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Texture MTF from images of natural scenes

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Abstract

The implementation of automatic, adaptive filters in consumer imaging devices represents challenges to sharpness and resolution evaluation. The widely used e-SFR and other methods based on sine-waves and line targets are not necessarily representative of the capture of natural scene information. The recent dead leaves target is aimed at producing texture-MTFs that describe the capture of image detail under automatic non-linear, and content-aware processes. A newer approach to the texture-MTF measurement that substitutes the dead leaves target with pictorial images is presented in this paper. The aim of the proposed method is to measure effective-MTFs indicative of system characteristics for given scenes and camera processes. Nine pictorial images, portraying a variety of subjects and textures, were set as targets for a DSLR camera and a high-end smartphone camera. Computed MTFs were found to be congruent with the dead leaves MTF. Scene dependency was reported mainly for the smartphone camera measurements, providing insight into the performance of the content-dependent processes. Results from the DLSR camera images, captured with minimum non-adaptive operations, were reasonably consistent for the majority of the scenes. Based on variations in scene-dependent MTFs, we make recommendations for scene content that is best for texture-MTF analysis.

Introduction

Extensive studies have been carried out on microscopic tone reproduction (sharpness) and resolution, since it is undeniable that edge and detail reproduction, which are associated with these attributes, are prime factors to consider when evaluating system performance and visual image quality. Multiple metrics have been developed to evaluate and compare systems' sharpness and resolution, the Modulation Transfer Function[1] (MTF) being the most established one [1]. One of its advantages is that the MTF of each component of the imaging system can be cascaded to produce the total MTF of the system. Similarly, the MTF of a system can potentially be cascaded with the human Contrast Sensitivity Function (CSF) to predict the perceived (spatial) image quality. [2] [3] [4] [5] [6] [7]

One of the most widely adopted methods to measure MTF exploits sharp slanted edge features. The slanted edge method as defined by ISO 12233 standard [8],which applies the concept of MTF as the spatial frequency response (SFR), consists in super-sampling the image of a sharp edge - usually printed - to obtain the system edge spread function (ESF). The line spread function (LSF) of the system is subsequently derived through first order derivative and the MTF is then calculated by the Fourier transform of the LSF. The concept of MTF is based on linear systems theory. Therefore non-linear processes applied to the images, such as demosaicing, adaptive noise reduction, sharpening or compression result in there being no single system MTF.

Often a point-wise linear model is adopted for the system. In this case the tone-transfer and spatial characteristics are considered as separable. The camera tone reproduction characteristics (OECF) [9] [10], for example, can be reversed through linearization. The alterations to the measured MTF generated by non-linear processing can have very different magnitudes depending on multiple factors. It has been shown, for example, that SFR measured from modern low contrast edge targets is only moderately sensitive to image gamma correction [11]. Not much published work has been presented on the MTF variation due to various non-linear algorithms present in camera pipelines.

One limitation to the e-SFR (slanted edge-SFR) method is its sensitivity to noise - when present at high magnitudes [12] . The MTF of a system computed with the slanted edge method may not be a representative measure of the system performance if adaptive image processing is applied. The reason being that non-linear automatic filters easily detect and sharpen edges, which were originally optically blurred, resulting to an 'optimistic' performance measure compared with the visual performance of the imaging system when capturing natural scenes. Furthermore, it is possible to have loss of detail in images that appear sharp due to contrast enhancement, but also very detailed images looking un-sharp because of low contrast [13].

According to Cao *et al.* it is therefore useful to differentiate between edges sharpness and texture sharpness [14]. When sharpening and automatic enhancing processing can be turned off it is possible to evaluate the near-the-optical/sensor system performance. Often this might not be possible, as in the majority of camera phones. Also, it might be of greater interest to evaluate the performance of the device in its normal use [15]. The exponential growth of the camera phones' industry has led to the development of MTF measurements that rely on test images with content that better resembles natural textures, with power spectra similar to these of real scenes [16].

We expect any adaptive image processing to result in the measured MTF varying with the type of test signal/method that is used. Scene-based MTF measures would also vary with particular test scenes that are used – by the same logic. We investigate this aspect of texture-MTF measurement by comparing results from several types of scenes.

Dead Leaves Method

The dead leaves target (resembling an image of a bed of randomly fallen leaves [14]) is used to measure the so-called textured-MTF. It exploits stochastic geometry for MTF measurement and consists of an assemblage of opaque uniform grey circles with different density and radiuses. It has been designed to reproduce occlusions phenomena and therefore produce low contrast edges at any scale and any orientation in order to reproduce the appearance of a

[1] In this paper by MTF we mean a function of spatial frequency that can be used to describe the capture and retention of information. As such, it is a more general form of the, e.g. optical, modulation transfer function (MTF) or corresponding system function of a linear system.

natural texture. Due to its geometrical model, the target is rotationally invariant, shift invariant, contains different level of contrast and is scale invariant (i.e. it's a fractal) meaning that its characteristics do not vary with viewing distance [14] [17]. The texture-MTF has been proven to have good correlation with human perception of texture sharpness [18].

To better simulate a natural texture, the target was also designed to have a power spectrum close to an inverse power function ($1/f^n$), typical of natural scenes [17]. The measurement of the texture-MTF is obtained from the square-root of the ratio of output (processed image) and input power-spectral density of the dead leaves image. The power-spectral density, most often referred to as noise power spectrum (NPS), is the Fourier transform of the auto-covariance function. So, for i being the 2D input signal to a linear system characterized by MTF $M(u,v)$ and $S_i(u,v)$ its noise power spectrum, then

$$S_o(u,v) = M^2(u,v)S_i(u,v) \quad (1)$$

where $S_o(u,v)$ is the noise-power spectrum of the output signal [1] [19]. Given that $S_i(u,v)$ is known (which in the dead leaves target case it is), by measuring $S_o(u,v)$ the $M(u,v)$ can be retrieved.

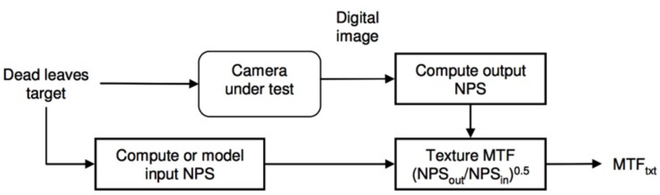

Figure 1: Outline of texture MTF measurement method [1].

In this paper we employ methods and tools used for the dead leaves MTF measurement and substitute the dead leaves target with images of natural scenes. Using natural scene images for testing capturing systems we produce MTFs that are scene dependent and camera processing/settings dependent, which can potentially be used to differentiate the system performance under specific input signal and capturing conditions.

Method

Test image selection and printing

Nine pictorial test images (Fig. 2) were created by producing 20x20 cm prints of captured natural scenes, on Epson Premium Semi Gloss paper [20], using the Epson Stylus Pro 7900 high quality professional inkjet printer. Images were purposely captured, so that a variety of disparate features were represented. The selected test set included images with disparate features:
- high contrast (stones) , low contrast (bricks);
- natural texture (grass, tree) , man-made texture (wall);
- high level of detail (grass, tree), low levels of detail (cloud, contrail);
- human beings (people), buildings (architecture);

The prints were mounted on 2mm thick cardboard through cold pressing to ensure that the test images would remain perfectly flat. An Imatest [21] dead leaves target, with a printed region of 284x213 mm, was also included in the test set for benchmarking purposes.

MTF determination

A professional DSLR camera (Canon 5D Mark II) and a top of the range camera phone (iPhone 6S) were chosen for camera evaluation, using the selected test images captured under uniform and controlled lighting [22]. The Canon DSLR is representative of systems with mainly manual controls, not significantly affected by automatic content-aware non-linear processes. It was set to capture Canon RAW files in Adobe RGB color space. Automatic noise removing options were turned off and the camera was set to ISO 100 and used in autofocus.

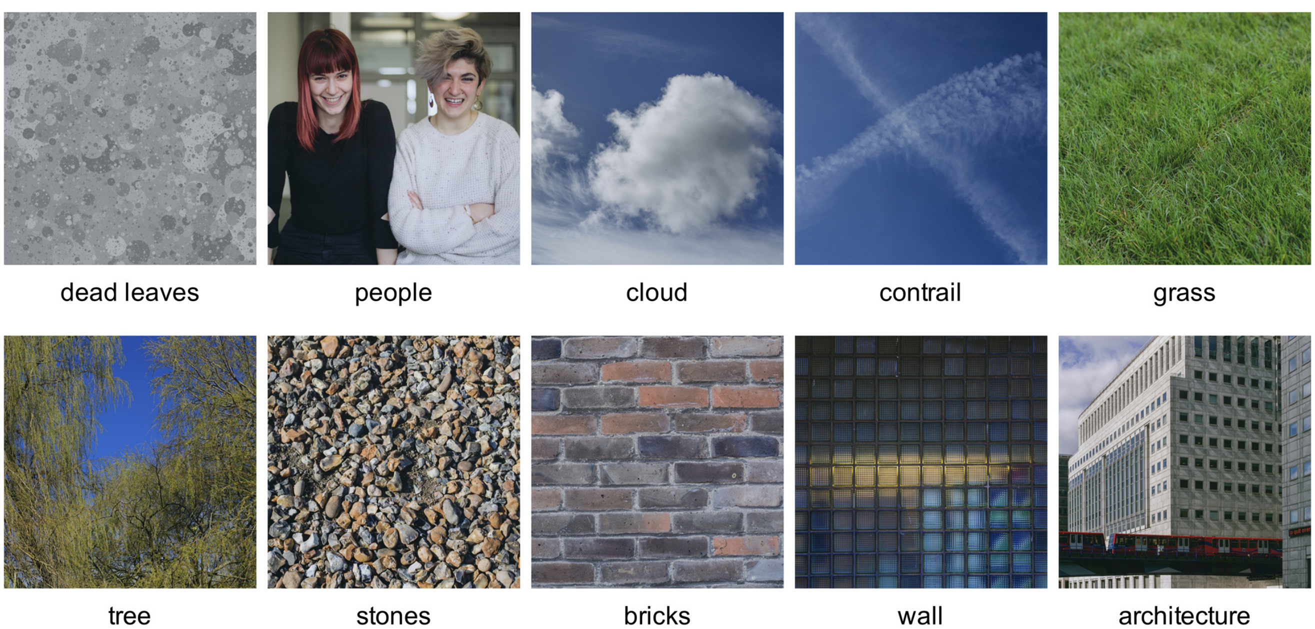

Figure 1: Dead Leaves target (top-left) and nine selected pictorial images.

The iPhone 6S was selected to investigate the effects of possible content-aware automatic enhancements and non-linear processing applied by the phone software, and consequently reflected on the measured MTF. As the native camera app only exports JPEG files, the 645PRO app by Jag.gr was used to obtain "image data at an earlier phase of Apple's development process, before any JPEG compression has been applied and which we can save as a TIFF. We're calling this a 'developed RAW' or dRAW " [23].
Both capturing devices were set on a tripod endowed of spirit level to ensure parallelism between the sensor and the targets' plane. Due to different pixel pitches, lenses and sensor sizes, the two capturing systems had to be set at different sensor-to-chart distances to operate similar sampling densities. In particular, as suggested by Imatest [24], the two systems were set so that their sampling density on the targets would be 140 ppi or lower (Table 1 and Table 2).

Canon 5D Mark II image size:	$5616x3744\ px$
min pixel sampling (on the target surface):	$140\ ppi$
min field of view (on the target surface):	$\left(\frac{5616px}{140ppi}\right)x\left(\frac{3744px}{140ppi}\right) = 40.1x26.7\ inches$

Table 1: Calculated size of minimum field of view (on the chart plane) to be included in order to achieve a max sampling of the target image of 140ppi by the Canon 5D Mark II.

iPhone 6s image size:	$4032x3024\ px$
min pixel sampling (on the target surface):	$140\ ppi$
min field of view (on the target surface):	$\left(\frac{4032px}{140ppi}\right)x\left(\frac{3024px}{140ppi}\right) = 28.8x21.6\ inches$

Table 2: Calculated size of minimum field of view (on the chart plane) to be included in order to achieve a max sampling of the target image of 140ppi by the iPhone 6S.

The printed and mounted test targets were then scanned with an Epson Perfection V850 Pro flatbed scanner to obtain digital image files, which were then used as input for the MTF analysis. The images were first scanned at 1200dpi and then resized, using bicubic interpolation, consistently with the corresponding images produced by the cameras under test. The uniform grey patches were also scanned (and proportionally resized) in order to retrieve information on noise introduced in the scanning process. Retrieving the input power spectrum by scanning the actual physical targets allowed removing the influence of the printer on the final computed SFR. As a payoff, the MTF of the scanner is introduced as a possible biasing variable influencing the results, but at least in a consistent manner. Previous tests confirmed that the scanner MTF, when set at 1200ppi, is good enough to be considered negligible (Equation 2) [25]. The scanned digital versions of the printed targets can therefore be considered almost 'perfect reproductions', at least in terms of sharpness and detail, of the printed targets.

$$\frac{Out(u,v)}{In(u,v)} = \frac{print(u,v)\cdot MTF^2{}_{camera}}{print(u,v)\cdot MTF^2{}_{scanner}} = \frac{MTF^2{}_{camera}}{MTF^2{}_{scanner}} \cong MTF^2{}_{camera} \qquad (2)$$

Note that, the modulation reduction produced by the imaging system is caused both by the optical components and the light sensitive sensor (CMOS). Resizing the input reference image to have the same pixel resolution as the output image means that the result of the comparison between the output and input signals will give information only regarding the loss in modulation produced by the optics. Resizing the input images produces a loss in resolution, and, if the input image is resized to the same dimension as the output image, then the size reduction has the same effect on the image that the CMOS sensor has on the signal projected onto it.

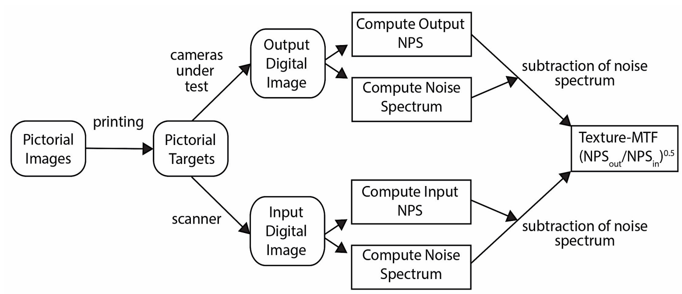

Figure 2: Outline of our methodology workflow.

Following digital image acquisition, all the images were cropped and linearized according to each system's OECF. The average size of the cropped images was 1045x1045 pixels, while the images of the dead leaves target (slightly smaller than the other targets) 800x800 pixels. Linearization was achieved via LUTs derived from measured densities and correspondent pixel values.

The MTF of each system was then computed for each test image according to the texture-MTF procedure developed for the dead leaves target [1]:

1. 2D planar de-trending of output image to reduce low frequencies bias [1];
2. computation of 2-D NPS as the square of the amplitude of the two-dimensional Discrete Fourier Transform (DFT) of the signal [20]:

$$S(u,m) = \left|\sum_{x=1}^{N/2}\sum_{y=1}^{N/2} I(x,y)e^{-2i\pi(mx+ny)}\right|^2 \qquad (3)$$

3. suppression of the zero frequency value;
4. radial averaging;
5. smoothing through 7 segments moving average;
6. steps 1-5 are repeated for image noise (derived either from uniform grey patch, or by subtracting the 'pure signal');
7. correction of computed signal NPS by subtracting image noise NPS [26];
8. steps 1-7 are repeated for the input reference image;
9. computation, frequency-by-frequency, of the square root of the ratio of corrected output and input NPS;
10. conversion of frequencies from cy/px to cy/mm (Canon 5D Mark II px pitch 0.0064mm, iPhone 6S: 0.00122mm)

Results

The proposed methodology produced MTF curves congruent with the MTF calculated from the dead leaves target, proving the robustness of our approach and confirming the suitability of the latter to represent an average natural texture. Fig. 5 shows MTF curves produced by each target for the Canon 5D Mark II.

The majority of the MTF curves have typical profiles, but there were exceptions. A few atypical MTFs, shown in Fig. 5b, were attributed to uncommon scene power spectra (Fig. 4). The *cloud*, *contrail* and *people* test images, produced, for both for the Canon 5D and the iPhone, very uncharacteristic curve shapes and a high level of irregular fluctuations. The *cloud* and the *contrail* have similar power spectra, which are characterised by minimal amounts of medium and high frequencies. As a consequence, it was predictable that the resulting MTFs would show little loss of modulation in the high frequencies. In other words, fine detail was already absent in the input signal, hence the relative difference between input power and output power spectra (in these frequencies) is very small. A small difference equals to a higher ratio, thus a higher MTF. The higher the power of a certain frequency in the input signal, the higher is the precision of measurement of the MTF for that frequency.

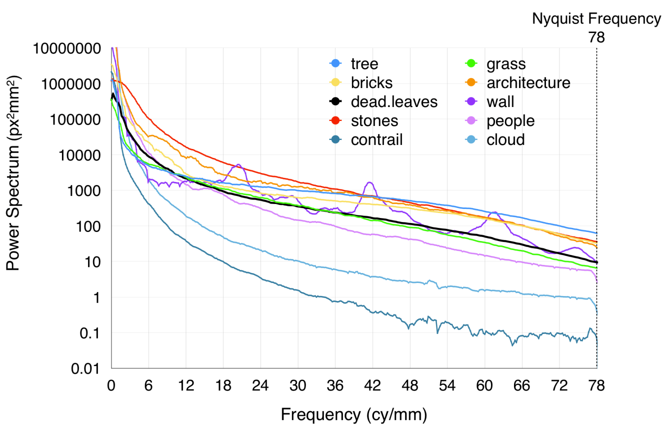

Figure 3: Input power spectra for each pictorial target (and dead leaves).

The *people* test image also produced a peculiar MTF curve. It is unclear how much of this unexpected behaviour is caused by noise and strong fluctuations in the input and output power spectra, but regardless of that, the two curves are very close for the whole frequency spectrum, suggesting very little loss of modulation in the imaging process (Fig. 6). Perhaps, the soft focus used for the portraits and out-of-focus background reduced substantially the fine detail content. Furthermore, the very fine detail on the faces (skin pores, eyelashes, etc.) have probably been smoothened in the resizing process that preceded the printing of the target, leaving mainly low and medium low frequencies in the test image itself.

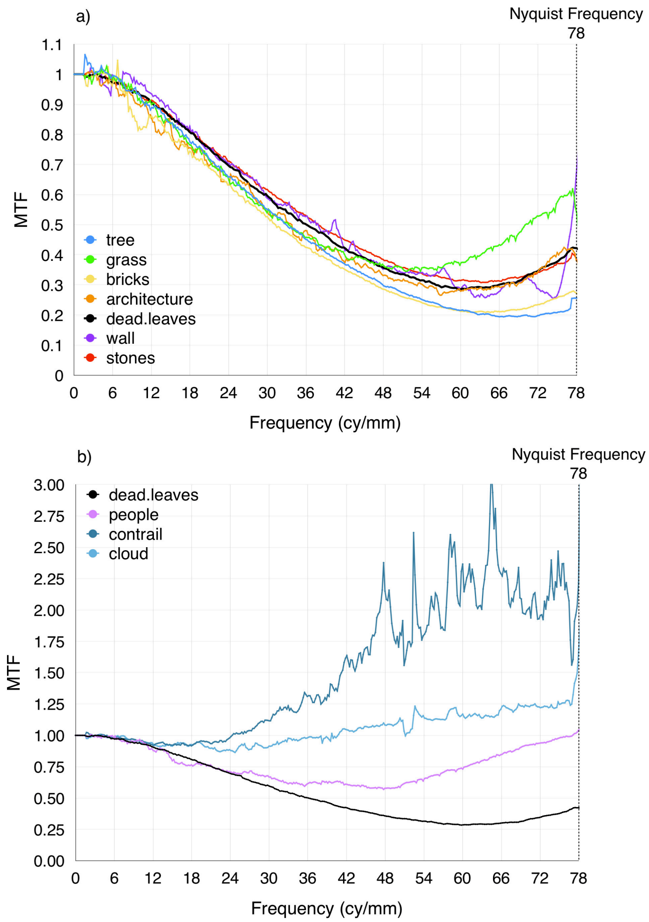

Figure 4: MTF curves produced using the dead leaves and all pictorial targets for the Canon 5D Mk II.

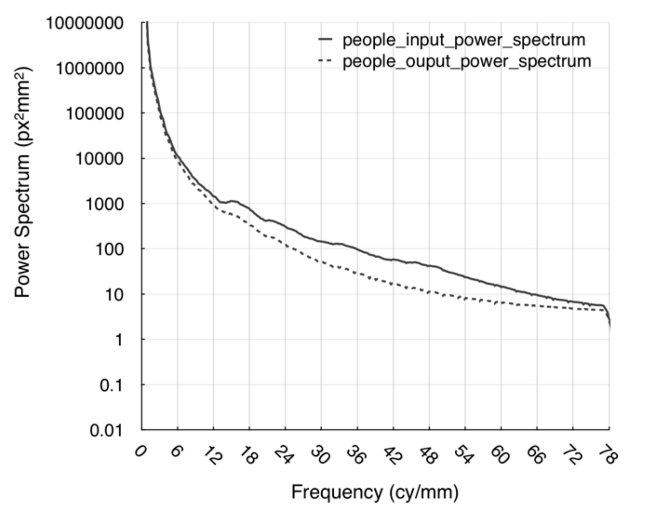

Figure 5: input and output power spectra of target 'people' shot with Canon 5D Mk II.

The MTF curves produced for the Canon DSLR by the remaining test images (*grass, tree, bricks, stones, wall* and *architecture*) are all very similar to the one produced by the dead leaves target, which seems to be an 'average' of all the computed curves. The similarity between the curves is an indication of the robustness of the method, i.e. printed pictures of natural and man-made real scenes can be used as targets for MTF measurements of an imaging system using the power spectrum analysis.

The *stones* test image produced an MTF that almost perfectly overlaps with that of the dead leaves, whereas *tree* and *grass* portray worse- and best-case scenarios regarding detail reproduction (Fig. 7).

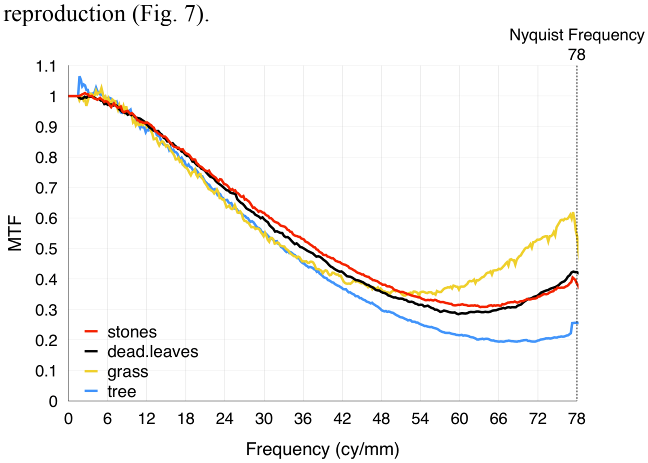

Figure 6:MTF curves produced by the dead leaves, stones, tree and grass targets shot with Canon 5D Mk II.

In the delineation of a hypothetical scene content that is for texture-MTF analysis we would therefore recommend natural or artificial textures that include high power in high frequencies. We found natural subjects to deliver smoother results due to the homogeneity of power distribution among all frequencies whereas artificial landscapes tend to have peaks for certain frequencies (ex. alternation of windows on a building or regular patterns) which may result in noisier curves – as for example the *wall* target (Fig. 8).

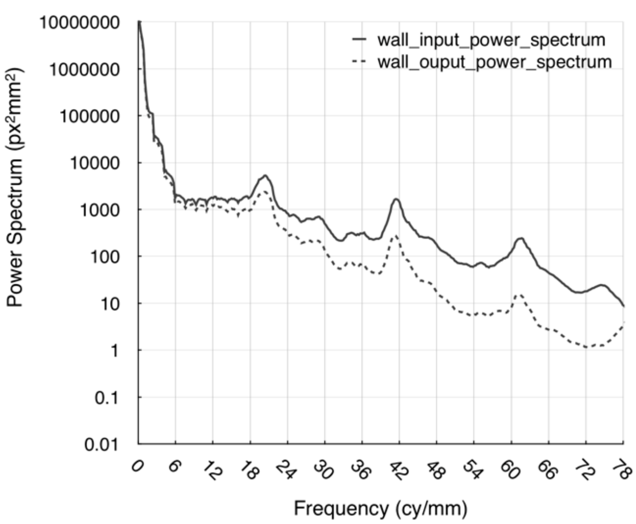

Figure 7: Input and Output power spectra for wall target shot with Canon 5D Mk II.

Regardless of small difference at the extremities of the spectrum, the majority of the test scenes (*grass, tree, bricks, stones, wall* and *architecture*) produced MTF curves that differed mainly in high frequencies, very close to the Nyquist frequency. This indicates negligible adaptive/non-linear processing has been applied to the RAW Canon image.

As expected, scene-dependent variations were found to be more important for the MTFs derived for the iPhone 6S camera (both dRAW and JPEG), due to the application of non-linear processes and scene-dependent compression (Fig. 9). This suggests that texture-MTFs derived from the dead leaves target may not be always representative of the system performance in real life scenarios, especially for automated systems like camera phones.

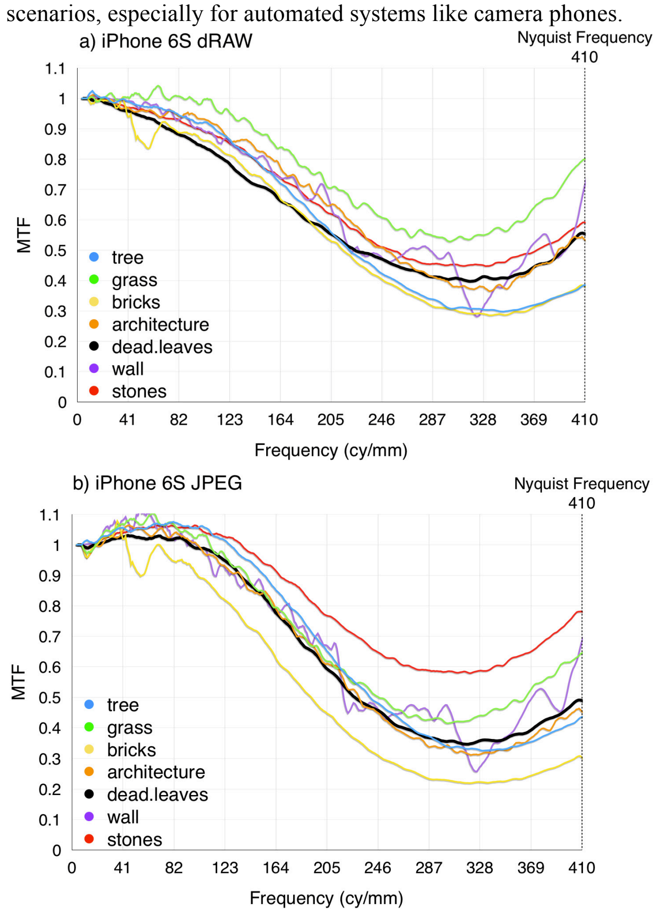

Figure 8: MTF curves for seven targets produced by images shot with a) iPhone 6S dRAW; b) iPhone 6S JPEG.

Variations of such magnitude between the iPhone MTF curves confirms that these pictorial images have been processed differently by the imaging system. Unlike the Canon system, where pictorial test images produced MTFs that differ only at high frequencies, MTF discrepancies here can be noticed at low frequencies as well. These discrepancies exceed the 4-6% relative error, characteristic of the dead leaves method [27]. The *grass* test image produced a curve showing a better system performance overall than the dead leaves, while the *tree* a better performance at low frequencies but poorer at high frequencies (Fig. 11).

Comparison of MTFs produced by dRAW and JPEG images of the same targets suggests that the big discrepancies between the curves are an effect of JPEG compression (Fig.10). Since the JPEG process, as well as the related artefacts, are scene dependent, their effect on the measured output power spectrum and resultant MTF are scene dependent too. Ringing and blockiness artefacts can easily be misinterpreted by the measuring algorithm and result in higher power spectra, and consequently in higher MTFs at high frequencies; of course the visual effect is not compatible [28] [29]. MTFs from JPEG images also have a characteristic hump at very low frequencies, produced by global and local contrast enhancements.

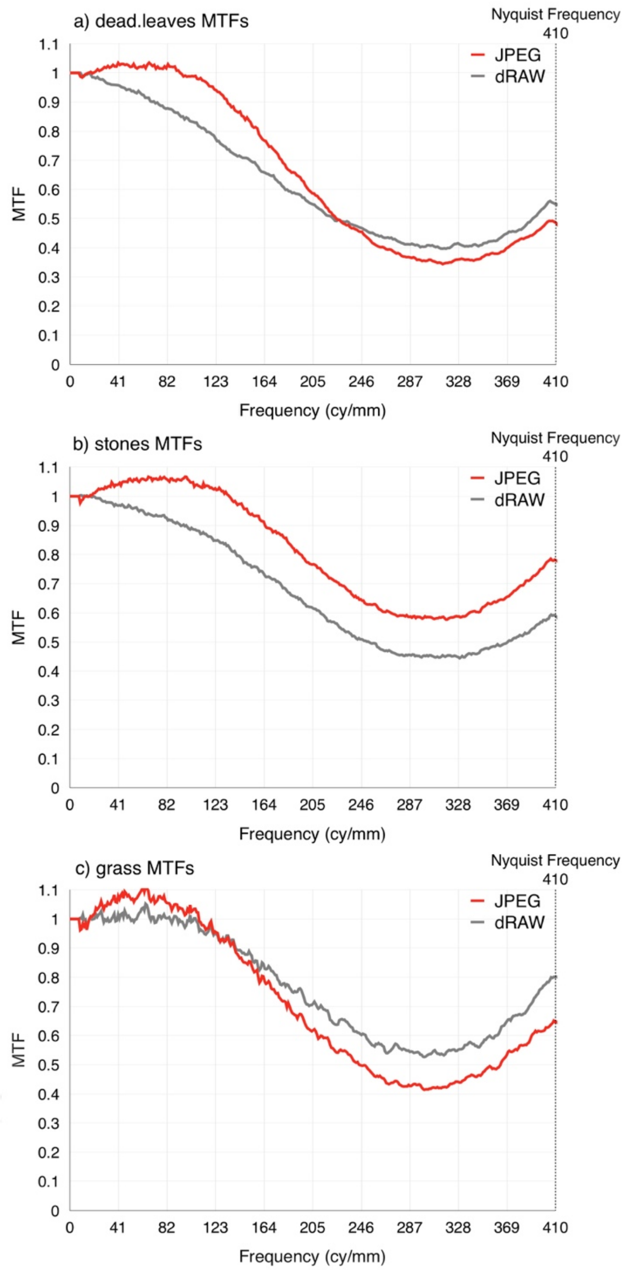

Figure 9: Comparison of MTF curves produced by iPhone 6S JPEG and dRAW images of the same targets.

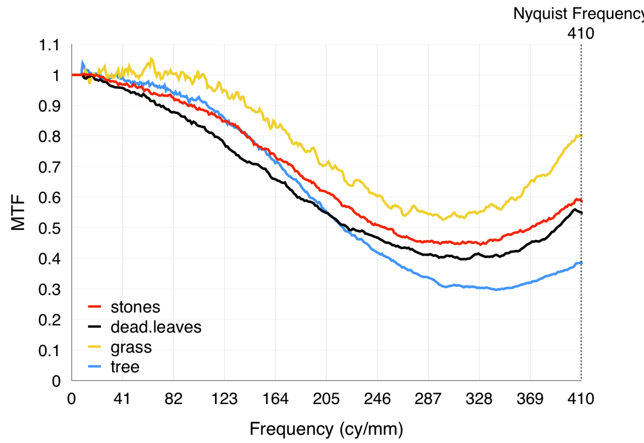

Figure 10: MTF curves produced by the dead leaves, stones, tree and grass targets shot with iPhone dRAW

All MTF curves derived for both Canon 5D and iPhone systems show the tendency to raise slightly at frequencies close to the Nyquist frequency. Increase in modulation at very high frequencies may be a consequence of aliasing, image interpolation, or fine noise, which have not been successfully removed in the measuring process with Mc Elvain *et al.* method [26].

Noise

A grey patch was also included next to the targets during test image capture, so that shot noise could be measured and detrended from the input signal, as described by Mc Elvain *et al.* [26]. We also tested an alternative noise measurement method based on subtraction of a 'pure signal' image (obtained through averaging of nine registered identical pictures) from one shot image. Note that, manual registration of the nine shots was found to be necessary despite the use of tripod and camera remote. Fig. 13 compares the MTF curves detrended from noise patterns that had been retrieved through two different methods i.e. noise obtained by subtraction of a pure (averaged) signal and noise obtained from a standard uniform grey patch included in each shot. Both methods led to almost identical results. We tested both systems in low noise conditions (average abundant light and low ISO setting).

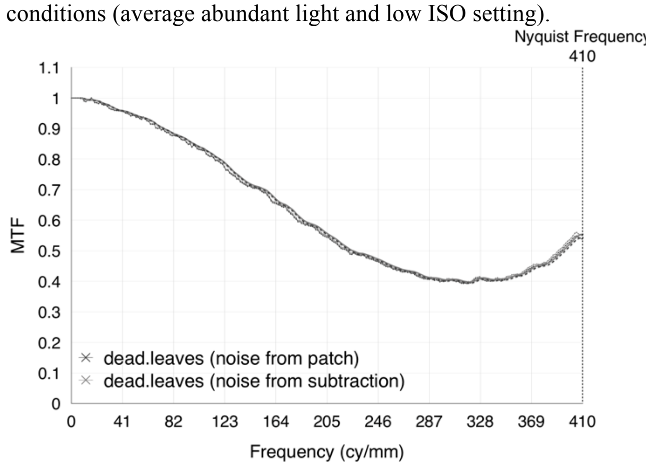

Figure 11: MTF curves obtained from the dead leaves target (shot with iPhone dRAW)

Conclusions

We developed and tested a new approach to the texture-MTF, typically measured with the dead leaves test target, which involves the use of pictorial test images portraying various natural and artificial textures. The method consisted of an extension of the traditional texture-MTF method based on a semi-reference of the system input and output NPS. We obtained MTF curves congruent with the dead leaves MTF for the majority of the test images, shot using minimum non-linear/content adaptive processes. However, there were test images with 'extreme' power spectra however, that produced atypical results.

Our results indicate that the dead leaves MTF can provide, in most cases, a representative system performance measure. Test images with high power in high frequencies were the most suitable test targets, since they allow a better estimate of the texture-MTF performance. Because of the way the MTF is retrieved from a semi-reference, errors or missing frequencies in the input signal lead to more optimistic measured MTFs. The curve relative to the cloud image, for example, is not erroneous but truly representative of the system performance with regards to that specific image. If some frequencies are missing in the input signal their power will not be degraded by the system and therefore the reproduction of that particular frequency for that particular image will be perfect, because there is nothing to reproduce.

Our proposed methodology allowed us to investigate the presence and behavior of scene dependent, automatic, non-linear processes. As expected, the MTF produced by the high-end phone camera with the different test images showed higher variability than the MTFs produced by the DSLR camera, with automatic processes switched off. A comparison between TIFF and JPEG camera phone captures allowed us to confirm that considerable scene dependent performance, and hence MTF variation, is due to compression.

On the basis of our findings we recommend including pictorial imagery in texture-MTF measurements – especially for automatic capturing systems - to retrieve realistic system performance information. We would not recommend recommend test images resembling the *cloud* image, for example, as the latter contains mainly low frequencies and thus its MTF curve gives information only on system performance for low frequencies. Information about low frequency reproduction can be retrieved already from images like the *tree*, *bricks* and *architecture*, which are characterized by high power at low frequencies and high frequencies.

We also employed an alternative method to using uniform patches to retrieve noise information, since local noise reduction filters could easily de-noise the image in automatic system processes. We took multiple shots of each image, registered and averaged them to retrieve a 'pure' signal image, and subtracted this from the noise. With the low levels of noise present in our test images, we found the two methods delivered compatible results. Further studies with increased noise levels could potentially explore differences in the two methods.

In future studies we aim at testing more scenes in order to better understand the relationship between scene content and system performance. Of interest is also to investigate correlations between scene-dependent MTF curves and perceived image sharpness.

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