Determining image sensor temperature using dark current

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ABSTRACT
The state of the art method for fingerprinting digital cameras focuses on the non-uniform output of an array of photodiodes due to the distinct construction of the PN junction when excited by photons. This photo-response non-uniformity (PRNU) noise has shown to be effective but ignores knowledge of image sensor output under equilibrium states without excitation (dark current). The dark current response (DSN) traditionally has been deemed unsuitable as a source of fingerprinting as it is unstable across multiple variables including exposure time and temperature. As such it is currently ignored even though studies have shown it to be a viable method similar to that of PRNU. We hypothesize that DSN is not only a viable method for forensic identification but, through proper analysis of the thermal component, can lead to insights regarding the specific temperature at which an individual image under test was taken. We also show that digital filtering based on the discrete cosine transformation, rather than the state-of-the-art wavelet filtering, there is significant computational gain albeit with some performance degradation. This approach is beneficial for triage purposes.

Introduction
A reliable method of linking media to their source camera is through the analysis of pixel non-uniformity (PNU) and the associated noise generated. In the state-of-the-art, this sensor pattern noise (SPN) is used to generate a photo-response non-uniformity (PRNU) trace often referred to as a fingerprint. When tested across the limited range of −7.9°C to 29.5°C it has been observed that this method is not affected by temperature. Lukas et al. goes as far as to state that PNU ‘is not affected by ambient temperature or humidity’ due to the simple fact that PRNU is the dominant trace component of PNU.

However, the works of both Kurosawa et al. and Matthews et al. have demonstrated that a critical component of PNU sensor noise, dark current (DSN), exhibits signal power which adds to the overall correlation energy during the original SPN method. Kurosawa et al. expanded upon the traditional method to generate a PNU hybrid trace model based on the inhomogeneous nature of both PRNU and Dark Current (DSN). Matthews et al. further expanded upon these works to propose a model showing how both DSN and lens effects
add to the correlation energy. Based on these works we see that DSN adds energy even when using sensors that have DSN correction methods. Since it is accepted that DSN is heavily temperature dependent\(^6\), we now question if the current SPN methods are immune to temperature bias as stated by\(^1\) given the new models proposed by\(^4\). Using this new model we believe dark current can be exploited to identify the temperature of a camera from an individual image.

In this paper, we examine the relationship between temperature, DSN and its effect on the accepted sensor pattern noise (SPN) methods using a discrete cosine transformation (DCT) filter instead of the computationally intensive wavelet filter. We achieve this using a lens cap applied during our image capture process to eliminate the interaction of light with our image sensor. We calculate the correlation across the temperature range of 10\(^\circ\)C to 50\(^\circ\)C in 5\(^\circ\)C increments before calculating a theoretical model for each of the cameras used in our experiments. This model is then used to contrast the photo-response non-uniformity (PRNU) SPN method against a DSN SPN only method similar to the hybrid SPN method in\(^3\).

The rest of the paper is organized as follows. In Related Work we document the prior efforts in this field and highlight our novel contribution. In Research Method our methods and experimental set-up is documented. The results of our experiments are presented Data Collection and Analysis before being discussed in Discussion. Finally, future work is presented, and the paper is concluded.

### Related work

A reliable method of linking images to their source camera is through the analysis of pixel non-uniformity (PNU) sensor noise to generate a PRNU trace often referred to as a fingerprint\(^1,3\). The basic premise of these methods is to apply a high pass filter to an image which isolates a noise residue directly related to the non-uniform nature of how the sensor outputs an electrical signal. This non-uniform output is due to manufacturing defects such as misalignment and inconsistent silicon dopant across a wafer during production\(^6\). An example of this can be seen in Figure 1.

A photo-diode consists of a junction of positively and negatively charged semiconductor material to form a depletion region. When a photon enters this depletion region it produces an electron-hole pair by transferring the energy of the photon to an electron resulting in the electron moving to a higher valence band or even becoming a free electron. We refer to these free electrons generated from photon energy as \(e_{PH}\). \(e_{PH}\) is stored in the N-well semiconductor region of the photodiode which causes the depletion region to shorten. The associated hole left by \(e_{PH}\) moves to ground via the P-type semiconductor. We refer to electrons generated due to the swapping of minority carriers without external excitation as dark electrons \(e_{DARK}\) the movement of which promotes dark current. The n-well region is gradually filled to capacity \(N_{max}\) by the combination of these electrons at which point the depletion region is removed:

\[
N_{max} = N_{ePH} + N_{eDARK}
\]  

This combination of \(e_{PH}\) and \(e_{DARK}\) results in a sensor output PNU that is linked both to the sensor’s PRNU and DSN. The inclusion of DSN in the SPN noise model is discussed in\(^6\). In our previous work\(^7,8\), we also shown that the state of the art method for generating noise residue traces based on PRNU\(^9\) contains additional forensic information in the form of lens...
Figure 1. (a) A cross section of a CMOS image sensor\(^\text{28}\). (b) Inconsistencies within the diode region can be visually observed between neighbouring pixels. While this will not effect the overall function of the sensor this is an example of pixel non-uniformity (PNU).
aberrations and dark current even when dark current removal or suppression techniques are employed on the integrated circuit (IC). This result verified the work previously highlighted in Kurosawa et al. and Knight et al. where it was shown that additional information could be obtained via a hybrid SPN DSN method to solve the blind source camera identity problem in a real-world setting.

To isolate the PNU effects, a three-stage process is used. The first stage is applying some form of filter to obtain a noise residue via the formula:

\[ Y = I - f(I) \]  

(2)

where \( Y \) is the noise residue obtained containing the SPN signal and \( f(\cdot) \) is the filter used to isolate the noise in the image. The second is the estimation stage where the SPN is estimated from a set of noise residues to remove the effects of random variables. Finally, the third stage is the post-estimation phase where the SPN can be enhanced for more accurate and precise camera identification.

Focusing on the first stage of this process much work has been done in the area of signal processing to provide alternative filters than the original filter based on a wavelet coring method seen in. The work of Li demonstrated the need for accurate highpass filtering since an image can contaminate the estimated PRNU if it contains significant high spatial frequency content such as edges, lines, contours and texture. Similarly, in our previous work edge effects of the image are taken into account before filtering to ensure effects such as ringing are taken into account within the estimate. A well-written summary of the state of the art regarding different filter techniques is discussed in the background work of Lawgaly and Khelifi before proposing an improved locally adaptive DCT (LADCT) filter and documenting its effectiveness.

This noise residue is also susceptible to high-frequency patterns such as those generated through JPEG compression. JPEG compression, being a lossy compression algorithm, will remove high-frequency components and thus lowers a potential correlation match between source and reference. All of this additional information is of value to a forensic investigation as it enables a more confident match to be established between camera and image in the context of the blind source camera identification problem when correctly accounted for. Understanding how to account for these additional sources of potential bias, however, is left to a suitably trained investigator and reinforces the already established work.

When tested across the limited range of \(-7.9^\circ C\) to \(29.5^\circ C\) it has been observed that this method is not affected by temperature. However, the theory as shown in Holst indicates that DSN is not immune to temperature and in fact bears an exponential relationship due to the relationship between dark current density and temperature following the equation:

\[ J_D \propto T^2 e^{-\frac{E_g}{kT}} \]  

(3)

SPN methods for solving the blind source camera identification problem have already been shown to be a valuable tool for both insurance providers and law enforcement. In Dirik et al. it was shown that SPN for a scanned image differs to that of a genuine photograph. Such a method has applications for insurance fraud when detecting scanned images vs genuine images of goods; for example when attempting to prove ownership.
However, PRNU has previously been ruled out as a useful tool for policing insurance fraud concerning vehicle collisions due to the inability to link a camera to a particular vehicle. In Kurosawa et al. five separate cases are given which shows the practical application of SPN methods for law enforcement ranging from sexually based offences to those resulting in death.

The Scientific Working Group on Digital Evidence (SWGDE) has previously released an error mitigation framework, which introduces a basic strategy to identify and mitigate sources of likely error within digital forensic tools. Among the quality control and tool testing measures described is finding ‘untested scenarios that introduce uncertainty in tool results.’ In this paper, we conduct tool testing of the SPN method in high-temperature environments to determine if the method is immune, particularly to the variances in temperature seen in vehicles during an Australian Summer. In this scenario, the dashboard of a car is known to fluctuate from 19°C due to climate control, to more than 60°C. This is known from the practical experience of the first author working in a proprietary setting for industry.

Even though SPN is considered to be a robust and mature tool for linking images to cameras, has undergone significant peer review, has calculable potential error rates and has reached a level of general acceptance within the digital forensic community there are still questions regarding some features of the physics behind the method.

**Research method**

As described above, a three-stage process is used to isolate SPN residues from discrete images and construct reference patterns. This process involves filtering, estimating the noise and then enhancing the result for more precise and accurate identification. Fundamentally, we use the same signal processing methods as described by with a change of filter.

For our filter, we use a discrete cosine transformation and apply an image mask as a high-pass filter in Matlab. This filter is similar to the one seen in Lawgaly et al., however we only employ a simple image mask as demonstrated in Figure 2. A cut off frequency of 150/1136πi is chosen to match the seminal work of Lukas et al. This mask is applied purely in the DCT domain as an implementation of ‘goldilocks’ filtering. The hypothesis is that simple filters run in quicker time with fewer resources required and thus can serve as

![Figure 2. The Gaussian high pass filter with cut off frequency (150/1136)πi in the DCT domain. The cut off frequency is chosen to replicate that of the wavelet coring method of.](image-url)
a useful tool for processing of large evidence datasets. To confirm this hypothesis an
isoplot is drawn using a Shainin like method. The isoplot demonstrates that the measure-
ments are similar and therefore accurately able to differentiate between an image that is
correlated verses one that is not using the DCT filter. While a loss of precision is seen, the
accuracy is similar and therefore comparable (Figure 3). Using Matlab to employ this DCT
filter, we then follow the same methods as employed by Goljan et al. 9 for stages two and
three of the standard method.

To isolate DSN uncoupled from other noise we need to control the temperature,
exposure of the image and other sources of noise such as onboard amplifiers. We also
need to ensure lens effects are reduced. Using three Sony IMX219 CMOS digital image
sensors mounted onto a Peltier plate temperature controlled device 19 we are able to
control the temperature of the device. This Peltier plate is attached to a metal plate which
extends into thin fingers of metal that the IC of the image sensor is secured on using
a custom 3D printed enclosure and thermal paste. The IC itself is located onto the metal
finger as opposed to the PCB of the camera to ensure the temperature of the sensor is
captured as opposed to the temperature of the PCB the sensor is mounted upon. To
measure the temperature of the sensor an MCP9808 solid state temperature sensor is
mounted on the reverse side of the metal finger underneath the sensor IC. This setup is
shown in Figure 4. The Sony IMX219 image sensors have built-in low dark current by
design 20 through the use of correlated double sampling both before and after the
Analogue to Digital Converter 21. Through the use of the Arduino controlled Peltier plate
device 19 we vary temperature between 10°C and 50°C in 5°C increments.

To control lens effects, we completely remove the lens of the camera and any light
entering the imaging column. The lens of the camera is removed and replaced with
a pinhole. This pinhole aperture is then covered with several layers of black electrical tape
to ensure no photons are allowed to enter the imaging column. Covering the aperture
ensures only dark frames are captured removing all PRNU from our SPN.

![Graph](image-url)

**Figure 3.** An isoplot contrasting the two methods of measuring correlation of PNU to an image under test.
Using a python script, we set exposure time to a constant $t = 1/1008s$, and the effects of internal amplifiers are controlled by setting a predetermined long wait time during the setting up of the camera to allow the gains to reach a stabilized point before setting the ISO light sensitivity to 800. This is a possible source of error in our method but, is a limitation in the Raspberry Pi firmware. Future implementations of this experiment should take advantage of the additional code to be included in a future release of the Raspberry Pi camera distribution\(^{22}\) to allow the manual setting of the Analogue and Digital gains\(^ {23}\).

Using the script, each image is then saved as a JPEG with 100QF setting with appended BAYER raw information to the end of the JPEG file. JPEG is used due to a limitation of the Raspberry Pi Camera API. While it is noted that JPEG at QF100 is not the same as lossless JPEG, the appended BAYER raw information is extracted to obtain a RAW format image.

Figure 4. The Arduino controlled Peltier plate device used for controlling the temperature of the cameras. Seen here is the mounting position used for the image sensor to obtain an accurate reading of the sensor as opposed to the PCB. The black mounting square (shown here) was replaced with an aluminium block for thermal sinking purposes before imaging was conducted.
using DCRAW\textsuperscript{24}. This BAYER raw format thus avoids all onboard processing steps of the digital pipeline within the image pipeline model of the Raspberry Pi Camera model\textsuperscript{8}. To extract the RAW information from JPEG file it is converted to TIFF using DCRAW as per\textsuperscript{12} using the command:

\[
dcraw -D -T -4 -W filename
\]

For each temperature interval, an image set of 100 dark frames is taken per camera. The reference pattern is then constructed by averaging the 50 noise residues together from the reference set at 30°C. This is the same process as seen in\textsuperscript{1} The noise residues from each temperature interval set is then correlated against this, or other extracted reference patterns of similar dimension with the result recorded.

**Results**

The results of each camera used in our method as a blind identified camera to a dark current reference pattern are shown in Figure 5. This graph omits the correlations from the non matched cameras for clarity. These omitted results are zero mean. The method is capable of discrimination between camera’s as previously shown in\textsuperscript{3,12}.

Using the theory presented in\textsuperscript{15} we apply a regression model to our results based on the dark current density model seen in Equation (3). This model has the exponential form $y = a e^{bt}$. Each model resolves with an adjusted $R^2$ value of .9449, .9787 and .9523 respectively for camera 1, 2 and 3 indicating a close movement of our DCT filtered DSN to the dark current density. Less than 6% error is noted in these models. There is a strong indication that the correlation is related to the DSN as hypothesized. These models are shown in Figure (6). We then overlay the models against the mean correlation result for each camera from Figure 5 in Figures 7, 8 and 9.

In each Figures (7–9), we identify that the mean of our correlation follows the theoretical DSN model up to a specific point. At this knee in the graph, the response then deviates to an approximate constant value. It is observed that this approximate constant correlation value occurs when the temperature of the DSN reference pattern matches that of the image set under test. Using this analysis, we determine an approximate temperature for each image set. Camera 01 is identified as 30.5°C, Camera 02 is identified as 28.35°C and Camera 03 is identified as 30.15°C. These results are recorded in Table 1.

![Figure 5. Correlation versus temperature plot across the three cameras.](image-url)
It was observed that a prohibitively long time was required to take images at the exact temperature required for each set. As such, all images under test were taken over the range $T = 30^\circ C \pm 2$ due to the thermal balance of the equipment used. The temperature sensor used for these experiments was an MCP9808. The sensor bounced around the setpoint due to several reasons including observed self-warming on the sensor during image capture and environmental conditions. As such, at the extremes of temperature, it would become difficult to wait for the experimental apparatus to set upon a fixed

**Figure 6.** The three theoretical DSN curves plotted against each other showing that each DSN response is unique.

**Figure 7.** Correlation versus temperature plot for camera one showing the correlation increase in accordance with the theoretical model to a limit which corresponds to the temperature of the image sets under test. Camera 1 identified temperature 30.5°C.
Figure 8. Correlation versus temperature plot for camera two showing the correlation increase in accordance with the theoretical model to a limit which corresponds to the temperature of the image sets under test. Camera 2 identified temperature 28.35°C.

Figure 9. Correlation versus temperature plot for camera three showing the correlation increase in accordance with the theoretical model to a limit which corresponds to the temperature of the image sets under test. Camera 3 identified temperature 30.15°C.

Table 1. Identified temperature of image sets.

| Camera  | Identified Temperature (°C) | Forensic Range (°C) | Actual Range (°C) |
|---------|-----------------------------|---------------------|-------------------|
| Camera 01 | 30.5                        | 26.0–35.0           | 28.0–32.0         |
| Camera 02 | 28.35                       | 23.85–32.85         | 28.0–32.0         |
| Camera 03 | 30.15                       | 25.65–34.65         | 28.0–32.0         |
temperature. To ensure a prohibitively long time was not needed to acquire images, all images were taken over a maximum 4°C range of the target temperature. When averaged this could cause the expected temperature of the image set to be between 28°C and 32°C however, it is more likely than not that the average of the images would be 30°C. Unfortunately, the temperature of the images under test was not recorded in the EXIF metadata meaning the exact temperature could not be determined.

The MCP9808 temperature device used in these experiments has an overall accuracy of ±0.25°C. Accuracies should, therefore, add to obtain an overall error of ±4.5°C of the expected target temperature of 30°C. Once this analysis is taken into account, we see that each camera has an accurate temperature result. We see that for each camera the forensic range should be as indicated in Table 1. From here we see that the result from each camera is aligned to the actual range of the temperature taken during the image acquisition phase.

Discussion

In our work presented here, it is not the first time DSN has been used as a forensic trace. However, it is the first time that a temperature dependency has been observed and used for forensic inference. While the work of⁵,²⁵ identified the use of DSN for unique forensic identification it is only now that we have further used the theory as presented in¹⁵ to determine the precise temperature that the image sensor was at during image capture. Determining temperature using SPN methods is contrary to the existing narrative seen in¹,² who suggest sensor pattern noise methods are immune to temperature variance. This is particularly relevant since in our work we have used DSN reference patterns against noise residuals which are traditionally used for PRNU based methods. Our image sets thus contain both DSN and PRNU making up PNU.

Whereas the current literature has shown a distinct direction in optimizing filters used for sensor-based methods¹¹ to create more precise results we have began a new focus to enable faster processing times. Such an approach may sacrifice precision. Lower precision does not lower the usefulness of the tool. The quicker exclusions can be made in the field means a focused effort can be made in a laboratory environment on evidence that requires robust examination. This would counter the current practice of bringing most devices back to digital forensic laboratories and allow a more efficient expenditure of resources. Excluding devices is particularly relevant in the application of images on what²⁶ refer to as Type 2 and Type 3 mobile devices. These are devices in which large amounts of stored data including images which have the ability to store such data indefinitely. Efficient resourcing to allow time critical decisions is paramount when forensic intelligence is looked at in the military context where time can be of the essence due to the involvement of austere environments, sensitive and high profile targets and the resultant need for rapid execution.²⁷ By indicating how a simple, good enough ‘Goldilocks’ filter can cut down on analysis times, we hope such tools can be adopted into on-site triage packages resulting in a more focused application of search warrants and more efficient use of forensic capabilities in the future. More work is required to verify the ability of such filters.
Conclusion and future work

In this paper, we have demonstrated a temperature bias in the method as first shown in and expanded upon in. This temperature bias present relates to the presence of dark current within an image and proves to be a useful forensic trace in its own right. We use this trace to isolate the temperature that an image is taken at independent of other sources such as EXIF metadata. This result is demonstrated across three CMOS image sensors of the same make and model and is experimentally linked to the dark current of the device. Further, even when engineering designs are implemented to minimize the effects of dark current at the sensor silicon level, the effects of temperature on the SPN methods are still apparent indicating dark current is never completely removed.

This study is, however, only an initial study into this physical phenomenon and should be conducted on a much broader sample. In the course of this study, we were exposed to a limitation in the ability of our lighting apparatus. This limitation resulted in an inability to vary the intensity of light that a scene was illuminated with. This work should be replicated using various exposure times and light intensity to measure the effects of dark current more thoroughly on the sensor pattern identification methods for the blind source camera problem. It is expected that light would also result in a variation in raw correlation obtained for each positive match. Such variances in correlation are expected to stack per the additive noise model and exacerbate the effects of either temperature or light intensity.

Additionally, our small sample of image sensors means that this study is not an all-encompassing commentary on the issue of the thermal effect of SPN. Given the vast array of CCD sensors still in use, and the fact that their technology is significantly different to the active pixel CMOS sensors used in this study, verification on CCD sensors should be considered. Since the mobile imaging market is significantly increasing in size and complexity (for example Apple products with multiple sensors for a single image) a more extensive array of tests against CMOS sensors should also be conducted as future work. This initial study, however, has demonstrated a significant change in thinking to the current literature that SPN methods are immune to temperature dependency and thus, a new avenue of research is now opened to explore and exploit this phenomenon for forensic purposes.

In this work we have shown a method for establishing the temperature of an image. Many cameras record temperature metadata. This method can be used to verify the veracity of this data point. Similarly, by cross referencing local weather databases the temperature of an image can be used to verify the GPS co-ordinates also stored within the image metadata. In the case of murder, we imagine a killer taking trophy images of their victims. Using this method we can verify the time of death estimation from the medical examiner by cross checking the temperature used in their calculations. We can then use these results to verify the metadata of the images ensuring the time of capture is consistent with not only the medical examiners calculations but also our own temperature verifications.

For child exploitation material, verifying the environmental temperature at which the image has been captured can provide further contextual clues as to the location of children in danger. For example, if the image has been captured in extremely warm temperatures during March we can suggest with some certainty that the image may have
been taken in the southern hemisphere. Similarly, if an image has been taken, outside at a cold temperature in December we may be in a position to suggest that the image was taken in a northern hemisphere location. This hypothesis requires further research, but is a promising area opened up in the identification of child abuse victims. We envisage this being useful in cold child exploitation cases where the location of an image in a database is not known but the camera which captured the image is. With further research we anticipate the ability to generate a baseline dark current response for a particular model of camera which will then make this type of tracking possible. Once a general geographical region is known the image can be handed over to local law enforcement for identification freeing up INTERPOL resources.

Fundamentally, temperature is a new forensic trace which shows promise in the area of media forensics and further research is required to understand its full potential in an field capacity.

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