Refined Measurement of Digital Image Texture Loss

Peter D. Burns
Burns Digital Imaging
Fairport, NY USA

ABSTRACT

Image texture is the term given to the information-bearing fluctuations such as those for skin, grass and fabrics. Since image processing aimed at reducing unwanted fluctuations (noise are other artifacts) can also remove important texture, good product design requires a balance between the two. The texture-loss MTF method, currently under international standards development, is aimed at the evaluation of digital and mobile-telephone cameras for capture of image texture. The method uses image fields of pseudo-random objects, such as overlapping disks, often referred to as 'dead-leaves' targets. The analysis of these target images is based on noise-power spectrum (NPS) measurements, which are subject to estimation error. We describe a simple method for compensation of non-stationary image statistics, aimed at improving practical NPS estimates. A benign two-dimensional linear function (plane) is fit to the data and subtracted. This method was implemented and results were compared with those without compensation. The adapted analysis method resulted in reduced NPS and MTF measurement variation (20%) and low-frequency bias error. This is a particular advantage at low spatial frequencies, where texture-MTF scaling is performed. We conclude that simple trend removal should be used.

Keywords: Imaging Performance, Image Quality, dead leaves analysis, texture MTF, trend removal, noise power spectrum

1. INTRODUCTION

The Modulation Transfer Function (MTF) is an established imaging performance metric that is well suited to certain sources of detail loss, such as optical focus and motion blur. As performance standards have developed for digital imaging systems, the MTF concept has been adapted and applied as the spatial frequency response (SFR). Measurement of the SFR is generally done using particular test target features such as edges [1, 2], repeating patterns of square or sign-waves. [3] However, the use of such special image features is challenged when the effective system characteristics vary with local image (scene) content. In some cases, for example when the processing of a test feature results in digital spatial processing that is different from that for natural scenes, the computed image quality measure may yield non-representative results. This has lead to the development of image quality methods that rely on computed test image content that in some ways resembles the ensemble of natural scenes. A proposed method to measure the capture and retention of image texture is the texture-MTF [4, 5]. This is based on the use of a computed image field comprising overlapping features, arranged at random. The most commonly used test target uses overlapping circles, and is referred to as a 'dead leaves' target.

2. DEAD-LEAVES MTF METHOD

The texture-MTF is a signal-transfer measure, based on the ratio of an output (processed image) measurement with the corresponding characteristic for the input target. The input target, as shown in Fig. 1, is intended to provide an image of pseudo-objects that would share general image characteristics with actual scenes. The image characteristic that is used to compute the signal transfer is the power-spectral density, also called the noise-power spectrum, of the dead-leaves field. An outline of the method is shown in Fig. 2.

A printed test chart that contains the dead-leaves element is captured by the digital camera being tested. For the resulting digital image the dead-leaves region is extracted and the noise-power spectrum is computed. The noise-power spectrum is a well-established statistical measure that is applied to imaging and other signal-processing applications. For a stochastic process the NPS is the Fourier transform of the autocovariance function. It expresses signal fluctuations (the variance) in terms of frequency components. As applied to imaging, the NPS is a two-dimensional function of spatial frequency. As for any statistical parameter, computing of the measured NPS from the digital image is normally regarded as estimating the underlying parameter. A common NPS estimate is the periodogram, which is used in the texture-MTF measurement, and discussed in more detail below.

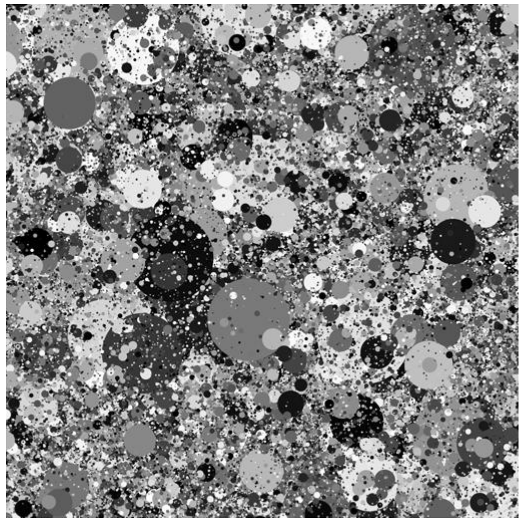

Figure 1: Dead-leaves test target

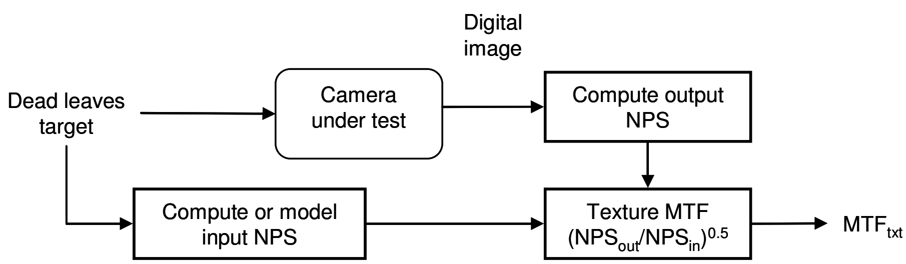

Figure 2: Outline of steps in the texture-MTF measurement

Continuing with Fig. 2, the texture-MTF is computed from the square-root of the ratio of the input (target) to output NPS. Although not always stated, the idea of using the signal spectrum to derive an effective MTF has its roots in linear systems analysis. Consider a stochastic signal (noise field) g having a noise-power spectrum $S_g(u,v)$ as an input to a linear system, characterized by an MTF, $M(u,v)$. If the input-output relationships are governed by the linear convolution equation, then the corresponding output noise-power spectrum is [6, 7]

$$S_f(u,v) = MTF^2(u,v)S_g(u,v) \, . \tag{1}$$

Equation (1) can be solved for $MTF(u,v)$. So if we measure S_f and S_g we can estimate an effective MTF based on the statistics of noise image fields. In this way, Fig. 2 represents an outline for an NPS-based MTF measurement that could be applied to various stochastic image fields. The development of practical standard methods, however, requires a more detailed recipe.

Over the last few years this basic method has been developed, and various steps have been added to make the method more reliable and accurate. In addition the details of the method that have been reported have evolved. The currently used procedure is as follows. [8]

1. Transform the captured image array of the target field to one encoded as proportional to luminance. This requires measurement of the camera Opto-Electronic Conversion Function (OECF).
2. Compute the noise-power spectrum as the square of the amplitude of the two-dimensional Discrete Fourier Transform (DFT) of the dead-leaves image region.

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

where the (N x N) luminance image array data are, $I(x, y)$, corresponding to the dead leaves region.

3. Compute the one-dimensional noise-power spectrum vector by a radial-average of this array, $P_d(v)$, where $v = (m^2 + n^2)^{0.5}$, and the radial frequency index, $v = 1, 2, ..., v_{\max}$.
4. Perform steps 2 and 3 for image noise that is estimated from an image region corresponding to a uniform 50% (reflectance) target step to obtain the NPS of the noise. $P_n(\nu)$ is the spectrum measured from this step, computed in the same way as Eq.(2) and scaled to remove the effect of different data array sizes.
5. This computed dead-leaves spectrum is corrected for image noise by subtraction

$$P_d^{'}(\nu) = P_d(\nu) - P_n(\nu). \tag{3}$$

6. Divide this array, frequency-by-frequency, by the modeled, or measured, spectrum for the specific target to yield a vector as the square of the effective MTF.

$$S(\nu) = \frac{P_d^{'}(\nu)}{T(\nu)}, \tag{4}$$

where $T(\nu)$ is the spectrum of the input target

7. Compute the square-root, frequency-by-frequency, of this array,

$$MTF_{txt}(\nu) = \sqrt{S(\nu)}. \tag{5}$$

8. Scale this vector to guarantee that it approaches 1.0 at low frequencies. Sometimes this is done by selecting a very low, non-zero frequency, such as 0.02 cy/pixel.
9. A summary measure, acutance, is computed by weighting the texture-MTF by a visual contrast sensitivity function (CSF). The texture acutance is computed as,

$$A_{ref} = \sum_{v=1}^{v\max} CSF(v), \qquad A = \sum_{v=1}^{v\max} MTF_{txt}(v) M(v) CSF(v) \tag{6}$$

where *M* is the modeled display MTF. The acutance is,

$$\text{acutance} = \frac{A}{A_{ref}}. \tag{7}$$

Note that the above procedure differs from some previously descriptions, e.g. [9, 10], where the radial integration step 3, was performed after (two-dimensional) MTF had been computed in step 7.

3. MEASUREMENT VARIATION

The texture-MTF relies on the estimation of component second-order image statistics, the input and output noise-power spectra. Statistics that are based on data that have stochastic components, such as randomly-placed objects, can be seen themselves as random variables. As such they are prone to variation and error. We are normally interested in minimizing such variation when we select data sets, testing conditions and any signal processing such as filtering or data fitting. We now address a straightforward approach aimed at improving the underlying NPS estimates.

3.1 Non-stationary Statistics

The noise-power spectrum is a second-order parameter of a stochastic process. A stochastic process is a set, or function, of random variables. For digital imaging applications our input data are recorded pixel values and their interpretation in a signal-space. In most cases the estimates used for image signal and noise analysis assume locally stationary statistical parameters, such as mean and variance. For practical system testing, however, recorded imaging characteristics can vary with field position.

Consider the optics for many compact and mobile-telephone cameras. The requirement of a thin device puts constraints on the image-forming optical elements. This results in a variation, roll-off, in exposure across the optical field particularly approaching the corners. While image processing operations in the camera attempt to compensate for this, residual fall-off often remains. In addition, the underlying exposure-dependent image noise variation can result in relatively higher noise levels at the corners compared to those for the center.

To understand the influence of such field-dependent behavior on noise estimates, we consider the sample variance. This is an element in almost all image noise analysis. Given a set of observations $\{x_i\}$, the variance estimate is

$$s = \frac{1}{N}\sum_{i=1}^{N} \Delta x_i^2 \ , \tag{8}$$

where Δx_i is the difference between each value and the constant sample mean. This assumes that the population mean and variance are not changing over the interval when the data were collected. If the observed data contain a non-constant trend, which we model here as the addition of a function, f then the observed data are

$$x_i^{'} = x_i + f_i \ , \tag{9}$$

then the sample variance will include the positive bias,

$$E[s] = \sigma_x^2 + \frac{1}{N}\sum_{i=1}^{N} f_i^2 \ . \tag{10}$$

$E[s]$ is the expectation, or long-term average and $\{f_i\}$ the set of sampled trend function values.

The non-stationary mean introduces a positive bias into the sample variance. The influence on the estimated NPS, however, is not uniform. Since the trends tend to be slowly varying across the image field, the bias that is introduced is greater at low spatial frequencies.

4. TWO-DIMENSIONAL TREND REMOVAL

In order to investigate the impact of non-stationary image statistics on NPS measurement used in the texture-MTF measurements, a simple two-dimensional trend removal operation was introduced into the procedure.[†] This was done for both the data sets for the dead-leaves and noise regions prior to computing the NPS. In order to avoid distorting the measurements by removing 'signal' fluctuations, we limited the correction to the subtraction of a two-dimensional linear (plane) fit to each data set.

4.1 Noise-power Spectrum results

Results for the observed reduction in the NPS for a noise region are shown in Fig. 3. These were computed from images from a digital camera with an ISO setting of 1600. Prior to computing the NPS the data were expressed as relative input exposure to the detector. The data range, therefore was [0, 1], which is also seen as the reflectance (factor) values for the printed target. In addition, scaling of the NPS estimate was computed so as to be consistent with normal imaging practice, yielding a conventional power spectral density, rather than the simple two-dimensional Discrete Fourier Transform (DFT) of Eq. (2).

[†] Details of a Matlab function for the 2-D polynomial fitting and trend removal are available from the author.

$$U(m,n) = \frac{1}{(dxN)^2} \left| \sum_{x=N/2+1}^{N/2} \sum_{y=N/2+1}^{N/2} I(x,y) e^{-2i\pi(mx+ny)} \right|^2, \tag{11}$$

where dx is the data sampling interval, which we expressed in pixels, i.e. $dx = 1$ pixel. The frequency sampling of the power spectrum estimate is therefore, $df = 1/(dx\,N)$ cycles/pixel. An advantage of this form of the power spectral density is that the result does not scale with the size of the data array used. As we see from Fig. 3, the linear trend removal resulted in a significant reduction in the measured NPS at low spatial frequencies.

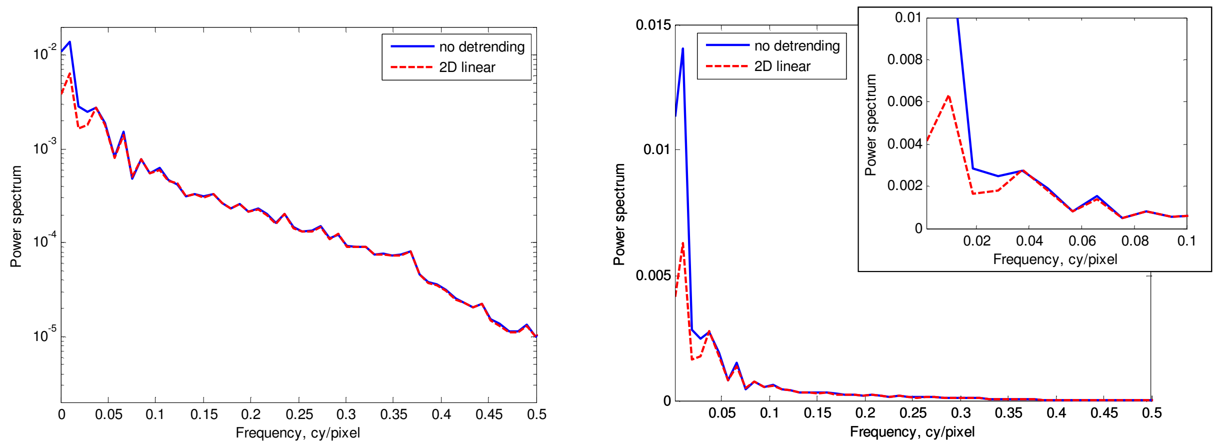

Figure 3: NPS for uniform (noise) region, with and without 2D linear trend removal for a digital camera (ISO 1600)

Perhaps a more important challenge is the trend removal from the dead leaves data set. The pixel-to-pixel signal variation is intentionally high, and going into this experiment, it was not obvious that the trend removal would have a significant impact on the results. Figure 4 presents the results for the same camera and setting. When plotted in the conventional way on semi-log axes, the differences in computed NPS are subtle. However, as the right-hand plot shows, we observed differences of 5% at low frequencies.

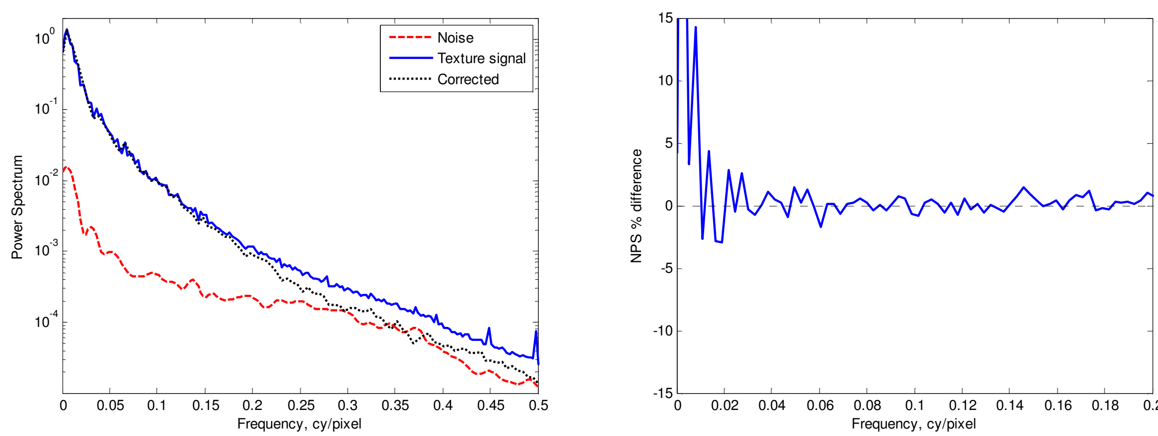

Figure 4: Results for the noise-corrected dead leaves NPS, with and without 2D linear trend removal. Left is the computed signal spectrum with removal. Right is the % difference due to trend removal. Results are for a digital camera (ISO 1600).

4.2 Texture-MTF Results

Having demonstrated the results for the NPS, we now present results for the corresponding texture-MTF. This was computed multiple times by replicating all elements in the method, including data region selection, and trend fitting. The MTF estimate is based on measured input and out noise-power spectra. Results for five replicate measurements for each treatment (with and without trend removal) are shown in Fig. 5. The error bars are for plus and minus one standard deviation for each individual measurement. Note that the measurement-to-measurement variation is less when trend removal is applied. The mean relative error reduction due to trend removal, averaged over all spatial frequencies [0, 0.5 cy/pixel] was 20%. For a lower frequency range [0, 2.5 cy/pixel], the reduction was by 26%.

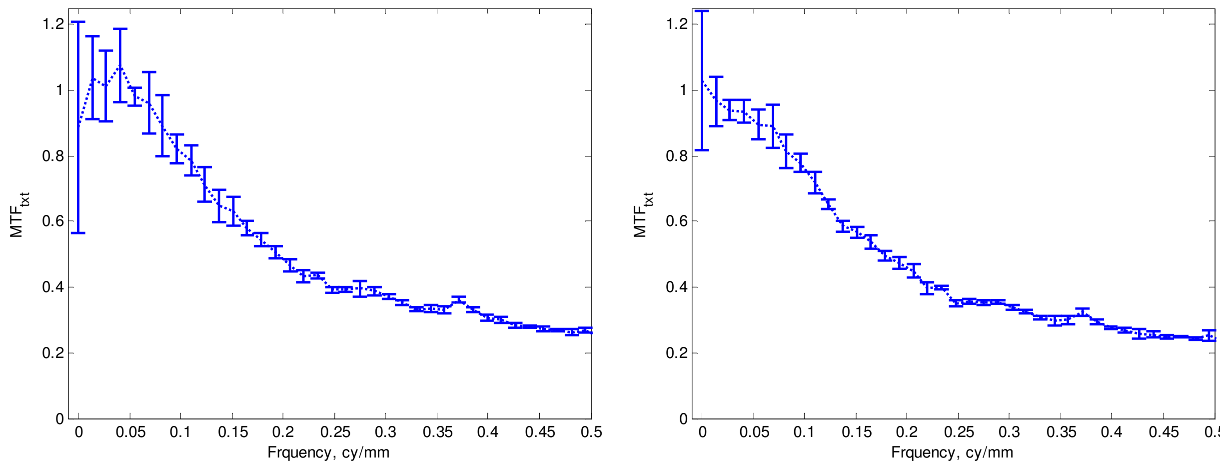

Figure 5: Texture-MTF measurement variation based on five replicates. Left without trend removal and the right is with 2D-linear fit and subtraction. Final scaling was done at 0.02 cy/pixel.

5. CONCLUSIONS

The texture-loss MTF method uses image fields of pseudo-random objects, such as overlapping disks. The method is based on component noise-power spectrum measurements, which are subject to estimation error. Our simple method for compensation of non-stationary image statistics is aimed at improving these NPS estimates. A two-dimensional linear function (plane) is fit to the data array, and subtracted prior to estimating the noise-power spectra. This was implemented and compared to current practice for texture-MTF evaluation. The adapted analysis method resulted in reduced NPS and MTF measurement variation (20%) and low-frequency bias error. Measurement improvement in this frequency-region is important because it is where texture-MTF scaling is performed. We conclude that simple trend removal should be used.

Acknowledgements

Many thanks to several the members of the I3A CPIQ initiative and ISO/TC42 teams for their discussions, in particular Uwe Artmann, Donald Baxter, Frédéric Cao, Herve Hornung, Don Williams and Dietmar Wueller.

REFERENCES

[1] ISO/TC WG18, [Photography – Electronic still picture cameras – Resolution measurements], ISO, (1998).

[2] Burns, P. D., “Slanted-Edge MTF for Digital Camera and Scanner Analysis”, Proc. PICS Conf., IS&T, 135-138 (2000).

[3] Loebich, C., Wüller, D., Klingen, B., Jäger. A., “Digital Camera Resolution Measurement Using Sinusoidal Siemens Stars,” Proc. SPIE 6502, 6502N (2007).

[4] Cao, F., Guichard, F., and Hornung, H., “Measuring texture sharpness of a digital camera,” Proc. SPIE 7250, 72500H (2009).

[5] Artmann, U. and Wueller, D., “Differences of digital Camera Resolution Metrology to Describe Noise Reduction Artifacts,” Proc. SPIE 7529, 7529L (2010).

[6] Dainty, C, J, Shaw, R., [Image Science], Academic, NewYork, 277 (1974).

[7] Goodman, J, W., [Statistical Optics], Wiley, New York, 68-74 (1985).

[8] Unpublished and separate e-mail communications with, F. Cao, U. Artmann and D. Williams (2012).

[9] Burns, P. D., “Estimation error in image quality measurements,” Proc. SPIE 7867, 78670H (2011).

[10] Burns, P. D. and D. Williams, “Measurement of Texture Loss for JPEG 2000 Compression,” Proc. SPIE 8293, 82930C (2012).