

Image Degradation from Hot Pixel Defects with Pixel Size Shrinkage

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Abstract

“Hot Pixels” defects in digital imaging sensors accumulate as the camera ages over time at a rate that is highly dependent on pixel size. Previously we developed an empirical formula that projects hot pixel defect growth rates in terms of defect density (defects/year/mm²) via a power law, with the inverse of the pixel size raised to the power of ~3, multiplied by the square root of the ISO (gain). We show in this paper that this increasing defect rate results in a higher probability that two defects will occur within a 5x5 pixel box. The demosaicing and JPEG image compression algorithms may greatly amplify the impact of two defective pixels within a 5x5 pixel box, spreading it into a 16x16 pixel box thus resulting in a very noticeable image degradation. We develop both analytical (generalized birthday problem formula) and Monte Carlo simulations to estimate the number of hot pixels required to achieve a given probability of having two defective pixels occur within a 5x5 square. For a 20 Mpix DSLR camera (360 mm²) only 128 hot pixels generate a 4% probability of two such defective pixels, which for pixels of size 4 μm may occur in 1.4 years at ISO 6400, and in 3.2 years at ISO 3200.

Keywords- active pixel sensor APS, imager defect detection, hot pixel development, APS defects rates, image degradation.

INTRODUCTION

One long term problem for digital imaging sensors (cameras) is that like all integrated circuit devices they continuously develop defects over time. These are not the result of fabrication related degradation that other integrated circuits experience, but rather cosmic ray induced in-field defects that begin to appear soon after fabrication. These defects are permanent in nature and their number increases continuously over the lifetime of the sensor. In regular ICs a single fault can render the circuit useless. Fortunately, imagers have the advantage that the appearance of defects (hot pixels) only causes some degradation in the image quality. The thrust of this paper is to explore when those defects create noticeable image degradation.

In our testing over the past decade we have shown [1-6] that “Hot Pixels” are the most common type of defects that develop as a camera ages (excludes fabrication time defects). Statistical methods strongly suggest that hot pixels are most likely caused by cosmic ray damage [1-3] and thus cannot be prevented. The intensity of a hot pixel increases with the image exposure time, but the underlying parameters change little after formation. Previously [9] we have developed an empirical power law formula which expresses the defect density rate D (defects per year per mm² of sensor area) as a function of the pixel size S (in microns) and sensor gain (ISO). In this, D is proportional to the inverse of the pixel size raised to about the third power (for APS or CMOS pixels), and to the square root of the gain. Hence, as pixel sizes decrease by a factor of 2, the defect density D grows by about 8 times, and with a doubling of ISO , D increases by about 1.4 times.

It is often argued that isolated defective pixels do not cause significant problems in images – what is a few defects among tens of megapixels? What we explore in this paper is how many

accumulated hot pixels can cause a significant (noticeable) degradation of the image. In particular, it is important to note that when two defective pixels are close enough then the color demosaicing algorithms and JPEG compression cause interactions that spread the damage to a large area which tends to be quite visible. Moreover, through analysis and simulation we show that it takes surprisingly a modest number of hot pixels, relative to the sensor size, before the probability of two pixels being close enough to affect 1% or more of cameras. Finally, we also estimate, using our measured hot pixel defect generation rate, how much time would elapse before such an image degradation would occur and conclude that it will take only a few years in many cases.

Hot Pixels

In our investigation of defect development in digital imagers we have gathered over 15 years of data [5,6], by performing manual calibrations on 29 cameras; commercial DSLRs, point and shoot cameras, and cell phone cameras. We found that hot pixels, which generate a signal that grows without illumination, were the dominating defect type.

A regular pixel under no illumination (dark field) shows only a very low signal growth with increasing exposure time due to the background noise of that pixel. Figure 1 shows the dark response of both regular and hot pixels of normalized pixel output versus exposure time (output level 0 represents no signal and 1 represents saturation). A good pixel’s dark response should be close to 0 (with some sensor noise) at any exposure time. A hot pixel has a component that increases linearly with exposure time. Hot pixels can be categorized into two types [5]: standard hot pixels, which have a dark current that increases linearly with exposure time; and partially stuck or offset hot pixels, which have an additional term that can be observed even at no exposure.

The response of any pixel to illumination is given by equation (1), where I_{pix} is the response or output, R_{photo} is the incident illumination rate, R_{dark} is the dark current rate, T_e is the duration of the exposure, b is the dark current offset, and m is the amplification from the ISO setting.

$$I_{pix}(R_{photo}, R_{dark}, T_e, b) = m * (R_{photo} T_e + R_{dark} T_e + b) \quad (1)$$

For most regular (good) pixels, both the dark current R_{dark} and offset b are, by design, as close to zero so the output response gives an almost direct measure of the incident illumination. However, for a hot pixel, R_{dark} is many times the typical dark current noise level. This dark current, combined with the offset b , create an additional signal that adds to the incident illumination, making the pixel output higher (i.e., brighter in pictures). With zero illumination or dark frame testing, the hot pixel offset model is shown in Equation (2).

$$I_{offset}(R_{dark}, T_e, b) = m * (R_{dark} T_e + b) \quad (2)$$

The dark response in Equation (2), called the combined dark offset, is nearly linear in the exposure time T_e . The parameters R_{dark} and b are extracted in our experiments by fitting a linear curve (Figure 1) to the pixel dark frame response versus the exposure time. For standard hot pixels, the offset b is zero and

they will have an impact on the image only in long exposures (larger than 1 second). In contrast, partially stuck hot pixels with a large offset b will appear as a bright spot in all images even for short exposures. The amplification of the pixel signal by the gain (ISO) setting also amplifies the values of both the hot pixel dark current R_{dark} and offset b .

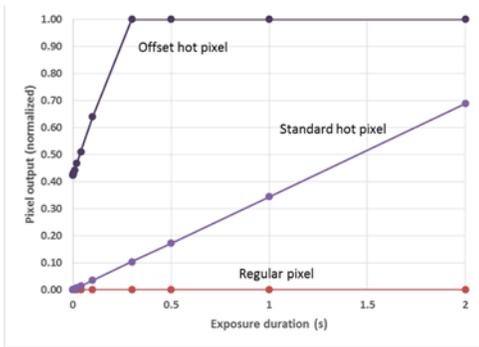


Figure 1: Comparing the dark response of imager pixels: a good regular pixel, a standard hot pixel, and an offset hot pixel.

In our previous work we have shown that hot pixel defects occurrences are randomly spaced across the imager [1-6]. Statistical analysis indicated that they are created by a random source such as cosmic rays [8]. The literature shows that other authors have reached a similar conclusion and have argued that neutrons seem to create the same hot pixel defect types [7,8].

Defect Growth Rate

In our ongoing research we have established the hot pixel count for some 29 cameras and by testing multiple times over time, the defect development rate. The cameras range from 7 μm pixels (DSLRs) with large sized sensors (860 and 364 mm^2) down to 1.34 μm cell phone cameras with small 24 mm^2 imagers. ISOs (gains) from 100 to 25,600 have been tested. We applied linear regression curve fitting to all our camera data over all ISOs and have developed in [7,9] an empirical power law formula to relate the defect density rate D (defects per year per mm^2 of sensor area) to the pixel size S (in microns) and sensor gain (ISO) via the following equations:

For APS pixels:

$$D = 10^{-1.16} S^{-3.03} \text{ISO}^{0.506} \quad (3)$$

For CCD sensors

$$D = 10^{-1.849} S^{-2.25} \text{ISO}^{0.687} \quad (4)$$

In Figure 2 a plot of the best fit Equation (3) is shown for the full test range. It is important to note that these equations indicate that the defect density increases drastically when the pixel size falls below 2 microns, and is projected to reach 12.5 defects/year/ mm^2 at ISO 25,600 (already available in many high-end cameras). This suggests that cosmic ray generated defects may limit further shrinking of the current small pixels.

The defect rate formula (3) gives designers an important estimate of how long it takes to reach a given defect density, and hence, the expected total number of hot pixels, for a given sensor via the parameters of pixel size, pixel area and the ISO at which the sensor is operated. Up until now our research has only looked at the impact of individual pixels on the sensor and considered the total number of hot pixels as a metric of when the picture is degraded. However, the formulas and the experimental results, show that significant numbers of hot pixels accumulate in reasonable periods of time. We therefore, consider in this paper the possibility of defect densities reaching the point where two adjacent hot pixels would interact to create a much more noticeable impact on the image quality.

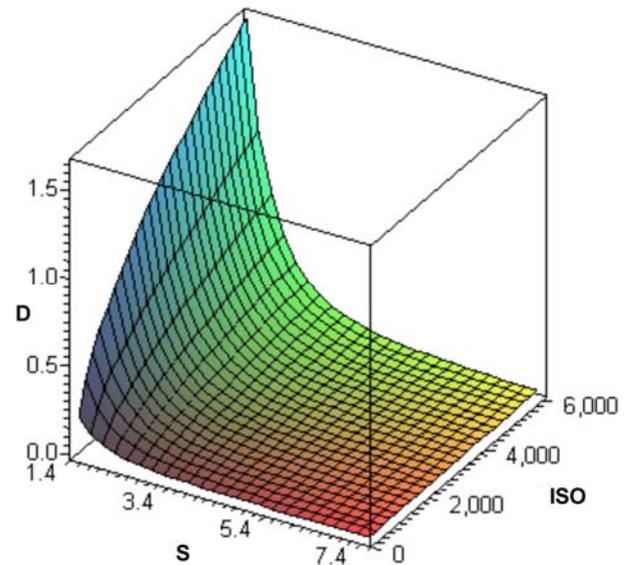


Figure 2: Fitted power law for APS: defect density (D =defects/year/ mm^2) vs. pixel size S (μm) and ISO (I) including the cell phone hot pixel data

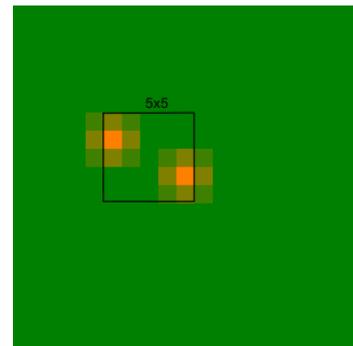


Figure 3: The impact of two hot pixels within a 5x5 box after demosaicing.

How often do two Hot pixels interact

As a first estimate of how often two hot pixels will lie close enough to create a noticeable interaction we can calculate the probability of two hot pixels appearing within a 5x5 box. A 5x5 square is selected because at this box size the demosaicing algorithms and/or the JPEG compression have the two pixels start to interact. This is the situation shown in Figure 3. To this end, we note that this question is similar to the generalized birthday problem. The original birthday problem is: given n people in a room, what is the probability P of two people having the same birthday within an $m=365$ day year. Using the generalized formula [10] we find that if n hot pixels occur on a sensor with m 5x5 pixel squares ($m=M_{\text{pix}}/25$) then the probability P of two hot pixels occurring in the same 5x5 square is:

$$P = 1 - \exp\left(-\frac{(n-1)n}{2m}\right) \quad (4)$$

Solving for the number of hot pixels (n) needed for a given sensor size m and probability P yields (for large m)

$$n = \sqrt{-2m \times \ln(1-P)} \quad (5)$$

Therefore, we can compute for a given sensor size the required number of hot pixels to get 1% of the cameras experiencing this problem.

Table 1: The number of hot pixels needed to get a probability P of a 10 MPix imager having two hot pixels within a 5x5 box.

P	1%	2%	4%	8%
n	90	128	180	259

Table 2: Number of hot pixels needed to get 1% of the cameras having two hot pixels within a 5x5 and a 7x7 pixel squares.

Sensor (MPix)	Square (Pix)	n	Square (Pix)	n
10	5x5	90	7x7	64
20	5x5	128	7x7	90
40	5x5	180	7x7	128

Table 1 shows that the number of hot pixels needed is quite modest for the 5x5 case. For example, for a 10 Mpix camera $P=1\%$ occurs with only 90 defects, which is only 0.0009% of the pixels. Doubling the probability to $P=2\%$ also results in a 1.414x increase in n to 128. Similarly, doubling the number of sensor pixels ($m=20\text{Mpix}/25$) gives the same result as increasing the hot pixels by 1.414x (to 128) – thus the fraction of pixels that need be defective decreases as the sensor pixel numbers increase. Table 2 also shows that if we allow the defects to be further apart (7x7 pixel box) the number of defects needed drops significantly to 64.

The birthday problem approximation is clearly a lower limit on this probability. We are using it to gain a first estimate of the range of hot pixel defects we need to explore. It ignores the cases where there are two defects in neighboring 5x5 squares that are close enough to interact. To truly investigate this we created a Monte Carlo simulation program that populated the 10, 20 and 40 Mpix sensors with the number of hot pixels predicted for, say the $P=1\%$ condition, in Table 1 (e.g., 90 defects for the 10 megapixel camera). Using 10,000 simulations as the base for a range of camera sensor sizes and probabilities we find that the accurate probability is 4 to 4.2 times that predicted by equation (5). The simulations show that for 90 defects in a 10 Mpix sensor, 4% of the cameras will have 2 hot pixels within a 5x5 square. Thus 1 in 25 cameras will show this event. This ratio holds up to the $P=10\%$ ($n=290$) value in (9), where the actual probability is 38%.

What is important here to note is that both the generalized birthday approximation and Monte Carlo simulations show that a relatively modest number of defects will result in two hot pixels close enough to interact in a significant number of cameras. What we will show next is that demosaicing and JPEG spread the effective size of the defects impact significantly.

Hot Pixel Interactions: Demosaicing & JPEG

A common error is to assume a single hot pixel would be so small in modern megapixel images that it would be missed, especially if displayed at lower resolution. What is important to realize is that a hot pixel's damage is spread by two important processing algorithms operating on the defect before the image is actually displayed: color demosaicing and JPEG compression. As will be shown next, the impact of both of these is to spread a hot pixel's effect to neighboring pixels in the image. Moreover, when two defects are near each other, the area impacted by the two hot pixels becomes much larger than that impacted by a single pixel. Figure 3 shows 2 hot pixels separated 5 apart horizontally and 3 vertically after the basic demosaicing algorithm.

Color Demosaicing converts the Bayer Color filter array (see Figure 4) into Red (R), Green (G) and Blue (B) values for each pixel. Bilinear interpolation is a linear demosaicing method, and

is the simplest but basic process applied before any other algorithm. It estimates the missing color based on the neighboring pixels from the same color channel. Thus the calculation of each color plane is an independent process. Although this method is fast, it suffers from poor image quality and moiré effect as well.

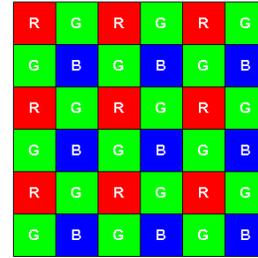


Figure 4: Bayer Color mask

Bilinear, while the most basic demosaicing, takes into account only nearest local conditions where it assumes smooth changes. Hence, it tends to produce image artifacts. For a hot pixel the bilinear algorithm spreads it into a 3x3 square of affected pixels. Figure 5 has a single red (R) hot pixel of 0.8 intensity on a uniform 0.5 green background after the bilinear demosaicing. Two important things happen. First the color of the R hot pixel spreads its R value to the neighboring G and B pixels causing an 9 times larger color shift. Secondly, the bilinear algorithm actually adds that color as an increased signal to the neighbors while not decreasing its own value, effectively increasing the intensity effect of the hot pixel by 2.5 times. A similar outcome happens if the hot pixel was a different color. In the example of Figure 3, the two close hot pixels now impact an area of 5x7. What is important to notice is how demosaicing spreads the error, especially when combined with JPEG compression

As shown in Figure 5 the JPEG compression algorithm spreads this effect much further. First consider a single Red hot pixel error of $I_{\text{offset}} = 0.8$ above a black background and look at the combination of the bilinear demosaicing (output as a lossless TIFF) and JPEG spreading the effect. Figure 5 first shows that the bilinear with only demosaicing spreads the error to a 3x3 pixel area, but with JPEG low compression (level 9) it spreads much further to an 8x8, and by high compression (level 3 which is often used) it is spreading to a 16x16 pixel area.

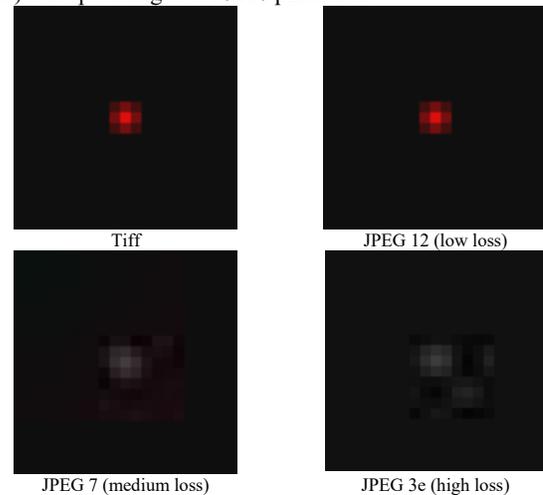


Figure 5: Single hot pixel ($I=0.8$) with bilinear demosaicing (tiff), JPEG levels 12 (low), 7 (medium) and 4 (high loss)

Now consider again having two hot pixels spaced apart within a 5x5 square as shown in Figure 6. A black background does not show this effect in a very clear way, so again we use a

uniform half intensity G background. Figure 6 shows both the actual image, and color intensity histograms which show the spread of the hot pixel into adjacent colors within this region. For just the bilinear demosaicing in Figure 6(a), with a lossless tiff compression (digital RAW type effect) the damage is spread from 2 pixels to 18 pixels, and the R color is spread to 3 levels.

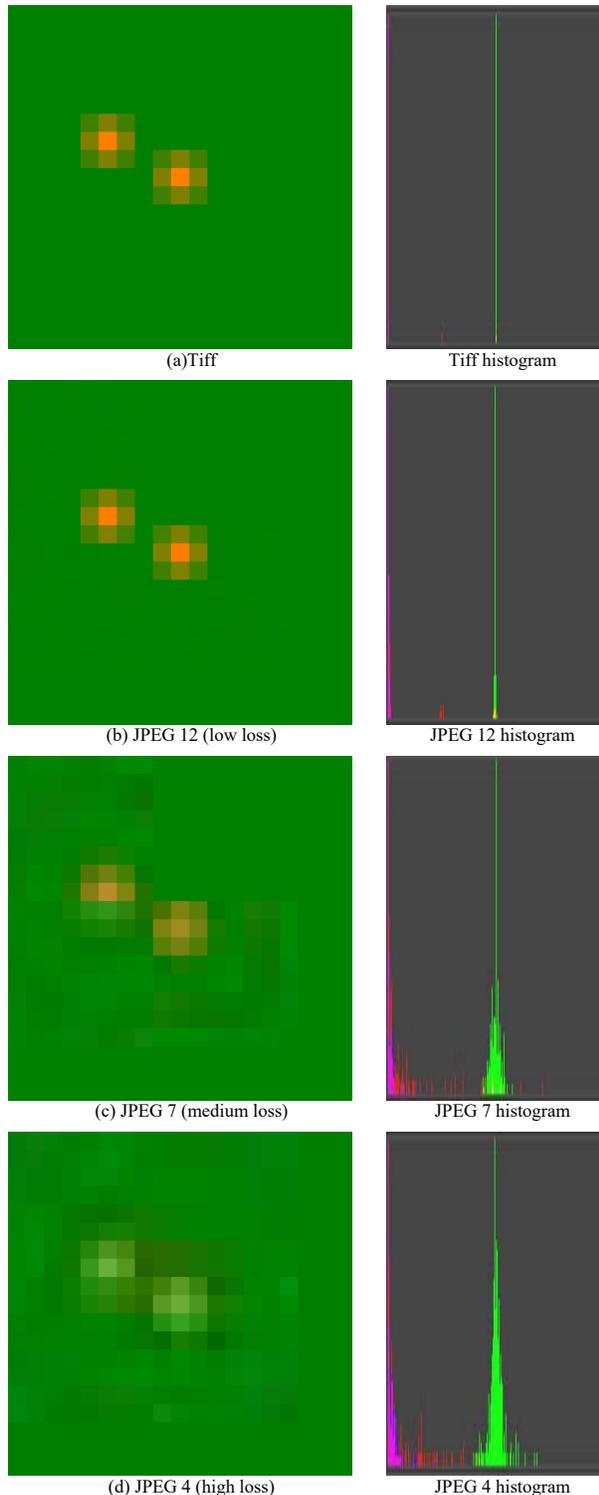


Figure 6: Two Red hot pixels in 5x5 square on the diagonal with uniform green background with bilinear demosaicing in (tiff), JPEG levels 12 (low), 7 (medium) and 4 (high loss). with histogram shows color spread

However, JPEG by its nature spreads the damage both in area and in color. At JPEG 12 (Figure 6(b) - lowest level of compression which is seldom used) the damage has spread to 24 pixels, with G now spreading to 4 levels (slight widening of its histogram area), R to 4 levels and while the B is unchanged at 0. For JPEG 7 (Figure 6(c) - the most common compression level) we see a new effect. The JPEG process first divides a picture into 8x8 pixel tiles before doing additional compression on the individual tiles. In this particular example the damage is spread to 3 of these 8x8 tiles, affecting 192 pixels. Note in the histogram that the G changes from a sharp line to wider spread of 25 levels, the R ranges from 0 to 191 in levels. Furthermore, the Blue is affected ranging from 0 to 48. These color shifts are important because creating both intensity and shifting color over a large area makes the damage much more noticeable. For JPEG level 3 (Figure 6(d) - high compression but still often used) the damage has spread to 4 tiles, affecting 250 pixel. The G has spread now to 80 levels, the R from 0 to 191 and the B from 0 to 60.

An important point here is that the location of the hot pixels relative to the JPEG tile boundary changes this effect. In the example in Figure 6 we placed the two hot pixels in two different tiles, which is a common case. Even if the two hot pixels were in a single tile, the spread of the bilinear demosaicing still results in multiple tiles be affected.

While these examples used two Red hot pixels, the effect of hot pixels of different colors is similar as shown in Figure 7. In this case both the R and B values are spread from 0 to 191 when using JPEG 7.

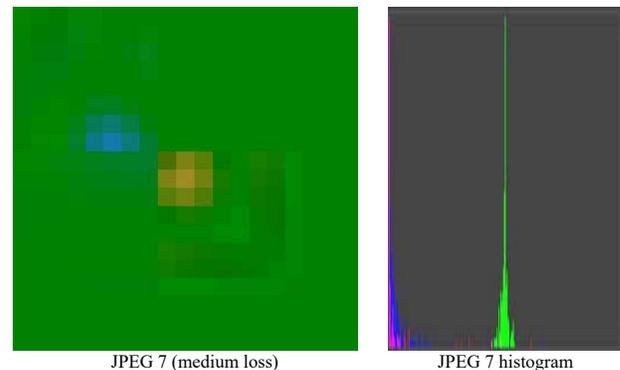


Figure 7: A Red and Blue hot pixels on the diagonal in 5x5 square with uniform green background with bilinear demosaicing at JPEG level 7

We chose the 5x5 spacing of hot pixels as ones being so close that the demosaicing effects were near to overlapping. Figure 8 shows that moving the hot pixels to a 7x7 separation still has significant effect if the JPEG is at level 4. Moreover, Table 2 shows that this larger spacing would require fewer hot pixels before significant degradation occurs.

Another point is that most cameras do not record the RAW data, but store JPEG (often level 7) freezing in these errors.

Impact of More Complex Demosaicing

Bilinear demosaicing is the basic process for converting the pixels of the color filter array into a color image. However, bilinear produces many image artifacts at object boundaries and so is never used by itself. Instead, higher level demosaicing algorithms are used with the two common ones being the Median method [11] and the iterative Kimmel method [12]. Figure 10 shows that even for a single pixel the higher accuracy demosaicings spread the defect with Median being about the same (but with a greater color change) but the higher accuracy Kimmel being worse creating a 7x7 damaged area.

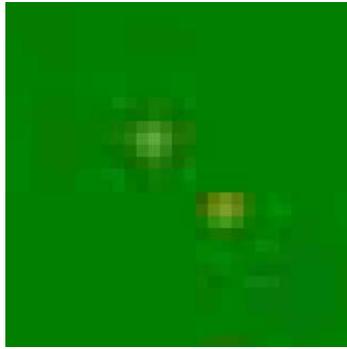


Figure 8: Two Red hot pixels on the diagonal in 7x7 square with uniform green background with bilinear demosaicing JPEG levels 4 (high loss)

Since the Median method creates the least damage of the higher demosaicing algorithms, we focus on its effect on the 2 hot pixels. Median demosaicing (Freeman [11]) starts with the Bilinear estimate. It then creates the differences between the colors (e.g., R-G) and applies a median filter for a certain area (e.g., 3x3) to all 3 differences. From this it establishes the missing colors for a given pixel (e.g., G and B for a R pixel) by subtracting or adding those medians to the pixel value a specific way. This method is especially useful in suppressing artifacts on object edge regions in the picture. Due to the large color variation at edges and the lack of information in the red and blue channels, the comparison with other color planes can suppress the interpolation error and artifacts in the final image. Median Demosaicing is often applied to a 3x3 pixel area or a 5x5 pixel area. What is notable in Figure 9 is that for hot pixels the 3x3 Median method tends to intensify the defect spot by adding additional colors.

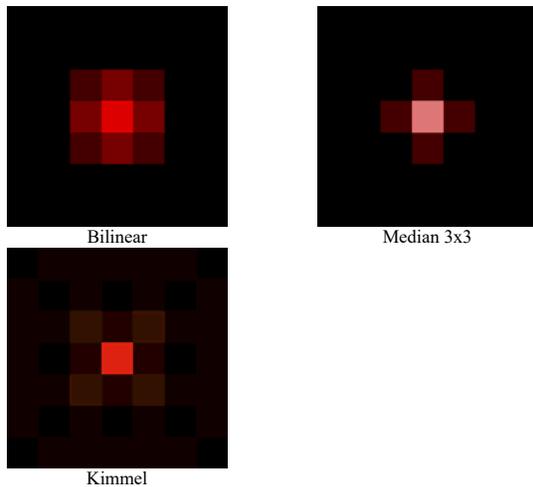


Figure 9: Single hot pixel ($I=0.8$) with different demosaicing algorithms bilinear, Median and Kimmel

Figure 10 shows a 3x3 Median demosaicing applied to the same two Red hot pixels as before. In Figure 10(a), for a tiff uncompressed image, the median creates a 10 pixel damage area spreading to two G levels by increasing the G at the hot pixel point to saturation (255) with also three R levels and a B of 128. This means the median adds intensity towards the white making the hot pixel more noticeable than with the bilinear. For the common JPEG 7 (Figure 10(b)) the median method results in three tiles and 192 pixels being affected. The G spreads out to 85 levels, much more than the bilinear case, while R goes from 0 to 162 and B from 0 to 80. Again this makes the defect brighter and more noticeable with the same large area.

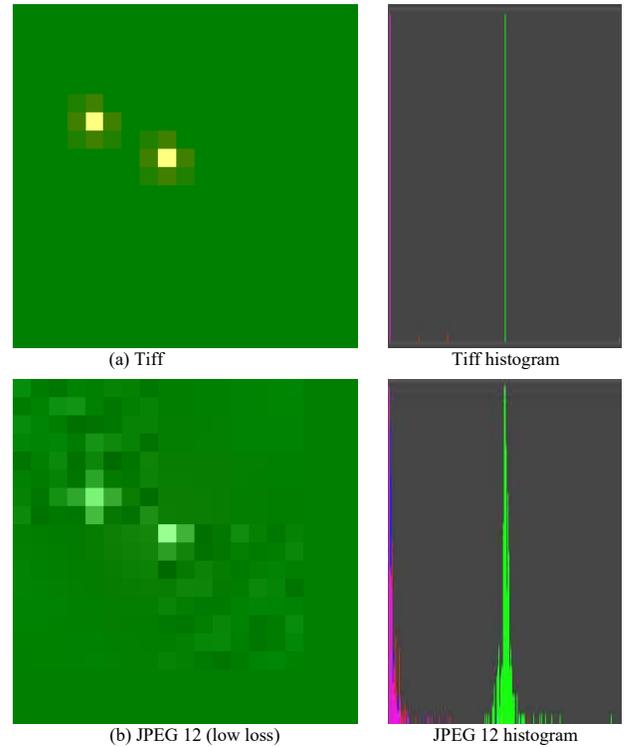


Figure 10: Median 3x3 demosaicing applied to two Red hot pixels in 5x5 square on the diagonal with uniform green background

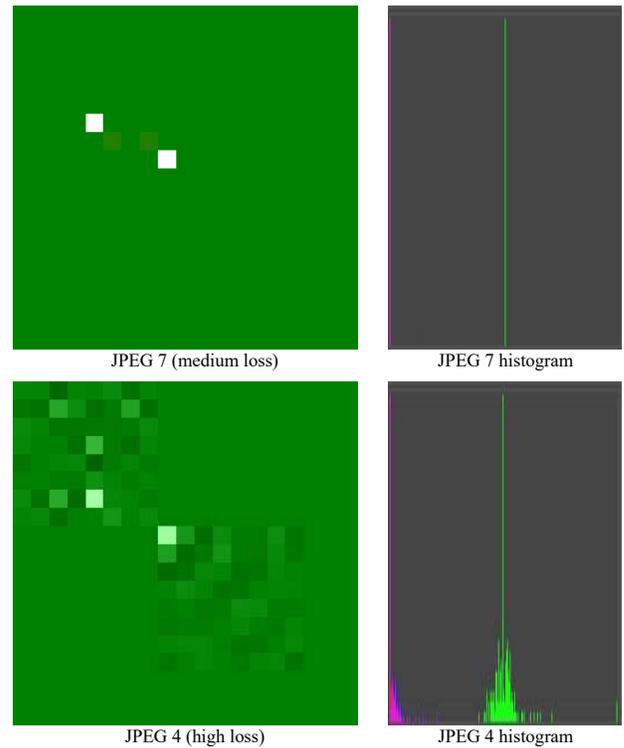


Figure 11: Median 5x5 demosaicing applied to two Red hot pixels in 5x5 square on the diagonal with uniform green background

Median is often done on a larger 5x5 moving pixel filter and this alternative has an interesting different effect. In Figure 11(a) (tiff uncompressed image) the median reduces the defect area to just two pixels, but adds saturation level G and B to create two bright white pixels. In Figure 11(b) the JPEG 7 compression

results in two tiles of 128 pixels being affected, but the G levels now spread from 0 to 255, the R from 0 to 191 and B from 0 to 80. The overall effect is to create in JPEG an even brighter image than the bilinear, though of somewhat smaller area.

The Kimmel demosaicing [12] is not shown here but involves an iterative method that integrates linear, weighted-gradient, and color ratio interpolation for at least 3 iterations. As the single pixel Kimmel in Figure 9 shows this results in even larger areas of damage for a single pixel, and more interaction between two adjacent pixels at even the Tiff level.

What has not been noted elsewhere is that these higher level demosaicing algorithms, in their attempt to correct the problems of image artifacts for regular image edges, enhance the effect of two nearby hot pixels especially by moving the single color hot pixels towards a whiter, brighter defects in the image.

Estimated Time to two Adjacent Hot Pixels

We have shown that two nearby hot pixels can create a significant damage area by the spreading of the damage done in the demosaicing and JPEG processes. The Monte Carlo simulation and generalized birthday approximation indicate how many hot pixels must occur before two nearby hot pixel occur at a given probability level. Using the defect rate equation (3) we can estimate for a given camera how long would it take before we can expect such an event to occur at a reasonable probability.

As a first test consider a typical DSLR level camera with a 20 Mega pixel sensor using 4.3 micron pixels. From Table 2 we see this occurs at a 4% probability (1 in 25 cameras) when 128 hot pixels occur for the conservative 5x5 pixel spacing condition. From our current data (reflected in the equation 3 fit) we can get estimates which are a function of image ISO at which the pictures are taken. This suggests that at ISO 6400 this would be 1.4 years for 4% of the cameras to show this. ISO 6400 is at the higher camera ranges which still exhibits reasonable noise levels. At the lower ISO 3200 (preferred for lower noise levels) it would be 3.2 years for the 4% probability. These are not unreasonable times for these expensive cameras to be used for. Moreover, if we take the 7x7 hot pixel spacing which we are starting to explore at ISO 6400, the 4% probability would occur in 1 year, while the ISO 3200 would be in 2.3 years. This suggests that there is a 1 in 25 chance that hot pixel damage will exhibit a noticeable effect in current DSLR cameras after only 3 year of use.

Conclusions

In this paper we have shown that having two hot pixels occur close enough (within 5x5 pixel box) to create an interaction in the images, has a much higher probability than had been assumed before. We developed a simple model, backed up by Monte Carlo simulations, for estimating the number of hot pixels needed for this to occur. Demosaicing and JPEG compression enhance this process so that the two hot pixels can create damaged image areas in the 100-200 pixel range. Using our defect rate empirical formula from actual camera tests we estimate such damage may be seen in roughly 1 in 25 cameras after 3 years.

Future work will explore the impact of more complex desmosaicing (Kimmel). We also will explore more extensively how the location of the hot pixels affects the area and number of damaged pixels. In addition there is the possibility that the 5x5 spacing we estimated is actually too conservative.

References

[1] J. Dudas, L.M. Wu, C. Jung, G.H. Chapman, Z. Koren, and I. Koren, "Identification of in-field defect development in digital image sensors," *Proc. Electronic Imaging, Digital Photography III*, v6502, 65020Y1-0Y12, San Jose, Jan 2007.

[2] J. Leung, G.H. Chapman, I. Koren, and Z. Koren, "Statistical Identification and Analysis of Defect Development in Digital Imagers," *Proc. SPIE Electronic Imaging, Digital Photography V*, v7250, 742903-1 – 03-12, San Jose, Jan 2009.

[3] J. Leung, G. Chapman, I. Koren, and Z. Koren, "Automatic Detection of In-field Defect Growth in Image Sensors," *Proc. of the 2008 IEEE Intern. Symposium on Defect and Fault Tolerance in VLSI Systems*, 220-228, Boston, MA, Oct. 2008.

[4] J. Leung, G. H. Chapman, I. Koren, Z. Koren, "Tradeoffs in imager design with respect to pixel defect rates," *Proc. of the 2010 Intern. Symposium on Defect and Fault Tolerance in VLSI*, 231-239., Kyoto, Japan, Oct 2010.

[5] J. Leung, J. Dudas, G. H. Chapman, I. Koren, Z. Koren, "Quantitative Analysis of In-Field Defects in Image Sensor Arrays," *Proc. 2007 Intern. Sym on Defect and Fault Tolerance in VLSI*, 526-534, Rome, Italy, Sept 2007.

[6] J. Leung, G.H. Chapman, Y.H. Choi, R. Thomson, I. Koren, and Z. Koren, "Tradeoffs in imager design parameters for sensor reliability," *Proc., Electronic Imaging, Sensors, Cameras, and Systems for Industrial/Scientific Applications XI*, v 7875, 7875011-0112, San Jose, Jan. 2011.

[7] G.H. Chapman, R. Thomas, I. Koren, and Z. Koren, "Empirical formula for rates of hot pixel defects based on pixel size, sensor area and ISO", *Proc. Electronic Imaging, Sensors, Cameras, and Systems for Industrial/Scientific Applications XIII*, v8659, 86590C-1-C-11 San Francisco, Jan. 2013.

[8] J. Leung, "Measurement and Analysis of Defect Development in Digital Imagers, MSc thesis, Simon Fraser University, School of Engineering Science, Burnaby, BC Canada, 2011.

[9] G.H. Chapman, R. Thomas, K.J. Meneses, P. Purbakht, I. Koren, and Z. Koren, "Exploring Hot Pixel Characteristics for 7 to 1.3 micron Pixels", *Proc. Electronic Imaging: Image Sensors and Imaging Systems 2018*, San Francisco Feb. 2018.

[10] J.E. Hill, "Birthday Paradox Calculations and Approximation", <https://www.untruth.org/~josh/beta/birthdayparadoxapproximation.pdf> (2015)

[11] W.T. Freeman, "Median Filter for Reconstructing Missing Color Samples," U.S Patent, 2724395, 1988.

[12] R. Kimmel, "Demosaicing: Image Reconstruction from CCD Samples," *Proc. Trans. Imaging Progressing*, vol. 8, pp. 1221-1228, 1999.

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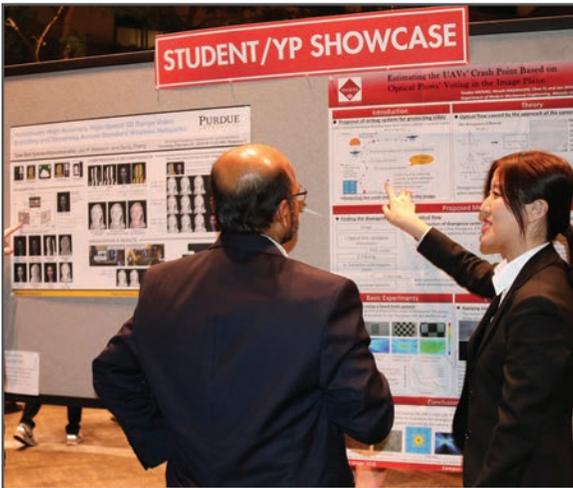
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