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RAW Image Quality Evaluation Using Information Capacity

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Abstract

In this article, we propose a comprehensive objective metric for estimating digital camera system performance. Using the DXOMARK RAW protocol, image quality degradation indicators are objectively quantified, and the information capacity is computed. The model proposed in this article is a significant improvement over previous digital camera systems evaluation protocols, wherein only noise, spectral response, sharpness, and pixel count were considered. In the proposed model we do not consider image processing techniques, to only focus on the device intrinsic performances. Results agree with theoretical predictions. This work has profound implications in RAW image testing for computer vision and may pave the way for advancements in other domains such as automotive or surveillance camera.

Introduction

Due to the ever-evolving nature of image processing techniques and applications, it becomes essential to have a reliable methodology to evaluate digital camera RAW performances. Indeed, despite improving image processing techniques applied to photography, the better a RAW image is, the better the final processed image will be. Consequently, there is a need from camera manufacturers to compare intrinsic performances of camera modules with different resolutions, different sensor sensitivities, and different optics.

To this end, manufacturers perform imaging system evaluation on processed and compressed images by considering a variety of metrics each related to a single type of image degradation. The challenge is to provide a single scalar metric by aggregating all these metrics, which would allow the manufacturer to rank devices with very different performances.

The goal of this article is to present a novel comprehensive metric designed to reliably assess the quality of a digital camera hardware. This metric provides the user with data on the lens and sensor performance of a given device. More precisely, performance is quantified with the amount of information available for each pixel of the image and for the entire image. This metric is named *Information Capacity* (IC). Knowing the pixel count and the bit depth of a sensor, one can easily compute the maximum achievable information. This maximum amount of information is impacted by some degradation indicators. The challenge is to measure these degradation indicators and see their impact on the information capacity. Thus, measurement protocols for each type of degradation are rigorously defined and executed.

Our method is based on theoretical analysis of the impact of degradation indicators on the information capacity. Techniques are known to assess sensor image quality by observing the impact of the blur, the spectral response, the noise, and the pixel count on the module's information capacity. In this work, we extent our model by considering the following degradation indicators: geometrical distortion, loss of sharpness in the field, vignetting and color lens shading. The impact of these degradation indicators on the information capacity is in general not trivial. We therefore chose the approach of assuming that every other degradation is corrected using an ideal enhancement algorithm and then evaluating how the correction impacts noise, color response, MTF, and pixel count as a side effect.

The idea of using Shannon's Information Capacity [1] as a measure of potential image quality of a digital camera is not *per se* new. In our previous work [2, 3] however, we have estimated information capacity under the assumption that it depended only on the noise characteristics, the color response, the blur, the and pixel count. In the model we propose here, we extend this model with many new degradation indicators. Furthermore, most degradation indicators do not stay the same within the image field. Thus, we have relaxed the assumption that degradation indicators are constant in the field and effectively integrate them in the information capacity estimation.

In his recent work, Koren [4] also proposed to use Shannon's information capacity as a figure of merit for predicting camera performance. However, while our work focuses on unprocessed RAW images, Koren's work addresses the case of processed JPEG and minimally processed TIFF images. This requires a different approach, as the noise needs to be measured jointly to the image signal, rather than in a separate location, since image processing may be different. To achieve this, the author estimates the signal level –which is proportional to the MTF– and the noise on a single shot of the sinusoidal Siemens Star chart. This work shows interesting results, but due to the limitation imposed by the processing applied to the images, only takes into account few and *ad-hoc* degradation indicators. Working with unprocessed images freed us from the need to measure every indicator on a single shot, thus allowing us to include more indicators, all measured in a well-known way and independently interpretable.

Other interesting results in producing a single scalar metric to encompass the effects of several degradation types (SNR, MTF, *etc.*) has been recently proposed by Jenkin [5]. Unlike our approach however, Jenkin's assumes a reference application for the captured image, namely object recognition in an automotive context. This allows the author to focus on meaningful predictors of overall performance, such as Contrast Detection Probability. A similar approach has been proposed by Kane [6], always in the context of detection in automotive imaging, considering the SNR of an Ideal Observer (or SNRI). In our work we have instead elected to maintain our framework agnostic with respect to the final application for the images taken by the system under test.

Proposed Framework

We assume that the information capacity of a single pixel in the center of the image can be expressed as $I = \text{CS} - \|\Delta s\|$, where CS is the color sensitivity in bits and Δs is the optical loss of information in bits, defined as

$$\Delta s = \int_0^{f_{\mathrm{Ny}}} \max\left\{\log_2 \circ \mathrm{MTF}(f);\ -b\right\} \mathrm{d}f,$$

with f_{Ny} the Nyquist frequency and b the number of bits per pixel (or *depth*) of the sensor.

Within this model, the information capacity is completely determined by the noise curve of the sensor, its color response, and the MTF of the lens [2]. If all considered degradation indicators are constant within the image field, then the total information capacity of the sensor will be the information carried by the central pixel times the total number of pixels on the sensor.

In this work, we relax this assumption and study the effect of a varying *Information Density* (ID) in the field.

Information Density in the Field

The first consideration is that the information density I is in fact a function of the position in the field if we consider in our model the following well-known degradation indicators:

- Vignetting
- Color Lens Shading
- Loss of Sharpness in the Field
- Geometrical Distortion

For all these degradation indicators, we have decided to make the approximation of using a radial model, which generally describes rather well these optical phenomena. While some slight deviation from a radial model is to be expected, as long as the value for each radius is taken as the average over the circle of that radius, the total information capacity for the image does not change. We therefore posit $I = I(r)$; in the following, we shall see the role that each degradation plays in the computation of the ID.

As mentioned above, the original model [2] was able to determine the information capacity of the sensor using only noise, color response, and MTF. The impact of other degradation indicators on the information capacity are in general not as well known or well modeled. We therefore chose the approach of imagining that every other degradation is corrected using an ideal enhancement algorithm and then evaluating how the correction impacts noise, color response, and MTF (and therefore the local information density) as a side effect.

Impact of Vignetting and Color Lens Shading on CS

Color Sensitivity (CS) is the number of reliably distinguishable colors up to noise. Roughly speaking, two colors are considered distinguishable if their difference is larger than the noise level. CS is therefore dependent on both the noise curve $\sigma(x)$ of the sensor and its white balance scales $\overline{\lambda}_0 = (\lambda_R; \lambda_B)$.

In the raw image, one of the effects of the lens is that the three channels R, G, and B are attenuated in the corners with respect to the center. However, rather than looking at the three channels separately, it is customary to analyze this phenomenon in terms of luminance and chrominance. We can therefore define a vignetting $V(r)$ and a color lens shading $S(r)$ as follows:

$$V(r) = \frac{G(r)}{G(0)},$$
$$\overline{S}(r) = \left(\frac{R(r)}{G(r)}; \frac{B(r)}{G(r)}\right).$$

Intuitively, we can interpret vignetting and color lens shading as a reduction of the amount and a shift in color respectively of the incoming light. The former translates in a decrease in SNR (because fewer photons are received), which becomes an increase in noise when vignetting is corrected. The latter translates in a change in illuminant that can be corrected using a different white balance. We can thus define:

$$\sigma_r(x) = \sigma\left(\frac{x}{V(r)}\right) \approx \frac{\sigma(x)}{\sqrt{V(r)}},$$
$$\overline{\lambda}_r = \left(\lambda_R \frac{R(r)}{G(r)}; \lambda_B \frac{B(r)}{G(r)}\right) = \overline{\lambda}_0 \odot \overline{S}(r).$$

Where in the first equation we assumed that the sensor is working in photonic regime, thus PRNU and dark current can be ignored. These two quantities allow us to evaluate the color sensitivity $\mathrm{CS}_r = \mathrm{CS}\left(\sigma_r, \overline{\lambda}_r\right)$ in a generic point of the field.

Impact of Loss of Sharpness in the Field on MTF

Optics tend to be sharper in the center and softer in the corners. For this reason, the MTF is typically computed at several points in the field at once. While in general a measurement of the MTF is not available for every point of the field, we assume that the variation is sufficiently well-behaved that we can safely interpolate its values for any point where a measurement is not available. Notice that while in real life this variation is not perfectly radial, in most cases we can safely assign a function $\mathrm{MTF}_r(f)$ to a distance r from the center by averaging the MTF of all points at that distance.

Impact of Geometric Distortion on MTF

Geometric distortion can be modeled as a variable focal length in the the field. As usual, we assume that the tangential variation is negligible and we denote the radial focal length as $\mathscr{F}(r)$. Let us consider the local magnification introduced by the non-uniformity of the focal length, $m_r = \frac{\mathscr{F}(r)}{\mathscr{F}(0)}$. We suppose that the distortion is smooth enough that at the scale of the PSF it can be assumed constant. In practice, this means that we assume that the PSF of the corrected image will be magnified but will retain its shape (while in reality it will be very slightly elongated in the sagittal direction). Under these assumptions, using the scaling property of the Fourier transform, the loss of information in the field can be written as:

$$\Delta s(r) = \int_0^{f_{\mathrm{Ny}}} \max\left\{\log_2\left(m_r \mathrm{MTF}\left(m_r f\right)\right);\ -b\right\} \mathrm{d}f,$$

with $\mathrm{MTF}(m_r f) = 0\ \forall f > f_{\mathrm{Ny}}$.

Combined Impact of All Degradation Indicators

Considering all degradation indicators, the information density becomes:

$$I(r) = \mathrm{CS}_{\sigma_r, \overline{\lambda}_r} - \left\| \int_0^{f_{\mathrm{Ny}}} \max\left\{\log_2\left(m_r \mathrm{MTF}_r\left(m_r \cdot f\right)\right);\ -b\right\} \mathrm{d}f \right\|.$$

Total Information Capacity

In absence of geometric distortion, each pixel on the sensor contributes its density to the total information capacity. While this may be true under hypothesis of a perfect lens, it no longer holds in presence of a geometric distortion and its corresponding correction. This is because the correction of a distorted image is no longer rectangular and needs to be cropped in order to be stored. Thus, some of its pixels will not end up in the final image and will not contribute to the total information capacity. Rather than a mere crop, the distortion correction might include some form of interpolation to fit the original number of pixels of the distorted image. However, the interpolated pixels are a combinations of those already in the image and thus they cannot increase the total information. Given the information density $I(r)$, we write the total information capacity as:

$$C = \int_0^{+\infty} r \int_0^{2\pi} \mathbf{1}(r,\theta) \cdot I(r)\, \mathrm{d}r\, \mathrm{d}\theta, \tag{1}$$

where $\mathbf{1}(r,\theta)$ is 1 if the pixel $\overline{p}$ of polar coordinates $(r;\theta)$ will be included in the final corrected image and zero otherwise. Notice that by radial symmetry we always have that

$$\int_0^{2\pi} \mathbf{1}(r,\theta)\, \mathrm{d}\theta = 4 \int_0^{\frac{\pi}{2}} \mathbf{1}(r,\theta)\, \mathrm{d}\theta,$$

and can therefore rewrite Eq. 1 as:

$$C = 4 \int_0^{+\infty} r \cdot A(r) \cdot I(r)\, \mathrm{d}r,$$

where

$$A(r) = \int_0^{\frac{\pi}{2}} \mathbf{1}(r,\theta)\, \mathrm{d}\theta$$

is a function that for every distance r from the center of the image tells us the number of pixels at that distance that will be included in the final image. For reasons that will be clear in the following, we call $A(r)$ the *Arc Function* of distance r.

Arc Function of an Undistorted Image

For an image without distortion, the value of $\mathbf{1}(r,\theta)$ is determined exclusively by whether the point $\overline{p}$ is included in the rectangle $\left[0; \frac{W}{2}\right] \times \left[0; \frac{H}{2}\right]$, where W and H denote the image width and height respectively. In the following we shall assume without loss of generality that $W > H$, *i.e.*, we consider the image in landscape orientation. Let us also be $D = \sqrt{W^2 + H^2}$ the length of the image diagonal. All points that satisfy this condition lay on the arc of radius r that fits in a quadrant of the image (see Fig. 1). Since these arcs are connected, for each r, $\mathbf{1}(r,\theta)$ must be 1 in a compact interval $[\theta_{\min}(r); \theta_{\max}(r)]$, thus

$$A(r) = \int_{\theta_{\min}(r)}^{\theta_{\max}(r)} \mathrm{d}r = \theta_{\max}(r) - \theta_{\min}(r),$$

By definition of radian, $A(r)$ is therefore the length of the above mentioned arc divided by its radius. To determine values of $\theta_{\min}(r)$ and $\theta_{\max}(r)$, we identify the following cases: 1) $0 \le r \le \frac{H}{2}$; 2) $\frac{H}{2} < r \le \frac{W}{2}$; 3) $\frac{W}{2} < r \le \frac{D}{2}$; $r > \frac{D}{2}$. Each arc will intersect the perimeter of the first quadrant of the image. We denote L the first

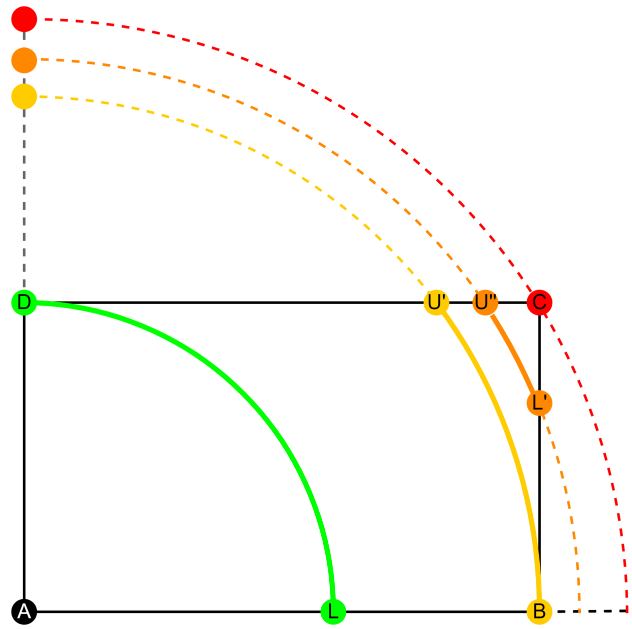


Figure 1. For each radius r, $A(r)$ is the length in radians of the corresponding solid arc.

and U the second intersection point in positive Cartesian order (see Fig. 1).

It can be shown, by considering each case, that that the complete form of $A(r)$ in the case of undistorted images, parametric with respect to W and H, is:

$$A_0(r, W, H) = \begin{cases} \theta_{\max}(r) - \theta_{\min}(r) & \forall r < \frac{D}{2} \\ 0 & \text{otherwise} \end{cases}$$

with

$$\theta_{\min}(r) = \begin{cases} 0 & \forall r \le \frac{W}{2} \\ \arccos \frac{W}{2r} & \text{otherwise} \end{cases}$$

$$\theta_{\max(r)} = \begin{cases} \frac{\pi}{2} & \forall r \le \frac{H}{2} \\ \arcsin \frac{H}{2r} & \text{otherwise} \end{cases}$$

Arc Function for a Distorted Image

First of all, let us model our distortion (and distortion correction). As always, we assume that the distortion is perfectly radial. This mean that in polar coordinates the phase θ of each point is unchanged, while its radius r is scaled by the magnification factor m_r: $\overline{p}_{\text{scene}} = (r;\theta) \longrightarrow \overline{p} = (m_r r;\theta)$.

In order to correct this distortion we therefore need to introduce a quantity $\omega_r = \frac{1}{m_r}$, that we call *correction warp*, to apply the inverse scaling: $\overline{p} = (r';\theta) \longrightarrow \overline{p}_{\text{corrected}}$, with:

$$\overline{p}_{\text{corrected}} = (\omega_r r';\theta) = (\omega_r m_r r;\theta) = (r;\theta) = \overline{p}_{\text{scene}} \tag{2}$$

However, in Eq. 2 we neglected the fact that, as a result of a radial distortion on a rectangular sensor, $\overline{p}$ forms a pseudo-image that is not rectangular and needs to be cropped. In order to study the impact of this crop on the arc function, we need to distinguish the different types of distortion, starting from the well-behaved cases of barrel distortion and pincushion distortion (see Fig. 2).

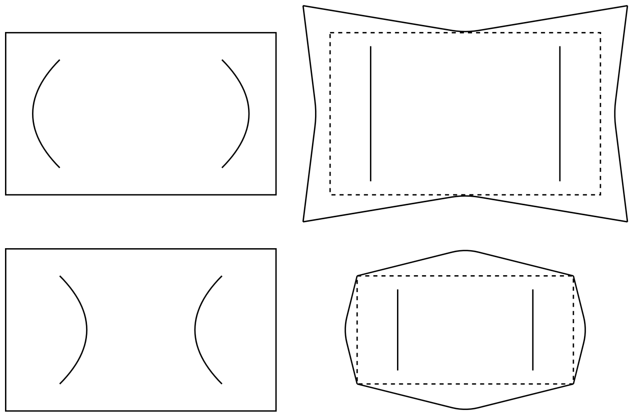
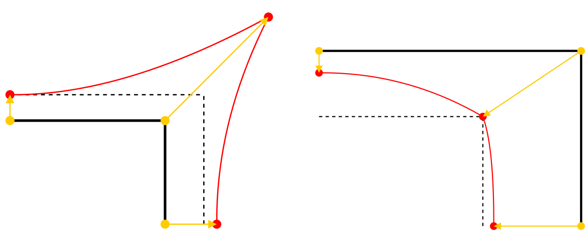


Figure 2. *Distorted image (left), corrected pseudo-image (right, solid) and final crop (right, dashed) for barrel (top) and pincushion (bottom) distortion.*



(a) Barrel Correction (b) Pincushion Correction

Figure 3. *Correction of barrel (a) and pincushion (b) distortion and relative crop.*

Barrel Distortion In case of barrel distortion, magnification decreases with r, therefore warping will increase with r and the image will be mapped into a concave pseudo-image (see Fig. 3a) that needs to be cropped into a rectangle. Here we assume that the crop taken will be the largest rectangle with the same aspect ratio as the original image that fits within the pseudo-image. Notice that in practice most distortion correction software will actually take a smaller crop, since the pixels close to the border will often have very low quality. However, they will always have a non-negative (albeit low) information capacity and we therefore include them in our calculation.

Since $\frac{\partial \omega_r}{\partial r}(r) > 0 \forall r > \varepsilon$ and $W > H$, the scale between uncorrected and cropped image will be given by $\omega_{\frac{H}{2}}$, thus the size of the cropped image will be $\omega_{\frac{H}{2}} \cdot W \times \omega_{\frac{H}{2}} \cdot H$. The arc function for a barrel distorted image will therefore be:

$$A_+(r, W, H) = A_0\left(\omega_r r,\, \omega_{\frac{H}{2}} W,\, \omega_{\frac{H}{2}} H\right) = A_0\left(\frac{\omega_r}{\omega_{\frac{H}{2}}} r, W, H\right).$$

Pincushion Distortion In case of pincushion distortion, magnification increases with r, therefore warping decreases with r. Since the warped pseudo-image is convex, the scale between uncorrected and cropped image will be given by the warp of its diagonal and will be $\omega_{\frac{D}{2}}$ (see Fig. 3b). The arc function for a pincushion distorted image will therefore be:

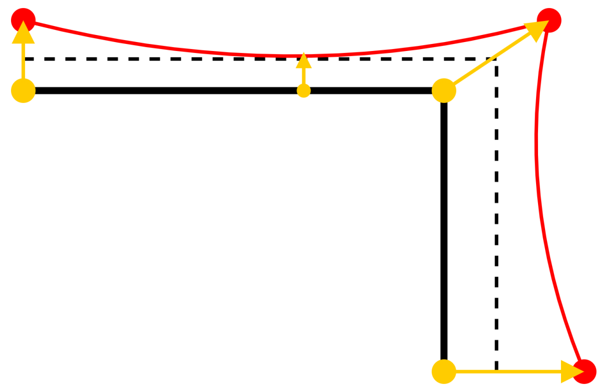


Figure 4. *Correction of mustache distortion and relative crop.*

$$A_-(r, W, H) = A_0\left(\omega_r r,\, \omega_{\frac{D}{2}} W,\, \omega_{\frac{D}{2}} H\right) = A_0\left(\frac{\omega_r}{\omega_{\frac{D}{2}}} r, W, H\right).$$

Generic Distortion We have seen how for both barrel and pincushion distortion, the arc function was simply derived from the arc function of an undistorted image, scaled by a factor depending on the ratio between the original image size and the crop size. We have seen that this ratio corresponds to the warp factor measured at a specific point in the image, namely point D in barrel distortion and point C in pincushion distortion (following the labeling in Fig. 1). This is the only point of the border of the corrected pseudo-image to also lie on the cropped border.

We call this point the *fixed point* of the distortion correction, because it will have the same relative position in the distorted and corrected images. Let us denote ρ the radial coordinate of the fixed point, we can rewrite both A_+ and A_- in a more general form as:

$$A_{\overline{\omega}}(r, W, H) = A_0\left(\frac{\omega_r}{\omega_\rho} r, W, H\right).$$

It stands to reason that, for a generic distortion profile ω_r, the problem of determining the arc function can therefore be reduced to the problem of determining the radial coordinate ρ of its fixed point. Let us imagine for instance the case of a mustache distortion, which starts as barrel distortion close to the image center and gradually turns into pincushion distortion towards the image border.

Since by hypothesis the crop is as large as possible, ρ will be the radius of the point with the lowest y-coordinate among the points on the border of the pseudo-image, *i.e.*, warped image of the border of the original image (see Fig. 4). As seen above, the points on the original upper border of the image have radii comprised between $\frac{H}{2}$ and $\frac{D}{2}$ their y-coordinate is

$$y(r) = r \sin \theta_{\max}(r) = r \sin\left(\arcsin \frac{H}{2r}\right) = \frac{H}{2}.$$

These points get warped into points of y-coordinate

$$y'(r) = (\omega_r r) \sin \theta_{\max}(r) = \omega_r \frac{H}{2}.$$

Since $\frac{H}{2}$ is constant, we get:

$$\rho = \arg \min_{r \in \left[\frac{H}{2}; \frac{D}{2}\right]} y'(r) = \arg \min_{r \in \left[\frac{H}{2}; \frac{D}{2}\right]} \omega_r.$$

Information Capacity and Lighting Conditions

So far, we have developed our reasoning under assumption that the noise curve $\sigma(x)$ of the sensor, where x is a gray level, is uniquely determined for each device. However, we know that the sensor has in fact a family of noise curves, parametric with respect to the ISO speed. It follows that we can therefore associate an Information Capacity to each ISO speed setting of the device. This raises the question on how to compare different devices –with potentially different ranges of ISO speed setting– in a fair manner. Our approach in this respect is twofold.

First, for each ISO speed setting assigned by the manufacturer to a sensor gain, we measure the actual ISO speed value as per the definition given in the ISO recommendation [7], as we know these could differ significantly.

Second, we express the Information Capacity as a function of the total exposure rather than as a function of the ISO speed value. In order to do this, we consider a reference scene where a uniform target of $R = 0.5$ reflectance is presented to the device: for each total exposure value H, expressed in $\text{lx} \cdot \text{s}$, there will be one and only one ISO speed value for which the target is correctly exposed, *i.e.*, for which it is represented with the gray level at half of the sensor's saturation value, $x = 0.5x_{\text{sat}}$. Using the ISO speed definition and under assumption of a Lambertian source and of lens transmission $T = 0.95$, we get:

$$\text{ISO} \approx \frac{377 \cdot \text{Ap}^2}{H \cdot T \cdot R} \cdot \frac{x}{x_{\text{sat}}} = \frac{377}{0.95} \cdot \frac{\text{Ap}^2}{H}$$

Of course this value could not correspond exactly to any of the ISO speed settings available on the device, in which case we perform a simple linear interpolation of the settings that envelop it.

Applying this process on a wide range of total exposures, we observe that the Information Capacity is linear with the total exposure, within the interval of total exposures for which the device can be properly exposed, meaning that an appropriate ISO speed exists to represent that amount of light without saturation (see Fig. 5). This result validates our choice of linearly interpolating the IC for intermediate values of ISO speed. For higher values, for which no ISO setting exists that would not saturate the picture, we assume the Information Capacity as constant –this corresponds to the fact of keeping the device at its base ISO speed– since the user experience would simply be to keep the ISO setting at its lowest and shorten the exposure time.

Module Lens Score

For the definition of a *lens score*, we reason as follows. Let us consider a sensor of size $W \times H$ and depth b bits. For this sensor, the maximum possible IC would be $C_{\text{max}} = bWH$. If the sensor had a perfect lens, but an actual color sensitivity CS_0, then its IC would be $C^\star = \text{CS}_0 WH$. The actual module has information capacity C. Therefore, with respect to a perfect lens, it lost $\Delta_{\text{opt}} = C^\star - C$. If the same loss were applied to a perfect sensor, its IC would be $C_{\text{lens}} = C_{\text{max}} - \Delta_{\text{opt}} = C + (b - \text{CS}_0)WH$. We therefore take C_{lens} as the lens score for the module. Notice that the result is the same no matter the total exposure H –or equivalent the ISO speed setting– at which CS_0. This is consistent with the fact that only the sensor performances are affected by the amount of light in the scene, not the lens.

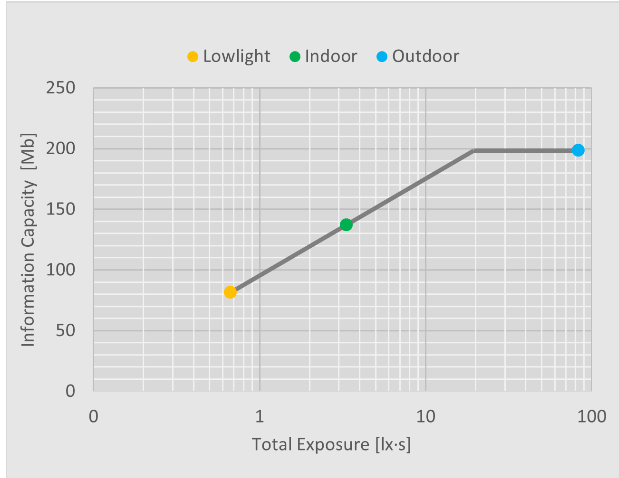


Figure 5. Information Capacity as a function of total exposure. The solid dots correspond to reference shooting conditions at which devices are compared. The device under test has a 1" sensor of 21 MP, an equivalent focal length of 35 mm and has been shot at aperture $f/8$.

Experimental Results

So far, our work has led to the development of a new comprehensive objective metric based on studying the impact of degradation on the camera module's information capacity.

In order to validate our approach, we have tested our approach against 15 real camera modules for mobile phones market that cover a variety of configurations, from low cost to flagships, in terms of sensor size, pixel count, focal length, and aperture. A summary of the specifications of these devices in given in Tab. 6.

Our results show a good correlation with the devices specifications from entry level to high-end to devices. In particular we observe that the Information Capacity behaves as one would expect with respect to the photosensitive surface of the sensor (expressed as the surface of the sensor divided by the F-Number of the lens squared) and its pixel count (see Fig. 7).

It is also worth noting that, for some devices, the information density can vary significantly within the field, accounting in some cases for a loss of 2 bits per pixel (see Fig. 8). Interestingly, this variation is not –as one might have expected– always strictly monotonic. Apart from proving the soundness of our approach, *i.e.*, the need to consider the degradation non-constant in the field, this variation also has another non-trivial implication.

Most photo applications, especially in the mobile world,

Parameter	Min. in dataset	Max. in dataset
Sensor diagonal ["]	1/5.22	1
Pixel count [MP]	4.4	108
Eq. focal length [mm]	15	95
Aperture [mm]	$f/8$	$f/1.6$

Figure 6. Parameters range of the test dataset.

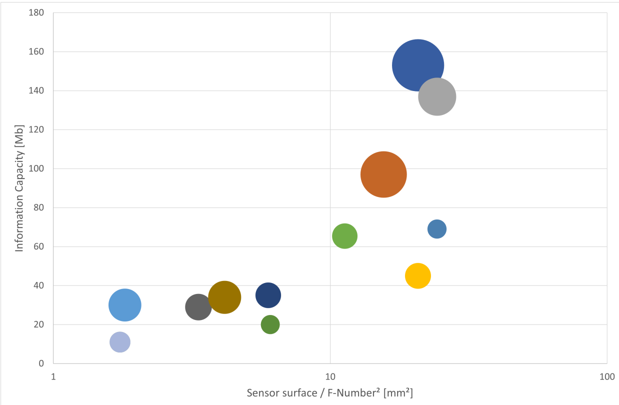


Figure 7. *Correlation between Information Capacity and device specifications. Dot size represents the pixel count.*

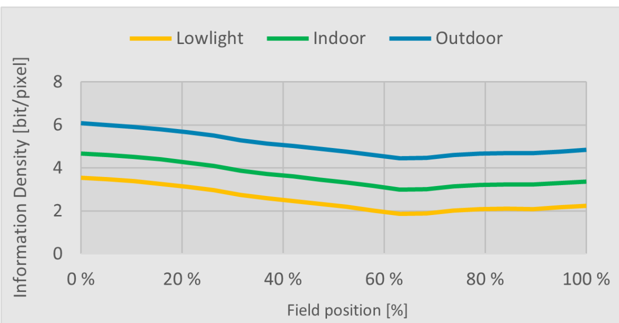


Figure 8. *Information Density as a function of the radial position. The device under test has a* $1/2''$ *sensor of* 12 *MP, an equivalent focal length of* 26 *mm and an aperture* $f/1.8$.

present nowadays a digital zoom feature. Barring specific and novel technologies such as super-resolution, virtually all these zoom features are in practice nothing more than a crop followed by a suitable interpolation. As we have mentioned above, interpolation does not increase the IC in an image, therefore, in a constant-density model, the device that has the highest IC content would maintain its advantage at any zoom factor. In our model, where the crop can be simply modelled by changing the parameters W and H of the arc function, this is not necessarily true. Let us consider a couple of devices A and B with the same total information capacity. However, A's IC is distributed more uniformly in the field while a B's is more densely packed towards the center of the image. In this case, the highest the zoom factor, the more device B would gain in comparison of device A (see Fig 9). This is an extremely useful observation for a manufacturer, which would not be possible without the introduction of a varying information density in the field.

Conclusions and Future Work

In this article we have presented the theoretical framework behind our novel benchmarking metric, based on Shannon's Information Capacity. This metric encompasses a wide variety of well-know image quality indicators regarding both the sensor and the lens behavior, which allows to better understand the limitations of the devices regarding raw image quality. The technical reports, comprised of both the Information Capacity and all the metrics

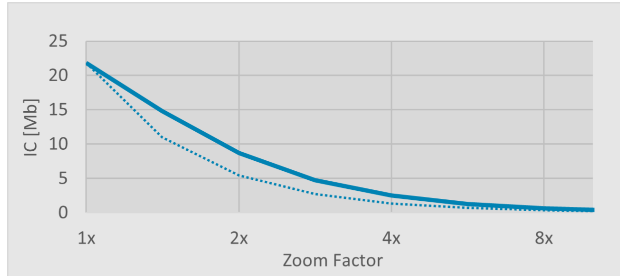


Figure 9. *Information Capacity as a function of zoom factor for a real device (solid line) and a theoretical device with constant Information Density in the field (dashed line). The device under test has a* $1/2.8''$ *sensor of* 20 *MP, an equivalent focal length of* 15 *mm and an aperture* $f/2.2$.

on which it is based, are used in the context of DXOMARK RAW project to help device manufacturers in choosing the most appropriate camera module.

In our future work we will further extend our framework by consider information density which variation is not necessarily radial but arbitrary within the field, and we will include even more degradation indicators for other artifacts such as flare.

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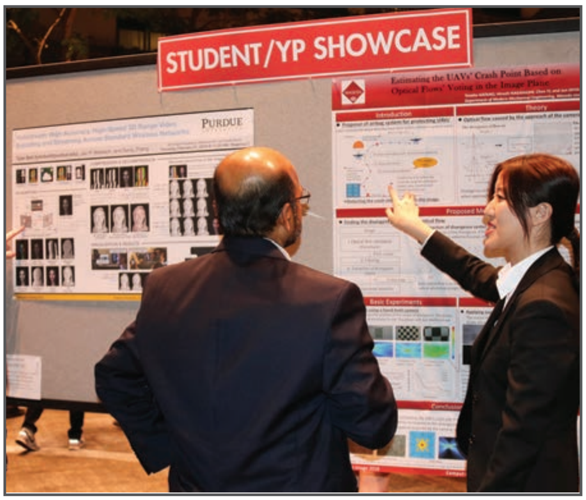

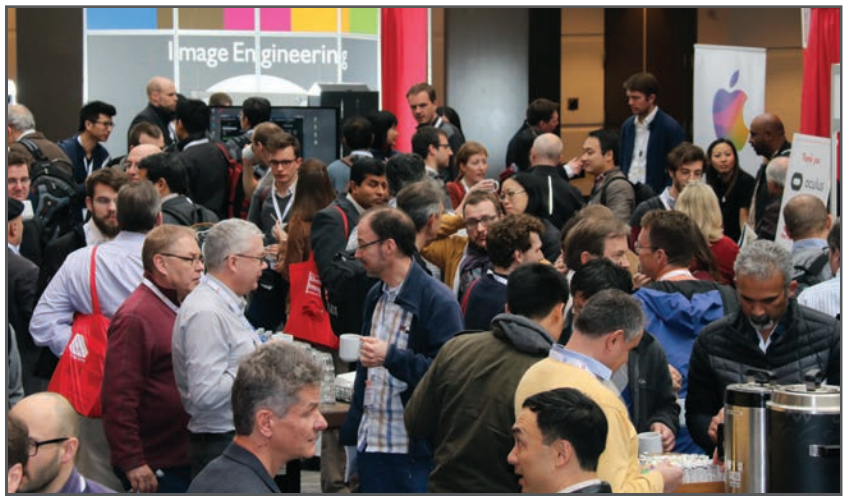

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