A Method for Determining the Dark Response for Scientific Imaging with Smartphones

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Abstract

The proliferation of smartphone technology has provided an unprecedented opportunity for greater community participation in collaborative scientific observations that were once out of reach due to cost, accessibility and ease of use. Currently, there have been several applications making use of the various sensors included in a smartphone, particularly the image sensor, which has been used in a wide range of scientific endeavours including air quality and medicine. Like all digital image sensors, the one included in a smartphone is subject to noise, particularly that related to dark current. The objective of this paper is to present the development and testing of a method to determine the dark response that a smartphone camera may experience under different temperatures representative of the environmental conditions under which the phone may be used for scientific imaging. This has required the development and testing of a specially developed app. This was tested in the evaluation and analysis of the dark response of a smartphone camera for the range of 8 ^{o}C to 38 ^{o}C. The mean of the dark response was relatively unchanged over this range. The method developed in this paper allows the quick and easy determination of the dark response of smartphone image sensors, enabling this to be readily subtracted from the signal in the development of scientific investigations using the smartphone image sensor.

Introduction

Smartphone technology offers many potential benefits in providing accessible image sensing technology coupled with communications functions and the ability to perform algorithms[1, 2, 3, 4], and recent examples of the use of smartphone imaging for scientific purposes include environmental monitoring, pathogen imaging and personal medicine[1, 2, 5, 6]. Smartphone imaging for environmental monitoring in particular has the advantages of portability, accessibility and modest cost when observing the natural world and monitoring environmental changes[2], and can supplement more traditional tools for science education[7, 8].

Like all imaging technology, smartphone cameras are nevertheless prone to the effects of electronic noise that dictates the suitability of the equipment for the intended purpose[9]. The most important sources of noise are the dark current due to the temperature-dependent but otherwise random generation of charge in pixel wells even when the sensor is in darkness, and the time-invariant fixed pattern noise due to variations in charge levels between different pixels[9, 10, 11]. This fixed pattern noise associated with dark current is commonly referred to as dark signal non-uniformity (DSNU)[10, 12]. As dark current is randomly generated, assumptions that it can be modelled using a Poisson or Normal distribution were found by Baer[9] to be incorrect and lognormal curves were found to be a better fit to the CMOS dark current data.

Given that smartphone image sensors have the potential for scientific use in a number of settings, their future applications require information on the size and characteristics of the digital response to dark noise so that this can be taken into account in the image analysis. Previous research has reported on the analysis of the dark noise in CMOS sensors[13, 14, 15]. However, there is currently no means of rapidly determining with the push of a button on the phone the dark response during the use of the phone for a scientific application. This requires a method to easily and quickly determine the dark response prior to taking an image for a scientific application. This paper describes the development and testing of a method to evaluate and analyse the digital response to dark noise of an inexpensive mid-range smartphone image sensor using a specially written Android app. This will be tested in a range of temperatures to simulate likely environments in which the image sensor may be used.

Method

Equivalent responses to dark current were made by calculating the average grayscale (intensity) response (scaled to 255) taken from bitmap photos from a white LG L3 smartphone (LG Electronics, Seoul, South Korea) with the lens completely covered to prevent light leakage to the image sensor. The grayscale (intensity) response is calculated using data from each colour (red, green, blue) channel by the following algorithm[16],

$$Grayscale = 0.299(red) + 0.587(green) + 0.114(blue) \qquad [1]$$

The amount that the scaled intensity response is affected by dark current mechanisms is more relevant in this context and accessible than attempting to measure the actual pixel dark current. The data was collected using an Android app specifically written to determine the mean dark response levels. Smartphones are mobile computing platforms that support custom made apps and possess sufficient processing capabilities to be able to compute scientific quantities internally, rather than downloading the data for processing through another platform (e.g. Matlab)[2, 17]. Smartphones use the Android programming platform which in turn mostly use the Java and XML programming languages, that can be used by the wider community to write programs, or ‘apps’ that provide a means to link the output obtained from smartphone internal sensors with algorithms that calculate scientific quantities. The method developed in this paper employs a specially written app that was programmed to be quick in calculating the relevant values and not to be resource intensive. It is comprised of a single activity with several tasks that are described in the following.

An initial user interface instructs the user to cover the outer lens of the camera before proceeding. None of the camera functions are altered by the Android app, as they are left on default or on the user selected image capture settings, the button is then pressed to open up the camera to take a photo. A camera intent is used to capture and retrieve the bitmap of the image taken via a content resolver algorithm. Each bitmap pixel is then converted to grayscale using equation 1. The log normal geometric mean ($\bar{x}^*$) and standard deviation or *measure of dispersion* (s^*) are calculated using the following expressions[18]:

$$\bar{x}^{*} = e^{\left(\frac{1}{n}\sum_{i=1}^{n} ln\, x_i\right)} \qquad [2]$$

$$s^{*} = e^{\left(\sqrt{\left(\frac{1}{n-1}\right)\sum_{i=1}^{n}\left(ln\frac{x_i}{\bar{x}^{*}}\right)^{2}}\right)} \qquad [3]$$

Finally, a dialog box displays the results and the frequency of each grayscale digital value is also shown.

A summary of the tasks and dependencies of the Android app are shown in Figure 1.

<Figure 1>

Each test determined the geometric mean and standard deviation of 20 photos taken in default camera settings, performed over 30 minutes at 4 different temperature controlled environments, kept constant at a precision of ±1°C. The temperature of each of the environments was 8°C, 22°C, 28°C and 38°C, and 20 images were employed for the dark response measurements at each temperature. This temperature range was employed as it is the expected ambient temperature range for temperate climates. The spread of the lognormal distribution was determined by Limpert[18],

$$\bar{x}^{*}\ {}^{*}/\ s^{*} \qquad [4]$$

Where the geometric standard deviation is multiplied and divided from the mean as opposed to added and subtracted as in normal distributions[18].

Results and Discussion

The distribution of the pixel values from each temperature observation approximates to a log normal distribution, characterised by a strong positively skewed peak and a long tail, shown in Figure 2 and summarised in Table 1. Each differently shaded column represents a different temperature. Apart from two maximum values for pixel digital numbers zero and two for 38^{o}C, the pixel numbers are within the lognormal distribution. At all temperatures, the greatest frequency of pixel digital values occurred below 10, dropping sharply. However, the maximum values recorded were significantly higher presumably due to ‘hot pixels’. The median pixel value remained at 4-5 digital values for all temperatures.

<Figure 2>

<Table 1>

Figure 3 shows the mean and extent of one standard deviation for each ambient temperature. A major outcome was that the change in temperature did not cause any significant change in mean dark signal. An interesting effect is that it appears that as temperature increased, the dark response appeared to decrease; however, as these values are all within a close range and within the error bars of other tests, this is likely to be due to random fluctuations in the image sensor, rather than any specific thermal effect.

<Figure 3>

The significance of the results is:

- Despite dark current being temperature dependent, the smartphone internal noise reduction and temperature control result in a near constant dark pixel intensity response with increasing temperature.
- The dark response is approximately 4-6 digital numbers, providing a reasonable offset noise level that can be calibrated for when the image sensor is used to measure the environment, such as in air quality and solar UV observations by Igoe[1, 17].

Despite each smartphone image sensor having a different response, due to differences in sensor architecture[1, 19], the app is not brand-specific thus can be adapted and used on any smartphone. The advantage of the developed method is that with the push of a button on the phone it allows the easy and rapid determination of the dark response of the phone. This can be used to subtract the dark response from the signal in the application of the phone image sensor in scientific applications.

Conclusion

A method has been developed and tested in this paper that allows determination of the dark response of smartphone image sensors. The method involved developing and testing a specially written app that allows quick and easy determination of the dark noise to enable this to be subtracted from the signal. This has not been previously available to provide the dark noise with the press of a button on the phone. The development reported in this paper will allow the implementation of this dark noise information in any future app that uses the image sensor pixel data and requires subtraction of the dark noise for the calculation of any parameters or information based on the pixel values. This allows the smartphone image sensor to be an effective and accessible tool in the development of scientific investigations by more people than ever before. This was applied in the analysis of the dark response from a smartphone image sensor at different temperatures from 8 ^{o}C to 38 ^{o}C. The results indicate that the dark response, due to image sensor dark current, is low, with small variation due to the lognormal distribution of pixel intensities. Critically, the results indicate that higher ambient temperature has very little effect on the dark response.

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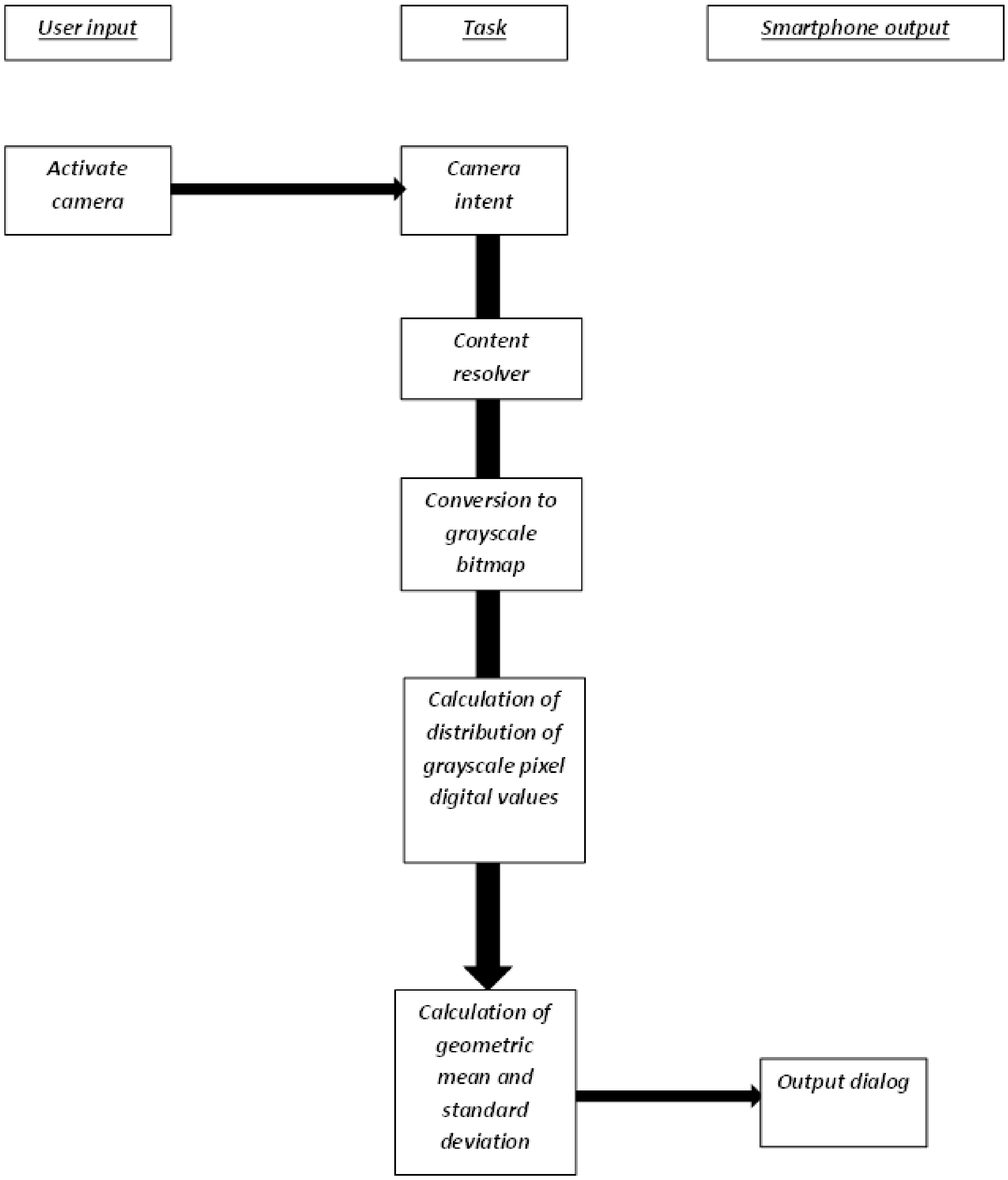
Table 1: Statistical summary of smartphone image sensor dark response at 4 different ambient temperatures.

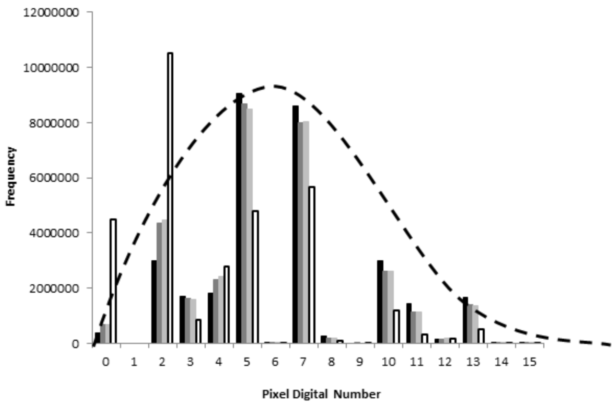
	Temperature (°C)			
	8	22	28	38
Geometric mean	6.41	5.95	5.94	3.96
Standard deviation	2.95	3.00	3.00	3.02
Maximum value	117	104	122	181

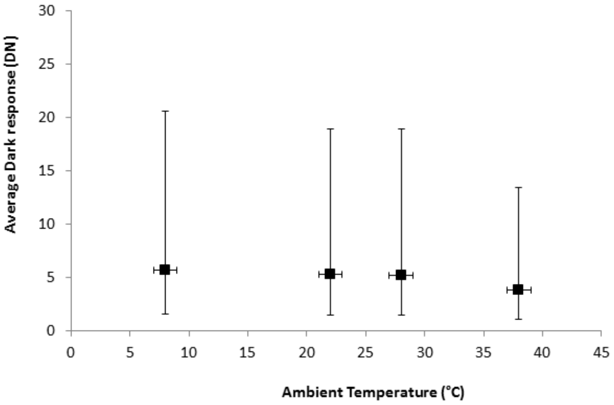
Figure 1: Flowchart of the Android app tasks with dependencies.

Figure 2: Plot demonstrating an approximate mean log normal distribution of the smartphone's image sensor dark response. The mean for each digital number was calculated over 20 images each. The lognormal approximation is represented by the dashed line.

Figure 3: Mean dark response (of 20 images taken at each temperature) as a function of ambient temperature. The vertical error bars represent one standard deviation from the mean. The horizontal error bars represent the temperature variation observed during the experiment.


User input
Task
Smartphone output
Activate camera
Camera intent
Content resolver
Conversion to grayscale bitmap
Calculation of distribution of grayscale pixel digital values
Calculation of geometric mean and standard deviation
Output dialog


12000000
10000000
8000000
6000000
4000000
2000000
0
Frequency
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
Pixel Digital Number


Average Dark response (DN)
30
25
20
15
10
5
0
0
5
10
15
20
25
30
35
40
45
Ambient Temperature (°C)