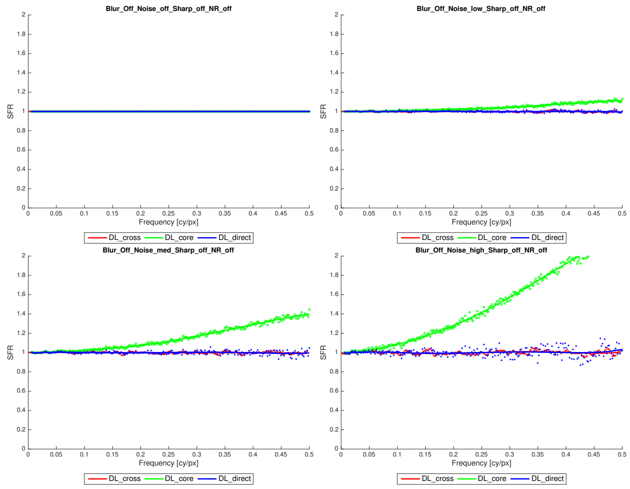

Figure 5. *Simulation results; SFR based on the analysis of the same Dead Leaves pattern using three different analysis methods. Solid line: 3rd degree polynomial fit of obtained data (dots).* ***Top:*** *No noise added.* ***Others:*** *Added white gaussian noise with a standard deviation of σ = 4, 8, 16 (8 bit scale range)(low, medium, high).*

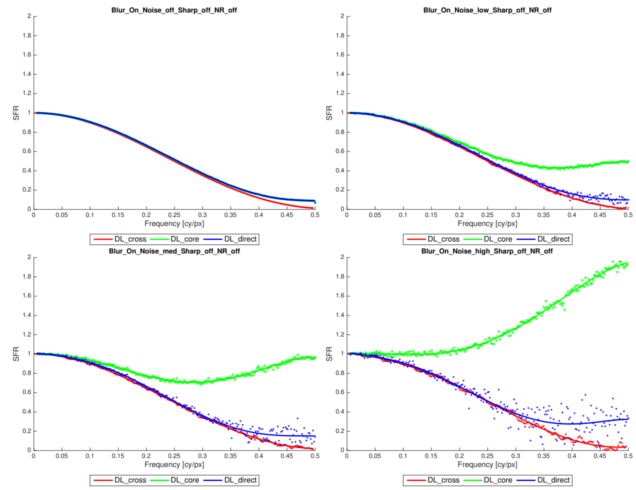

Figure 6. *Simulation results; SFR based on the analysis of the same Dead Leaves pattern using three different analysis methods. Solid line: 3rd degree polynomial fit of obtained data (dots).* ***Top:*** *Blur filter applied, no noise added.* ***Others:*** *Blur filter applied, added white gaussian noise with a standard deviation of σ = 4, 8, 16 (8 bit scale range)(low, medium, high)).*

As the filter kernel is known, we can directly calculate the expected SFR from it. We see that DeadLeaves_cross provides exactly the expected result, while the two other methods give a slightly higher response in the higher spatial frequencies. We also observe the huge influence by the added noise to the image on the SFR, while the impact is even higher as observed without the blur filter applied.

Simulation Details

The different parts for the DeadLeaves_core and DeadLeaves_direct are shown in Figure 7. The plots are created for the same noise level that are also used for the comparison of the different analysis methods. "Image", "Noise" and "Target" stand for the different power spectra as used in Equation 1 and 2. "Corrected" equals the nominator in Equation 2, so this is the PS_{image} corrected by the PS_{noise}.

We can see that the PS_image is increasing with increasing amount of noise added. This directly explains the huge influence of the noise on the DL_core method.

The target itself has significant lower power in the high spatial frequencies compared to lower frequencies. An optical low pass effect of a lens (or here a blur filter) will additionally reduce the power in the high spatial frequencies. The corrected signal gets very low for high spatial frequencies, so in regions of larger 0.35 cy/px, we see an increase in the SFR of DL_direct due to the devision by a low, noisy signal.

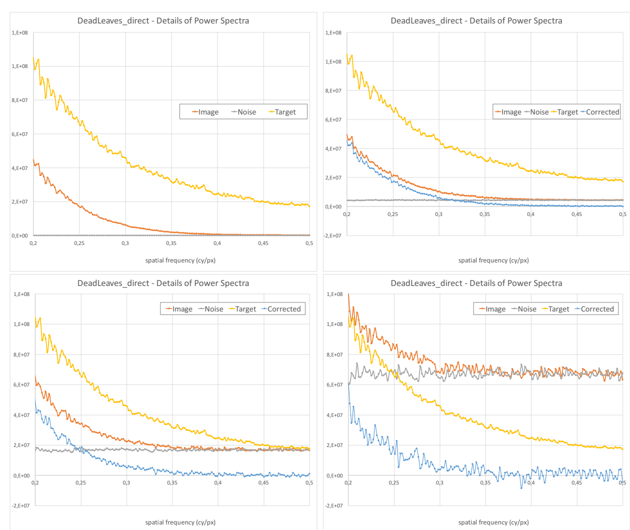

Figure 7. *Direct comparison of different components that lead to the DeadLeaves_direct results as shown in Figure 6 Detail of the power spectra used to calculate the DeadLeaves_direct SFR (frequency range [0.2...0.5]. From top to bottom: No noise, low, medium and high noise. Corrected equals PS_image - PS_Noise*

SFR-Differences

From the SFR results of the same images with the different methods, we see that added noise does not influence the SFR based on DL_cross, while the DL_core results are very much influenced. Also DL_direct is influenced by the noise. Therefore the easiest way to measure the noise on the dead leaves target is to compare the results of the different methods.

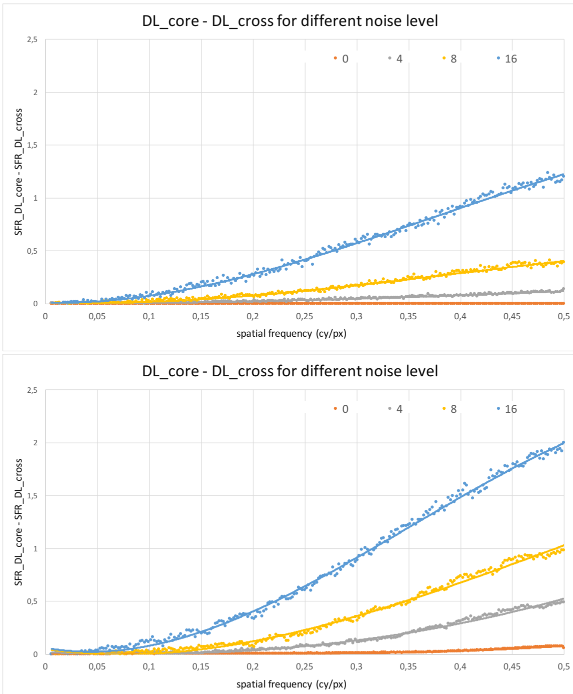

Figure 8. *The difference between the SFR obtained from DL_core and DL_cross method for the four different noise level also used for the other simulations ($\sigma = 0, 4, 8, 16$) Solid lines are polynomial trend lines.* ***Top:*** *No Blur Filter* ***Bottom:*** *Blur Filter applied*

As the DL_core method is highly influenced by the noise and DL_core the least, it is most obvious to use the difference between these two methods to get an indicator for the amount of noise we find in the image. Figure 8 shows the difference in the obtained SFR with and without the blur filter applied. As discussed earlier, the difference increases with increasing spatial frequencies. And the difference is larger for the blurred image compared to the non-blurred image.

Reconstruction

In a further simulation, we follow the idea to separate the components that lead to the increased PS_{image}. The PS_{image} is basically a combination of the PS_{target} multiplied with the optical transfer function and power from the added noise. As we have seen, that the DL_cross method is hardly influenced by the noise, we can assume that the provided transfer function by this method can be used to separate the components. Equation 5 shows the approach. We assume that PS_{target} multiplied with the SFR obtained according to the DL_cross method represents the image before noise was added, the difference between this item and the PS_{image} forms the reconstructed power spectrum of the noise in the image.

$$PS\_Noise_{reconstructed} = PS_{image} - (PS_{target} \times SFR_{DL_{cross}}) \quad (5)$$

The PS_Noise for different noise level is shown in Figure 9. We see that the added noise is white and the power increases with the standard deviation. The noise was added to a uniform gray patch without any image content.

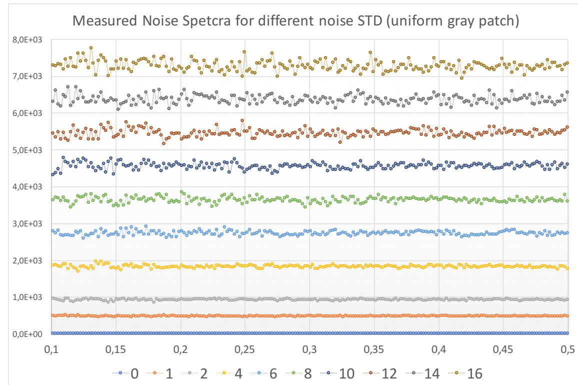

Figure 9. *The measured Noise Power spectrum of the added noise. X-Axes show spatial frequencies in the range [0.1...0.5] The measured PS_Noise on uniform gray patch*

The reconstructed noise according to Equation 5 can be observed in Figure 10. The spacing is very similar to the spacing in Figure 9, so the increasing noise also results in an increasing reconstructed noise level. We see a non-white noise. In the high spatial frequencies, we get a much higher reconstructed noise level compared to the lower spatial frequencies. In case the blur filter was not applied, the difference between low and high spatial frequencies reduces. That means that we measure a higher reconstructed noise the lower the power in the image before the noise was added.

Noise Reduction

We used the Noise reduction filter offered by Adobe Photoshop to remove some noise form the image. The original images (DeadLeaves and Noise patch) are equal to "medium" in the previous simulations, so white gaussian noise with a standard deviation of 8 (8-bit scale) was added. The intensity of noise reduction was chosen with level 2, 4, 6, 8 and 10. "Detail Sharpening" and "Detail preservation was set to "20" (max. = 100).

From all methods we can see(Fig.12), that the different level of noise reduction slightly increase the texture loss, while the highest level increases significantly compared to the others.

Figure 13 shows the difference between DL_core and DL_cross. We see the reduction of noise added to the dead leaves pattern.

The table in Figure 11 shows the numerical results. The reconstruction of the noise and the difference between DL_core and DL_cross show the effect as expected. The noise decreases more on the uniform patch than on the dead leaves pattern. All three approaches show very similar ratios of noise increase. In the maximum level of noise reduction, the texture loss is very strong and we get similar noise level on the uniform patch and the dead leaves structure again.

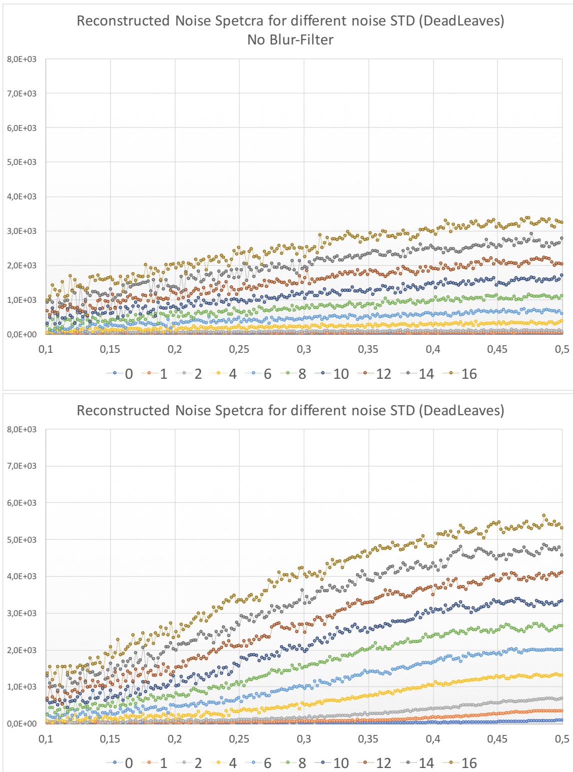

Figure 10. *The reconstructed noise power spectrum. X-Axes show spatial frequencies in the range [0.1...0.5] Reconstructed Noise accoring to Equation 5 on DeadLeaves patch.* ***Top:*** No Blur Filter ***Bottom:*** Blur Filter applied

	NR0	NR2	NR4	NR6	NR8	NR10
SNR	15,842	17,583	20,138	22,588	22,898	24,868
Variance	64,266	52,170	39,772	31,591	30,698	26,006
Diff	0,166	0,161	0,147	0,136	0,136	0,084
Diff_sec	0,150	0,145	0,132	0,122	0,121	0,071
Reconstruction	2,58E+06	2,50E+06	2,32E+06	2,18E+06	2,16E+06	1,46E+06
	NR0	NR2	NR4	NR6	NR8	NR10
SNR	100%	89%	73%	57%	55%	43%
Variance	100%	119%	138%	151%	152%	160%
Diff	100%	103%	111%	118%	118%	149%
Diff_sec	100%	103%	112%	119%	119%	153%
Reconstruction	100%	103%	110%	115%	116%	144%

Figure 11. *Numerical results; Noise added ($\sigma = 8$) followed by noise reducton in Adobe Photoshop. Noise reduction levels 0,4,6,8,10; SNR and Variance measured on the uniform gray patch. Diff equals the difference of the integrals of DL_core and DL_cross. Diff_sec is the same as Diff, just limited to the frequency range of [0.25...0.5] ; "Reconstruction" according to Eq.5, integral over complete frequency range. Upper part: Absolute values; Lower part: Relative to NR0.*

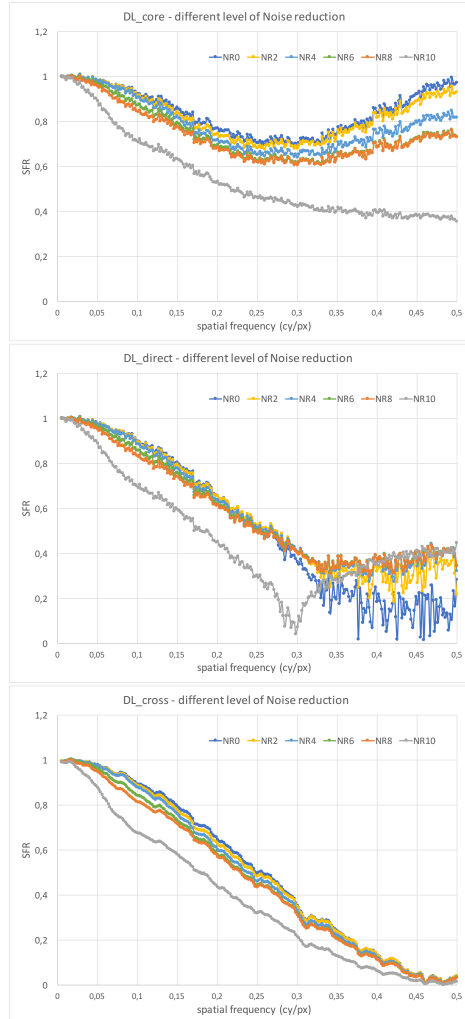

Figure 12. *The SFR based on three different methods; Noise added ($\sigma = 8$) followed by noise reducton in Adobe Photoshop. Noise reduction levels 0,4,6,8,10*

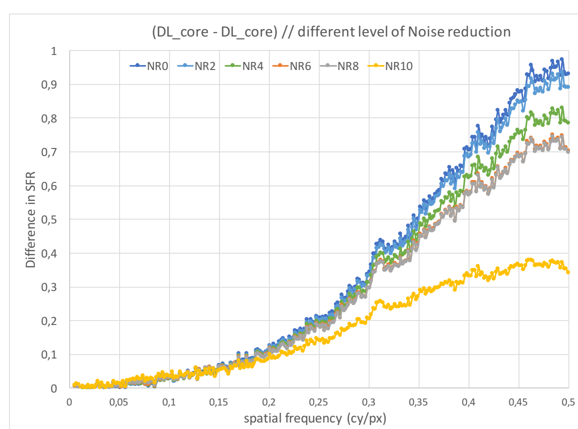

Figure 13. *The difference in DL_core and DL_cross; Noise added ($\sigma = 8$) followed by noise reducton in Adobe Photoshop. Noise reduction levels 0,4,6,8,10*

Conclusion

In this paper we presented work that can lead to a measurement procedure that will allow to measure noise on dead leaves pattern. The simulation results look promising as they can reflect the expected result in case noise reduction is applied to an image.

The differences in the three presented methods to analyze the dead leaves structure for the spatial frequency response are depending on the level of noise and can therefore be used to describe the noise. The reconstruction of noise using the information obtained from the DL_cross approach is interesting, but did not show a benefit over the more simple way of calculation the difference of the SFR.

Future work

The work presented in this paper is a promising start for further investigations.

- Perform intensive testing on real camera data.
- Create numerical results based on the obtained reconstructed power spectrum.
- Conduct psychophysical studies to get the human perception included, as for example in the metric "Visual Noise" in comparison to signal to noise ration (SNR)

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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.