

Estimating an Image Sensor's Temperature for Darksignal-correction

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ABSTRACT

An approach for darksignal-correction is presented that uses a model of each pixel's darksignal, which depends on the sensor's settings (integration time and gain) and its temperature. It is shown how one can improve the outcome of such a darksignal-correction strategy by using the darksignal of some pixels in order to compute an estimate of the sensor's temperature. Experimental results indicate that the darksignals' dependency on temperature and gain is more complex than considered in up-to-date darksignal models. In this paper it is shown how one can cope with this complex behaviour when estimating the temperature out of the darksignal. Experimental results indicate, that our method yields better results than using temperature measurements of dedicated temperature sensors.

Keywords: darksignal, darksignal-modelling, darksignal non-uniformity (DSNU), darksignal-correction, fixed pattern noise, dark current, CMOS, image correction

1. INTRODUCTION

A picture that has been taken with a digital camera consists of the desired signal, i.e. the picture, and undesired noise. This noise originates out of various sources and is widely distinguished into two classes: non-deterministic noise and so-called deterministic or fixed-pattern noise (FPN).¹ One main part of the FPN is the darksignal which arises from the fact, that a pixel will have a non-zero value even if it hasn't been exposed to light during the integration time. This darksignal can be – and often is – corrected by subtraction of the values of some pixels that are shielded from light (so-called optically black pixels (OB-pixels)). This method has the advantage of needing a rather short amount of time, on the other hand it corrects not for the entire darksignal due to the fact that each pixel does have a more-or-less unique darksignal (darksignal-nonuniformity DSNU). A correction-signal that has been computed out of the values of a few OB-pixels, therefore can only correct average-pixels.

Another method also often used is the subtraction of a darkframe, i.e. a frame that has been taken with the same settings but with closed shutter. While this method yields better results in correcting the pixel specific DSNU, its drawbacks are an amplification of the temporal noise by a factor of $\sqrt{2}$ and that another frame has to be taken. The amplification of the temporal noise can be lowered by taking the average of multiple darkframes which of course needs even more time. Additionally this method suffers from the fact that the darksignal not only depends on integration time and gain but also on the pixels' temperatures. This is problematic because the image sensor gets heated up by the operation of itself and the rest of the camera's electronics.

Hence a lot of work has been done on modelling the darksignal, so as to compute a virtual, noise-free darkframe. The simplest approach of modelling the darksignal is a linear function of the integration time, which consists of an offset, independent from every parameter and a darkcurrent, i.e. the slope of the darksignal over the integration-time. However this approach ignores the temperature-dependence of the darksignal, this isn't a problem as long as the sensor is temperature-stabilized. Because such a temperature-stabilization isn't feasible for every camera, efforts have been made to model the darksignal as a function of temperature and integration time (e.g.^{2,3}) or as a function of a temperature-/darksignal-indicator.⁴ For the first approach the sensor's temperature has to

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be known in order to compute a virtual darkframe. This could be done by using temperature sensors that are attached to or incorporated into the sensor. However, this leads to further problems as these sensors are always more-or-less apart from the actual pixels and may be erroneous.

Widenhorn et al. used a temperature indicator in⁴ which is an estimate of some hot-pixels' darksignal, i.e. pixels with a high darkcurrent. In this paper we present a darksignal-correction method that consists of two steps. At first an estimate of the sensor's temperature is computed from the darksignal of the pixels or a set of pixels – e.g. the OB-pixels. In a second step this temperature is used to compute a virtual darkframe, using a novel type of darksignal-model. We introduce our novel darksignal-model in section 2. Section 3 deals with theoretical and practical problems that arise when the temperature is estimated using this model, and the meaning of the estimated temperature. How we use our model in order to estimate the sensor's temperature is explained in section 4. Section 5 introduces different measures of confidence that can be used in order to get one estimate for the temperature out of the estimations from all pixels. We further evaluate our model in section 6.

2. DARKSIGNAL-MODEL

Up-to-date darksignal-models like the one used in³ or² are highly inspired by the theoretical descriptions of a photodiode's darkcurrent: I.e. they use a term that increases exponentially with rising temperature. We started with using the model from³ which suited our data quite well until we analysed the sensor's behaviour at higher gain settings (i.e. higher ISO speeds). The darksignal tends to decrease with rising temperature at high gain and short integration time, contrary to the model which can't explain such an effect. Said effect can be seen in fig. 1 & 2 where the darksignal of a single pixel is shown for different temperatures and integrations times at ISO-speed 200 and 3200. at ISO-speed 200 (fig. 1) the darksignal shows the expected exponential temperature-dependency, but the same pixel shows a darksignal that decreases with increasing temperature at ISO-speed 3200 and short integration times (2). The model doesn't incorporate such effects because the model is mostly based on a photodiode's behaviour. The sensor of course consists of more than some photodiodes and further is accompanied by various electronics for which it is quite possible to have some temperature-dependent characteristics.

The same effect has been observed by Kuusk in² with a spectrometer module. Most of the published work on darksignal-modelling known to us, however does not consider such effects because it is based on so-called raw-values of consumer-cameras (e.g.⁵) or on the output of industrial cameras (e.g.⁶). At least for consumer cameras it is well known, that this raw-data isn't raw at all.⁷ The raw-data of consumer-cameras normally is clamped against OB-pixels or even corrected by dark-frame-subtraction (usually at high integration times). Thus the darksignal that is observed in the raw-data of consumer cameras usually is only the residual of some darksignal-correction-methods, and therefore this data isn't suitable for the examination of the original darksignal. Hence we are using a Leica M camera that has been endowed with a modified firmware, that allows us to take real-raw data, that hasn't been altered at all.

We started to design a new model by starting with the emva-model and analysing its residuals at various settings. We ended with a model that is – in its details – tailored for the examined CMOS image sensor (i.e. a Leica-Max-Sensor with 24MP and two integrated temperature sensors). Its basic ideas however should be adaptable to other sensors as well. The model describes a pixel's darksignal as stated in eq. 1, where the first term describes the offset of column j which depends on the ISO-speed and the second is an offset for each individual pixel in line i and column j . The third and fourth term are the temperature dependant effects, that are the dark current $dc_{0R|i,j}$, which doubles every $T_{D|i,j}$ degree Celsius, and a term that depends linear on the temperature, where the slope $m_{i,j}$ is negative.

The model's part that describes the darkcurrent is based on the physical description of this effect, the other parts however are somewhat empirically. They have been designed based on observations of the emva-model's deviation from actual darksignal-measurements and further incorporate knowledge about the sensor's architecture.

The column offset describes a part of the darksignal that depends neither on temperature nor integration-time, and which has been observed to be constant per column, but depends on the ISO-speed in a non-linear way. The ISO-speed is set via an analogue-amplifier (g_a) per column and a subsequent digital gain (g_d). The non-linearity can be described by assuming a negative offset prior to the analogue gain ($o_{a|j}$) and a positive offset that is added after the analogue gain and before the digital gain ($o_{d|j}$).

It has to be mentioned, that there are some pixels (ca. 26000 $\hat{=} 0.1\%$) that do not behave like the majority

(e.g. their darksignal is not a linear function of the integration time or they are electronically defect) and hence deviate strongly from our model. These pixels are therefore declared as "defect in the sense of our model".

$$d_{i,j}(t_i, T, s_{iso}) = (o_{a|j}g_a(s_{iso}) + o_{d|j})g_d(s_{iso}) + o_{pix|i,j} \\ + (s_{iso} - 200)(m_{i,j}T) + \left(dc_{0R|i,j}t_i 2^{\left(\frac{T-T_R}{T_D|i,j}\right)} \right) g_a(s_{iso})g_d(s_{iso}) \quad (1)$$

3. THEORETICAL BOUNDS ON TEMPERATURE ESTIMATION

Our main goal is to find the temperature T_o for which the model's error gets minimal. Where we use the root mean square error for a measured darksignal d_{im} and a computed darksignal d_{mod} (eq. 3 & 4), as error-criterion. The darksignal d_{im} of course is unknown after taking a picture because it is masked by the actual (desired) picture. But also if no light impinged on the sensor, the darksignal would stay unknown because of the temporal noise. Therefore the modelled darksignal will deviate from the measured darksignal, even if we consider the model to be perfect, and the pixel's temperature, integration time and gain-setting, as known. That means a pixel's measured darksignal can be described as the – perfectly parametrized – modelled one plus the temporal noise n_{temp} and a systematic error e_{mod} which describes the model's imperfections:

$$d_{im|i,j} = d_{mod|i,j} + n_{temp} + e_{mod}. \quad (2)$$

Said temporal noise consists of different parts originating from various sources of which one is the darksignal itself. That is because the darksignal is a stochastic process whose probability distribution is the poisson distribution. Therefore the measured darksignal can be regarded as a random variable which is compound of various random variables, of which one is the actual darksignal. There have been efforts to model the resulting noise,⁸ we however decided to assume a normal distribution, which is a common assumption. Under this assumptions $d_{mod|i,j} + e_{mod}$ becomes the mean of said random variable and n_{temp} is a normal distributed random variable with zero mean and a variance that varies from pixel to pixel.

Therefore T_o minimizes e_{mod} , which furthermore implies, that a global temperature-estimate can only be perfect if spatially variations in temperature do not lead to changes in darksignal that are greater than the temporal noise. If we assume e_{mod} to be zero, then T_o is the sensor's real temperature (i.e. e_{mod} also contains errors which arise from less-optimal controlling of the temperature during the model's calibration).

$$RMSE_m(d_{im}, d_{mod}) = \sqrt{\sum_i \sum_j (d_{im|i,j} - d_{mod|i,j})^2} \quad (3)$$

$$T_o = \arg \min_T (RMSE_m(d_{im}, d_{mod}(T))) \Rightarrow e_{mod} = \min \quad (4)$$

As already mentioned, the temperature that we're looking for is that temperature, that minimizes the model's error, that means it doesn't have to be the actual physical temperature. This definition of the optimal temperature simplifies the problem of finding the right temperature, or determining whether the calculated temperature is right. The model's error can be easily determined by comparing the model's predictions with actual darkframes and the optimal temperature T_o therefore can easily be determined by minimizing the model's error using a minimization-algorithm. This temperature of course will deviate from the real temperature of the sensor, however it shouldn't deviate strongly from the real temperature, if the model's systematic error isn't too big and it should be the real temperature, if the model doesn't have any systematic error.

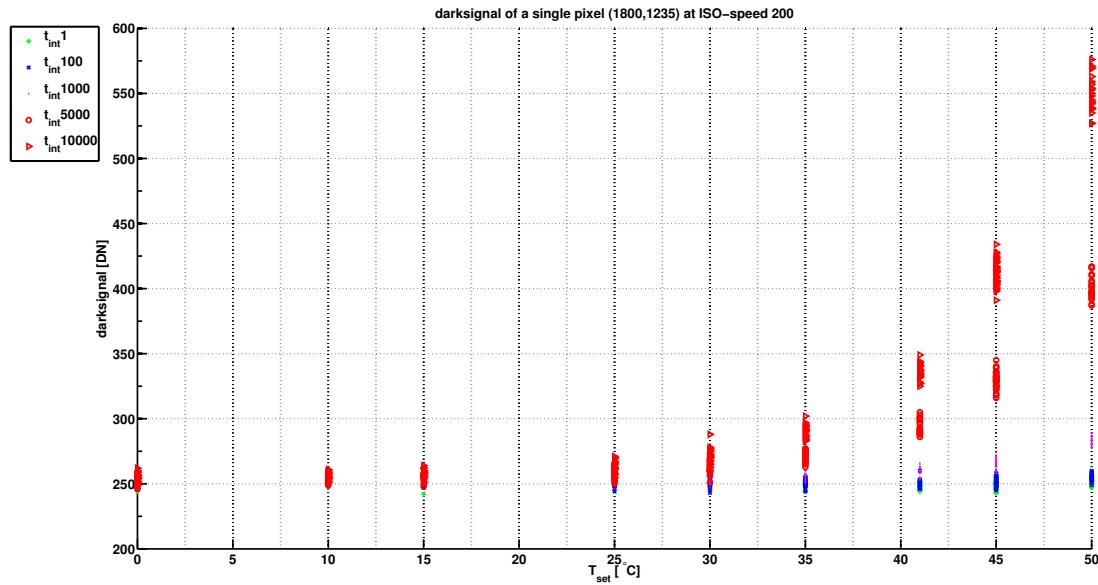


Figure 1. A typical pixel's darksignal at different integration times and temperatures and low gain (ISO 200, 25 pictures for each integration-time/temperature combination)

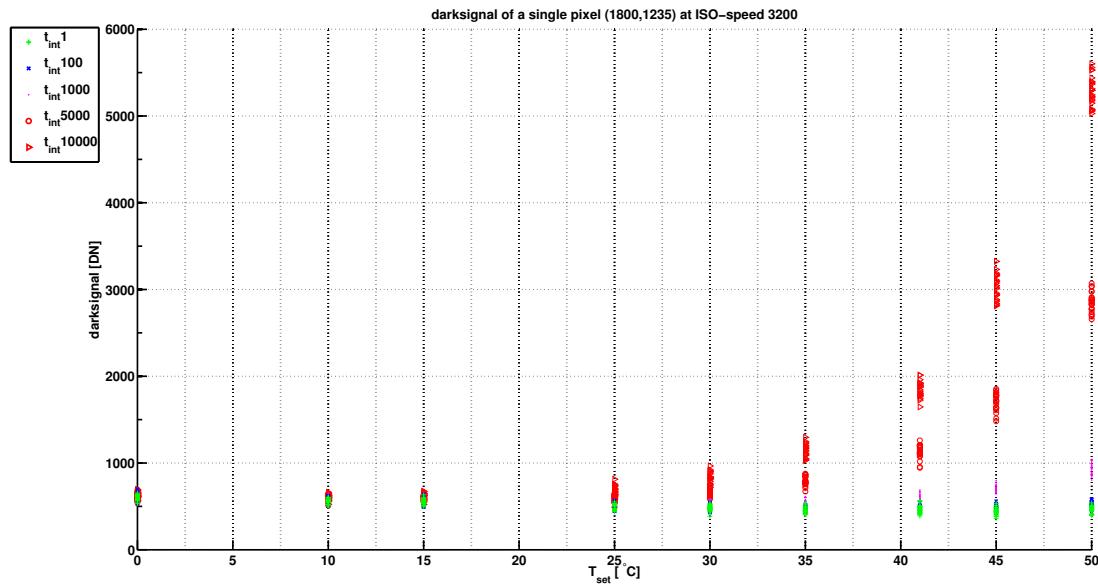


Figure 2. A typical pixel's darksignal at different integration times and temperatures and high gain (ISO 3200, 25 pictures for each integration-time/temperature combination)

4. TEMPERATURE-ESTIMATION STRATEGIES

The task of estimating the temperature of the sensor is not only problematic because of the noise as discussed in the previous section. Additionally eq. 1 isn't solvable for T . The last could be dealt with in two ways: use a search algorithm in order to find the temperature T_o that minimizes the model's error, or estimate the temperature using the "dominant effect". The last way is based on the fact that the darksignal is dominated by the darkcurrent at long exposure times and high temperatures, while the linear part dominates at low temperatures and short integration times.

When using the dominant temperature-dependent effect, a problem arises due to the fact that the non-dominant part changes less with temperature at the given settings, but isn't zero. Therefore it has to be removed from the measured darksignal at first. To do so, the sensor's temperature is needed, however as the non-dominant part depends less on temperature, an error in the assumed temperature does not lead to a big error in this part. Hence we estimate the non-dominant part by using the temperature measurements of the image sensor's temperature sensors. The rest of the darksignal can be used to calculate a temperature estimate, after subtraction of the non-dominant part (i.e. its estimation) and the other parts that do not depend on temperature.

Thus our three temperature estimation strategies are: (I) using the darkcurrent (eq. 5), (II) using m_T (eq. 6) and (III) searching the temperature that minimizes the model's error (eq. 7). The third method is the computational most expensive method and is only supposed for testing purposes. However it also only computes one temperature for the sensor, while the other two strategies compute one temperature-estimate for each pixel, out of which one temperature for the sensor has to be calculated.

$$\text{I: } T_{i,j} = \left(\frac{\log \left(\frac{(d_{im}|_{i,j} - ((o_{a|j}g_a(s_{iso}) + o_{d|j})g_d(s_{iso}) + o_{pix|j}) - (s_{iso} - 200)(m_{i,j}\tilde{T}))}{dc_{0R|i,j}t_i g_a(s_{iso})g_d(s_{iso})} \right)}{\log(2)} \right) T_{D|i,j} + T_R \quad (5)$$

$$\text{II: } T_{i,j} = \frac{\left(d_{im}|_{i,j} - ((o_{a|j}g_a(s_{iso}) + o_{d|j})g_d(s_{iso}) + o_{pix|j}) - \left(dc_{0R|i,j}t_i 2^{\left(\frac{\tilde{T} - T_R}{T_{D|i,j}} \right)} g_a(s_{iso})g_d(s_{iso}) \right) \right)}{m_{T|i,j}(s_{iso} - 200)} \quad (6)$$

$$\text{III: } T_o = \arg \min_T [RMSE_m(d_{im}, d_{mod}(T))] \quad (7)$$

5. MEASURE OF CONFIDENCE

Using a numerical search algorithm in order to find T_o may result in perfect (in terms of RMSE) virtual darkframes, but this comes with high computational costs. Our idea to overcome this problem is to define a measure of confidence, that would be proportional to the quality of the temperature estimation of a given pixel at a given integration time, ISO speed and a first coarse temperature estimate, that could be acquired by using the image sensor's temperature sensors. Widenhorn et al. used a similar idea in,⁴ however they classified a group of pixels to be good temperature estimators, our approach does not binary classify the pixels, but instead tries to give a measure on each pixel's temperature-estimation-quality, which furthermore changes depending on the sensor's settings. That means a pixel which might have a low confidence measure at, e.g. short integration times, and which therefore shouldn't be trusted too much at short integration times, could become a good temperature estimator at longer integration times.

This measure of confidence could be used in various ways, e.g. a threshold could be defined, above which a pixel becomes a good temperature estimator, or the sensor's temperature could be computed as a weighted mean over all the pixels' temperature estimates, where the weights are the pixels' confidence measures. The last one is the strategy that we have chosen for our examinations. We further tested two different types of confidence measures, one based on error propagation and one being more empirical.

As the first is based on error propagation, it assumes that the error is non-systematic and normally distributed, assumptions that can't hold for the darksignal. However we think that it still holds some information about the quality of a pixel's temperature estimation. The confidence measure of this type for strategy I is given in equation 8, the one for strategy II in equation 9.

The second type of confidence measure has been empirically developed by comparing the outputs of temperature estimation strategy I & II with the model's parameters and with basic considerations of the temperature-sensitivity in mind. A pixel is a better temperature estimator if it isn't too noisy, that is why the reciprocal of the standard deviation $\sigma_{i,j}$ of each pixel is in both confidence measures (eq. 10 & eq. 11). A good temperature indicator should be very sensitive to temperature, therefore a low dark-current and a high (T_D) lead to a low confidence for strategy I (eq. 10) and a low $|m_{i,j}|$ to a low confidence for strategy II. Additionally, pixels that have a very high signal are not very trustworthy, as it could be, that their signal is below the maximum value ($CLIP$) only because of the temporal noise. Therefore the erf-term lowers the confidence measure for pixels which have such a high-value, according to the model.

The confidence measures that have been designed that way haven't been derived from the model or else, however they don't need estimates of the darksignal itself, which is an advantage over the error-propagation-based one for strategy I (eq.8). Furthermore, we decided not to use the error-propagation based ones, because our examinations showed that they do not perform better than the empirical ones.

$$c_{e,I|i,j}(T_{Tsensor}, \sigma_{i,j}, t_i, s_{iso}) = \frac{1}{1 + \sigma_{i,j}^2 \left| \frac{T_{D|i,j}}{\log(2)(ds_{i,j} - o_{pix|i,j} - (o_{a|j}g_a(s_{iso}) + o_{d|j})g_d(s_{iso}) - (s_{ISO} - 200)m_{i,j}T_{Tsensor})} \right|} \quad (8)$$

$$c_{e,II|i,j}(\sigma_{i,j}, t_i, s_{iso}) = \frac{1}{1 + \sigma_{i,j}^2 \left| \frac{1}{(s_{iso} - 200)m_{i,j}} \right|} \quad (9)$$

$$c_{I|i,j}(T_{Tsensor}, \sigma_{i,j}, t_i, s_{iso}) = \frac{dc_{0R|i,j}t_i 2^{\left(\frac{T_{Tsensor} - T_R}{T_{D|i,j}} \right)}}{\sigma_{i,j} T_{D|i,j} \left(1 + \text{erf} \left(\frac{CLIP - d_{i,j}(t_i, T_{Tsensor}, s_{iso})}{\sqrt{2\sigma_{i,j}^2}} \right) \right)} \quad (10)$$

$$c_{II|i,j}(T_{Tsensor}, \sigma_{i,j}, t_i, s_{iso}) = \frac{|m_{i,j}|}{\sigma_{i,j} \left(1 + \text{erf} \left(\frac{CLIP - d_{i,j}(t_i, T_{Tsensor}, s_{iso})}{\sqrt{2\sigma_{i,j}^2}} \right) \right)} \quad (11)$$

6. EVALUATION

The model has been calibrated for a given Leica Max Sensor using a large set of darkframes. This set has been taken using a climate chamber in which the sensor and an imaging board were placed. The sensor had been shielded from light and the temperature had been thoroughly controlled using the climate-chamber's temperature sensor and the image sensor's temperature sensors. We took 4650 dark frames with combinations of four different ISO speeds, four different integration times and eleven different temperatures (further information can be found in table 1).

We took another set of darkframes, using six different ISO speeds, four different integration times and three different temperatures (further information can be found in table 2). We used this set in order to evaluate the temperature estimation strategies (and the darksignal model itself).

We found that our darksignal-model, and hence also the temperature-estimation strategies, didn't perform well when we used other ISO-speeds than the ones we used when we calibrated our model. This effect is worst for low analogue gains (low ISO-speeds) and even leads to invalid temperature estimation at some settings. First examinations of this problem indicate that not only the analogue gain should be calibrated thoroughly before calibrating the darksignal, but it also seems to have a larger influence on the darksignal's temperature-dependency as we had expected.

The darksignal model however performed well at the analogue gains that have been used during the calibration-process, as did the temperature estimation strategies. The results for every tested (T_{set}, t_i, s_{ISO}) -combination are shown in figure 4 where we plotted the median of the model's error for all pixels for each of these combinations (the average of the RMSE over all pixels is just slightly higher than the median). Using the temperature-estimation-strategies leads to a lower error than using the measurements of the temperature sensors and – besides at low integration times at high temperatures and ISO 800 – to lower errors than correcting the darksignal by capturing

and subtracting a darkframe. However the usage of the model leads to high isolated errors, due to single pixels that do not behave like the model (i.e. typical pixels), e.g. pixels that are non-linear in reference to the integration time.

Hence it can be seen in fig. 6-8 that the model-based corrections perform better for most of the pixels, however the results are deteriorated by a "salt and pepper" type of noise which is caused by aforementioned non-typical pixels. It has to be noted, that the non-clamped (upper) images in fig. 6-8 have to be looked at with care, because high negative average errors are clamped to zero before the gamma-correction. Hence the lower ones which are clamped to the OB-pixels before the demosaicing do show errors that are hidden in the upper ones, due to the fact, that the clamping to the OB-pixels' values corrects the average error of the model.

s_{ISO}	200	800	3200	6400					
$t_{exp}[ms]$	1	1000	5000	10000					
$T_{set}[^{\circ}\text{C}]$	0	10	15	20	25	30	35	40	45

Table 1. parameter-settings of the calibration set, 25 dark-frames have been taken for each $(s_{ISO}, t_{exp}, T_{set})$ -combination

s_{ISO}	250	400	640	800	1000	3200			
$t_{exp}[ms]$	1	250	4000	15000					
$T_{set}[^{\circ}\text{C}]$	8	13	25	33					

Table 2. parameter-settings of the evaluation set, 10 dark-frames have been taken for each $(s_{ISO}, t_{exp}, T_{set})$ -combination, no pictures have been taken at $T_{set} = 13^{\circ}\text{C}$ for $s_{ISO} = 800$ & $s_{ISO} = 3200$ and $T_{set} = 25^{\circ}\text{C}$ has only been tested at $s_{ISO} = 250$ and $s_{ISO} = 400$

7. SUMMARY

We showed that it is possible to optimize model-based darksignal-correction by estimating the image sensors temperature with the same model used for correction. These optimizations are measurable however they are visually quite small. We expected that it should be possible to correct for spatially variant temperatures, however the effect of (reasonably produced) spatial variances in temperature seems to be masked by temporal noise (at least with the sensor used in this study).

While the benefits of temperature estimation against the temperature measurement using the temperature sensors that are integrated into the image sensor are very small, the benefits of using a darksignal-model vs. using a darkframe are clearly visible, yet this also applies to its drawbacks. I.e. the increased temporal noise due to darkframe subtraction is clearly visible, using a darksignal model on the contrary leads to single pixel errors due to single pixels that behave different than the model, therefore more pixels' values have to be corrected afterwards (i.e. calculated from the neighbouring pixels' values). On the other hand it's not necessary to take another frame when using a darksignal model.

While many up-to-date works on darksignal correction with darksignal models considered integration time and temperature as parameters for their models, we also focused on the gain-settings (i.e. ISO-speed). Our work shows that this leads to further problems, as the gain itself has to be calibrated and the sensor tends to behave very differently at various gain-settings.

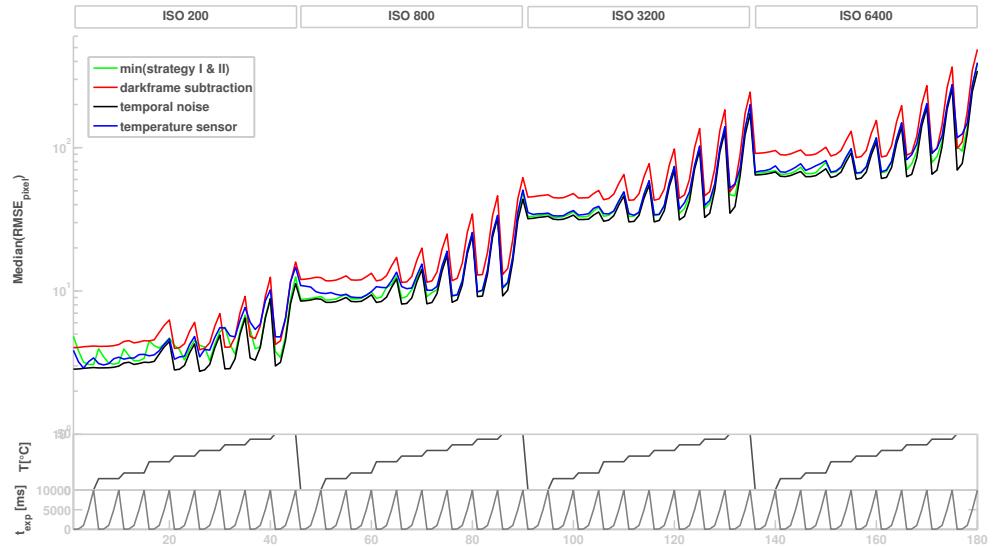


Figure 3. RMSE for different darksignal-correction methods calibration-set

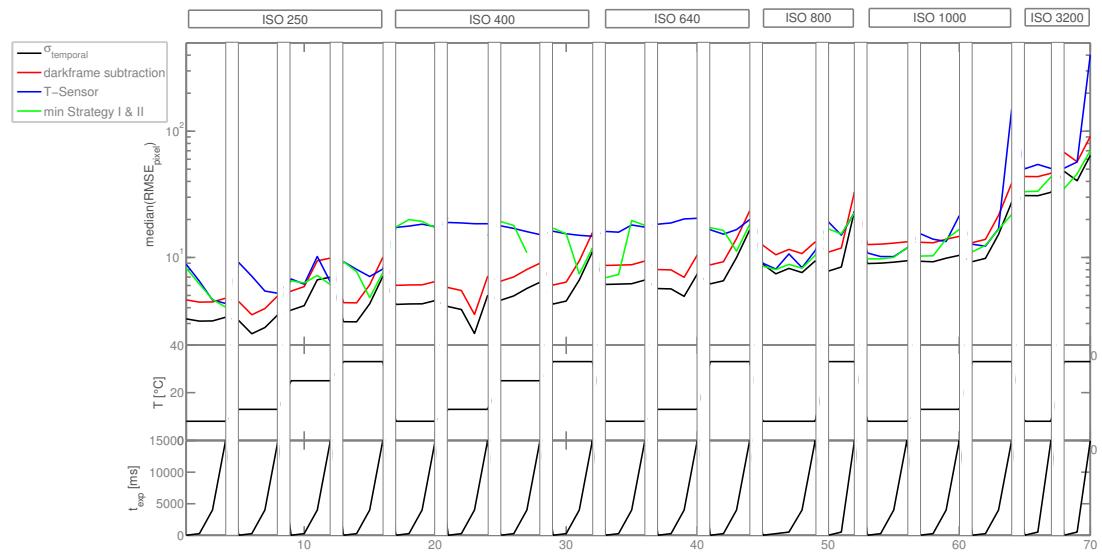


Figure 4. RMSE for different darksignal-correction methods evaluation-set 1, using the confidence measures defined in eq 10 ans 11

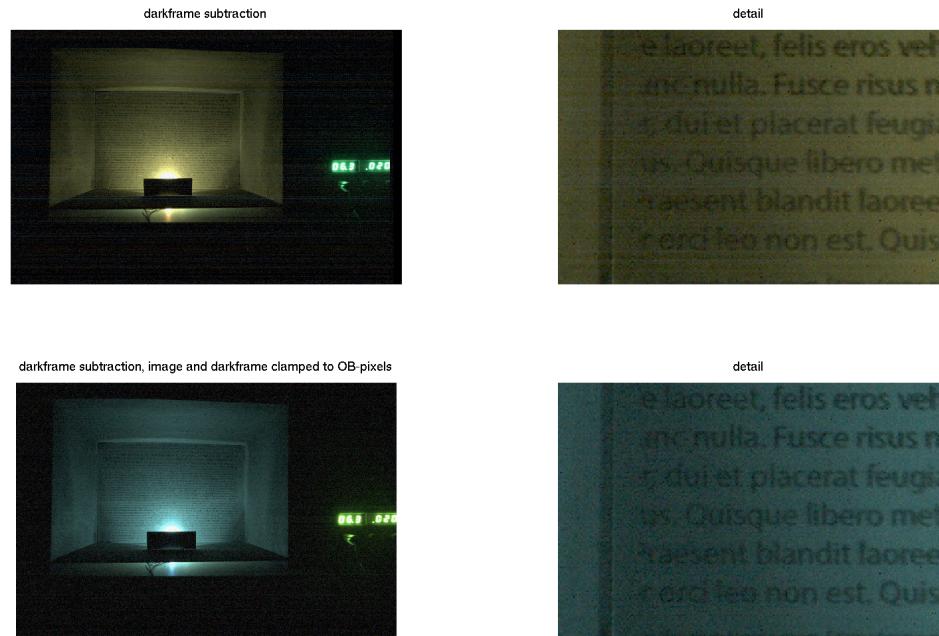


Figure 5. Image corrected using dark-frame subtraction ($s_{ISO} = 6400$, $t_{exp} = 8s$)

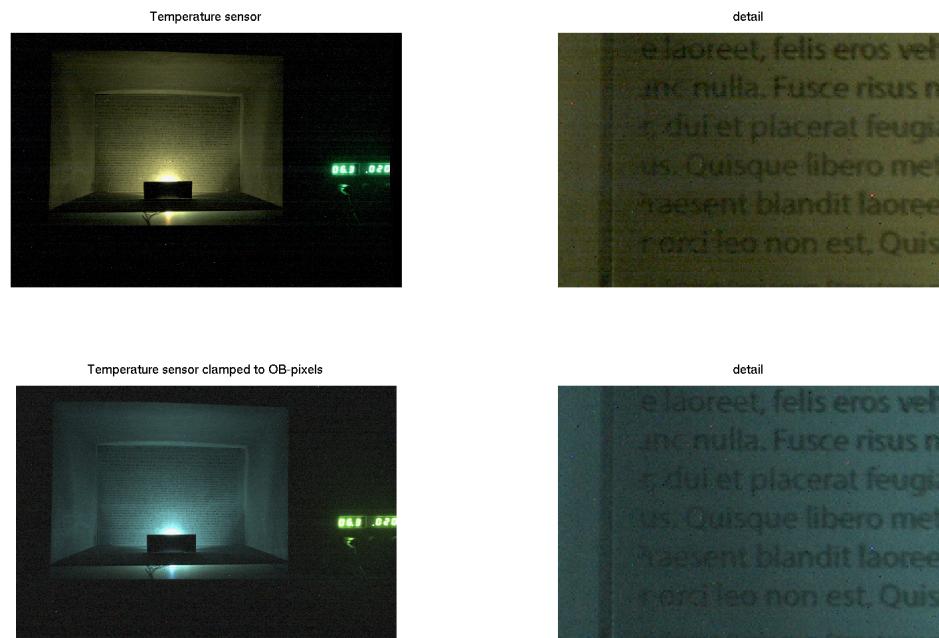


Figure 6. Image corrected using the average of the temperature sensors' values ($s_{ISO} = 6400$, $t_{exp} = 8s$, $T_{Sensor} = 19.5421^\circ\text{C}$)



Figure 7. Image corrected using temperature estimation strategy I and confidence measure eq.10 ($s_{ISO} = 6400$, $t_{exp} = 8s$, $T_I = 19.1995^\circ\text{C}$)



Figure 8. Image corrected using temperature estimation strategy III ($s_{ISO} = 6400$, $t_{exp} = 8s$, $T_{III} = 21.8011^\circ\text{C}$)

REFERENCES

- [1] Holst, G. and Lomheim, T., [*CMOS/CCD Sensors and Camera Systems*], Press Monographs Series, JCD Publishing (2011).
- [2] Kuusk, J., “Dark signal temperature dependence correction method for miniature spectrometer modules,” *Journal of Sensors* **2011** (Apr. 2011).
- [3] EMVA, “EMVA standard 1288,” (Nov. 2010).
- [4] Widenhorn, R., Dunlap, J. C., and Bodegom, E., “Exposure time dependence of dark current in ccd imagers,” *Electron Devices, IEEE Transactions on* **57**(3), 581–587 (2010).
- [5] Dunlap, J. C., Sostin, O., Widenhorn, R., and Bodegom, E., “Dark current behavior in dslr cameras,” in [*IS&T/SPIE Electronic Imaging*], 72490N–72490N, International Society for Optics and Photonics (2009).
- [6] Porter, W. C., Kopp, B., Dunlap, J. C., Widenhorn, R., and Bodegom, E., “Dark current measurements in a cmos imager,” in [*Electronic Imaging 2008*], 68160C–68160C, International Society for Optics and Photonics (2008).
- [7] Artmann, U., “HOW RAW IS ”RAW”?,” technote, Image Engineering.
- [8] Goossens, B., Luong, H., Aelterman, J., Pizurica, A., and Philips, W., “Realistic camera noise modeling with application to improved hdr synthesis,” *EURASIP Journal on Advances in Signal Processing* **2012**(1), 171 (2012).