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Computer Exercise. Characterization of infrared imaging sensors

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Preparations

Read *The Ultimate Infrared Handbook for R&D Professionals*, chapters 1 and 2.

Content

Part 1: Basic physics and measurement of infrared radiation.

Part 2: Hands-on experiments with a live IR-camera. In this part you will use a simple handheld IR-camera and do some simple experiments that illustrate some basic properties of IR-imaging.

Part 3: Non-uniformity correction of IR-images. Images from an IR-camera typically have a lower quality than a standard camera for the visible range. This is because it is more difficult to implement the necessary measurement process for an IR-sensor, that makes each pixel produce a uniform response to an incoming uniform radiation. In this part of the exercise, you will find out how to deal with this problem.

Part 1

The Ultimate Infrared Handbook for R&D Professionals does not give the explicit formula for Plank's radiation law for blackbodies. Here it is

$$M(\lambda, T) = \frac{2\pi h c^2}{\lambda^5 (e^{hc/\lambda kT} - 1)} \tag{1}$$

where $M(\lambda, T)$ is the spectral emittance or spectral excitance. If λ is given in meters it has a physical unit of Joule/second/meter^2/meter, or Watt/meter^3. T is given in Kelvin (K), and

c is the speed of light,
h is the Planck constant,
k is the Boltzmann constant.

It can be shown that the integral over Planck's law for all wavelengths of a blackbody gives that the total radiated energy is
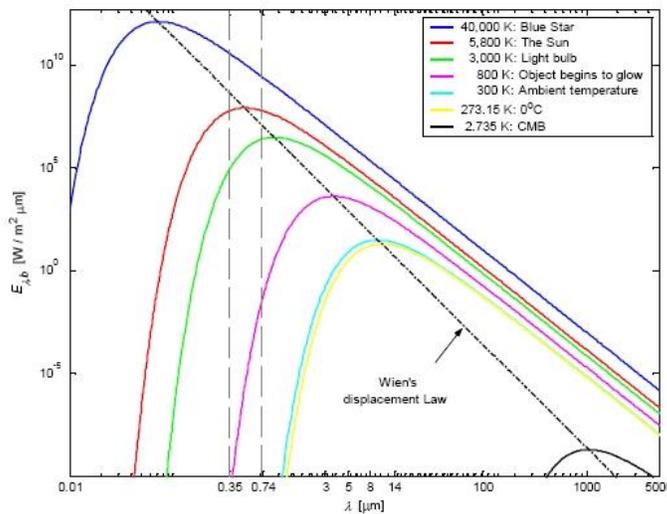
$$W = \sigma T^4 \; [W/m^2], \tag{1}$$

where σ is the Stefan-Boltzmann's constant. For a greybody,

$$W = \varepsilon_S \sigma T^4 \ [W/m^2],\tag{1}$$

where ε_S is the emissivity, see also (6).

In the figure below the spectral emittance $M(\lambda, T)$ is plotted as a function of λ for different temperatures T. Notice that the wavelength is given μ-meters and that the plot has a logarithmic scale both on the wavelength and the emittance.

For infrared sensors the emittance is measured only within certain well-specified wavelength bands λ_1 and λ_2, e.g., 3-5 µm and 8-12 µm for the sensors used in part 3 of this exercise, by integrating the spectral emittance $M_\lambda(\lambda)$ in the corresponding range:

$$M_{\lambda_1 - \lambda_2}(T) = \int_{\lambda_1}^{\lambda_2} M_\lambda(\lambda, T)\, \partial\lambda \tag{4}$$

This means that for a specific camera, for which λ_1 and λ_2 are specified and fixed, we can compute the integrated emittance that can be detected by the pixel as a function of the temperature T of the object. It is not possible to derive an analytic expression, but it can be computed numerically by a simple approximation of the above integral as a finite sum.

At your help, there is a Matlab script:

part1script.m, that contains a skeleton for a script that produces all the necessary computations for an approximation of the emittance in (4).

Q1: *Before you come to the exercise: What are the numerical values of c, h, and k, in Planck's radiation law? Give them in SI-units*

c =
h=
k =

You need to give the values for these constants in the script. Check that this is done. You also need to specify lambda1, lambda2, and *n* = the number of terms in the approximation of (4). One of the sensors you will look at in part 3 has $\lambda_1 = 3.5$ µm and $\lambda_2 = 5$ µm. Finally, you need to specify for which temperatures the integrated emittance is computed and plotted. Start with the range 1 to 1000 K. Choose a suitable *n* and run part1script to compute and plot the integrated emittance as a function of temperature.

Q2: What does the function look like? Is it linear, or what?

At some configuration this sensor can detect a maximum in-band irradiance of 40 W/m^2, and becomes saturated for intensities above that.

Q3: Which temperature does this intensity correspond to?

The digital output signal µ [*DN*, digital number] increases linearly with the detected radiance L [W/m^2/sr]. For an ideal blackbody source $L=M/\pi$. Disregarding the atmospheric influence this is expressed in

$$\mu = K_1 \int_{\lambda_1}^{\lambda_2} L_\lambda(\lambda, T) \tau_\lambda(\lambda)\, \partial\lambda + K_0 \tag{5}$$

where K_1 is the overall system gain and τ_λ is the spectral transmission of the optics. Besides the source, there are additional signal contributions (due to e.g. internal emission) which will add a bias K_0. The digital output signal µ can be transformed and presented in units of radiance or temperature.

In some IR-sensors, the intensity measurement at a pixel can be done over a relative large wavelength range, but often it is limited by an optical filter in front of the sensor, a filter that defines λ_1 and λ_2.

Q4: How can you change the upper or lower wavelength limits to increase the temperature range of this sensor?

The ratio between the emittance from a real source, M_S, and the emittance from an ideal blackbody source, M_{BB}, at the same temperature is called the spectral emissivity, ε_S

$$\varepsilon_S(\lambda) = \frac{M_S(\lambda)}{M_{BB}(\lambda)} \tag{6}$$

If ε_S is a constant < 1 for all wavelengths the source is called a greybody for which $L=\varepsilon_S \cdot M/\pi$. In the general case ε_S is a function of wavelength. Some approximate values of ε_S is shown in the table below (from http://www.eplus-innovation.com/knowledge.asp).

Emissivity — METALS

Material	Emissivity (ϵ)
Aluminum alloy-oxided	0.40
Aluminum-highly polished	0.04-0.06
Aluminum-oxidized	0.11-0.31
Aluminum-Anodized sheet	0.55
Brass-Oxidized	0.60
Brass-polished	0.03
Chromium-polished	0.10-0.38
Copper-polished	0.02-0.05
Copper-heated at 600˚C	0.57
Gold-pure, highly polished	0.02
Iron-polished	0.21
Iron-oxidized	0.94
rusted iron plate	0.65
Iron-rough steel plate	0.94-0.97
Lead-gray and oxidized	0.28
Mercury	0.09-0.12
Nickel-polished	0.12
Nickel-oxidized	0.37-0.85
Platinum-pure polished plate	0.05-0.10
Platinum-wire	0.06-0.16
Silver-pure and polished	0.02-0.03
Stainless steel-polished	0.16
Stainless steel-oxidized	0.74-0.87
Tin-bright	0.07-0.08
Tungsten-filament	0.32-0.39
Zinc-polished commercial pure	0.05
Zinc-galvanized sheet	0.23

Emissivity — NONMETALS

| Material	Emissivity (ϵ)
Asbestos Board	0.96
Asphalt, tar, pitch	0.90-0.98
Brick-red and rough	0.93
Brick-fireclay	0.75
Carbon-filament	0.53
Carbon-lampblack	0.96
Cement	0.54
Ceramic	0.90-0.94
Concrete	0.92-0.97
Frost crystals	0.98
Glass	0.80-0.95
Human skin	0.98
Ice	0.96-0.98
Marble-polished light gray	0.90
Paints, lacquers, varnishes Black	0.90-0.95
Paints, lacquers, varnishes aluminum paints	0.55
Paints, lacquers, varnishes flat black lacquer	0.96-0.98
Paints, lacquers, varnishes white lacquer	0.95
Paper	0.94
Plastic	0.84-0.94
Porcelain-glazed	0.92
Propellant-Liquid rocket engine	0.90
P.V.C.	0.91-0.93
Quartz-opaque	0.75
Rubber	0.95-0.97
Sand	0.90
Snorw	0.96-1.00
Soil	0.92-0.95
Tape-Masking	0.92-0.95
Wallpaper	0.85-0.90
Water	0.95-0.96
Wood-planed oak	0.82-0.89

Part 2

Hands-on experiments illustrating some basic properties of IR-imaging.

There are two main classes of *infrared detectors*: thermal detectors and photon detectors. The camera you will use in these experiments is based on an array with thermal detectors.

Characteristic features for a thermal detector :
- Based on a temperature change of a response element
  $\Rightarrow$ Slow response, a typical frame rate is up to 50 Hz (video rate)
- No cooling required
  $\Rightarrow$ Technically simple and cheap (compared with the photon detector)

- Lower sensitivity than the photon detector
- Ideal thermal detector: If radiation falls on the detector at different wavelengths but with constant power, and plot with output signal vs. wavelength is as follows

μ [DN]

wavelength [λ]
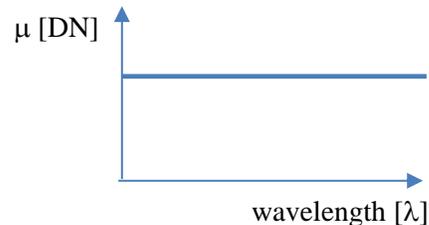
Characteristic features for a photon detector:
- Based on a photon-electron interaction
  $\Rightarrow$ Fast response, a frame rate > 10000 Hz is possible
- Requires cooling below 80 K to give good performance in the infrared region
  $\Rightarrow$ Technically complex and expensive
- High sensitivity
- Ideal photon detector: If radiation falls on the detector at different wavelengths but with constant power, a plot with output signal vs. wavelength is as follows

μ [DN]

wavelength [λ]
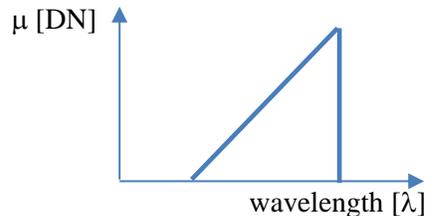
Task 1. The default camera setting of the emissivity is 0.95, which is in good agreement with the emissivity of human skin (~ 0.98). Use the camera to measure the apparent temperature of your or friend's skin. Does the value seem reasonable? Can you think out the apparent temperature if the emissivity setting is changed to an erroneous value, e.g. 0.30? Find out the answer using the camera!

Task 2. A problem with imaging in the infrared region is that expensive lens materials such as germanium must be used, due to that the transmission of ordinary lens materials is very poor. Investigate the infrared transmission of the glass plate! Now compare with the transmission of the plastic bag. Can you find out why plastic lenses are not used in infrared imaging?

Task 3. The camera is not needed in this task. As you have found out the camera is not able to see through e.g. the table. The "see-through" ability is achieved using longer wavelengths, 70 µm – 3 mm (i.e. the THz region). However, based on the characteristic features for a thermal detector, it should be possible to use the camera to "see-through" but the camera needs to be both modified and complemented. Can you figure out what modification and complement is required? Hints: Consider Task 2 and the figure below (you can also compare a motorist daytime and nighttime).
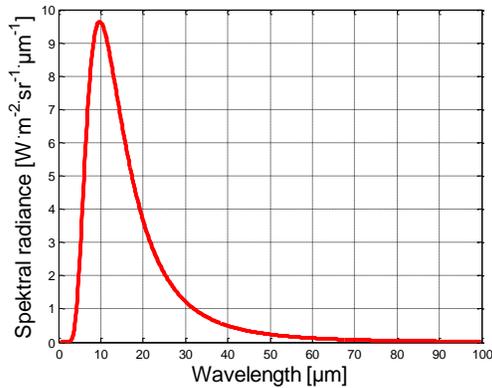
The figure shows the spectral radiance at the temperature 25 °C. The maximum emittance is found between 8-12 μm, which is the approximate spectral range for the infrared camera you are using in these hands-on experiments.

Part 3

Imaging systems based on staring arrays have high sensitivities and high frame rates (compared to the corresponding scanning systems). One disadvantage is that the sensitivities of the detector elements in the same sensor (detector signal/incident radiance) are different, corresponding to a type of static pixel noise (FPN, fixed pattern noise), which will decrease the sensor performance. This applies particularly to detector materials used in the infrared spectral range, where FPN is the main noise contribution.
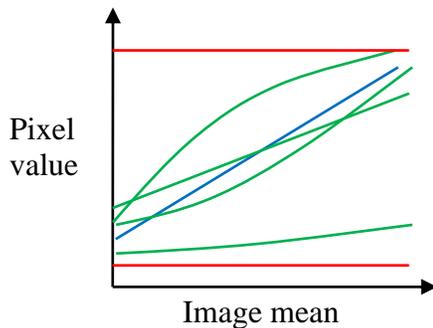

Figure: Schematic sketch of different responses of some pixels in a detector array resulting in fixed pattern noise (for clarity the differences between the responses have been exaggerated in the figure). Blue = a normal pixel; red = truly dead pixels, green = bad pixels.

Useful Matlab commands

imagesc: scales data and displays data as an image

colormap(gray):   sets the current figure's color map to "gray"; this presentation is preferable for most infrared images.

axis image: sets the aspect ratio so that width and height of the pixels are equal in size.

$A*X = B \implies X = A\backslash B = inv(A)*B$

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Sensor 1: Multispectral sensor (AIM)

All blackbody reference data are loaded into Matlab workspace: *load* Refdata1, etc.

A multispectral sensor collects data in several spectral bands at the same time. This sensor is based on a cooled MCT-detector[1] with the spectral range 1.5-5.2 µm. The number of pixels in the focal plane array is 288x384. The sensor is equipped with a rotating filter wheel containing four band pass filters (see figure below).

The full frame rate is 4x25 Hz. Generally the ability to detect an object increases with the number of spectral bands and the width of the spectral range covered by the spectral bands. However, having several spectral bands and a broad spectral range also makes the camera more technically complex – and more expensive.
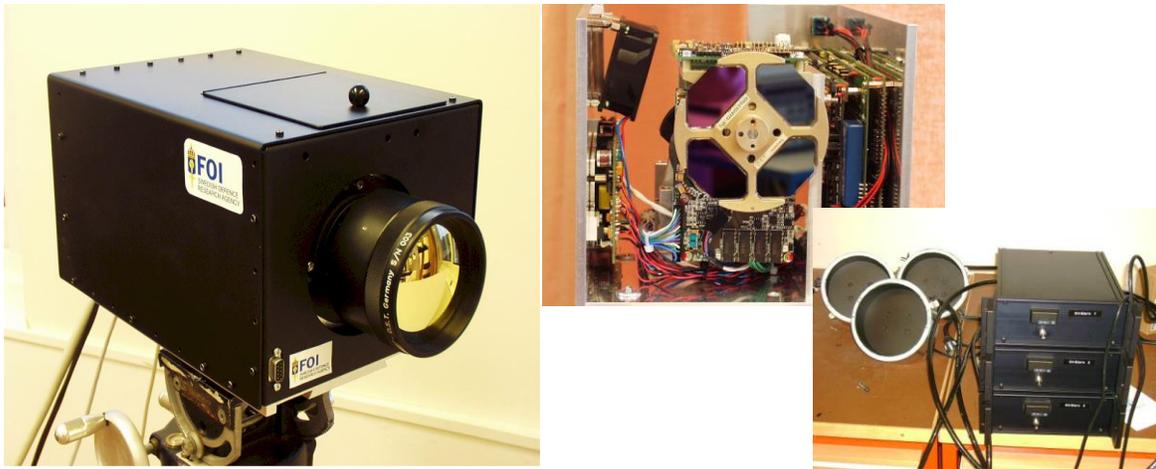

Figure: To the left is shown a multispectral sensor based on an MCT detector with the optics mounted, next to the right is shown the uncovered camera with the rotating filter wheel containing four band pass filters: Filter 1 (1.55 – 1.75 µm), Filter 2 (2.05 – 2.45 µm), Filter 3 (3.45 – 4.15 µm), Filter 4 (4.55 – 5.2 µm). To the right are shown three blackbody references.

The data used in the exercise has been collected in the spectral band 4.55-5.2 µm (filter 4). Refdata1, Refdata2 and Refdata3 are registrations of blackbody references (homogeneous surfaces) at three different temperatures. In particular FPN is a characteristic feature for the detector material MCT. In addition the detector array was severely degraded at the time for the measurement which is reflected by a large number of bad pixels. This can be observed as salt and pepper in the image.

Refdata1: registered blackbody reference at 3.5 °C during 0.8 s (288x384x20, double)
Refdata2: registered blackbody reference at 22 °C during 0.8 s (288x384x20, double)
Refdata3: registered blackbody reference at 34 °C during 0.8 s (288x384x20, double)
Scenedata: registration of "Slestadsrondellen" during 0.8 s (288x384x20, double)

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[1] Mercury Cadmium Telluride

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A. Plotting the sensor data

A-1. The Matlab script **`part3_A.m`** plots an image of a blackbody (e.g. the first image in the first blackbody reference data set, Refdata1) and look at the pixel values over the array. An ideal sensor would only show the temporal noise, which can be observed as random pixel fluctuations over the array. Does the pixel noise seem to be randomly distributed over the array?

The integrated radiances for the temperatures 3.5, 22.5, 33.5 °C are 0.809, 1.58 and 2.25 [W/(m^2,sr)], respectively.

A-2. Add code to **`part3_A.m`** and plot the three image means vs. the three integrated radiances for the reference data sets. An image mean is estimated by averaging the pixels over the array in the first image in the data set (the difference between using only the first image and all 20 images in the calculation is here negligible). The image means should be linear to the radiance levels. One can expect that the image mean ≈ 0 at a radiance level = $0 \Leftrightarrow$ the curve is a line through the origin. Is the curve a line through the origin? If not, can you find any explanation?

(Hint: For an ordinary digital camera the optical power on the detector is close to zero when the lens is covered, but what about an infrared camera?)

A-3. Identify the row (Y) and column (X) numbers for one bad pixel ("salt" or "pepper") and one "normal" pixel. Plot the single pixel values against the image means for the three levels and compare the results for a bad pixel and a "normal" pixel. Also plot two bad pixels where the value is not constant over time and which typically appears as not quite white salt and not quite black pepper. Two examples of such bad pixels are (200, 117) and (153, 204) respectively.

A-4. Plot also these four pixels over time (there are 20 time points in each data set). The Matlab command "squeeze" is convenient here. Compare the temporal noise for these four pixels. The temporal noise for a bad pixel which is truly dead (a pixel showing one constant value over time) is of course zero, but what about the other pixels? Is there any difference?

Summary of A
In an ideal sensor all pixels have the same response and the same temporal fluctuation (variance). As has been shown a real sensor is not ideal. The non-ideality also concerns sensors in the visual region, but here the non-uniformity is small compared to sensors in the infrared. Different methods are available to perform non-uniformity corrections (NUC). Below a method based on polynomial fitting is presented [1].

B. Reference based NUC

As has been shown under A, the response curve of a single pixel tends to be non-linear. An algorithm for polynomial fitting has been proposed by Schultz and Caldwell [2]. For

pixel j the difference ΔY_j between the pixel value Y_j and the mean value $<Y>$ of the N detectors in the array is fitted by the nth order polynomial of $<Y>$ according to

$$\Delta Y_j = Y_j - \langle Y \rangle \approx \sum_{i=0}^{n} C_{ij} \langle Y \rangle^i = \Delta Y_j^c \qquad j=1,2 \ldots N \qquad (7)$$

where ΔY_j^c is the estimated correction term. The corrected pixel value is denoted Y_j^c and is obtained as

$$Y_j^c = Y_j - \Delta Y_j^c \qquad (8)$$

If a second degree polynomial is used, the approximation (7) turns into

$$\Delta Y_j^c = C_{0j} + C_{1j}\langle Y \rangle + C_{2j}\langle Y \rangle^2 \qquad (9)$$

To estimate the coefficients C_{ij}, homogeneous radiating surfaces are registered at $n+1$ radiation levels (=3 for a 2nd degree polynomial). By eliminating $\langle Y \rangle$ from (9), see Appendix A, the corrected value Y_j^c is obtained as

$$Y_j^c = -\frac{1+C_{1j}}{2C_{2j}} \pm \sqrt{\frac{(1+C_{1j})^2}{4C_{2j}^2} + \frac{Y_j - C_{0j}}{C_{2j}}} \qquad (10)$$

The figure below shows schematic sketches of nonuniformity corrections with nth order polynomials.
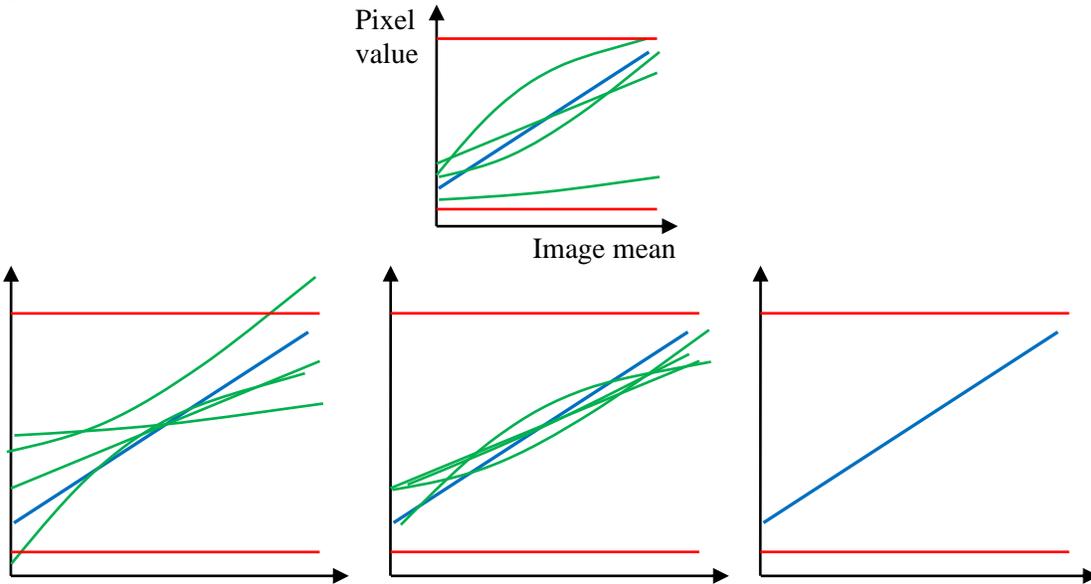

Figure: Upper: uncorrected data; blue = a normal pixel; red = truly dead pixels, green = bad pixels. Lower: ideal non-uniformity corrections. Lower left: a 0th order correction; lower middle: a 1st order correction; lower right: a 2nd order correction.

Ideally, the highest polynomial degree should give the best correction. One reason why this may not apply to all pixels is that the fixed pattern noise is not totally fixed but changes over time. A schematic example is shown in the figure below:
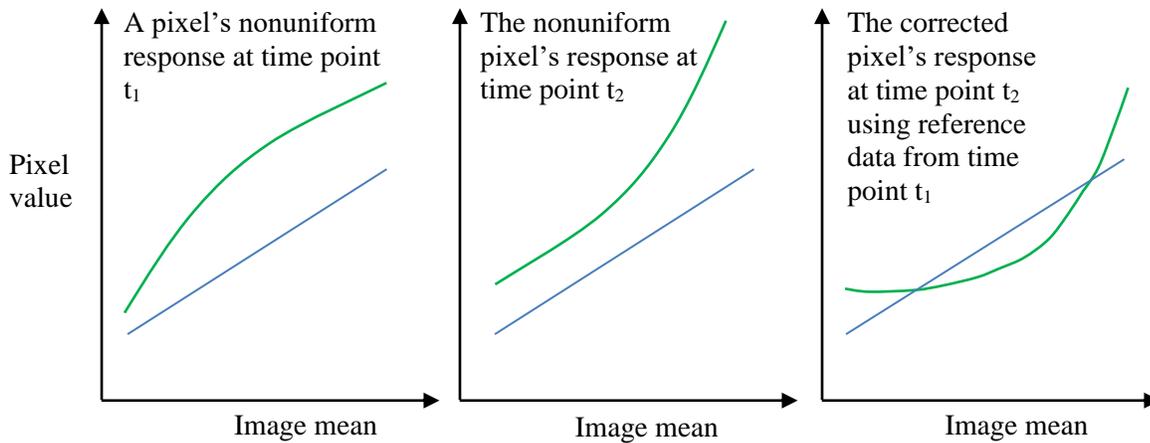

Figure: A non-uniform correction using a 2nd degree polynomial; the blue line marks an average pixel's response. The offset and the slope are corrected (right) but due to pixel drift the 2nd order correction has made the correction worse. In this case a better result had been obtained by a 1st order polynomial.

In B-1, B-2 and B-3 below, a rawdata image is compared with the results after a NUC using a 0th-degree (offset), a 1st-degree (linear) and a 2nd degree (square) polynomial fitting. By visual inspections, assign values on a (relative) 10 degree-scale in the table following B-3, where the raw image is given the value = 1, and a fictive "perfect" image (=an image where *all* pixels seem to have exact the same response) the value = 10.

B-1. Use `part3_B.m` and plot an uncorrected scene image (raw data image). Note that the point for this image is 1 in the table below.

B-2. Plot a NU corrected scene image. Compare the NUC results using 0th-degree (offset), 1st degree and 2nd degree polynomial fitting. ~~Use the Matlab command "imcontrast" to adjust the contrast in the images. Are there any differences? Store the corrected images by proper names for later use, e.g. for a 0th degree polynomial fitting: OI_c0.~~ Give subjective points for these 3 images in the table below.

B-3. Repeat B-2 with identification and replacement of the bad pixels using median filtering. The difference between uncorrected data pixels and median filtered pixels is used for identification of the dead pixels. A pixel is defined as a bad pixel if the difference (uncorrected pixels – median filtered pixels) > K, where K is an arbitrary value that is varying between datasets and/or sensors. For the distributed dataset a K value = 1000 gives a good result. The value of the bad pixel is replaced with the corresponding pixel value in a median filtered image. Give subjective points for these 3 images in the table below.

You do not need to store the data generated under B-3.

Note: With a larger K value, e.g. K > 100000, the amount of "salt and pepper" in the image becomes larger. On the other hand a too low value on the difference will cause a number of "normal" pixels to be identified and defined as bad pixels – and replaced. To identify and replace bad pixels is a compromise between minimization of the amount of salt and pepper in the image and retention of as much of the original information as possible.

	Point (1-10)
Image data	**Visual inspection**
Raw	**1**
NUC 0th	
NUC 1st	
NUC 2nd	
NUC 0th + dp repl	
NUC 1st + dp repl	
NUC 2nd + dp repl	

B-4. Median filtering is the method used to identify the bad pixels in B-3. Suggest another method to identify bad pixels? Hint: remember example A-4.

C. Image quality measures

A NUC will never be perfect and residual fixed pattern noise will therefore be added to the temporal noise:

$$\sigma_{tot}^2 = \sigma_{temp}^2 + \sigma_{spat}^2 \tag{11}$$

In B-1 – B-3 the quality of the NUC methods was evaluated by a visual inspection. However, if the amount of data is large, a substantial time may be needed to select the most optimal NUC methods by visual inspections. In addition, by a (subjective) visual inspection, it is not always obvious which NUC method is the most optimal and therefore the results will depend on the individual observer. Root-mean-square error (RMSE), UIQI or Q (universal image quality index) and roughness (ρ) are four proposed measures of the goodness of the NUC to describe the quality of the correction with an objective number instead of a (subjective) visual inspection.

Collect the results you obtain in C-1 – C-3 in the table after C-3. Use **part3_C.m**.

C-1. RMSE

RMSE [4] measures the improvement by a NUC. RMSE is defined as the square root of the average (over the entire array and block of frames) of the square of the difference between the corrected (the "true") pixel signal and the non-corrected pixel signal

$$RMSE = \sqrt{\frac{1}{N}\sum_{j=1}^{N}\left(\langle y_j\rangle - \langle x_j\rangle\right)^2} \quad ; \qquad [RMSE \geq 0] \tag{12}$$

where x_j denotes a pixel in the uncorrected image. With no improvement $RMSE = 0$.

C-1a. Calculate $RMSE$ in an image from Scenedata, before and after NUC including replacement of bad pixels. Cut the upper right corner in the image before the calculation (~ the columns 351-384) which contains the cluster with bad pixels.

C-2. UIQI

The universal image quality index UIQI (also denoted Q) [5] measures the improvement by an NUC and compares the image before (x) and after (y) a NUC. UIQI is expressed in the following equation

$$UIQI = \frac{4\cdot\sigma_{xy}\cdot\langle x\rangle\cdot\langle y\rangle}{\left(\sigma_x^2 + \sigma_y^2\right)(\langle x\rangle^2 + \langle y\rangle^2)} \qquad ; [-1 \leq UIQI \leq 1] \tag{13}$$

where $\bar{x}$, $\bar{y}$, σ_x and σ_y are the mean and standard deviation of both images. With no improvement $Q = 1$. (13) can be rewritten

$$UIQI = \frac{\sigma_{xy}}{\sigma_x\cdot\sigma_y} \cdot \frac{2\cdot\langle x\rangle\cdot\langle y\rangle}{\langle x\rangle^2 + \langle y\rangle^2} \cdot \frac{2\cdot\sigma_x\cdot\sigma_y}{\sigma_x^2 + \sigma_y^2} \tag{14}$$

The first component is the correlation coefficient between x and y. The second component measures the relative difference between x and y. The third component measures the contrast difference between the images.

C-2a. Calculate Q in an image from Scenedata, before and after NUC including replacement of bad pixels. Cut the upper right corner in the image before the calculation (~ the columns 351-384) which contains the cluster with bad pixels.

C-3. Roughness ρ

The roughness ρ [6] for an image is defined as

$$\rho(f) = \frac{\|h_1 * y\|_1 + \|h_2 * y\|_1}{\|y\|_1} \qquad ; [\rho \geq 0] \tag{15}$$

where h_1 is a horizontal mask [1, -1], $h_2 = h_1^T$ a vertical mask, $\|y\|_1$ is the L_1 norm of the image = the sum of the magnitudes of all pixels. For a uniform image $\rho = 0$, and increases with the pixel-to-pixel variation in the image.

C-3a. Calculate ρ in an image from Scenedata, before and after NUC including replacement of bad pixels. Cut the upper right corner in the image before the calculation (~ the columns 351-384) which contains the cluster with bad pixels.

Image data	RMSE	Q	ρ
Raw	0	1	
NUC 0th			
NUC 1st			
NUC 2nd			
NUC 0th + dp repl			
NUC 1st + dp repl			
NUC 2nd + dp repl			

D. Discussion section B and C

In practice a NUC based on a 1st degree polynomial is most common, followed by an offset correction. A 2nd degree polynomial fitting is not used as often, why?

What is the basic difference between the three image quality metrics studied in this exercise, considering eq. (12), (13) and (15)?

Which quality measure is in best agreement with your visual inspection in B?

~~The quality metrics RMSE and Q compare two images and return values of the change, instead of absolute values. Do these metrics tell if a change is positive or negative? If scene data and reference data are registered at different time points they may not match each other and in this case a reference based NUC will distort the scene data. Can you find out a solution to this problem?~~

E. Comparison with a standard camera

In the previous sections you have been looking at image data collected with a quite old infrared camera. The quite noisy data made it easier to see differences before and after the correction steps. In this section, you will compare with an infrared camera that is more representative of a standard infrared camera. Data are found under 'Multiband' and are loaded into Matlab workspace as before: *load* Refdata1, etc.

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E-1. Plot a scene image and make a visual comparison with a scene image from the first camera

E-2. Residual non-uniformity (RNU) is a measure used to quantify fixed pattern noise in image data from uniform surface radiators. It is defined

$$RNU = \frac{\sigma_{spat}}{DR} \cdot 100\%$$

where DR is the dynamic range, which is 2^{14} for both cameras.

Use Refdata2 (both cameras). In a first step the data is averaged over time so that most of the temporal noise is eliminated. In a second step the standard deviation gives the spatial noise σ_{spat}. In camera 1 the columns 351-384 contains a cluster with bad pixels in the upper right corner which are excluded in the calculation of σ_{spat}. In camera 2 the first row contains a time code in the upper right corner which is excluded in the calculation of σ_{spat}. Using Matlab, σ_{spat} is calculated as

```
RefdataTempAve=mean(Refdata2,3);
Camera 1: sigmaspat = std2(RefdataTempAve(:,1:350))
Camera 2: sigmaspat = std2(RefdataTempAve(2:512,:))
```

A RNU value below 0.1 % is a very good result. What can you say about the FPN quality of the first and the second camera ?

E-3. If time remains and you are interested, you can of course repeat the steps A through D also with the second camera.

References

[1] Gerald C.Holst, *Electro-optical imaging system performance*, Fifth edition, JCD Publishing Co (2008)
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Appendix A: Schultz approximation

Schultz (polynomial fitting):

$\Delta Y_j = Y_j - \langle Y \rangle \approx \sum_{i=0}^{n} C_{ij} \langle Y \rangle^i = \Delta Y_j^c;$

Ideally only temporal noise will remain after the correction and $Y_j^c \approx \langle Y \rangle$ for all pixels j

Offset:

$Y_j^c = Y_j - C_0$ (A1)

1st degree:

$Y_j - Y_j^c = C_{0j} + C_{1j} \cdot Y_j^c$

$Y_j - C_{0j} = (1 + C_{1j}) \cdot Y_j^c$

$Y_j^c = \frac{Y_j - C_{0j}}{1 + C_{1j}}$ (A2)

2nd degree:

$Y_j - Y_j^c = C_{0j} + C_{1j} \cdot Y_j^c + C_{2j} \cdot (Y_j^c)^2$

$Y_j - C_{0j} = (1 + C_{1j}) \cdot Y_j^c + C_{2j} \cdot (Y_j^c)^2$

$(Y_j^c)^2 + \frac{(1 + C_{1j})}{C_{2j}} (Y_j^c) - \frac{(Y_j - C_{0j})}{C_{2j}} = 0$

$Y_j^c = -\frac{1 + C_{1j}}{2C_{2j}} \pm \sqrt{\left(\frac{1 + C_{1j}}{2C_{2j}}\right)^2 + \frac{Y_j - C_{0j}}{C_{2j}}} = -\frac{1 + C_{1j}}{2C_{2j}} \pm \sqrt{\frac{(1 + C_{1j})^2}{4C_{2j}^2} + \frac{Y_j - C_{0j}}{C_{2j}}}$ (A3)