DIGITAL PHOTOGRAPHY ANALYSIS: ANALYTICAL FRAMEWORK FOR MEASURING THE EFFECTS OF SATURATION ON PHOTO RESPONSE

NON- UNIFORMITY

by

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Digital Photography Analysis: Analytical Framework for Measuring the Effects of Saturation on Photo Response Non-Uniformity

Thesis directed by Associate Professor Catalin Grigoras

ABSTRACT

Over the years, and through various research, it has been found there are many ways to analyze digital photography to determine its source camera for the original capture. There are many factors to consider when analyzing photography, such as the device used, the environment of the capture, the software used to process the image and any alterations or editing which may have been done. One very important technique of camera source identification is to analyze photo response non-uniformity (PRNU). It has been found every camera, or more specifically every camera's sensor, reacts differently in various conditions. The photo response non-uniformity acts as a fingerprint for a camera. In this paper, we will explore the various techniques used to determine the source of a photo. We will also explore how the unique PRNU fingerprint responds to various situations, including environments of high saturation, artificial light and natural light. Chapter 4 will provide the framework for analyzing such images through multiple case studies using different devices. This study will provide a basis and explanation of how multiple levels of saturation can affect PRNU through the camera's sensor during capture.

The form and content of this abstract are approved. I recommend its publication.

Approved: Catalin Grigoras

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CHAPTER I

INTRODUCTION

This thesis involves studying the background of camera sensors, how they react to environment, specifically pertaining to light sources, and above all, how a camera's fingerprint reacts to saturation in capture. There are many ways to authenticate an image; however, little studies have been conducted on the effects of saturation on photo response non-uniformity (PRNU), or a camera's sensor fingerprint. Every camera is different; this also pertains to identical makes and models. It is important to understand how PRNU relates to image authentication and how it can be a useful tool in determining an image's source. Unfortunately, with any forensic science discoveries, there are also anti-forensics to consider. As our community moves forward in digital imaging research, there are others who may be using the research for ill practice. Determining the effects on authentication measurement techniques will allow an understanding of how one might employ anti-forensics in this area. This paper will focus mainly on the effects of saturation on PRNU through original camera studies, both from digital still and mobile phone cameras. It is here where light will be shed as to if and how one can intentionally produce false readings for personal gain.

History of Camera Sensors

It has been defined that an image is a variation of light intensity of a reflection as a function of position on a plane; however, to capture an image, means to convert the information to signals which are then stored on a device. In electronic photography, there are two primary methods of storage: analog and digital. In analog cameras, image signals from the camera's sensor are converted and stored as video signals; whereas, in digital cameras, they are converted and stored as digital signals [1]. Before information can be converted into a signal

and stored on a device, the camera itself must have the proper hardware to do so. The focus of this study will be digital cameras, mainly cameras in mobile devices. There are many components to even the smallest of digital cameras, such as: lens barrels, multiple lenses, a lens mount and the information chip, as seen in Figure 1 [2]. Located on the information chip, is the camera's sensor, or the heart of the camera.



Figure 1 Camera Module of Mobile Phones

To understand a camera's sensor, one must first comprehend how information reaches it. A camera lens is responsible for focusing light onto the sensor. The image sensor converts this light into electronical signals. As an image is captured, the light passes through the lens and falls onto the sensor, which consists of small photo-detectors. These detectors are also referred to as pixels. There are two different types of image sensors: Charged Coupled Device (CCD) and Complementary Metal-Oxide Semiconductor (CMOS). Regardless of type, sensors cannot distinguish between various light wavelengths. In other words, the sensors cannot identify individual colors. It is the responsibility of the filter in front of the sensor to assign color to the corresponding pixels of a capture [2]. There are a few differences between the CCD and the CMOS sensor. It was October of 1969, when George Smith and Willard Boyle invented the charge-coupled device (CCD). This was widely used in digital photography in analog cameras because it produced very high quality images. However, in the 1970's the CMOS sensor was invented and offered higher speeds for transfer than the analog chip known as the CCD. It is here where digital photography presented more options [3].

Digital Photography

As previously mentioned, the heart of a digital camera is its sensor. There is a very important difference in the two sensors known as CCD and CMOS. The difference lies in how charges are passed through the pixels. In the older CCD model, the pixel's charge is transferred through output nodes and assigned to be converted into voltage. From there, the charge is then buffered and sent off-chip as an analog signal. In other words, the work of transferring light into a charge is outsourced. The output's uniformity is high which results in very high quality photographs. All of the pixels can be devoted to light capture which aids in this higher quality. This contributed to the CCD model's popularity. This was the case until the CMOS model could be put into widespread production in the 1990's. The CMOS became popular because it required lower power consumption and lowered fabrication costs. The CMOS sensor works by each pixel having its own charge-to-voltage conversion and includes amplifiers, noise-correction and digitization circuits so the output of the chip consists of digital bits. Because of this, the uniformity, or the quality, is lower; however, it is parallel and allows for higher transfer speeds [3].

There is a common thread between both the CCD and CMOS sensors, and that is the way color is read during capture. As mentioned before, the sensor cannot see color on its own. It relies on a filter in front of the sensor to assign color to each pixel. This filter is referred to as the Bayer Pattern color filter array (CFA). The Bayer Pattern works by adding two green pixels, one red pixel, and one blue pixel in each square of four-by-four pixels. By this process, each pixel can register one of the three primary colors and any missing color values can be gathered from its neighboring pixels [4]. So the process starts as a scene is captured, it passes through the lens of a camera, through the filters and then to the CFA. Once color is assigned to the pixels of the sensor, the RAW image is then stored before processing and compression stages occur within the camera [5]. This digital photography flow can be seen in Figure 2.



Figure 2 Digital Image Acquisition Pipeline

Another common thread between the CCD and CMOS sensors are what is called sensor noise. Both produce sensor noise; however, how each sensor responds and corrects this noise varies between the two sensor types. For example, in very saturated, or highly lit environments, overexposure of individual pixels can occur. This is referred to as antiblooming. The CMOS sensor presents better noise correction in these situations as it handles signal conversion for each pixel individually; whereas, the CCD sensor handles signal conversion as a whole and is dependent on conversion off-sensor [6]. In a CCD sensor, there

are four different types of noise sources: Read Noise, Dark Current, Photon Noise, and Pixel Response Non-Uniformity. Read Noise (RN) is noise caused by thermally induced motions of electrons in the output amplifier. This noise can limit the performance of a CCD sensor, but can be reduced in lengthier read out times. Simply stated, the faster the readout, the more noise is present. Dark Current is a noise which is caused by thermally generated electronics in the CCD sensor, but can be eliminated by cooling the CCD. Photon Noise is when the sensor detects photons in an unpredictable fashion. To explain, photons are distributed to the sensor, pixel-by-pixel. So basically, Photon Noise is when the pixels acquire unequal amounts of photons across the entire sensor. It is an uneven distribution of photons. It is also referred to as "shot noise". Pixel Response Non-Uniformity, simply put, is a defect in the silicon of the sensor by the manufacture. This is why every camera sensor possess a different fixed pattern noise. To correct this defect and remove the noise, flat fielding, or frame averaging, can be a technique used [7]. Much like the CCD sensor, the CMOS sensor also has noise obstacles. Notable issues with the CMOS sensor are high-level dark current shot noise and reset noise. Shot noise has already been addressed with the CCD sensor; however, the CMOS sensor also possesses reset noise. It is produced from thermal noise causing fluctuations in voltage in the reset level for any given pixel [8]. Due to the noises produced from sensors, it creates more characteristics to be studied in each individual camera. These noises will be explained in more detail later.

Authentication

There are a many ways to determine an image's source camera through image authentication. Such information can be found in an image's file structure, in an image's source properties and through the image's sensor pattern. A lot of research has been conducted around analysis of these techniques, to include using Exiftool to review file format/EXIF data and camera properties, using HxD, JPEGSnoop, X-Ways or MATLAB to run metadata keywords and even researching how a camera distinctively compresses its images. These techniques and tools, although beneficial in providing file data information, are not to be considered authentication tools, but rather tools which aid in obtaining further information about an image's source. Some of these methods, however, such as analyzing hex data and metadata keywords, can be manually altered. A camera's sensor is the true fingerprint and is difficult to alter. A camera's sensor is imperfect from the start, straight from the manufacture. No sensor, nor its pattern, is identical. Each camera produces its own unique noise. This is commonly coined as "camera ballistics". Much like scientists can determine which firearm a bullet was fired from, scientists can also determine which camera was used for a photo capture. There are many different types of camera noises to consider: temporal noise, photon noise, dark current noise, readout noise, quantization noise, spatial noise, fixed pattern noise, and photo response non-uniformity (gain noise). Temporal noise is a combination of all noises which can change a pixel's value. In CCDs, the charge is shifted so many times during readout that temporal noise is considered the most dominate noise source for those sensors. Photon noise, coined as "shot noise" earlier mentioned, is from an uneven distribution of photons into the pixels. Dark current noise is created by electrons that evolve through thermal processes of the pixel. This noise can be reduced by cooling of the sensor. Readout noise is when the charge, or electrons, is converted into voltage. This noise is directly related to readout speed. As previously mentioned, the faster the readout speed, the more noise is apparent. Quantization noise is when A/D conversion occurs, or when voltage is converted into a digital value. Spatial noise occurs when the pixels are exposed to a homogeneous light and react

differently due to varying sensitivity levels. It is most dominate in the CMOS sensors, as the pixels are read out through different circuits. Fixed pattern noise, also called dark signal non-uniformity (DSNU), is the difference between the lowest and highest measured values for all active pixels in the array. Photo response non-uniformity (PRNU) has often been referred to as the difference between what a camera sensor's ideal response to light should be and what the true response is on the pixels [9].

CHAPTER II

PHOTO RESPONSE NON-UNIFORMITY

As previously stated, the PRNU is considered the fingerprint of a camera's sensor. There are two main categories of noise which fall under PRNU, or a camera's sensor imperfections and signature. Those categories are temporal noise, or random noise, and fixed pattern noise (FPN). Random noise is when the location and time of occurrence of pixel differences is unpredictable. Fixed noise, on the other hand, is when occurrence is based on location due to an underlying structure. Fixed noise will appear constant in every photo taken from that particular device. Fixed pattern noise consists of dark signal non-uniformity (DSNU) and photo response non-uniformity (PRNU). DSNU is considered an offset between pixels in the dark. It is measured in the absence of light and can be corrected by subtracting a dark frame. PRNU is just the opposite. It is seen as a variation between pixels under a certain amount of illumination. It is corrected by offset and gain for each pixel. PRNU is a signal dependent noise and is created due to a variation amongst pixels in their sensitivity to light. Figures 3-5 show examples of random noise, fixed pattern noise and a typical pattern of PRNU [10] [11].



Figure 3 Example of Random Noise



Figure 4 Example of Fixed Pattern Noise



Figure 5 Example of PRNU Pattern from a Kodak V550 Camera (magnified)

Identification

Photo response non-uniformity can be divided into two separate components: individual detector uniformity and array divide uniformity. The variation in responsivity between adjacent pixels is considered high-frequency PRNU. High-frequency PRNU is when the FPN pattern appears more evident in the brighter areas of an image than the darker areas. Identifying tolerances on defective or "hot" pixels is usually done using a high-frequency PRNU pattern. Low-frequency PRNU is a good measure to use when evaluating the variations in responsiveness from one side of the photo array to the other. It is also referred to as photoresponse shading. Generally speaking, when manufactures refer to PRNU, they are referring to the low-frequency rather than the high-frequency measure. The low-frequency measure displays the difference in response levels between the most and the least sensitive pixels across the sensor array under uniform illumination conditions. The degree of non-uniformity in PRNU is related to a few factors: amplitude of the non-uniform pixels, the pixels' polarity, the pixels' location, the pixel's total count, the pixel's distance between non-uniform pixels and the column amplitude. When measuring PRNU is important to note what causes a weak or strong signal pattern for better comparison results. For example, red and infrared (IR) light produce a strong PRNU pattern than the blue and green wavelengths captured. This is due to the deeper penetration lengths at the end of the spectrum (the redder end). At the redder end of the spectrum, photons encounter more defect sites and material variations. It is important to understand obstacles prior to selecting a model to use for PRNU fingerprint measurement. It is also crucial to remember the purpose of such measurement and suspect images involved [12].

There are many forensic uses for measuring a sensor's PRNU pattern such as camera identification, device linking, recovery of processing history and detection of digital forgeries. These tasks aid in criminal investigations and can link a suspect to a particular camera and/or contraband image. PRNU is typically reliable for making these determinations and although PRNU is stochastic, or random in nature, the life span is very stable. PRNU has multiple credible properties. It has dimensionality – it provides large information content. It has universality – all sensors will exhibit its own PRNU pattern. It has generality – the fingerprint is present in every capture regardless of camera settings or content environment. It has stability – the pattern can withstand time under various environmental conditions such as temperature and humidity. Lastly, PRNU has robustness – it can survive lossy compression, filing, gamma correction and other forms of processing within the camera or through outsourced software [13].

Measurements

There are a few different methods in measuring a camera's PRNU sensor pattern. The most widely accepted model consists of running a reference pattern from a particular camera against the image in question. To start, a reference pattern must be obtained by capturing 30-50 flat field images with the device. A flat field is a solid color, preferably light, displaying illumination without heavy saturation. Once these frames are captured, an average must be taken for the best possible estimate of the sensor pattern. Using MATLAB, a code can be run

to obtain the correlation coefficient between the reference pattern and the subject image to determine its linear relationship. A correlation coefficient (CC) is a measure of the strength of the straight-line or linear relationship between two variables, in this case, the reference image and the subject image. The CC will have a value ranging between +1 and -1. To interpret the correlation, it must be understood what the values indicate. A value of 0 indicates no linear relationship between reference image and subject image. A value of +1 indicates a perfect positive linear relationship, or both variables increase in its values through an exact linear rule. A value of -1 indicates a perfect negative relationship, or one variable increases in value while the other decreases in value. Values between 0 and 0.3 (0 and -0.3) indicate a weak positive (or negative) relationship through a shaky linear rule. Values between 0.3 and 0.7 (-0.3 and -0.7) indicate a moderate positive (or negative) relationship through a fuzzy-firm linear rule. Values between 0.7 and 1.0 (-0.7 and -1.0) indicate a strong positive (or negative) linear relationship through a firm linear rule. A value of "r" squared is the percent of variation shared between the two variables being examined. All of these values can make the linear determination if the relationship is already known. If the relationship is unknown or nonlinear, the CC will be useless and questionable [14].

After covering the basic model and correlation coefficient values, other models will now be discussed. The second model for PRNU measurement consists of measuring the CC just the same as mentioned in the first model; however, in this model, exposure time of the reference images is taken into account. In other words, instead of taking flat field images one after another to average together for one solid PRNU reference pattern, the flat field images will be taken at various exposure or integration times. This allows the sensor to cool between captures and reduces thermal noise and dark current in each of the 20-50 reference images. So as a result, each reference photo is a strong pattern reference prior to the frame averaging process. Figure 6 shows the sensor output with light input as a function of the exposure time. Note the sensor starts to saturate at 400 ms [15].



Figure 6 Sensor output with light input as a function of different exposure times

The next model is referred to as color-decoupled PRNU (CD-PRNU). It is believe the color interpolation process of photo capture creates noise which affects the readout of the PRNU pattern. When a scene passes through the lens and into the color filter array (CFA), the camera assigns one color per pixel. This is part of the color interpolation process within the camera. Artificial colors are obtained through this process which are not a part of the scene itself nor the camera hardware. Couple-decoupled PRNU is a method which proposes to decompose each color channel into 4 sub-images, then extracts the PRNU noise from each sub-image. This will eliminate the additional, artificial noise created by on-board processing. Once the sub-images are obtained, they are compared against the subject image from the same camera. It was noted during the experiment of this method that CD-PRNU correlation coefficient figures are slightly higher than the traditional PRNU method. This is to infer the

CD-PRNU provides more positive results in strong linear relationships between reference images and subject images [16].

The last method to measure PRNU is to utilize the traditional PRNU-frame averaging method, but also further adopt a model which entails comparing only the larger components of the two signals. It is suggested this method is more accurate for determining the linear relationship between a reference image and a subject image because it increases the correct detection possibility and decreases the computational complexity of using the whole PRNU pattern as opposed to just the larger components it carries. Through the algorithm of this method, it was found that highly saturated images, or even areas of an image, carry no PRNU information; whereas, dark location carries a weak PRNU signal. The idea is to obtain a PRNU pattern from illumination, with little dark current and no high saturation. In the first, most often used, model of PRNU extraction previously mentioned, it is necessary to extract PRNU by subtracting the denoised version from the original image. So to obtain the correlation coefficient, the reference image is directly compared to the subject image for PRNU pattern. In this algorithm, it is proposed that the PRNU pattern should be extracted from both the reference images and the subject image, both undergo removal of color interpolation, then the reference residual images to be averaged and compared to the subject residual image. In other words, the reference images have their PRNU pattern extracted individually prior to frame averaging, then compared to the pattern, itself, of the subject image. Figure 7 displays the results of PRNU extraction from a subject image and Figure 8 shows the model algorithm and how to utilize the PRNU pattern once obtained. This method of PRNU extraction and comparison is preferred by some as traditional PRNU extraction poses many issues such as addition of shaping noise, background noise left as the extraction is not perfectly contentadaptive, evidence of small-magnitude high-frequency noise and, as mentioned in the previous CD-PRNU model, cameras can only capture one color per pixel [17]. These are all valid factors which affect the readout of the PRNU pattern. Unfortunately, these are only to name a few.



Figure 7 Denoising filters used to obtain residual image of subject or test image



Figure 8 Diagram of large component extraction algorithm

CHAPTER III

ARTIFACTS

Regardless of model algorithm used to extract PRNU and compare to a subject image, there are always artifacts to consider. These artifacts can provide false readouts and incorrect correlation coefficients. These objects found in the PRNU pattern could be due to multiple factors, such as the color interpolation process, excess background noise, artifacts due to heating of the sensor and quick exposure time, additional shaping noise, defective pixels, alterations or edits and heavy saturation. Some other artifacts include those specific to select cameras. Special care must be given to acknowledge these artifacts to prevent false readings and misinterpretation. Gloe, Pfennig and Kirchner reported a case study from the Dresden Image Database which revealed similar artifacts found in certain camera models. The cameras explored were the Nikon CoolPix S710, the FujiFilm J50 and the Casio EX-Z150. It was found the Nikon CoolPix S710 presented a diagonal line artifact in all its captures. The FujiFilm J50 images exhibited a slight horizontal shift and the Casio EX-Z150 displayed irregular geometric distortions. On one hand, these artifacts can be beneficial in further device identification; however, on the other hand, these artifacts can prove detrimental to a case if the examiner is uncertain or unaware of these model-specific pattern issues. One of the major challenges of camera identification by use of PRNU is the suppression of non-unique artifacts. These are artifacts which are specific to a camera model or make. These artifacts, however, may be very similar to those in a PRNU pattern of a different device altogether. Figures 9-10 show examples of known-model artifacts in PRNU [18].



Figure 9 Nikon S710 diagonal artifact



Figure 10 Casio p-maps with artifacts at various focal lengths in lens distortion

Defect Pixels

As already established, a camera's sensor will always have defects to the silicon by the manufacture. This is inevitable. These defects, among others, display across the array of the PRNU fingerprint in different ways. One display of imperfection might show as defective or dead pixels. Dead pixels are any pixel with intensity below a specified percentage of mean. Defective pixels are any pixel that deviates from the mean light field intensity by more than a specified percentage of mean. These defective and dead pixels mentioned above are those in light field space. If a defective pixel exists in dark field space, it is considered a "hot" pixel. Typically, CMOS sensors have an on-chip algorithm to correct defective or dead pixels, or this could be done through the camera's processing stage. If multiple dead or defective pixels exist,

the camera's onboard processing may not be able to correct them all. In these cases, provided there are limited defectives, this can prove fruitful in the PRNU pattern analysis [19]. Although uncorrected defective pixels aid in camera identification the best, corrected defective pixels can still give insight as to their original state even post-processing. This is done by analyzing the pixel values individually. A corrected pixel, when captured with uniform illumination, will appear either much lower or much higher in value than its surrounding pixel neighbors. This is a good indication this was once a defected pixel which has been corrected during post-processing and can still prove in aiding in camera identification [20]. To test or check the value of a pixel, Mathworks has developed a code referred to as "impixel" to be used in the MATLAB program. This code can provide the pixel values of RGB images, grayscale images and binary images. This aids in the determination of pixel value comparison to neighboring pixels which provides an indication of defective pixels within a PRNU fingerprint [21]. Defective pixels are only one artifact which affects the PRNU fingerprint.

Compression

There are many artifacts which can affect the PRNU readout. Another artifact is compression. There are two main types of compression: lossy and lossless compression. Lossy compression refers to data compression, or shrinkage in size, in which information is lost, but it is unnecessary information. The data is still mostly intact. Lossless compression is shrinkage without any data or information loss. All the data is still intact. An example of this is when a raw image file is compressed to a portable network graphics (PNG) file. A PNG compression is an example of lossless compression. An example of lossy compression is when a raw image file is compressed to a joint photographic experts group (JPG) file. The image is still intact, but some information is lost and the file may appear a bit grainy or pixelated. In the lossy scheme, a JPEG converts the color in images into a suitable color space and processes these color components independently from one another.

Compression is performed in three basic steps. The first step is called the discrete cosine transform (DCT). This technique is when an image is divided into 8x8 or 16x16 nonoverlapping blocks. From there, each block is shifted from an unsigned integer to a signed integer. The DCT transformation occurs and the signal is converted into elementary frequency components. The remainder of the image consists of visually significant information and is concentrated in a few coefficients of the DCT [22]. The second step is quantization. This step is defined as a division of each DCT coefficient by the corresponding quantizer step size, followed by rounding to the nearest integer. It is this step where the most information is lost. The third and final step is entropy coding. The DCT quantized coefficient are lossless coded and written into a bitstream. It is here where Huffman tables are formed. These tables are from the Huffman algorithm and are viewed as a variable-length code table, which presents a source symbol for the lossy compression [23]. Lossy compression is the higher compression rate, of about 10x the original size, with some information loss. Lossless compression is used to compress raw images into smaller images without information or data loss (i.e. PNG). This compression is at a rate of 2x the original size [24]. After analyzing how an image is compressed, we must explore how this affects the PRNU pattern of an image.

When an image is compressed, specifically through lossy compression, it creates the block artifact, commonly seen in JPEG images. Although the PRNU fingerprint is robust and can survive certain levels of compression, heavy lossy compression compromises the PRNU pattern and causes an impairment in camera identification. There is also an issue of recompression. This is the image processing operation of decompressing an image, possibly changing the uncompressed image, and then compressing the image again. If using the same quantization tables as the initial compression, further degradation will not occur. However, if using different quantization tables from the first compression, additional degradation will occur and the PRNU fingerprint may be lost. Photo-editing programs will often introduce different quantization tables from the camera's JPEG to the software's JPEG resaved image. This will alter the PRNU pattern [25]. So to summarize, lossless compression does not alter the PRNU fingerprint enough to cause much error in camera identification; however, lossy compression and alterations through editing software programs will degrade the pattern and may prevent a positive identification.

Alterations

It has already been discovered the effects of compression on the PRNU fingerprint. Studies have also been conducted about editing effects on PRNU, specifically pertaining to image forgeries and the ability to still identify a camera source through such alterations. Video and analog cameras often have distinctive scratches on the film and negatives. This makes it easy to identify the origin of an image even with alterations and overexposure; however, in the age of digital photography and software editing, it has been more challenging. There are many different filters used in software editing programs. These filters are used to attack pixel values by assigning them new values based on neighboring pixels. When a filter is used on a color image, the three values (red, blue, green) are determined separately. In the study by Bouman, Khanna, and Delp, five filters were tested on an original image, then compared to an average to test for the PRNU pattern and the effects of each filter on the image. The filters used were blurring, weighted blurring, histogram equalization, sharpening and pseudo-random noise. It is said that the closer a correlation value is to 1, the more similar it is to the camera's noise pattern and a more positive camera identification can be made. From this study, it was found that all the source cameras could be matched to the subject images, regardless of filter or editing progress; however, some filters degrade the pattern more than others. From the five filters tested and from most damaging to least damaging to the PRNU were histogram equalization, blurring, pseudo-random noise, sharpening and weighted blurring. This was just one notable test of filter effects on PRNU within the scientific community [26].

Saturation

Much like defective pixels, compression and editing affect a camera's PRNU readout, so does image saturation. First, we must differentiate between certain terms. The term luminance refers to the intensity of light emitted from a surface in a given direction. The term saturation refers to the state or process which contains the maximum amount of Chroma or purity. It is of the highest intensity of hue and free of admixture of white. There have been little studies of the effects of highly saturated scenes on the PRNU fingerprint. Before we can compare low-color verses high-color saturated photos against reference images from their camera source, we must explore dynamic range. The dynamic range is the number of exposure stops between the lightest white and the darkest black in a digital camera. It is tricky to determine the darkest useable black in a digital camera as the darker tones produce more noise pattern. In the lighter areas of a scene, there will be less noise pattern visible [27]. So we have established lumination is necessary for a good readout of PRNU; however, a scene that is too bright or too dark will disguise the pattern making it more difficult to read and compare to the camera's reference images. This leads us to the saturation experiment.

CHAPTER IV

FRAMEWORK FOR MEASURING SATURATION EFFECTS ON PRNU

In this study, I looked at ten different camera models, shown in Table 1. The Table shows camera make and model, type of sensor, image resolution, ISO and image format. A camera's ISO number represents its sensitivity to light. In other words, the lower the ISO number, the lower the random noise exists and the pattern noise will be easier to detect [28]. I took 30-40 flat field photos and averaged them for one solid reference PRNU fingerprint per camera model. From there, I analyzed ten low-color saturated and ten high-color saturated image captures per camera to determine exactly if and how saturation affects the PRNU fingerprint. I calculated the correlation coefficient figures and examined which camera model best preserved the pattern fingerprint in highly saturated environments. I notated the camera make and model, the settings and image capture conditions. First, I took 30-40 flat field photos, of a solid neutral color and applied the MATLAB code found in Figure 11 [29]. I then took ten low-color photos with each camera. From there, I took another ten high-color photos with each camera, some outside with natural light and some inside with artificial light. Once the reference photos were averaged for one solid residual pattern and the subject photos were taken, I compared them to each other to determine correlation coefficient figures in each environment. After those numbers were calculated, I was able to determine if and how saturation affects the PRNU readout.

DEVICE	SENSOR	RESOLUTION	ISO	FORMAT
Samsung Galaxy S3	CMOS	3264x2448	80	JPEG
LG G4	CMOS	5312x2988	50	JPEG
Nokia Lumia 635	No light/proximity sensor	2592x1456	100	JPEG
LG G3 Vigor	CMOS	3264x2448	100	JPEG
Slate 8 Tablet	CMOS	2560x1920	50	JPEG
Alcatel One Touch Tablet	No light/proximity sensor	2560x1920	100	JPEG
GoPro Hero3	CMOS	2592x1944	100	JPEG
Kodak EasyShare V1003	CCD	3648x2736	80	JPEG
Canon Powershot G2	CCD	2272x1704	100	JPEG
Motorola Nexus6	CMOS	4160x3120	40	JPEG

 Table 1
 Devices and Specifications

```
% read + average all JPGs in a folder
%
clear all;
%------ Detect files ------
dir1=uigetdir; % select the JPG folder
cd(dir1); % DOS cd to dir1
D=dir('*.JPG'); % dir for JPG files
[a,b]=size(D); % a = number of JPG files
M1=[D(1).name]; % first file
M1i=imread(M1); % read image
I=im2double(M1); % read image
I=im2double(M1); % convert to double
for k=2:a
M2=[D(k).name];
Mi=imread(M2);
Mi=im2double(Mi);
I=I+Mi; % add new image to the previous
end
clear M1i
imwrite(I,name1); % save the averaged image
disp('Average computed and saved.')
```

Figure 11 MATLAB code for frame averaging for residual pattern

Camera Studies

For the study, I took ten separate camera devices and calculated an averaged residual photo and compared it to ten low-color photos and ten high-color or high-color photos from the same devices. I then took an average of the correlation coefficient figures from each camera for the low-color and the high-color photo study. For the purpose of this paper, details

will be given for three of the ten cameras studied. Picked at random, the cameras which will be highlighted here are the Nokia Lumia 635, the LG G3 Vigor and the Kodak EasyShare V1003. The Nokia and the LG are both cellular devices. The Kodak is solely a digital camera. Figures 12-14 show samples of low-color saturated and high-color saturated photos from the Kodak used in the study. Also shown is the Kodak PRNU reference image derived from flat field frame averaging. All of the low-color photos taken with each camera were of doors, walls, furniture and anything else of low saturation or very neutral colors. The high-color photos were mostly taken outside at high noon daylight displaying bright blue skies, greenery and flowers. It must be noted these photos were taken in the daylight, but not with direct sunlight, sunbeams or sunbeam reflection. This ensured the proper collection was made to show the deepest colors of the spectrum without heavy luminance or reflection of high sunlight. It should also be noted these photos consisted of many different environments; however, they mostly consisted of heavy blues and greens. As mentioned previously, PRNU patterns are most dominate in red or IR scenes.





Figure 12 Kodak Low-Color Image Figure 13 Kodak High-Color Image



Figure 14 Kodak PRNU Reference Image

The images above, and similar images for each camera, were used in this experiment. Using written code in MATLAB, I ran the residual image, or PRNU reference, against the lowcolor photos and then ran the residual image against the high-color photos. To explain this further, the code promotes a clipping effect. In this process, a white box is displayed on the test image to show where pixel saturation is being clipped for analysis. It is clipped in a percentage format which can be shown in Figures 15-18. From that analysis, the correlation can be drawn. When viewing the results, it will be found that some percentages of pixel saturation, or measurement via clipping, stop at 55% as opposed to 70% or higher in other images. This is due to each camera capture presenting different resolutions and dimensions. The clipping process starts as a perfect square of data taken from the top left of the photo at 0% or 1%. This square increases a certain percentage with each level of pixel saturation clipped until the clipping achieves the largest perfect square based on the size of the image and the increment of the increase. In an ideal experiment, resolution and picture dimensions are exactly the same from one camera model to another; however, this cannot always be achieved. Due to that factor of the experiment, the actual percentage of pixel saturation varies.





Figure 15 Pixel Saturation at 10%



Figure 17 Pixel Saturation at 50%

Figure 18 Pixel Saturation at 70%

It should be noted this will not affect the final results in comparing correlation between one camera model and another and between low-color and high-color saturated photos. At each level of pixel saturation, the correlation coefficient is assigned between -1 and 1 to determine the linear relationship between subject images and the PRNU reference. These numbers will signify how strong the match is between a subject image and a camera possibly used to capture that image. Tables 2-4 and Figures 19-21 show the Nokia, LG G3, and the Kodak camera correlations to their own PRNU in both low-color and high color saturated environments. It should be noted the correlation figures in these tables are of one low-color and one high-color photo from the each camera.

Percentage of Pixel Saturation	Low-Color Saturation	High-Color Saturation
0%	0.30851	0.025203
1%	0.30624	0.024962
3%	0.30462	0.024815
5%	0.30269	0.024525
6%	0.29985	0.024159
8%	0.29708	0.023876
10%	0.29382	0.023423
12%	0.28972	0.022952
15%	0.28583	0.02268
17%	0.28048	0.021974
20%	0.27545	0.022316
24%	0.26923	0.021258
27%	0.26366	0.021192
31%	0.25609	0.020398
35%	0.24897	0.019251
40%	0.2405	0.018241
45%	0.23138	0.015694
50%	0.22134	0.01467
55%	0.21073	0.014389

 Table 2
 Nokia Lumia 635 Low vs. High-Color Saturation



Figure 19 Nokia Lumia 635 Plot Low-Color vs. High-Color Saturation

Percentage of Pixel Saturation	Low-Color Saturation	High-Color Saturation
0%	0.0010026	-0.00039006
1%	0.00098032	-0.00039935
2%	0.00089497	-0.00037365
4%	0.00093415	-0.00054247
5%	0.0010093	-0.00050572
8%	0.0010536	-0.00050318
10%	0.0011603	-0.00056076
13%	0.0010981	-0.00057124
16%	0.0010595	-0.00053795
20%	0.0010098	-0.00054959
24%	0.0010974	-0.00073298
28%	0.0012627	-0.00051283
33%	0.0011283	-0.00042726
38%	0.00089573	-0.00045035
44%	0.0011883	-0.00036856
50%	0.0015186	-0.0004383
56%	0.0018156	-0.00037294
63%	0.0011286	-0.00010892
70%	0.0011585	0.00054099
77%	0.0011454	0.00013703

 Table 3
 LG G3 Vigor Low vs. High-Color Saturation



Figure 20 LG G3 Plot Low-Color vs. High-Color Saturation

Percentage of Pixel Saturation	Low-Color Saturation	High-Color Saturation
0%	0.21285	0.085872
1%	0.21016	0.084553
2%	0.20763	0.084215
4%	0.20472	0.083154
5%	0.20148	0.081153
8%	0.198	0.079486
10%	0.19403	0.077688
13%	0.19	0.0759
16%	0.18494	0.074382
20%	0.18004	0.072829
24%	0.17472	0.069823
29%	0.16966	0.06686
33%	0.1632	0.062687
39%	0.15664	0.061329
44%	0.1494	0.058998
50%	0.14232	0.058393
57%	0.13366	0.056248
63%	0.12448	0.053903
70%	0.1126	0.0515

Table 4 Kodak EasyShare V1003 Low vs. High-Color Saturation



Figure 21 Kodak EasyShare Plot Low-Color vs. High-Color Saturation

Based on the correlation figures from the Nokia Lumia 635, it can be said that the lowcolor saturated photo has a weak positive relationship through a shaky linear rule as the numbers range between 0.2 and 0.3. Although the saturated photo shows lower correlation to the camera's actual PRNU reference image, ranging between 0.01 and 0.02, it still falls under the same category: weak positive. The correlation figures for the LG G3 show a large difference between low-color and high-color environments. These differences are great enough to fall into different categories. The low-color photo, with a range of 0.001 and 0.0011, falls under a weak positive, while the high-color photo, with a range of -0.0003 and 0.0001, falls under a weak negative correlation. The correlation figures for the Kodak EasyShare show similar to that of the Nokia camera. The low-color photo produced better results than that of the high-color photo; however, all correlation coefficients are between 0 and 0.3, which indicate a weak positive linear relationship to the PRNU pattern for that camera.

Final Results

After reviewing all the relationships between subject images and PRNU patterns, I compared the correlation coefficient figures to make a determination between the different camera models. Tables 5-6 show the breakdown of each camera and the results of the low-color and high-color saturation photos. In Table 5, it shows the lowest correlation and the highest correlation of all ten low-color saturation photos taken for each camera model. Table 6 displays the lowest and highest correlation of all ten high-color saturation photos taken for each camera model.

Device	Low-Color Saturation (Lowest CC)	Low-Color Saturation (Highest CC)
Samsung S3	0.039618	0.095084
LG G4	0.00194	0.10441
Nokia Lumia 635	0.012831	0.30851
LG G3 Vigor	0.000211	0.0010026
Slate 8 Tablet	0.13728	0.38318
Alcatel Tablet	0.012415	0.10434
GoPro Hero3	0.039513	0.16715
Kodak EasyShare	0.073982	0.21216
Canon Powershot	0.0063403	0.026674
Motorola Nexus6	0.088532	0.16229

 Table 5
 Low-Color Saturation Correlation Coefficients per Camera Model

 Table 6
 High-Color Saturation Correlation Coefficients per Camera Model

Device	High-Color Saturation (Lowest CC)	High-Color Saturation (Highest CC)
Samsung S3	0.02052	0.038594
LG G4	0.023825	0.055266
Nokia Lumia 635	0.014389	0.049567
LG G3 Vigor	-0.000162	0.0030136
Slate 8 Tablet	0.092558	0.32575
Alcatel Tablet	0.032627	0.074759
GoPro Hero3	0.018619	0.055404
Kodak EasyShare	0.050754	0.17164
Canon Powershot	0.0049013	0.029744
Motorola Nexus6	0.03563	0.16579

It was found that the Nokia Lumia 635, the Alcatel Tablet, the Slate8 Tablet, the GoPro Hero3, and the Nexus6 produced much better results when the PRNU pattern was compared to low-color image verses a high-color image. High-color saturation clearly made a difference in camera identification with those particular devices. It was also found in most models tested, the higher the pixel saturation level, the closer in numbers the low-color and high-color correlations were when compared to each other. Based on the correlation of each photo, whether low-color or high-color saturation, it can be determined that all figures fall between -

0 and 0.3+ which indicate either a weak positive, weak negative, or in some cases, moderate positive correlation. Furthermore, it was found the ISO level and whether photos were taken indoors or outdoors were of little importance; however, the sensor type did play a significant role in the study. Two of the ten cameras contained CCD sensors: the Kodak and the Canon Powershot. The PRNU fingerprint of these cameras were not grossly affected by high-color saturation compared to the CMOS cameras researched. Figures 22-28 further illustrate low-color vs. high-color saturation correlation coefficients in the remaining seven devices.



Figure 22 Samsung Galaxy S3 Plot of Low-Color vs. High-Color Saturation



Figure 23 LG G4 Plot of Low-Color vs. High-Color Saturation



Figure 24 Slate 8 Tablet Plot of Low-Color vs. High-Color Saturation



Figure 25 Alcatel Tablet Plot of Low-Color vs. High-Color Saturation



Figure 26 GoPro Hero3 Plot of Low-Color vs. High-Color Saturation



Figure 27 Canon Powershot G2 Plot of Low-Color vs. High-Color Saturation



Figure 28 Nexus6 Plot of Low-Color vs. High-Color Saturation

CHAPTER V

CONCLUSION

Through this study, it has been noted that a camera's sensor, the ISO, or sensor's sensitivity to light, and scene environment plays a role in determining a camera's PRNU pattern-to-subject image correlation. This study was conducted to determine if saturation affects PRNU pattern readout and if so, could it be considered a form of anti-forensics. After the research concluded, it has been determined high-color saturated images do affect a camera's PRNU fingerprint, especially in certain tablets and camera models; however, it does not affect it enough to create a false positive nor does it totally prevent positive camera identification. It does however, disguise the fingerprint enough to create lower positives in correlation figures. The results of high-color saturation do not affect the PRNU fingerprint enough that it will not cause anti-forensics to occur, but it will aid researchers and examiners to be mindful of the environment of an image capture. Factors which should be considered when explaining camera identification in relation to PRNU fingerprint are color saturation levels, camera models, their sensors, if the scene of a capture is high in infrared or red hues, how the flat field reference images were captured and how frame averaging was conducted. If an examiner understands all the factors which cause weak positives, it will allow him to further explain the linear relationships in his report.

Based on the findings of this experiment and the research conducted, it can be said the scientific community could benefit from additional research surrounding frame averaging with respect to exposure time of reference images and testing the PRNU fingerprint against different camera battery levels and environmental temperatures. There could be more analysis on dark signal non-uniformity (DSNU) regarding the thermal component, which depends on the

temperature and exposure times of capture. There could be more emphasis on decomposed PRNU (DPRNU) experiments and how well the PRNU fingerprint upholds when the artificial component is separated from the physical component to allow PRNU collection without the interference of interpolation noise. These are just a few areas which could prove very valuable to the community for further authentication purposes.

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