Information capacity:
a measure of potential image quality of a digital camera

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ABSTRACT

The aim of the paper is to define an objective measurement for evaluating the performance of a digital camera. The challenge is to mix different flaws involving geometry (as distortion or lateral chromatic aberrations), light (as luminance and color shading), or statistical phenomena (as noise). We introduce the concept of information capacity that accounts for all the main defects than can be observed in digital images, and that can be due either to the optics or to the sensor. The information capacity describes the potential of the camera to produce good images. In particular, digital processing can correct some flaws (like distortion). Our definition of information takes possible correction into account and the fact that processing can neither retrieve lost information nor create some. This paper extends some of our previous work where the information capacity was only defined for RAW sensors. The concept is extended for cameras with optical defects as distortion, lateral and longitudinal chromatic aberration or lens shading.

Keywords: digital photography, image quality evaluation, optical aberration, information capacity, camera performance database

1. INTRODUCTION

The evaluation of a digital camera is a key factor for customers, whether they are vendors or final customers. It relies on many different factors as the presence or not of some functionalities, ergonomic, price, or image quality. Each separate criterion is itself quite complex to evaluate, and depends on many different factors. The case of image quality is a good illustration of this topic. A digital camera is invariably composed of three subsystems: an optic, a sensor and digital processing. Optics all have their particular design, sensors have different size and pixel count, digital processing can be parameterized on the camera, or even be achieved by third party software. Every part of the system has qualities and defects. Devising methods and protocols to measure these individual performance is already a big issue. This is only halfway to the customer request, who basically wants to know what the best camera is. Therefore, a huge amount of information has to be synthesized in a few or even a single number. Standards organizations have been working on the topics for many years. Characterization of many parts of a camera has been described in ISO standards. More recently, the I3A Camera Phone Image Quality[1] (CPIQ) has been working on the objective characterization of cameras and its relation to subjective image quality.

In this paper, we will adopt a different point of view. A camera aims to capture light and its spatial distribution and reproduce it on a plane. A good camera should allow this capture with a good accuracy, that is to say with as many details as possible and unbiased. In other terms, it should capture a large amount of "good" information.

A series of measurement results on about 80 cameras has been published on DxOMark.com[2]. Results are essentially related to sensor noise. On the other hand, resolution is not completely factored; there is only a normalization of noise measurement that reduces the resolution of sensors to a relatively low resolution in order to make comparisons. In this case, it turns out that noise is essentially dependent on sensor size. This paper aims to complete the analysis by properly

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introducing resolution. In this case, we cannot ignore the influence of lens either, with all the possible defects[3]. In this article, we propose the information capacity as an objective measurement that takes into account sensor noise, spectral responses and optical aberrations at the same time.

On the other hand, the information capacity we propose deals with RAW images. One of the main reasons is that, for DSLR, raw converter is the user's choice, between many competitive solutions on the market. Also, raw converters evolve quite fast, at least faster than camera bodies and lenses, because they still benefit from the exponential growth of computing power. A raw converter cannot create information but only lose some or change the organization of information. Computing the RAW information capacity removes the bias of the raw converter, and also permits to anticipate the fact that some aberrations can be digitally corrected. To illustrate this point, consider the example of geometric distortion. A distorted image contains "bad" information in the sense that the spatial organization is not as expected on a perfect (pinhole) camera. However distortion correction methods have been used for a long time in computer vision, in particular 3D reconstruction. Some raw converters or other software integrate this kind of correction, and some camera manufacturers also embed such corrections on the camera chip. Therefore, we can consider that the geometrical effect of distortion can be cancelled out by digital processing. However, this correction is not priceless in terms of image: there is a local loss of resolution. This is well known for very wide-angle lenses, for which field of view is traded against distortion and resolution on the image border. The general point is that a correction algorithm can organize the information contained in the raw image differently, but cannot (or should not) create new information. Of course, distortion in an image damages the subjective quality. We consider that a correction algorithm can be designed so that the image quality attribute related to the defect can be optimal.

Therefore, what we are interested in is the amount of information that has been lost due to the defect, and cannot be recovered from the image itself.

The outline of the papers is as follows. In Sect. 2, we introduce the notion of local information capacity as the product of local resolution and local dynamic. We then review the main characteristics of a camera, in terms of sensor and optics aberrations and how they individually influence the local information capacity in Sect. 3 and 4. We present how to gather local contribution in Sect. 5, leading to a global definition of information capacity accounting for sensor and optics characteristics. In Sect. 6, we show some measurements and comparisons on real cameras before concluding.

2. INFORMATION CAPACITY

2.1 Definition

We choose to represent the performance of a camera by measuring the amount of information it is able to capture. This amount of information has to be understood as in Shannon's work[4], that is the size of the channel that is necessary to transmit the image. Image information is completely determined by resolution and dynamic. The first one is related to the details that a camera can spatially render and the second one to the level of contrast that the camera can capture. This contrast can be related to two different notions: the dynamic range which is the maximal contrast that the camera can measure without saturation, and the SNR that can be related to the smallest level of contrast that can be discriminated from noise.

Resolution can be defined as a number of pixels, giving the number of elementary elements used to describe the spatial organization of the image. It is well known that even though the number of pixels of the sensor should be related to the resolution of the camera, this notion is actually more complex. Indeed, it should also account for loss due to the fact that the optical system cannot be perfect. Both the optics and the sensor introduce a certain amount of blur, which has to be integrated in the definition of resolution.

Similarly, the bit depth of the sensor (which is the number of bits used to encode gray levels) is only a first rough estimate of the real photograph dynamic. For instance, noise whatever its sources) has to be taken into account. Dynamic is better measured in a logarithmic scale. This is both compliant with perception since the eye does not have a linear response to illumination and to information theory since the number of bits that are need to encode a value is proportional to the logarithm of this value. Moreover, photographers also measure light in Exposure Value (EV) which is a base 2 logarithm.

Therefore a general definition of the information capacity of a camera is

$$C = R \times D.$$

The main difficulty is to properly define resolution and dynamic, both as simply as possible, and as completely as possible, that is by taking all the properties of the camera into account.

In previous works[5,6,7], we were interested only in sensor performance. Therefore, resolution only integrated pixel blur (sensor MTF) and lens diffraction limit, and sensor noise through its color sensitivity.

2.2 Local resolution and local dynamic

The main goal of this paper is to extend this model, by incorporating real lens characteristics. Most of optical aberrations are field dependent. Therefore, their influence on resolution and dynamic shall be described locally. Information capacity can also be expressed as a local quantity. The global information capacity of the camera is obtained by summing these local contributions.

At each spatial position x, we will define the local resolution $R(x)$ and the local dynamic $D(x)$. Each aberration contributes as a loss to either resolution or dynamic. We will sequentially review them.

We will see that the main defects can be easily interpreted in terms of resolution or dynamic. More precisely, the next section will define the contribution to information capacity of

- Lens blur and longitudinal chromatic aberration
- Lateral chromatic aberration
- Lens distortion
- Lens shading

3. DYNAMIC

3.1 Color sensitivity

This part was already included in previous work[5], so we will only go through essentials. The color sensitivity is the number of colors that a sensor can discriminate up to noise. In order to compare sensors with different spectral responses, we compute this number of colors in a common space, for instance sRGB. We now shortly describe the procedure for three channels sensors. It can be generalized for other types of sensor, but it is slightly more complex. The procedure is similar to the one in ISO 17321[9] and is as follows. For a given illuminant, apply a white balance correction such that the three channels respond to the illuminant spectrum with the same digital value. Then, compute the color correction matrix (CCM) mapping the white balance corrected values to sRGB target values, such that the color deviation in CIELab between a given target and the measured values is minimized (still for this illuminant). In practice, we use the 18 color patches of a Gretag MacBeth colorchecker. The camera values can either be measured on a real shot, or reconstructed from spectral responses. From noise characteristics on the RAW sensor, white balance scales and CCM, we compute the noise covariance matrix in linear sRGB. We denote by $\sigma_i^2(r,g,b)$, $i = 1, 2, 3$, the three eigen values of the covariance matrix.

The color sensitivity is defined as

$$CS = \int \frac{dr\ dg\ db}{\prod_{i=1,2,3} \max\left(1, \sigma_i(r,g,b)\right)}.$$

The integrand represents the density of colors that are possible to discriminate. Remark that color sensitivity both accounts for dynamic range (the ratio between the highest possible and the lowest with SNR=0dB) and the value of SNR along the whole sensor dynamic. Since dynamic is better expressed in logarithmic scale, we shall consider $\log_2 CS$

Color sensitivity gives the number of colors for an input triple R, G, B on the raw sensor, no matter their spatial distribution. This will be discussed further.

Raw noise characteristics could theoretically depend on field position. However, for all the sensors we have been testing, noise is constant through the image field. White balance scales and color matrix might not be constant because sensor spectral responses may not be constant in the field. This is the case for very slim camera as camera phones that show important color shading. For DSLR, these variations can be neglected.

3.2 Light shading

Lens shading is an optical aberration that makes the image darker on the side than at the image center. It has mainly two different sources[3]. The first one is sometimes called natural vignetting and corresponds to the "cosine-fourth law". The second one depends on the optical design and corresponds to light rays that are lost on the border of one or several optical elements, lens or pupils. For zoom lenses, it is very dependent on shooting parameters as focal length and aperture (f-number).

It is described by an attenuation factor $V(x) \in (0,1)$ giving the relative illumination between position x and the image center (assumed to be the position of maximal illumination for simplicity). Obviously, lens shading is related to image dynamic. Let us denote by b the bit depth of the encoded raw image. The local loss in terms of exposure value is

$$\Delta_V = \max\left(\frac{1}{2}\log_2 V(x), -b\right).$$

This loss assumes that noise in photonic (which is the case for medium to high lights). In this case, noise is proportional to the signal square root. In the formula defining color sensitivity, it can easily be seen that losing one f-stop, yields a loss of color sensitivity equal to 3/2.The max is simply related to the fact that we cannot lose more bits that initially allocated to encode the signal.

3.3 Aperture and transmission

The amount of light going through the optics is related to the size of the aperture and the transmission of the lens. What actually matters is the sensor exposure. It is very easy to see that sensor exposure is proportional to the ratio of the focal length and the pupil diameter (the f-number). It is not an easy task to independently measure the lens aperture and the transmission factor of the lens. However, we do not need that much information. Only the relation between the incoming light flux and the sensor exposure is useful to our purpose. This is perfectly described by the T-stop. The T-stop of a lens is the aperture value (f-number) of a lens with 100% perfect transmission factor yielding the same sensor exposure as the measured lens. The T-stop is lower than the actual f-number because lens transmission is below 100%. For a given lens, T-stop and manufacturer f-number usually differ from a multiplicative constant (hopefully close to 1). It is worth noting that a photographer will choose the aperture value in order to optimize the exposure of the picture, but also the depth of field. This is neglected in the present analysis, which is equivalent to assume that the scene is located in the plane of best focus. Also, we cannot know how the photographer wants to play with depth of field. We only consider T-stop on the lightness aspect.

A lens with a low f-number (wide aperture) allows more light on the sensor. Therefore, it either allows shorter exposure time or a lower ISO value for the same exposure time.

To evaluate the influence of exposure, we consider two use-cases:

1. Studio: there is as much light as needed and the camera is set on a tripod. Minimum ISO is used for all aperture values.
2. Outdoor action: scene illuminance is 5000lux, exposure time is 1/2000s.

For each use case, we consider that an object with 100% reflectance should exactly reach sensor saturation. Following the definition ISO sensitivity (ISO standard 12232), the ISO that is necessary to reach this sensor exposure is

$$ISO = 312\frac{T^2}{L \cdot t}$$

where T is the T-stop value, L the illuminance (in lux) and t the exposure time (in s). For studio use, the picture is always shot at minimal ISO. For both other cases, the ISO will be set higher in general. If the camera does not allow high enough ISO values, a digital gain is applied to simulate this ISO.

The value of the color sensitivity is considered at the computed ISO value. A digital gain of 2 is assumed to decrease color sensitivity by 1.5 bit (pure photonic noise).

4. RESOLUTION

4.1 Lens blur and Bayer sampling

Except light shading, lenses aberrations primarily impede resolution. Even a perfect lens is limited by diffraction, which only depends on aperture. In practice blur is also worsened by other types of aberrations, e.g. spherical aberration. For DSLR with a large range of aperture values, blur is optimal for medium values of aperture, typically f/5.6 or f/8.0. For large aperture, it is more difficult to perfectly focus the larger light beam (typically because of spherical aberration). For small aperture, diffraction becomes dominant and represents an unbreakable wall to resolution.

Whatever it source, blur reduces image resolution since it consists in a local averaging of light at different spatial positions. The blur spot is field dependent due to some high order aberration as field curvature. It is dependent on light wavelength. For instance, the focus position may depend on the wavelength (longitudinal chromatic aberration) which leads to wavelength dependent blur.

Following Shannon's information theory, the loss of information related to a convolution is related to the logarithm of the modulation transfer function. Let us denote by k a convolution kernel applied on a signal sampled on DR bits. The number DR is the dynamic range of the sensor, which is ratio (in base 2 logarithm) between the saturation value of the sensor and the smallest values such that the signal to noise ratio (SNR) is more than 1. As a first approximation, it corresponds to the bit depth of the sensor. Let us denote by $K$the MTF of k, that is the modulus of its Fourier transform. The number of bits needed to encode the signal is

$$\Delta_{blur} = 4\int_{\left(0,\frac{1}{2}\right)^2} \max\left(0, DR + \log_2 K(f_x, f_y)\right)\, df_x\, df_y. \quad (1)$$

The max in the integrand corresponds to the fact that the loss cannot be greater than the number of bits primarily encoding the signal. The logarithm of the MTF can be seen as a resolution loss. Remark that the resolution loss is multiplicative: if we consider two convolution kernels $k_1$and k_2 the Fourier transform of $k_1 * k_2$is the product of the Fourier transform $K_1$and K_2. If we neglect the non-linearity in (1) due to signal quantization, the resulting loss is the sum of the loss due to $k_1$and $k_2$individually.

Interestingly enough, this formula actually considers resolution in terms of bits or dynamic, because Shannon's purpose was to determine the size of the channel needed to transmit a blurry signal.

Now, we also have to consider that on a Bayer sensor, the three color channels are not sampled at full resolution. The red and blue channels are sampled at half resolution in each direction, while the green one is sampled twice faster. For the red and blue channel, frequencies are only used in the domain $D_{RB} = \left\{\max\left(|f_x|, |f_y|\right) \leq \frac{1}{4}\right\}$. For the green channels, the sampled frequencies are described by $D_G = \left\{\left|f_x + f_y\right| \leq \frac{1}{2}\right\}$. Therefore, the number of bits for each pixel is

$$\Delta_{blur} = \int_{D_{RB}} \max\left(0, DR + \log_2 K(f_x, f_y)\right)\, df_x\, df_y \quad \text{for red and blue}$$

$$\Delta_{blur} = \int_{D_G} \max\left(0, DR + \log_2 K(f_x, f_y)\right)\, df_x\, df_y \quad \text{for green.}$$

The local resolution is $R = \frac{\Delta_{blur}}{DR}$. If the MTF is identically equal to 1, we find that the local resolution on R and B is $\frac{1}{4}$ and equal to $\frac{1}{2}$ on the green channel. In practice, it is a bit lower due to optical blur.

4.2 Longitudinal chromatic aberration

Chromatic longitudinal aberration is due to the dependence of the focus distance on wavelength. Therefore the blur spot is not the same on the different wavelength. Longitudinal chromatic aberration is for instance responsible for artifacts like blue or purple fringing. For each color channel, computing the loss due to different blur kernels is straightforward by (1).

4.3 Lateral chromatic aberration

Lateral chromatic aberration (LCA) is due to the fact that magnification is wavelength dependent (see Fig. 1). It results in a local shift of the color channels with respect to one another which creates color fringes that are particularly visible along edges with a high level of contrast. It is locally possible to apply the right displacement to the color channels so that the shift between them is minimal. This is how LCA is usually corrected, and the correction can be almost perfect in the sense that color fringes become almost invisible. A translation basically introduces no loss of information, if performed suitably. However, something that is not taken into account in this analysis is the blur produced by LCA for each channel.

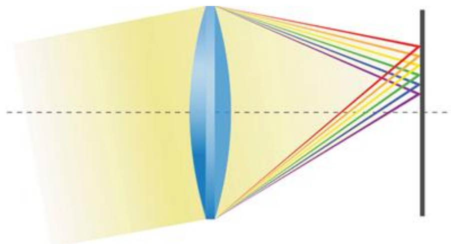

Figure 1. Lateral chromatic aberrations introduce blur on the sensor. Blur spot size is related to sensor spectral responses.

Indeed, LCA assumes a value for each wavelength. Each color channel integrates the different wavelengths according to some spectral response, incorporating lens transmission, IR filter and sensor response. Let us first consider the case of a single channel with spectral response $r(\lambda)$ assuming high values around a wavelength λ_0. Let us denote by $f(x,\lambda)$ the magnification at point x for wavelength λ. By Taylor expansion, we can approximate

$$f(x,\lambda)\approx f(x,\lambda_0)+\alpha(\lambda-\lambda_0).$$

A light beam with spectrum $s(\lambda)$ focusing at position x_0 at wavelength λ_0 will produce one dimensional blur spot with profile equal to $s.r(\lambda_0+(x-x_0)/\alpha)$ The MTF of this blur spot is also one dimensional and equal to the modulus of the Fourier transform of $s.r$ up to a scale factor α. Equation (1) can then apply to compute the resolution loss. In particular, for a neutral object, s is simply the spectrum of the illuminant of the scene.

4.4 Lens distortion

Lens distortion is another field aberration that implies that lens magnification varies in the image field. The major consequence of distortion is that straight lines in the scene appear curved in the image. This can make image quality questionable but the subjective quality of the image depends a lot upon the scene. Architecture photographs are more affected than landscapes or even portraits. However, the deformation due to distortion can mostly be calibrated, usually with good accuracy. Calibration must be performed for each focal length. It does not depend on aperture, or very little. For certain lenses, distortion can depend on the distance to the scene, making the correction a bit inaccurate. However, we can consider that straight lines can be straightened, at least for visual inspection. Does that mean consider that distortion has no impact on information capacity? Actually not since distortion yields a resolution loss.

In order to see why, let us consider the two main types of distortion, and suppose that we correct distortion. Assume that the scene to be shot is a rectangle with the same aspect ratio as the sensor. The focal length is adjusted as tight as possible, so that the image after distortion correction exactly fit the rectangle, with no crop.

Consider first the case of negative distortion, also called barrel distortion on Fig. (2). The focal length (usually measured at the center) can be chosen slightly larger than for an undistorted image, until one side of the shot rectangle touches the image border. If the distortion profile is monotonous, this will occur on the shortest side of the image. The scene to be shot is contained in the black grid and is mapped on the gray grid by distortion correction. Therefore, the part of the image that has been acquired between the edge of the black grid and the grey grid is going to be lost. This part was not intended to be framed so it is not a big loss. However, in order to fill the empty space, the image has to be distorted back and the correction is a local expansion of the image. Let us denote by $v(x)$ the correction function of distortion. A point at position x in the original image frame F becomes $v(x)$ after correction. If $v(x)\notin F$, the point is excluded of the image and is not useful information. Therefore, we only count the points such that $v(x)\in F$.

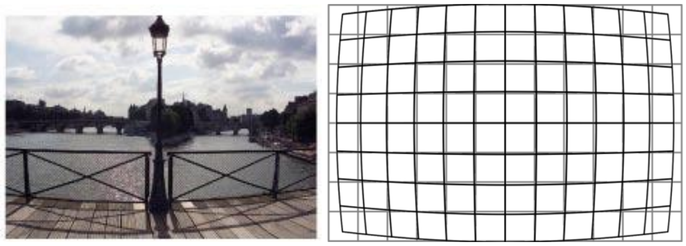

Figure 2. Barrel distortion. Some information in the corners is not useful and is discarded by geometric correction.

Conversely, for positive (or pincushion) distortion (Figure 3), the focal length has to be shorter than expected, so that the corners of the scene are inside the image field. Again, there are parts of the image that are going to be lost.

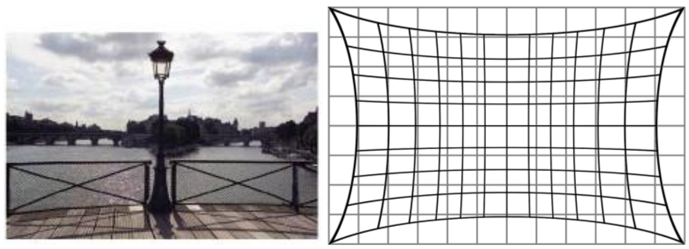

Figure 3. Pincushion distortion. Correction discards some information on the sides.

5. SUMMING LOCAL CONTRIBUTIONS

The local information capacity for a pixel is obtained by multiplying the effective number of red, green and blue pixels by the effective dynamic.

$$C(x) = \left(R^R(x) + R^B(x) + R^G(x)\right) \cdot (CS(x) + 3\Delta_V(x)).$$

The information capacity of the camera is obtained by summing over the whole Bayer grid

$$C = \sum_{v(x)\in F} C(x).$$

Remark that if the sensor contains N pixels, the sum above also contains N terms. Light shading loss is multiplied by 3 because there are three color channels. Note that the possible relative attenuation of the channels (color shading) is integrated in the local color sensitivity, through the variation of white balance and color correction matrix in the field.

6. CAMERA MEASUREMENTS

In order to make real camera measurement, we measure MTF, distortion, light shading and sensor spectral responses.

MTF through field are measured on a slanted checkerboard and the SFR is measured following ISO standard 12233[8]. We make measurement on raw images so that the sensor response is linear. MTF is measured on the three color channels, in the horizontal and vertical directions. For the sake of simplicity, we assume that the two-dimensional MTF is separable and equal to the product of the MTF in the horizontal and vertical direction. Remark that the effect of lateral chromatic aberration is already included in this measurement.

Distortion is measured on a target made of glass (for better planarity) which features a grid of black dots on a white background. Lens shading is measured on the same target, after digital removal of the black dots. The illumination is uniform with a 5% error margin, but this error is removed by calibration.

Color sensitivity is evaluated from sensor noise characteristics and sensor spectral responses. The white balance scales and the color correction matrix are relative to a specific illuminant (D50 in this paper). For DSLR sensors, the variations of spectral responses in the image field are negligible.

Sensor ISO sensitivity is measured with no lens directly in RAW format. It is usually lower than the manufacturer ISO sensitivity. Knowing the sensitivity of the sensor, it is possible to estimate the sensor exposure, and deduce the T-stop of an optic. The T-stop is a bit higher than the f-number, the difference being due to lens transmission. We usually measure lens transmission between 85% and 90%, depending on the optical formula.

6.1 Studio case

In the first series of experiment, we assume that light is not limited. The camera is also set on a tripod. In this case, we use the sensor optimal noise characteristics.

The first measurement is a zoom lens AF-S Nikkor 24-70mm mounted on a Nikon D3x (24Mpix 36x24mm full frame sensor). We compute the information capacity for each focal length and aperture value. We also evaluate the information capacity loss for lens distortion, blur/lateral chromatic aberration, lens shading and sensor response (noise and spectral sensitivities). The loss for a given aberration is computed as follows: we consider a camera with the same defects as the one we measure except that it is perfect for a single measurement. For instance, we assume that MTF is identically equal to 1, and everything else is equal. The losses are not completely independent but it is a good approximation.

The results are in Table 1.

Table 1. Information capacity of Nikon D3x, AF-S Nikkor 24-70mm f/2.8

Information Capacity (Mbits)

f#\focal length	24	35	50	70
2.8	529	538	518	497
5.6	522	559	562	547
8	515	557	564	565
11	523	548	553	562
22	502	518	515	528

Distortion loss (Mbits)

f#\focal length	24	35	50	70
2.8	6.6	0.4	0.7	0.3
5.6	6.6	0.4	0.8	0.3
8	6.5	0.4	0.8	0.3
11	6.7	0.4	0.8	0.3
22	6.6	0.4	0.7	0.3

Blur loss (Mbits)

f#\focal length	24	35	50	70
2.8	62	60	74	96
5.6	77	50	47	65
8	84	52	45	48
11	76	61	55	51
22	96	91	93	83

Sensor loss (Mbits)

f#\focal length	24	35	50	70
2.8	43	43	42	40
5.6	41	44	44	43
8	41	44	45	44
11	42	43	44	44
22	40	41	41	42

Lens shading loss (Mbits)

f#\focal length	24	35	50	70
2.8	14	15	20	19
5.6	7	5	6	4
8	7	5	6	2
11	7	6	6	2
22	8	5	5	4

The total information capacity is about 550Mbits, which is about 22.9 bits/pixel. Of course this exceeds the bit depth of each pixel, but the underlying assumption is that color channels are correlated and demosaicing can optimally recover the correlation. Lens blur and sensor noise are the main sources of loss for this camera and this use case. Sensor loss is almost independent from the lens characteristics. Lens blur is optimal at 50mm f/8 which is not too surprising. For wide aperture, it is harder to control aberrations. For narrow apertures, diffraction blur becomes dominant. Information capacity is optimal at 70mm-f/8, but is actually almost identical at 50mm-f/5.6 and 70mm-f/8, since blur as the largest influence. Distortion is almost negligible. Of course, the visual effect of distortion is very bad for some type of pictures, but the assumption that was made is that it can be corrected (provided distortion parameters are known). The correction yields a loss of information, but is actually almost painless. Lens shading is larger for wide aperture and in a lesser extent for short focal lengths, but it is stable above 35mm and f/5.6.

Let us now test this same lens on a Nikon D3 (full frame, 12Mpix). The results are in Table 2.

Table 2. Comparison of information capacity for Nikon D3x and Nikon D3, AF-S Nikkor 24-70mm f/2.8

Information Capacity (Mbits) D3x

f#\focal length	24	35	50	70
2.8	529	538	518	497
5.6	522	559	562	547
8	515	557	564	565
11	523	548	553	562
22	502	518	515	528

Information Capacity (Mbits) D3

f#\focal length	24	35	50	70
2.8	276	280	274	268
5.6	284	290	291	291
8	283	289	289	291
11	280	286	286	290
22	269	275	274	278

For the studio case, light is not a limiting factor, so we can expect that the D3x information capacity is almost twice the information capacity of D3. This is indeed the case. The optimal ratio is 1.947 at 50mm-f/8. For more narrow apertures, this ration decreases a bit, due to diffraction blur. This limitation will be harder if the size of pixels keeps on decreasing.

Let us now compare two fixed focal length lenses, Canon 50mm f/1.8 II and Canon 50mm f/1.2L USM, both mounted on a Canon EOS 1Ds Mark III (21 Mpix, full frame). For a wide aperture values, the fast lens shows slightly lower information capacity. The slight difference comes from blur. The explanation is that there are more optical constraints to design a wide aperture lens. However, this use case does not take light limitation into account, which is the main reason a photographer would like a f/1.2 lens. This will be studied in the next section. For f-numbers more than 2.8, the f/1.2 lens is as good as the other one, which is a true performance (that can also explain the price difference between both optics).

Table 3. Comparison of information capacity of Canon 50mm f/1.8II and Canon 50mm f/1.2L USM, mounted on Canon EOS 1Ds Mark III. Studio use case.

f#	Canon 50mm f/1.8 II	Canon 50mm f/1.2L USM
1.2		411
1.8	431	
2.8	471	468
5.6	485	486
8	484	485
11	480	482
16		472
22	451	

6.2 Outdoor action case

In this section, we no longer assume that light is not limited. We assume that illuminance is good (5000lux) but that exposure time has to be short (1/2000s) in order to avoid motion blur. Since the amount of light is determined by the product of these quantities, any other scenario keeping this product unchanged will yield the same results thereafter. We assume that a 100% reflectance object must saturate the sensor. The user then changes the ISO setting of the camera in order to obtain the correct exposure. Inside the camera, it amounts to apply some gain (whether analog or digital) until the exposure of the picture is good. In most cases, scenes also contain some specular objects, and the photographer may want to keep some headroom to preserve highlights. However, this only offset the ISO setting and is equivalent to a change of the scenario. Indoor low light environments can be considered with the same arguments.

The minimal ISO sensitivity necessary to obtain the required exposure is given by

$$ISO = 312\frac{T^2}{L \cdot t}$$

where T is the T-stop value, L the illuminance (in lux) and t the exposure time (in s). For the chosen use case, we obtain $ISO = 124.8\,T^2$. Therefore, even for very low f-number, the ISO is higher than the minimal ISO setting. In this case there is a clear advantage to have a fast lens. Wide aperture lenses also have a lower depth of field, which can be good or bad depending on the intention of the photographer. We do not take depth of field into account in this study.

Table 4. Comparison of information capacity of Canon 50mm f/1.8II and Canon 50mm f/1.2L USM, mounted on Canon EOS 1Ds Mark III. Outdoor case (5000lux, 1/2000s).

f#	Canon 50mm f/1.8 II	Canon 50mm f/1.2L USM
1.2		390
1.8	379	
2.8	375	374
5.6	315	313
8	277	278
11	244	246
16		205
22	167	

In this case, the maximal information capacity is attained for the wider aperture. The loss between the studio case and the outdoor case is still very low for the f/1.2 lens but already important for the f/1.8 lens.

7. CONCLUSION AND PERSPECTIVES

We refined the concept of information capacity defined in previous works[6], by defining the information loss due to the main optical aberrations: blur, chromatic aberrations, light shading and distortion. It is worth noting that the information capacity was defined for a scene shot at the optimal focus distance. In real situations, only a part of the scene is at focus, and depth of field also has to be taken into account. The information capacity in an out-of-focus plane is obviously much lower than the one we computed. In a forthcoming work, we will add the depth component to information capacity. In particular, we will study the information capacity of EDoF (extended depth of field) systems and show that these systems essentially distribute the information capacity more evenly across the different depths.

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