Measuring texture sharpness of a digital camera

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ABSTRACT

A method for evaluating texture quality as shot by a camera is presented. It is shown that usual sharpness measurements are not completely satisfying for this task. A new target based on random geometry is proposed. It uses the so-called dead leaves model. It contains objects of any size at any orientation and follows some common statistics with natural images. Some experiments show that the correlation between objectives measurements derived from this target and subjective measurements conducted in the Camera Phone Image Quality initiative are excellent.

Keywords: Image Quality Evaluation, dead leaves model, sharpness, texture, modulation transfer function, SFR, power spectrum.

1. INTRODUCTION

This article deals with the evaluation of image quality, and particularly the preservation of textures. The evaluation of image quality is a broad subject, which becomes even more relevant today as we face a speed-up in new digital camera technologies. Not only the high end cameras are probably better than ever before, but there is a huge diversity of cameras, particularly due to the emergence of new devices as camera phones.

A paradigm of image quality evaluation is that there exists a global scale: it is always possible to say that an image looks better than another one. Therefore, the Holy Grail of image quality evaluation is to give a single figure to characterize the quality, which is also very sensible in a marketing point of view. Some techniques[1] propose a single metric which is independent of the content. However, this is a really coarse description since it does not appear why the image has a bad quality.

A general methodology is presented in the book of Keelan[2]. The image quality is determined by several attributes which are chosen as orthogonal as possible (as brightness, colorfulness, sharpness, graininess etc…). These attributes are then characterized by metrics. In order to measure repeatable metrics, these are computed on target images following very strict protocols. These metrics are then correlated to subjective measurements, to quantify the perceptual quality of the image taken by the camera.

This paper intends to propose a new target and a measurement aiming to quantify the ability of a camera to reproduce fine textures and details.

2. SHARPNESS MEASUREMENT

Sharpness is the attribute related to the preservation of fine details. However, this is untrue that it is only a high frequency phenomenon[14]. Very low resolution images can appear sharp, in the sense that edges are sharp, although they do not contain any details, as television broadcast. Two notions of sharpness are necessary: edges sharpness and texture (fine details) sharpness. In traditional silver halide photography, the ability of a camera to restitute details was related to

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the quality of the optics and the film grain (usually related to its ASA/ISO sensitivity). It could be visually evaluated on edge and wedges patterns. Digital imaging has completely changed the rules:

- It is possible to numerically enhance edges.
- As a consequence, it is possible to have sharp images with no details and blurry images with fine details, which seems at first completely counter intuitive.
- Denoising algorithms can remove the possibly strong impulse, but then creates a coarser noise with lesser intensity.

The ISO[3] standard 12233 proposes to measure the MTF (modulation transfer function) by measuring precisely the Spatial Frequency Response (SFR) of the system to an edge. This method has several advantages:

- It is local so measurements can show the dependence of the system to field position.
- It is accurate and particularly adapted to measure the response of optics, which completely determines the response of a camera with a linear behavior.
- It optimally characterizes edge sharpness (the target is an edge).

However, there are also drawbacks:

- It is sensitive to noise since all information is contained on a very small area around the edge. The rest is noise only.
- Image and Signal Processing of cameras (ISP) always have noise reduction abilities. These algorithms are mostly non linear
- Digital processing can detect edge patterns and can enhance them very locally. Therefore, the response to an edge might not be representative of the whole image, in particular in textures.

Because of digital processing, an image can have very sharp edges but a very small amount of details for instance in foliages, grass or furs. We deduce that the SFR measurement is not sufficient to qualify the performance of a camera. We need to find a pattern that cannot be easily fooled by local processing as local automatic edge enhancement.

3. FINDING THE GOOD TARGET

3.1 Requirements

It must be noted that we want the measurement to be as independent as possible of other image quality attributes, whenever possible. In these conditions, what are the good properties that a target for texture preservation measurement should satisfy?

First, we want to be able to characterize camera with any resolution, from cell phone camera to DSLR. Therefore, the measurement should be independent of the device resolution. Also, measurement can be done at any distance. From this, we conclude that the target must be scale invariant and contain all frequencies.

Texture can appear at any level of contrast and images can be shot at different levels of exposure. Therefore, the target should contain all the possible contrasts.

Also, textures can also appear in any direction. Therefore, the target must be rotation invariant.

It is also desirable to make measurements throughout the image field. Therefore, the image should be shift invariant.

It is also nice to create a target which looks like a real texture. The main difficulty here is that it is very difficult to define exactly what a texture is. Textures obviously have a part of randomness, however they are still organized. In particular, they can be created by similar objects at different depth, and thus occluding each other.

To sum up, a good target should be

- Scale invariant
- Rotation invariant

- Shift invariant
- Contrast/exposure invariant
- Contain edges and occlusions like a real texture
- Not easily improved by abusive amount of processing

3.2 The dead leaves model

The dead leaves model was introduced by Matheron[4], inventor of the theory of random sets and Mathematical Morphology. The initial application was geostatistics, especially for oil resource searching. The dead leaves model is obtained by drawing random shapes that occludes each other in the plane, like dead leaves falling from a tree. More rigorously, consider a uniform Poisson process $(x_i)_{i\leq 0}$, where x_i is a position in the plane.

Also consider some closed sets $T_i$with random size r_i and centered at the origin. The dead leaves model is generated by

$$\bigcup_{i\leq 0}(T_i + x_i)$$

The set $T_i + x_i$ is the leaf at time i. We call the visible part of leaf i_0 the set of points (possibly empty) x that satisfy $x \in T_{i_0} + x_{i_0}$ and for all $j > i_0$, $x \notin T_{i_0} + x_{i_0}$. Similarly, the visible leaf at point x is the the leaf T_{i_0} with

$$i_0 = \sup\{i\ s.t.\ x \in (T_i + x_i)\}.$$

To generate an image of dead leaves, we assign a gray level or a color to a leaf. The value of the image at position x is the value of the visible leaf at point x. In the following, we assume that the position of the leaves is uniformly distributed in a square (uniform Poisson process) and that the size of the leaves follows a power law, that is, the distribution of the size R is

$$P(R = r) \propto \frac{1}{r^{\alpha}}.$$

As discussed by Lee et al.[5], a maximal or minimal value has to be set, since a power law has not a finite integral. For instance, the leaves can be discs with random radius and random gray level, uniformly distributed between 0 and 255. Figure 1 depicts a trial of this model.

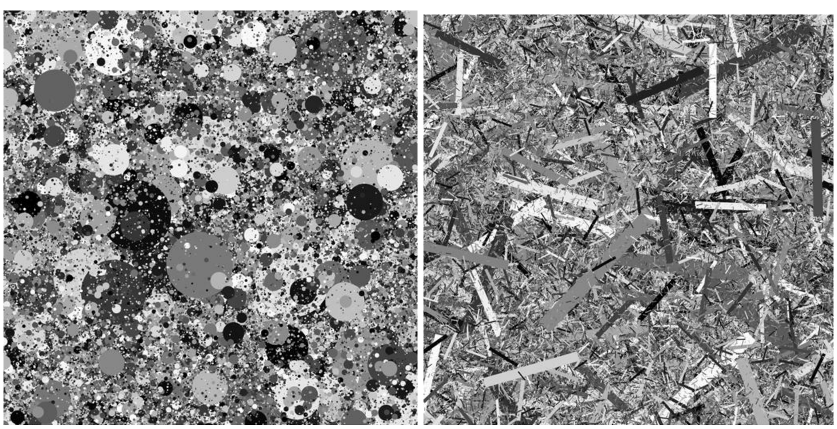


Fig. 1 An image of dead leaves model generated by discs (left) and with similar rectangles with random orientation (right).

Lee et al. also discussed the scale invariance properties of such an image. The conclusion is that to have full scale invariance, the power law has to be a power -3.

However, because of the minimal size introduced for the convergence of the law at size 0, the model cannot be strictly scale invariant. For leave shapes that are not discs, the model can still be made statistically rotation invariant by randomly drawing the orientation of shapes. Figure 2 illustrates such an example where the leaves are similar rectangles, with orientation uniformly distributed in $(0, \pi)$.

The dead leaves model has two great properties:

- By nature, it can reproduce the occlusion phenomenon, which is a low level cause of the perception of depth[9].
- Some statistics of dead leaves images follow the distribution of the same statistics in natural images.

It is known from the works of Ruderman[6] (see also[7,8]) that some statistics like the power spectrum or wavelet coefficients follow a power law in natural images, that is the power law is proportional to $1/f^{\alpha}$. The value of α varies with the content of the image: more textured images correspond to a higher value of α. The value 2 is interesting since it implies complete scale invariance of the image.

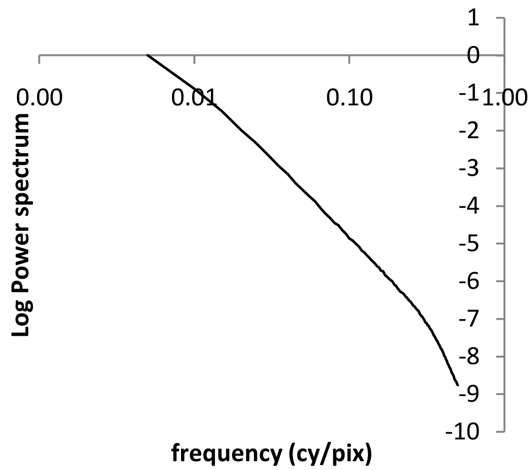


Fig. 2. Power spectrum of the dead leaves model (disks). It remarkably follows a power law.

The dead leaves model remarkably satisfies the same property. As an example, Fig. 2 shows the log-power spectrum of the circular dead leaves of Fig. 1. For very high and very low frequency, the power spectrum shows deviation from a power law, depending on the minimal size (bounded from below by the pixel size) and the maximal size (bounded from above by the image size). However, between frequency 0.05 and 0.25 cycle/pixel, the slope of the curves is -1.857 with a regression coefficient of 0.9996. If we print the target with high enough resolution on a large enough support, we can only use this part of the spectrum. Therefore, it can be assumed that the target indeed follows a power law.

Also, the target should arguably be less contrasted than the figures above. Textures are probably not inherently low contrast, but signal processing will usually not have any problems for high contrast textures. Therefore, in order to catch the relevant behavior, as far as image quality evaluation is concerned, we designed a low contrast target. In order to be insensitive to the camera tonal curve, a gray scale is appended on the side. The image is then linearized by inverting the gray scale as shot by the camera. Some markers are also added for automatic processing of the shots. Figure 3 shows the target we used in our experiments.

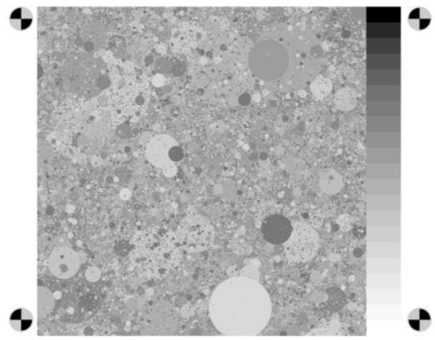


Fig. 3. The dead leaves target. It integrates markers for automatic detection and a gray scale for OECF compensation

3.3 Comparison with existing targets

As different examples, Fig. 4 shows target that can be used for usual sharpness measurements. On the left, the target contains slanted edges throughout the field. The second one is a sine Siemens Star. The third one is the log-F contrast target exhibiting a chirp in frequency with varying amplitudes. The last one is a target containing white noise as proposed in[10]. These targets have different good and bad properties, regarding the texture preservation measurement.

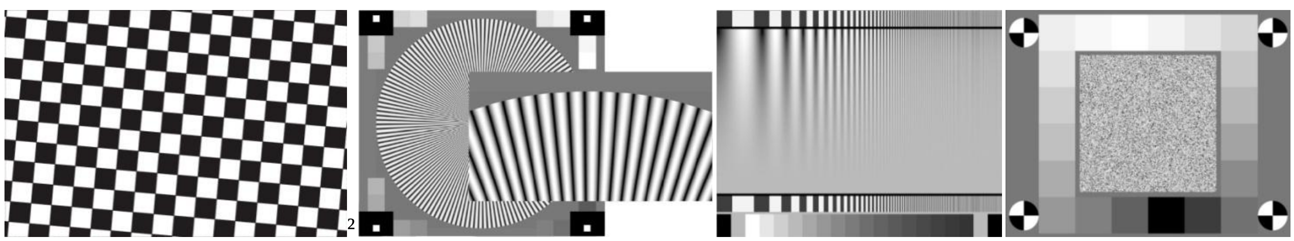


Fig. 4. Different targets for sharpness measurements. Their properties are summarized in the following table. None of them are satisfying for texture quality measurement.

	SFR target	Sine Siemens Star	Log-F contrast	Noise Target	**Dead Leaves**
Scale invariant	No	Partly	Yes	Yes	**Yes**
Shift invariant	Yes	No	No	Yes	**Yes**
Exposure invariant	No	No	Yes	Yes	**Yes**
Rotation invariant	No	Yes	No	Yes	**Yes**
Texture like	No	No	No	No	**Yes**
Robust to denoising	No	Yes	Partly	Partly	**Yes**

4. TEXTURE PRESERVATION MEASUREMENT

We saw that we can very reasonably assume that the power spectrum of the dead leaves target follows a power law. For a perfect camera, this should remain true. Therefore, a basic idea is to shoot a picture of the dead leaves target and observe the shape of its power spectrum. Moreover, since in the case of the particular dead leaves target, the ground truth is known, dividing the power spectrum of the image by the one of the unprocessed target yields the power spectrum of the system (optics+sensor+processing). Therefore, this provides the MTF of the system, computed on a dead leaves target. A result is shown on Fig. 5. It is worth noting that, contrarily to a regular MTF SFR, the information in high frequencies can be very accurate even though the power spectrum assumes very low values. Indeed, the target contains edges everywhere, at any scale. On the contrary, the high frequencies of a slanted edge are only contained around the edge, while a shot of the edge contains high frequencies everywhere because of noise.

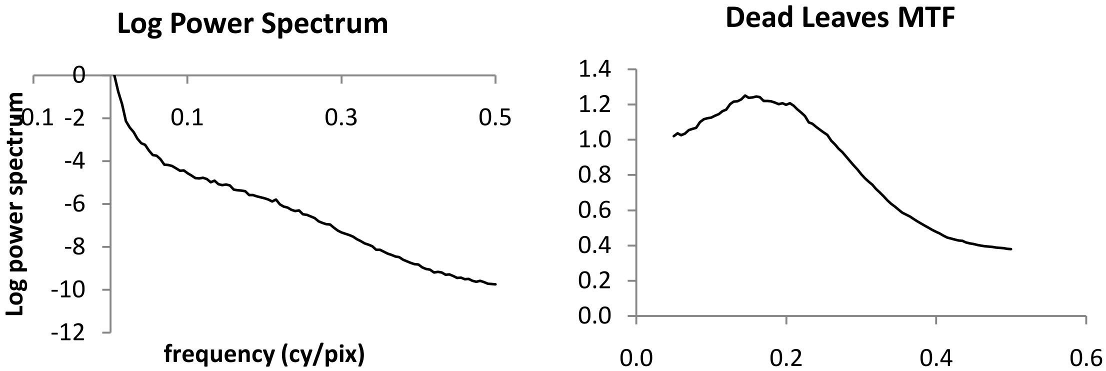


Fig. 5. Power spectrum of the dead leaves target on a camera phone. By dividing this power spectrum by the known power spectrum of the target, a MTF can be computed. It characterizes the modulation of the processing on a texture.

Since the power spectrum is normally not defined at the origin (it is a power law), the dead leaves MTF may be less accurate for very low frequencies. We then choose to assume that it has the same value as the regular MTF at a frequency 0.01cycle/pixel.

Since the dead leaves target is composed of many edges in every direction scale, and level of contrast, we could expect the dead leaves MTF and the SFR MTF to be equal. Their ratio or their difference depends on the processing (RAW conversion, including possible sharpening and denoising).

5. EXPERIMENTAL RESULTS

5.1 Synthetic degradation

Figure 6 shows the dead leaves MTF of the target on which different amount of sigma filtering[11] have been applied. Stronger filtering amounts severely decreases the MTF as foreseen. The same filtering is applied on a slanted edge. In this case, the stronger the filtering, *the higher the MTF (SFR)*! Indeed, it is well known that sigma filters have a sharpening effect.

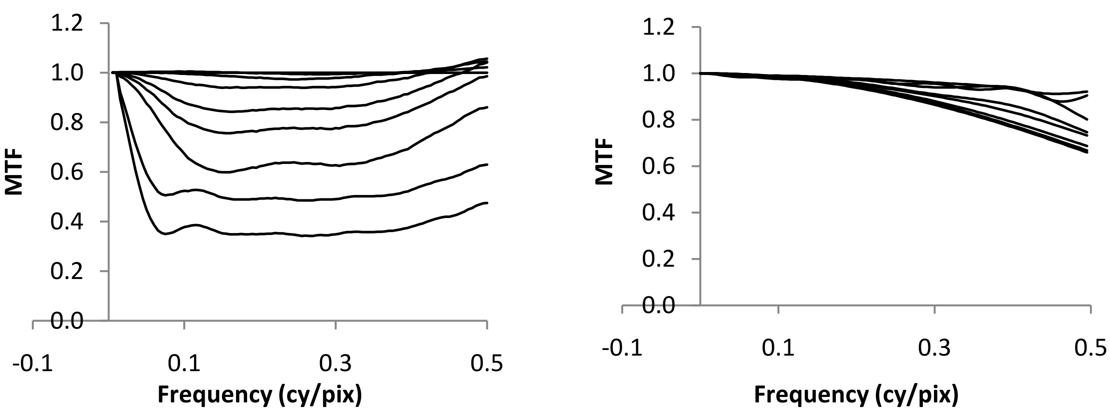


Fig. 6. Left: Dead leaves MTF for different amounts a sigma-filtering: more filtering decreases the MTF and degrades the texture. Right: the MTF computed on a slanted edge. The MTF actually *increases* with the amount of filtering, due to the sharpening effect of the sigma filter.

5.2 Correlation with subjective measurements

In order to check the relevance of the dead leave target measurement, some correlations were done in the I3A Camera Phone Image Quality working group[12]. The experiments were conducted by Phillips, Jin, Chen and Clark[13].

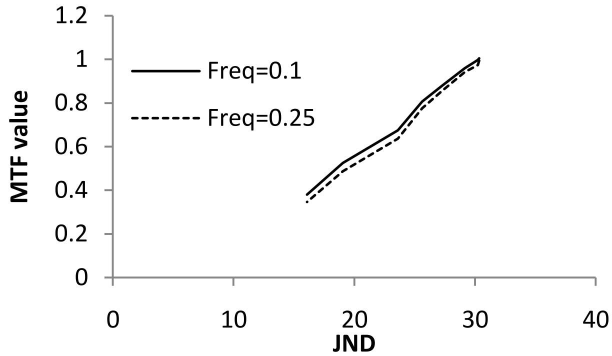


Fig. 7. Correlation between JND scale and dead leaves MTF at different frequencies. The correlation coefficient is higher than 0.99

Different amounts of sigma-filtering were applied to a set of photographs of natural scenes (containing textures). The subjective degradation was evaluated by a set of non imaging expert observers and scaled in terms of JND (Just Noticeable differences[2, 12]). The same degradations were applied to an image of the dead leaves target. Correlations were then sought for between the JND scales and the MTF values at different frequencies. The correlation for frequencies 0.1 cy/pix and 0.25cy/pix (that is 20% and 50% of Nyquist frequency) are depicted on Fig. 7. The R^2 correlation coefficient is more than 0.99. For more extreme frequencies, as 0.01cy/pix and 0.5 cycle/pix (Nyquist frequency), the correlation is slightly less good but still remains over 95%.

5.3 Experiments on real shots

The following experiment was performed with a Nikon D3 with a fixed focal length 50mm and a camera phone (Nokia N80). Some crops are shown on Fig. 8.

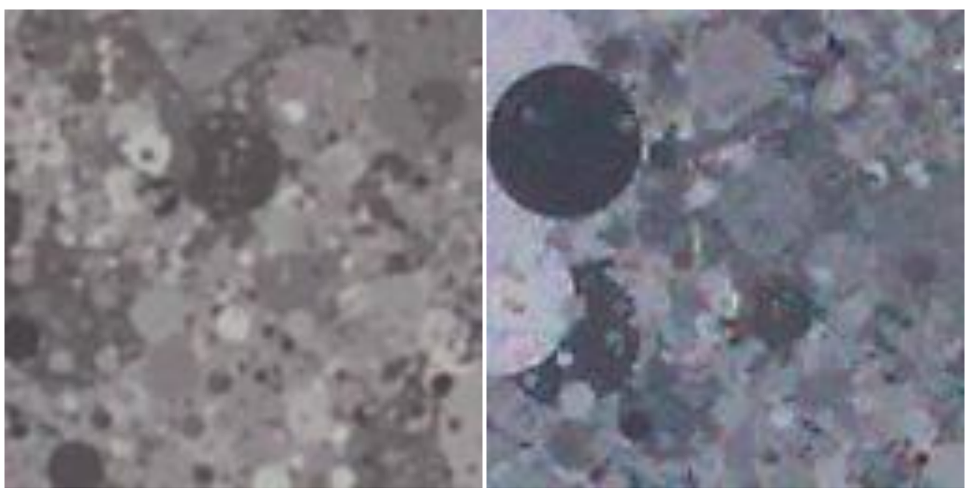
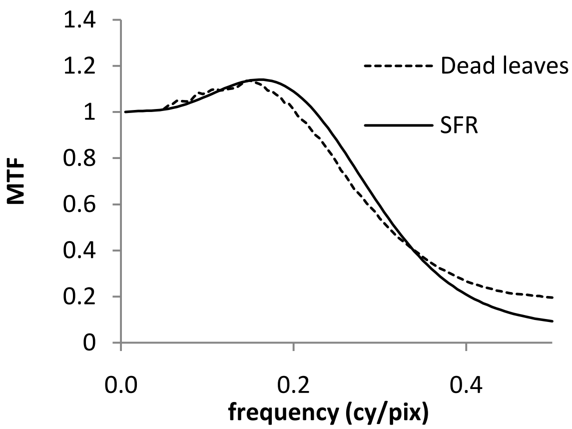


Fig. 8. Crops (128x128) of shots of the dead leaves target with Nikon D3 (left) and Nokia N80 (right).

The MTF with the SFR methods are actually close with both DSLR and camera phone. Of course the DSLR has a higher resolution, so thinner details are expected for a given field of view. On the DSLR, the difference between the MTF SFR and MTF dead leaves is small (see Fig. 9). On the other hand, the camera phone exhibits a different behavior: the dead leaves MTF drops fast even for low frequencies. It remains higher for frequencies close to Nyquist. This kind a behavior can be interpreted as follows: in order to prevent noise amplification, sharpening algorithms are adaptively applied on edges. The dead leaves target is too complex for the camera phone and its edges are not sharpened, hence the loss in low frequencies. For high frequencies, other artifacts as noise and JPEG compression keep the level of the MTF higher. Moreover, the variation of chrominance is also much larger on the camera phone.



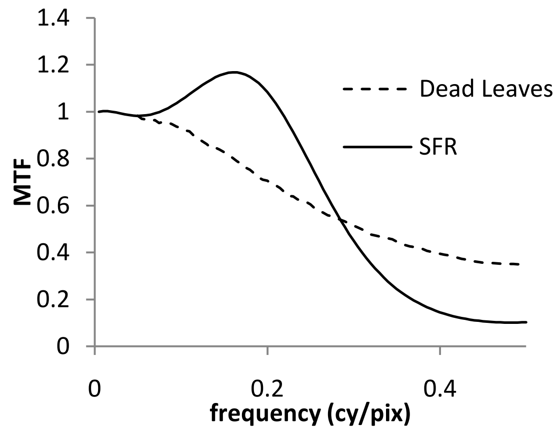


Fig. 9. Difference between dead leaves MTF and MTF SFR (slanted edge method) for a Nikon D3 (left) and camera phone Nokia N80 (right)

We think that problems can be expected when dead leaves MTF and SFR are very different. The paradigm is the following: the SFR describes the behavior of the camera on a single, isolated edge. On the other hand, the dead leaves target contains edges at any position, any orientation and any level of contrast. A camera that renders textures in a suitable way should be able to process the edges of the dead leaves as single edges, and therefore give the same MTF. On raw images, this happens to be very accurate. The difference between the two curves in only due to the processing.

6. CONCLUSION

The dead leaves target allows the evaluation of the quality of textures delivered by a camera. Contrary to the slanted edge method, every part of the image contains some information, making it difficult to fool for classical edge enhancement algorithms. Moreover, the target contains any level of contrast, orientation and size, thanks to its fractal nature. Experiments showed an excellent correlation with subjective measurements in terms of just noticeable differences. Further validation still needs to be made. In particular, the influence of the correlation (or lack of correlation) between MTF SFR/dead leaves has to be further investigated. A good image must have sharp edges (not too sharp), and contain details in textures. As some of our experiments show, these two facts are some independent in some extent, so both MTF are necessary to evaluate the quality of a camera.

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