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Article

A Sensor-Based Approach to Image Quality

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Summary: In the past 20 years a large effort has been made to characterize the image quality of remote sensing systems. The image quality can actually be measured only by the quality of the final product (e. g. object detection, classification). One option now is to use the national image interpretability rating scales (NIIRS), because NIIRS is related to object detection. From an engineering standpoint a task-based scale, like NIIRS is not well suited, because it cannot be derived from the fundamental sensor and scene behaviour. Therefore, the aim of this paper is to derive an image quality criterion, based on the physical characteristics of sensor and scene. To assess the image quality, we compare the output of the real sensor with the output of an ideal sensor based on a local mean square error (LMSE). This criterion, we abbreviate in the following with IQC (image quality criterion).

Zusammenfassung: *Ein sensorbasierter Ansatz zur Bestimmung der Bildqualität.* In den letzten 20 Jahren wurde ein großer Aufwand zur Beschreibung der Qualität von Fernerkundungsbildern betrieben. Die Bildqualität kann letztlich nur durch die Beurteilung der Qualität des Endproduktes (z.B. Objektdetektion, Klassifizierung) eingeschätzt werden. Eine Möglichkeit ist die Verwendung des NIIRS (national image interpretability rating scales), da sich NIIRS auf die Objektdetektion bezieht. Vom Standpunkt des Sensorentwicklers ist NIIRS aber nicht gut geeignet, da es nicht von den grundlegenden Sensorparametern und den Szenencharakteristika abgeleitet werden kann. Deshalb wird in dieser Arbeit ein Bildqualitätskriterium vorgeschlagen, das auf diesen Größen beruht. Wir vergleichen hierzu den Output eines realen Sensors mit dem eines auf die entsprechende Aufgabe zugeschnittenen idealen Sensors mit Hilfe eines local mean square error (LMSE) Kriteriums. Dieses Kriterium kürzen wir im Folgenden mit IQC (image quality criterion) ab.

1 Introduction

For the characterization of image data or products often the spatial resolution (ground sample distance) is used which is related to detector pixel size and focal length. But there are several other influences of the imaging system that affect image sharpness and need to be considered. These other parameters are e. g. the point spread function (PSF) and signal-to-noise ratio (SNR) of the image product (Jahn & Reulke 1995). An image quality metrics can be established for any imaging system, given a characterization of the system in terms of blur and additive distortion (noise, non-linearity, compression, artefacts, preprocessing) when observing a certain scene described by its radiance. In general, image quality depends on the ultimate task of image data evaluation and cannot be defined for every image likewise. For instance, to measure star positions the quality of the deep space image is better if the image is blurred whereas the image should be sharp if objects are to be detected or recognized. Because there is not one best image quality measure here we propose an image quality criterion which is task-based and sensor-based.

To solve a definite task such as object detection or recognition in definite environment (e. g. the detection of a car in an agricultural area illuminated by solar radiation) with a space-borne sensor, that sensor will be optimized to give best performance for solving

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that task (and, usually, related tasks). That means that the sensor parameters such as focal length, aperture and so on are fixed, and the illumination (in a certain range) is given too. Under these conditions an ideal sensor can be defined which gives best image quality. A real sensor which deviates more or less from the ideal one, provides worse image quality. That task-based and sensor-based approach differs from older approaches to be discussed in the following.

The most popular quantity for the description of the image quality is NIIRS. NIIRS has been developed by the imagery resolution assessments and reporting standards (IRARS) committee. It consists of different levels from 0–9. Higher values mean a capability to support a more detailed object analysis.

Leachtenauer et al. (1997) introduce the general image quality equation (GIQE):

$$NIIRS = 10.251 - a \cdot \log_{10} GSD + b \cdot \log_{10} RER \\ -c \cdot G/SNR - d \cdot H \tag{1}$$

GIQE is an apparent image quality (IQ) metric that measures the quality of object detection in terms of ground sample distance (GSD) and additional measures namely the relative edge response (RER), the signal-to-noise ratio (SNR), and an additional component to take care of the image restoration.

GSD is the most important factor and is related to the Nyquist frequency. Larger GSD decreases NIIRS. RER is defined as the slope immediately before and after an edge as a fraction of the edge height. A larger RER is related to a sharper point spread function (PSF) of an image and increase NIIRS. An increasing SNR results also in a decrease of the factor *G/SNR* and therefore in an increase of NIIRS. Often, before delivering the data will be modified in a preprocessing step. It includes also image enhancement algorithms. This leads to an improvement in image sharpness, but at the same time also an overshoot at the edges and an increase in noise. The gain G evaluates the noise after sharpening, and the overshoot term H measures the magnitude of ringing in the edge response of the imaging system.

Problems of applying quality metrics in remote sensing are pointed out in Miettinen (2004). He introduces the 2D latent NIIRS metric based on the power spectrum of additive incoherent noise.

In the paper from Kim & Park (2010) an image quality metric using the phase quantization code (PQC) is depiced. Dumic et al. (2010) present an approach to the objective quality evaluation that could be computed using the mean difference between the original and tested images in different wavelet sub-bands. Wavelet coefficients are used to compute an image-quality measure (IQM). IQM is defined as perceptual weighted difference between coefficients of original and degraded image.

Image quality affects image processing results, e. g. automated classification of images. In Yan et al. (2009) a database of reference images was established that could enable automated, customized image quality modification to improve classification of new images. They introduced also a task-based definition of image quality.

Gerwe et al. (2009) present a new information theoretic image quality evaluation (ITIQUE) for modelling and predicting NIIRS performance based on the visual information fidelity (VIF) IQ assessment metric. The evaluation shows a good agreement with the general image quality equation.

Image quality measure (IQM) is calculated traditionally in the image spatial domain. In the paper Shih & Fu (2008) they present a method of transforming an image into a low-dimensional domain based on random projection. From the transformed domain, it is possible to calculate the peak signal-to-noise ratio (PSNR) and apply fuzzy logic to generate a low-dimensional quality index (LDQI). The LDQI can approximate the IQM in the image spatial domain.

The paper from Schueler (2008) focuses on the system engineering trade-off driving almost all remote sensing design efforts, affecting complexity, cost, performance, schedule, and risk: image quality vs. sensitivity. The relationship between image quality and sensitivity is introduced based on the concepts of modulation transfer function (MTF) and signal-to-noise ratio (SNR) with examples to illustrate the balance to be achieved by the system architect to optimize cost, complexity, performance and risk relative to end-user requirements.

Chen et al. (2008) focus on mutual information-based quality measure and weighted averaging image fusion. Based on an image formation model, they obtain a closed-form expression for the quality measure and mathematically analyze its properties under different types of image distortion.

Shnayderman et al. (2006) present a greyscale image quality measure that can be used to predict the influence of different noise sources, based on singular value decomposition. The measure was applied to different test images using six types of distortion (JPEG, JPEG 2000, Gaussian blur, Gaussian noise, sharpening, and DC-shifting).

An objective sensor based image quality measure has to take into account sensor specific characteristics, e. g. PSF & SNR. The approach is to compare the actual measured data with simulated image of an ideal sensor.

Therefore, in this paper we propose the usage of a new image quality criterion, namely local mean square error (LMSE), for describing the mean deviation of gray values generated by both ideal and real sensors.

This paper is organised as follows. Section 2 introduces the image quality measure, in section 3 we present some results and comparison between NIIRS and IQC and section 4 comes up with conclusions.

2 The new Image Quality Criterion

As mentioned in the introduction, here the quality of an image or the quality of the image generating sensor is assessed by comparing the output of the sensor with the output of an ideal sensor, i. e. we consider as a measure of quality a quantity $Q_{i,j}$ which is proportional to the averaged gray value deviation

$$Q_{ij} \sim \left\langle \left(G_{i,j} - G_{i,j}^{ideal} \right)^2 \right\rangle \tag{2}$$

Here, $G_{i,j}$ is the measured (i. e. noisy and blurred) gray value at pixel (i,j). The angle brackets $\langle \ldots \rangle$ denote the average of that measure over all pixels of the sensor to assess the image as a whole or over local regions of the image. The signal generation process is explained more in detail in (Jahn & Reulke 1995).

The ideal sensor is characterized by

- given sensor parameters such as focal length, aperture, pixel size,
- no disturbances from the environment,
- no dark current,
- quantum efficiency $\eta_\lambda^{qu} = 1$ and optical transmission $\tau_\lambda^{opt} = 1$ within the considered spectral range $[\lambda_{min}, \lambda_{max}]$,
- diffraction limited optical point spread function (PSF),
- ideal pixel PSF (box shaped function),
- linear and noise free electronic channel with delta-shaped impulse response,
- analogue digital unit (ADU) with infinite small quantization step.

By definitions adopted here, images generated by that sensor have best quality at given illumination. The measure Q depends on certain sensor parameters $p_1,\ldots,p_n$ (focal length, aperture, pixel size,…). Therefore, in principle, one could minimize the function $Q(p_1,\ldots,p_n)$ in order to optimize the sensor, but this is not considered here.

The electron number generated in pixel (i,j) of the ideal sensor is given by

$$N_{i,j}^{ideal} = \left\langle N_{i,j}^{ideal} \right\rangle + \xi_{i,j}^{ideal} \,, \quad \left\langle \left(\xi_{i,j}^{ideal} \right)^2 \right\rangle = \left\langle N_{i,j}^{ideal} \right\rangle \tag{3}$$

$\xi_{i,j}^{ideal}$ is the noise of the signal electron number which cannot be avoided even in the ideal case. Because of the Poisson distributed photon or electron noise, the variance $\left\langle \left(\xi_{i,j}^{ideal} \right)^2 \right\rangle$ is equal to the averaged electron number $\left\langle N_{i,j}^{ideal} \right\rangle$, which can be calculated as follows:

$$\left\langle N_{i,j}^{ideal} \right\rangle = A \cdot \int_{\lambda_{\min}}^{\lambda_{\max}} d\lambda \cdot \lambda \cdot L_\lambda^{ideal} \left(x_i, y_j \right)$$
$$\left(A = \frac{\pi}{4} \cdot \frac{1}{f_\#^2} \cdot F_{pix} \cdot t_{\text{int}} \cdot \frac{1}{h \cdot c} \right) \tag{4}$$

with $f_\#$ = f-number of optics, F_{pix} = pixel area, t_{int} = illumination (integration) time, h =

Planck's constant, c = speed of light in vacuum.

Furthermore

$$L_\lambda^{ideal}\left(x_i, y_j\right) = \iint dxdy\, H_\lambda^{ideal}\left(x_i - x, y_j - y\right) \cdot L'_\lambda\left(x, y\right) \quad (5)$$

Here, $L'_\lambda(x,y)$ is the radiance in front of the sensor. H_λ^{ideal} is the point spread function (PSF) of the whole imaging system. The quality measure is defined with respect to that radiance. The generated electrons or charges $\left\langle N_{i,j}^{ideal}\right\rangle$ will be changed at the pn-junction of the photodiode into an electrical voltage. Let $U_{i,j}$ be the voltage in front of the ADU. Then we have with eq. 3

$$U_{i,j}^{ideal} = \alpha \cdot N_{i,j}^{ideal} = \alpha \cdot \left\langle N_{i,j}^{ideal}\right\rangle + \alpha \cdot \xi_{i,j}^{ideal} \quad (6)$$

The multiplier α is given by $\alpha = U_{\max} / N_{sat}$ with U_{max} the maximal ADU input voltage and N_{sat} the saturation electron number. The gray values $G_{i,j}$ (output of ideal sensor) are given by

$$G_{i,j}^{ideal} = U_{i,j}^{ideal} \quad (7)$$

and we obtain from eqs. 4, 5, 6, and 7

$$\begin{aligned} G_{i,j}^{ideal} &= \alpha \cdot A \cdot \int_{\lambda_{\min}}^{\lambda_{\max}} d\lambda \cdot \lambda \\ &\cdot \iint dxdy\, H_\lambda^{ideal}\left(x_i - x, y_j - y\right) \cdot L'_\lambda\left(x, y\right) \\ &+ \alpha \cdot \xi_{i,j}^{ideal} \end{aligned} \quad (8)$$

Now we consider the real imaging sensor. As in eq. 3 we obtain the electron numbers $N_{i,j} = \left\langle N_{i,j}\right\rangle + \xi_{i,j}^{el}$ with

$$\begin{aligned} \left\langle N_{i,j}\right\rangle &= A \cdot \int_{\lambda_{\min}}^{\lambda_{\max}} d\lambda \cdot \lambda \cdot \tau_{\lambda,i,j} \\ &\cdot \iint dxdy\, H_\lambda\left(x_i - x, y_j - y\right) \cdot L'_\lambda\left(x, y\right) \\ &+ \left\langle N_{i,j}^{D+U}\right\rangle \end{aligned}$$
$$\left(\tau_{\lambda,i,j} = \tau_{\lambda,i,j}^{opt} \cdot \eta_{\lambda,i,j}^{qu}\right), \quad \left\langle \left(\xi_{i,j}^{el}\right)^2 \right\rangle = \left\langle N_{i,j}\right\rangle \quad (9)$$

Here, $\left\langle N_{i,j}^{D+U}\right\rangle$ is the mean electron number in pixel (i,j) generated by dark current and environment (e. g. radiation of instrument parts in infrared). $\tau_{\lambda,i,j}^{opt}$ is the (optical) transmission and $\eta_{\lambda,i,j}^{qu}$ the quantum efficiency. The conversion of electrons in voltages U now is in difference to the ideal sensor (see eq. 6) non-linear with an additional noise:

$$U_{i,j} = f\left(N_{i,j}\right) + \xi_{i,j}^K = f\left(\left\langle N_{i,j}\right\rangle + \xi_{i,j}^{el}\right) + \xi_{i,j}^K \quad (10)$$

$\xi_{i,j}^K$ with variance $\sigma_K^2 = \left\langle \left(\xi_{i,j}^K\right)^2 \right\rangle$ is the noise of the read-out channel (which was neglected for the ideal sensor in eq. 6).

Here we consider the case that the conversion characteristic $f(N)$ of the read-out channel only differs marginally from linearity. These characteristics include the three noise-components photon noise, dark current, and the read- or read-out noise. So, the expression in eq. 10 can be developed in a Taylor series and truncated after the first term:

$$\begin{aligned} &f\left(N_{i,j}\right) = \alpha \cdot N_{i,j} + \delta f\left(N_{i,j}\right), \\ &\left|\delta f\left(N_{i,j}\right)\right| << \alpha \cdot N_{i,j} \end{aligned} \quad (11)$$

Then based on eqs. 10 and 11 it approximately holds that

$$f\left(\left\langle N_{i,j}\right\rangle + \xi_{i,j}^{el}\right) \approx \alpha \cdot \left[\left\langle N_{i,j}\right\rangle + \xi_{i,j}^{el}\right] + \delta f\left(\left\langle N_{i,j}\right\rangle\right) \quad (12)$$

and using eq. 10 leads to

$$\begin{aligned} &U_{i,j} \approx \alpha \cdot \left\langle N_{i,j}\right\rangle + \delta f\left(\left\langle N_{i,j}\right\rangle\right) + \xi_{i,j} \\ &\left(\xi_{i,j} = \alpha \cdot \xi_{i,j}^{el} + \xi_{i,j}^K\right) \end{aligned} \quad (13)$$

Now we consider the ADU: $[0,U_{max}]$ is the range of the input signal. That range is represented by $M = 2^n$ gray value steps (n bits). Let Δ be the quantization step, i. e. $\Delta = U_{\max} / M$. The non-linearity of analogue to digital conversion then is described by $G = g\left(U\right)$ with

$$g\left(U\right) = \left[\frac{U}{\Delta} + 0.5\right] \cdot \Delta \quad (14)$$

Here, $[x]$ is the integer part of the real number x. We remember that in the ideal case $g^{ideal}\left(U\right) = U$ holds.

For each real number $z > 0$ the inequality $0 \le z - \left[z\right] < 1$ is true. Then the ADU error is confined to $-0.5 \cdot \Delta < g\left(u\right) - U < 0.5 \cdot \Delta$. We interpret the error $g\left(U\right) - U$ as ADU noise

ξ^{ADU} and assume a uniform distribution in $-0.5\cdot\Delta < \xi^{ADU} < 0.5\cdot\Delta$. Then, we get as a result of a rectangular distribution (Jähne 2005)

$$\left\langle \xi^{ADU} \right\rangle = 0\,,\quad \left\langle \left(\xi^{ADU}\right)^2 \right\rangle = \sigma_{ADU}^2 = \frac{\Delta^2}{12} \tag{15}$$

Using eq. 13 and considering that $G_{i,j} = g\left(U_{i,j}\right)$ describes the analog-to-digital conversion of real sensors, the gray values of the real sensor are given by

$$\begin{aligned} G_{i,j} &= g\left(U_{i,j}\right) = g\left(\left\langle U_{i,j}\right\rangle + \xi_{i,j}\right) \\ &\approx g\left(\alpha\cdot\left\langle N_{i,j}\right\rangle + \delta f\left(\left\langle N_{i,j}\right\rangle\right) + \alpha\cdot\xi_{i,j}^{el} + \xi_{i,j}^{K}\right) \\ &= \alpha\cdot\left\langle N_{i,j}\right\rangle + \delta f\left(\left\langle N_{i,j}\right\rangle\right) + \alpha\cdot\xi_{i,j}^{el} + \xi_{i,j}^{K} \\ &\quad + \xi_{i,j}^{ADU} \end{aligned} \tag{16}$$

We now consider the quality measure $\left\langle\left(G_{i,j} - G_{i,j}^{ideal}\right)^2\right\rangle$: According to eqs. 3, 6, 7 and 16, and using an approximation of eqs. 11 and 16 we obtain

$$\begin{aligned} G_{i,j} - G_{i,j}^{ideal} &\approx \alpha\cdot\left(\left\langle N_{i,j}\right\rangle - \left\langle N_{i,j}^{ideal}\right\rangle\right) \\ &\quad + \delta f\left(\left\langle N_{i,j}\right\rangle\right) + \alpha\cdot\left(\xi_{i,j}^{el} - \xi_{i,j}^{ideal}\right) \\ &\quad + \xi_{i,j}^{K} + \xi_{i,j}^{ADU} \\ &\approx \alpha\cdot\left(\left\langle N_{i,j}\right\rangle - \left\langle N_{i,j}^{ideal}\right\rangle\right) \\ &\quad + \delta f\left(\left\langle N_{i,j}^{ideal}\right\rangle\right) + \alpha\cdot\left(\xi_{i,j}^{el} - \xi_{i,j}^{ideal}\right) \\ &\quad + \xi_{i,j}^{K} + \xi_{i,j}^{ADU} \end{aligned}$$

and

$$\begin{aligned} &\left\langle\left(G_{i,j} - G_{i,j}^{ideal}\right)^2\right\rangle \\ &\approx \left[\alpha\cdot\left(\left\langle N_{i,j}\right\rangle - \left\langle N_{i,j}^{ideal}\right\rangle\right) + \delta f\left(\left\langle N_{i,j}^{ideal}\right\rangle\right)\right]^2 \\ &\quad + \alpha^2\cdot\left\langle\left(\xi_{i,j}^{el} - \xi_{i,j}^{ideal}\right)^2\right\rangle + \sigma_K^2 + \sigma_{ADU}^2 \end{aligned} \tag{17}$$

The linear components are removed, because we assume that the different noise components are uncorrelated and the average of noise and signal components (e.g. $\left\langle\left\langle N_{i,j}\right\rangle\cdot\xi_{i,j}^{el}\right\rangle$) vanish.

Using $\Delta = \alpha\cdot\frac{N_{sat}}{2^n}$ and the variance of a rectangular distribution $\sigma_{ADU}^2 = \frac{1}{12}\cdot 2^{-2n}$ we can introduce the normalized quality measure

$$\begin{aligned} Q_{i,j} &= \frac{\left\langle\left(G_{i,j} - G_{i,j}^{ideal}\right)^2\right\rangle}{\left(\alpha\cdot N_{sat}\right)^2} \\ &\approx \left[\frac{\left(\left\langle N_{i,j}\right\rangle - \left\langle N_{i,j}^{ideal}\right\rangle\right)}{N_{sat}} + \frac{\delta f\left(\left\langle N_{i,j}^{ideal}\right\rangle\right)}{\alpha\cdot N_{sat}}\right]^2 \\ &\quad + \frac{\left\langle\left(\xi_{i,j}^{el} - \xi_{i,j}^{ideal}\right)^2\right\rangle}{N_{sat}^2} + \frac{\sigma_K^2}{\left(\alpha\cdot N_{sat}\right)^2} + \frac{1}{12}\cdot 2^{-2n} \end{aligned} \tag{18}$$

Now we discuss the measure $Q_{i,j}$ in more detail: The eq. 18 consists of deterministic and noise terms. The first two terms are deterministic. The contribution to $Q_{i,j}$ is the deviation $F_{i,j}^{(1)} = \left\langle N_{i,j}\right\rangle - \left\langle N_{i,j}^{ideal}\right\rangle$ of mean electron numbers.

The following equations until and including eq. 24 regard the nominators only because the denominator can in this context be considered as constant.

According to eqs. 4, 8 and 9 we obtain

$$\begin{aligned} F_{i,j}^{(1)} &= A\cdot\int_{\lambda_{\min}}^{\lambda_{\max}} d\lambda\cdot\lambda \\ &\cdot\iint dxdy\left[\tau_{\lambda,i,j}\cdot H_\lambda\left(x_i - x, y_j - y\right) - H_\lambda^{ideal}\left(x_i - x, y_j - y\right)\right] \\ &\cdot L_\lambda'\left(x,y\right) + \left\langle N_{i,j}^{D+U}\right\rangle \end{aligned}$$

Introducing the deviation $\delta\tau_{\lambda,i,j} = 1 - \tau_{\lambda,i,j}$ from the ideal case $\tau = 1$ ($\tau = \tau^{opt}\cdot\eta^{qu}$) we can write

$$\begin{aligned} F_{i,j}^{(1)} &= A\cdot\int_{\lambda_{\min}}^{\lambda_{\max}} d\lambda\cdot\lambda \\ &\cdot\iint dxdy\left[H_\lambda\left(x_i - x, y_j - y\right) - H_\lambda^{ideal}\left(x_i - x, y_j - y\right)\right] \\ &\cdot L_\lambda'\left(x,y\right) - A\cdot\int_{\lambda_{\min}}^{\lambda_{\max}} d\lambda\cdot\lambda \\ &\cdot\iint dxdy\,\delta\tau_{\lambda,i,j}\cdot H_\lambda\left(x_i - x, y_j - y\right)\cdot L_\lambda'\left(x,y\right) \\ &+ \left\langle N_{i,j}^{D+U}\right\rangle \end{aligned} \tag{19}$$

Here, the first term characterizes the PSF error, whereas the second summand is generated by deviations of optical transmission and quantum efficiency from ideal values. $\left\langle N_{i,j}^{D+U}\right\rangle$ describes the contribution from dark current and non-signal radiation. The PSF-error

$$F_{i,j}^{PSF} = A \cdot \int_{\lambda_{\min}}^{\lambda_{\max}} d\lambda \cdot \lambda \cdot \iint dxdy \left[H_\lambda \left(x_i - x, y_j - y \right) - H_\lambda^{ideal} \left(x_i - x, y_j - y \right) \right] \cdot L'_\lambda \left(x, y \right) \quad (20)$$

strongly depends on the radiance $L'_\lambda(x,y)$ of the observed scene. In particular, it vanishes if the radiance does not depend on the spatial coordinates *x,y* (homogeneous scene). Therefore, there is no signal-independent quality measure. It must be related to a spatial scene or at least to a certain class of radiances describing background and objects.

$F_{i,j}^{PSF}$ also can be expressed in the spatial frequency domain:

$$F_{i,j}^{PSF} = A \cdot \int_{\lambda_{\min}}^{\lambda_{\max}} d\lambda \cdot \lambda \cdot \iint dk_x dk_y \left[\tilde{H}_\lambda \left(k_x, k_y \right) - H_\lambda^{ideal} \left(k_x, k_y \right) \right] \cdot \tilde{L}'_\lambda \left(k_x, k_y \right) \cdot e^{i \cdot 2\pi \left(k_x \cdot x_i + k_y \cdot y_j \right)} \quad (21)$$

Here, $\tilde{H}_\lambda(k_x,k_y)$, $\tilde{L}'_\lambda(k_x,k_y)$ are the optical transfer function (OTF) and the 2D-Fourier transform of the radiance, respectively.

Sometimes quality measures use the OTF (or MTF) at Nyquist frequency. But generally the whole OTF function is necessary to express image quality correctly. Only under special assumptions concerning the radiance $L'_\lambda(x,y)$ or its Fourier transform $\tilde{L}'_\lambda(k_x,k_y)$ (eq. 21) can it be approximated to depend only on $\tilde{H}_\lambda(k_x,k_y)$ and $\tilde{L}'_\lambda(k_x,k_y)$ at the Nyquist frequency.

The transmission error (second term in eq. 19)

$$F_{i,j}^{\tau} = -A \cdot \int_{\lambda_{\min}}^{\lambda_{\max}} d\lambda \cdot \lambda \cdot \iint dxdy\, \delta\tau_{\lambda,i,j} \cdot H_\lambda \left(x_i - x, y_j - y \right) \cdot L'_\lambda \left(x, y \right)$$

can be written approximately as

$$F_{i,j}^{\tau} = -A \cdot r\left(x_i, y_j \right) \cdot \int_{\lambda_{\min}}^{\lambda_{\max}} d\lambda \cdot \lambda \cdot S_\lambda \cdot \delta\tau_{\lambda,i,j} \quad (22)$$

For estimation $L'_\lambda(x,y)$ was factorized in $r(x_i,y_j)$ a wavelength-independent reflectance and S_λ the spectral dependent radiance term. The OTF at Nyquist frequency is also integrated in S_λ.

Therefore, the image quality contribution $F_{i,j}^{(1)} = F_{i,j}^{PSF} + F_{i,j}^{\tau} + \left\langle N_{i,j}^{D+U} \right\rangle$ can be estimated easily.

The second contribution to $Q_{i,j}$ (eq. 18) $F_{i,j}^{(2)} = \delta f\left(\left\langle N_{i,j}^{ideal} \right\rangle \right)$ describes the deterioration of image quality by the non-linearity of the electronic channel (read out circuit). If the non-linearity is weak (fulfilled for most CCD devices), the function $f(N)$ (eq. 11) can be approximated by

$$\begin{aligned} f\left(N_{ij} \right) &= \alpha \cdot N_{ij} - \beta \cdot N_{ij}^2 , \\ \delta f\left(N_{ij} \right) &= -\beta \cdot N_{ij}^2 \quad \left(\beta \cdot N_{sat} << \alpha \right) \end{aligned} \quad (23)$$

Using the approximation

$\left\langle N_{i,j}^{ideal} \right\rangle \approx A \cdot \int_{\lambda_{\min}}^{\lambda_{\max}} d\lambda \cdot \lambda \cdot S_\lambda \cdot r\left(x_i, y_j \right)$ we obtain

$$F_{i,j}^{(2)} = -\beta \cdot \left\langle N_{i,j}^{ideal} \right\rangle^2 \quad (24)$$

Now, the systematic part of the quality measure (eq. 18) can be written as

$$Q_{i,j}^{syst} = \left[\frac{\left(\left\langle N_{i,j} \right\rangle - \left\langle N_{i,j}^{ideal} \right\rangle \right)}{N_{sat}} + \frac{\delta f\left(\left\langle N_{i,j}^{ideal} \right\rangle \right)}{\alpha \cdot N_{sat}} \right]^2 \approx \left[\frac{F_{i,j}^{(1)}}{N_{sat}} + \frac{F_{i,j}^{(2)}}{\alpha \cdot N_{sat}} \right]^2 \quad (25)$$

Now we consider the contribution of noise to the quality measure (eq. 18):

Using the formulas eqs. 3 and 9

$\left\langle \left(\xi_{i,j}^{el} \right)^2 \right\rangle = \left\langle N_{i,j} \right\rangle$, $\left\langle \left(\xi_{i,j}^{ideal} \right)^2 \right\rangle = \left\langle N_{i,j}^{ideal} \right\rangle$,

the part $F_{i,j}^{(3)} = \left\langle \left(\xi_{i,j}^{el} - \xi_{i,j}^{el,ideal} \right)^2 \right\rangle$ is given by

$F_{i,j}^{(3)} = \left| \left\langle N_{i,j} \right\rangle - \left\langle N_{i,j}^{ideal} \right\rangle \right| = \left| F_{i,j}^{(1)} \right|$, and we obtain

$$Q_{i,j}^{noise} = \frac{\left| F_{i,j}^{(1)} \right|}{N_{sat}^2} + \frac{\sigma_K^2}{\left(\alpha \cdot N_{sat} \right)^2} + \frac{1}{12} \cdot 2^{-2n} \quad (26)$$

The formulas eqs. 25 and 26 allow the estimation of the systematic and random contributions to the image quality measure $Q_{i,j}$ in every pixel (i,j). To obtain a more global measure characterising the whole image, $Q_{i,j}$ can be averaged over all pixels of the image.

3 Results and Discussion

In order to assess the developed method we compare simulated image data with parameters from real data. We evaluate these data in the vicinity of an edge. The mean gray value there is 176. With the standard deviation $\sigma = 1.4$ we have a signal-to-noise ratio of about 125 (green channel). The sensor is characterized by $N_{sat} = 300{,}000$, $U_{max} = 1$ V. Then, the mean electron number (without PSF) is $\langle N \rangle = \langle N^{ideal} \rangle \approx 207{,}000$. The PSF is assumed as a Gaussian with standard deviation σ_{PSF}. Fig. 1 (left) shows the mean electron numbers $\langle N^{ideal}_{PSF} \rangle$ and $\langle N^{real}_{PSF} \rangle$ for $\sigma^{real}_{PSF} = 5 \cdot \sigma^{ideal}_{PSF}$

Here, we study only the influence of the PSF to the image quality. Therefore, only the contribution

$$Q_i^{syst} = \left[\frac{\left(\langle N_i \rangle - \langle N_i^{ideal} \rangle \right)}{N_{sat}} \right]^2$$ is considered.

$$Q_i^{noise} = \frac{\left| \langle N_i \rangle - \langle N_i^{ideal} \rangle \right|}{N_{sat}^2}$$ shows the same behaviour, but is much smaller and therefore is not investigated here.

Fig. 1 (right) displays the function Q_i^{syst} for the case $\sigma^{real}_{PSF} = 5 \cdot \sigma^{ideal}_{PSF}$.

As it must be, $Q_i^{syst} = 0$ holds in the homogeneous image region whereas the quality near the edge is worse because of the PSF caused blur. Tab. 1 shows the dependence of $\max\left\{ Q_i^{syst} \right\}$ from the parameter $\sigma^{real}_{PSF} / \sigma^{ideal}_{PSF}$.

Of course, with increasing parameter $\sigma^{real}_{PSF} / \sigma^{ideal}_{PSF}$ also the area around the edge with worse image quality increases which is not taken into account in Tab. 1.

Tab. 1: Quality in dependence of $\sigma^{real}_{PSF} / \sigma^{ideal}_{PSF}$.

$\sigma^{real}_{PSF} / \sigma^{ideal}_{PSF}$	$\max\left\{ Q_i^{syst} \right\} \cdot 10^4$
1	0.0
2	1.3
3	2.9
4	4.1
5	4.9
…	
10	7.2

For comparison the IQC with NIIRS we investigate an IKONOS image (green channel) from Dresden. For images in a usual dynamic range the Poisson distributed photon noise dominates and again dark and read-out noise will be neglected here. Only the PSF and additional components from pre-processing influence the image quality. Fig. 2 (right) shows the comparison between the image quality measure and traditional NIIRS. This plot is a result of changing $\sigma^{real}_{PSF} / \sigma^{ideal}_{PSF}$ relation as seen in Tab. 1. The plot shows a linear part for $IQ \geq 10^{-4}$ (image quality, relative measure, no unit). This is equivalent with the results from (Jones 2004). He calculated for IKONOS with an average GSD = 0.93 m an average NIIRS 4.49 ± 0.19.

The parameter PSF and SNR are evaluated from the real image data. The PSF or RER was calculated from image edges (edge spread function - ESF), the SNR was derived from homogeneous areas in the images. The SNR

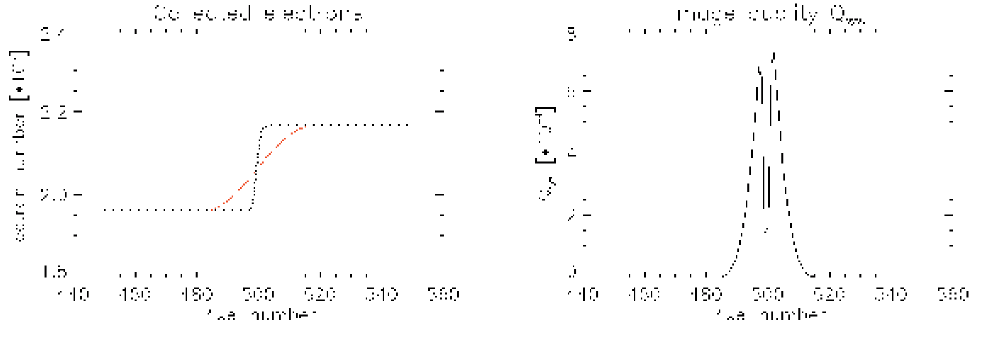

Fig. 1: Electron number (dashed line: electron number for the ideal case) and resulting function Q_i^{syst} (right).

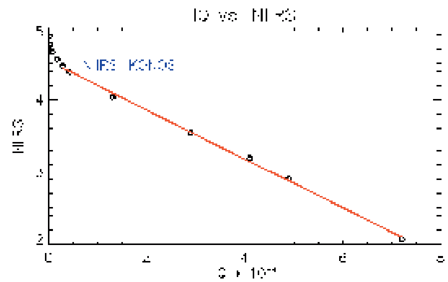

Fig. 2: Test case IKONOS image acquired at 8.7.2007 (left) and comparison with NIIRS.

in the considered region is 125 with a mean of 175 (in digital numbers) and a standard deviation of 1.4. The RER (σ_{PSF}^{real}) is 0.55 (1.25). The resulting NIIRS corresponds to the results from Jones (2004).

Remarkable is the non-linear increase below $IQ < 10^{-4}$. It shows also the potential for further improvement of the sensor.

4 Conclusion and Outlook

In this paper a sensor based method for calculation image quality was proposed. It is based on the consideration of the deviation of an ideal sensor to a real one, using sensor-specific parameters.

Experimental results show that the proposed method is consistent with the subjective quality score such as NIIRS. The key advantage of the new criterion is that it can be derived directly from the sensor parameters. In addition, artefacts may be detected directly (from the deviation to the ideal sensor). The potential for the improvement of the sensor can be deduced also by comparison with the ideal sensor.

To conclude, the development of a concept for image quality will require an in-depth analysis of the imaging system, as well as a careful analysis of the definitions for quality. It must be checked for further studies, whether an ideal sensor should be described by a delta function PSF and without photon noise.

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