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FPGA-based Implementation of Estimating Saturated Pixel Values in RAW Image

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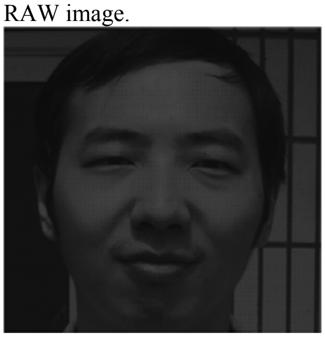
Abstract

Pixel saturation is very common in the process of digital color imaging. From the perspective of optics, the CCD or CMOS achieve the maximum charge. It is important to relate an image to the light of the scene from which the image was captured. This paper presents a hardware implementation with a FPGA circuit of an algorithm to estimate saturated pixels in RAW image based on the principle of Bayesian estimation. In order to improve the accuracy of Bayesian estimation, the digital morphological dilation and connected component labeling are used to divide the saturated region. There may be three kinds of color saturation for each region. The Bayesian algorithm based on Xu' work was used to deal with 1-channel saturation. We improved the 2-channel saturation algorithm using the unsaturated channel to predict the saturation. We proposed the 3-channel saturation using surrounding pixels. Experiments show the proposed method in hardware implementation is more effective in correcting two or three color channel saturation.

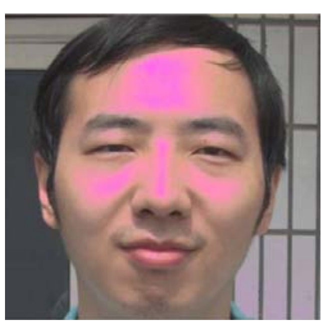
Keywords: Saturated pixels correction; FPGA; Bayesian estimation; RAW image

1. Introduction

In digital imaging we often encounter with the problem of pixel saturation, because of that the dynamic range of digital imaging system is often far less than full luminance range of many natural scenes. Figure 1(a) shows RAW images achieved by CCD or CMOS sensor. During the white balance of RAW image, the saturated pixels change the relative RGB values and results in magenta artifacts, as shown in Figure 1(b). Since saturated dots are marked in RAW data, saturated pixels in magenta will be covered by white. Therefore, clipping saturated value will lose the information in highlight area of image, which can be seen in Figure 1(c). Therefore, it is important to estimate saturated pixel values in RAW image.



(a) Raw image



(b) Saturated image

(c) Covering saturated pixels result

Figure 1. IS&T logo (note the use of bold and italics)

Previously, several works have been reported to solve this problem [1-9]. Zhang et al. [1] proposed a method based on the principle of Bayesian estimation applied to RAW image. Xu et al. [2] improved this Bayesian algorithm by dividing the saturation area into different label areas. For different label areas, it uses the Zhang's algorithm to estimate the saturated value. Xu's work didn't implement in RAW image.

The reference works didn't have a good correction strategy in 2-channel or 3-channel color saturation, because they used the saturated pixels to predict the saturated color channel. In this paper we present an improved method considering hardware implement. We use the Bayesian algorithm based on Xu's work [2] in 1-channel saturation. In 2-channel saturation, we use the other unsaturated channel to predict the two saturation channels based on Bayesian algorithm, which is more accurate than the previous methods that used the saturated color channel for estimation. For 3-channel saturation, we use the maximum fixed saturated color channel value in surrounding area to estimate the saturation values which it suits the hardware implement perfectly.

2. Method

2.1 Basic Flow

It is well known that RAW image needs subsequent image processing to be displayed correctly on the monitor. The workflow depicted in Figure 2 illustrates the procedure of a simple visual output image from the RAW sensor data. The method proposed in this paper acts after the *demosaicing* module in the dashed box. A *mosaicing* module can be applied to *RGB_out* for getting corrected RAW data.

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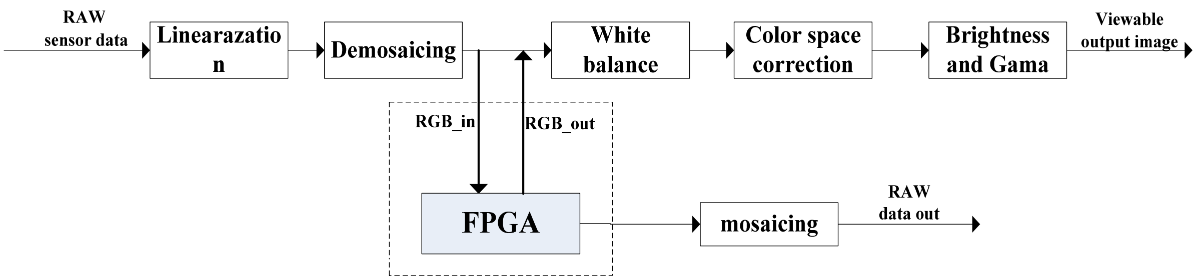

Figure 2. The workflow of a simple visual output image from the RAW sensor data

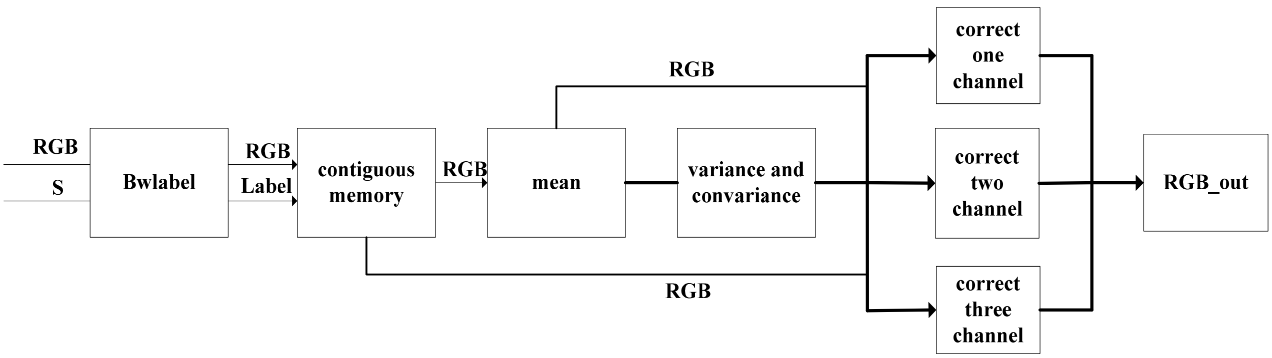

Figure 3. The hardware implementation circuit structure diagram

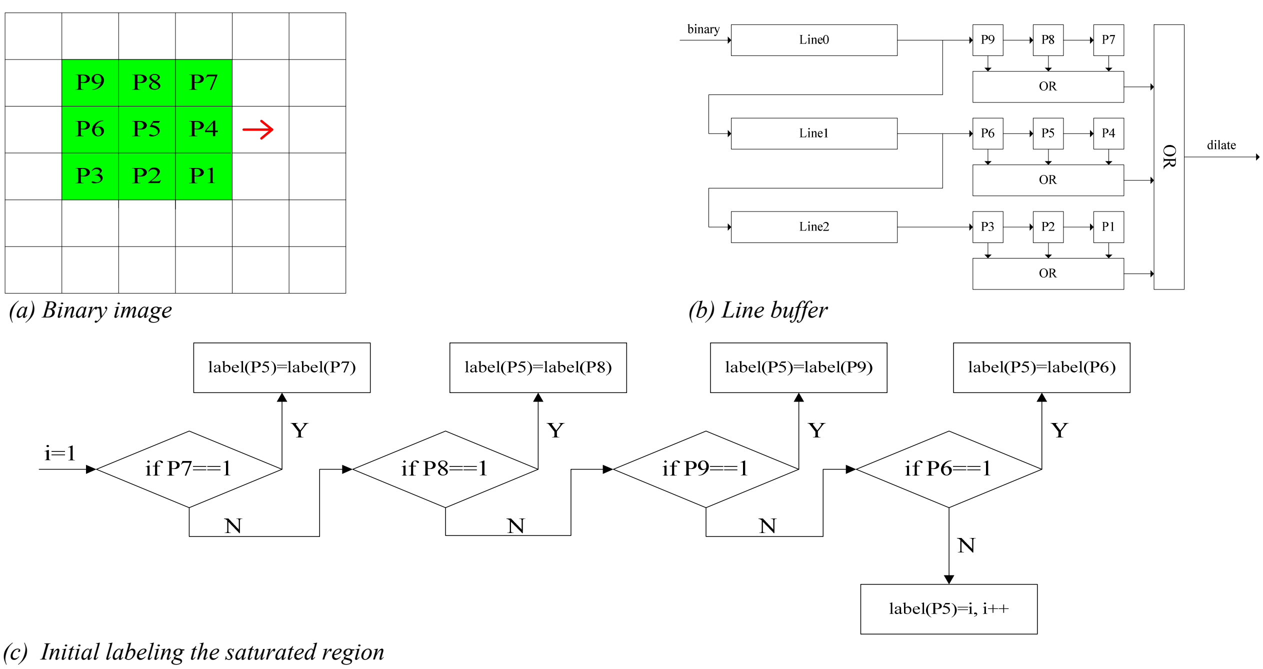

Figure 4. Hardware implementation morphological operations

The hardware implementation circuit structure diagram is shown in Figure 3. The hardware algorithm first realized dilation and connected component labeling in the *Bwlabel* module. *S* denotes the saturation threshold. Then, RGB data of each connected area is stored in *contiguous memory*. Assuming the maximum label of the connected area is *k*. For each area, image data was read for three times in pipeline. Firstly, the mean of all unsaturated color channels was calculated in the *mean* module.

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Secondly, the variance and covariance of all unsaturated color channels were calculated in the *variance and covariance* module. Till now, the prior information was obtained. Thirdly, the saturated pixel values in each area begin to be corrected one by one. There will be three kinds of pixel saturation, and each was fixed using different algorithmic module. Finally, the fixed RAW image can be got from the *RGB_out* using the *mosaicing* module.

2.2 Digital Morphological Dilation and Connected Component Labeling

Image pixels were processed in *Bwlabel* module from left to right and then from up to down. During the process of hardware implementation, the Altera hardware custom mega function Shift register (RAM-based) was used to realize dilation operation, as shown in Figure 4(a-b). We set P5 as a saturated pixel in image, as shown in Figure 4(a). Figure 4(b) shows the result of P5's dilation. After that, the green mask moved a pixel to right to calculate the next pixel dilation. In practice, a circular disk was chosen as the optimal structuring element, whose radius value is four. This option can result in an isotropic extension of the saturated regions.

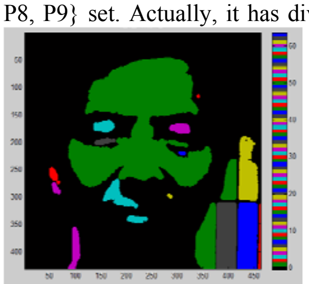
The connected component labeling is realized by the way similar to Figure 4(a-b). By reading the dilate data in pipeline firstly, the initial label is obtained according to the label of the surrounding area as illustrated in Figure 4(c). At the beginning, the initial value of parameter i is 1. By reading the initial label image secondly, the final output label P5 is the minimum label in {P6, P7, P8, P9} set. Actually, it has divided a different region by making discrete label in this procedure. In order to obtain the sequential label, while each change of initial label on P5 to the minimum label, we record the relationship between P5 and minimum label into a vector table at the same time. Finally, we refresh the firstly obtained label recording to the vector table. The label is sequential to be suit for hardware implementation. In the hardware implementation, a contiguous memory was set up to store the label image for subsequent processing.

Figure 5(a) shows image of Figure 1(a) after labeling, and saturated pixels separated to several areas. Figure 5(b) shows the three channels distribution of full RAW image. As controls, figure 5(c-d) shows the three channels distribution of two areas. It can be seen that, the unsaturated RAW data's distribution of each area is more suit for normal distribution than the full image.

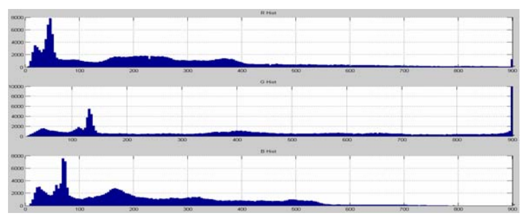
2.3 Correct 1-Channel Saturated Pixels

It is known that the distribution of the saturated pixels in color channels is normal with a mean value μ_{x_s} and variance S_{x_s} [1]. For each labeled area, we can calculate the mean and variance value separately. It is important to select pixels that have none of the color channels clipped, and use the same selection for calculating all statistics.

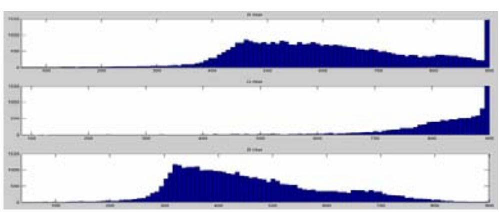
The true values of the saturated color channel are greater than or equal to the saturation value s. Then the saturation channel is estimated by computing the expected value of the posterior distribution according to equations (1) and (2) in Zhang [1], conditional variance and mean formula is used. Without loss of generality, here we assume that R and G color channel were saturated, defining vector $Y_1 = (R\ G)^T$ and $Y_2 = B$ color channel which is used to predict Y_1.Then, the distribution of conditional Y_1 with



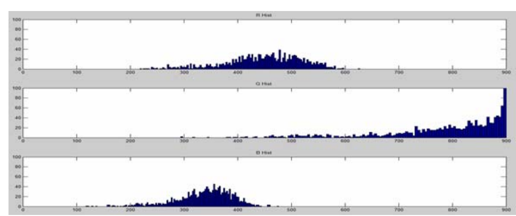
(a) Figure 1(a) after labeling



(b) Pixels distribution of full image



(c) Pixels distribution of region 1



(d) Pixels distribution of region 10

Figure 5. Image after labeling

$$E(X_s \mid Y_k = k, Y_s \ge s) = \mu_{x_s} + \frac{1}{Z}\left(\frac{S_{x_s}}{2\pi}\right)^{1/2} \exp\left(-\frac{(s-\mu_{x_s})^2}{2S_{x_s}}\right), \qquad (1)$$

$$Z = \frac{1}{\sqrt{2\pi S_{x_s}}}\int_{s-\mu_{x_s}}^{\infty} \exp\left(-\frac{x^2}{2S_{x_s}}\right)dx. \qquad (2)$$

2.4 Correct 2-Channel Saturated Pixels

In the previous work [1-2], the saturated color channel is used to predict the other saturated color channel values for the 2-color channel saturated pixels. In this work, we use the other unsaturated color channel to predict the 2-color saturated pixels. A standard

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the unsaturation values of Y_2 is normal with a mean equation (3) and a variance equation (4),

$$E(Y_1 / Y_2 = B) = \begin{pmatrix} \mu_R + (B - \mu_B) covRB / covBB \\ \mu_G + (B - \mu_B) covGB / covBB \end{pmatrix}, \quad (3)$$

$$\mathrm{cov}(Y_1 / Y_2 = B) = \begin{pmatrix} covRR - cov^2 RB / \mathrm{cov}\, BB & covRG - covRB \bullet covGB / covBB \\ covRG - covRB \bullet covGB / covBB & covGG - cov^2 GB / covBB \end{pmatrix}, \quad (4)$$

where μ represents mean of the color channel and *cov* denotes the covariance between of the two color channel in the equation (3) and (4).

In order to save the hardware resources and accelerate implementation, we just use the result of equation (3) to replace the 2-color channel saturated pixels. And the compromise has a negligible influence on our fixed values.

2.5 Correct 3-Channel Saturated Pixels

For the 3-channel saturation we proposed a hardware implementation method based on moving mask to restore the color and intensity in high light area of the image. Similar to the hardware custom mega function Shift register in Figure 3, we use the maximum fixed saturated color channel value to replace the 3-channel saturated values in surrounding area. For instance, we calculate the R value in 3-channel saturation as follows,

$$R(all\_sat) = \max(s, \max(\{P_1, P_2, P_3, P_4, P_6, P_7, P_8, P_9\})). \quad (5)$$

Other color channels are the same as the R color channel corrected. The 3-channel saturation pixels can be restored color as well maintaining the high intensity by this method.

3. Experimental Results and Discussion

In this study, the RAW data were achieved from camera SONY RX 100II output-.ARW format with 12 bits per pixel. The design has been specified in VHDL targeted on a consumer FPGA chip Altera EP4CGX150DF31C7. It was designed by Quartus II 13.0 sp1(32 bit) and simulated in Modelsim SE 10.1c combined with Matlab R2014a. The image in Figure 1 has a size of 431×464 pixels. The hardware resource used in FPGA according to the equations (1-4) can be seen in Table 1. The maximum frequency (Fmax) in our FPGA design can reach about 110MHz, and the whole procedure read image data about 7 times to output the result. When the input clock is set to 100MHz, the connected component labeling takes about only 8ms, and the hardware fixed component takes about 2ms. The whole process takes about 10ms simulated in the Modelsim. Therefore, the more saturated pixels in RAW data, the more time will be cost.

In Table 1, *calexp* component realizes equation (1). *Correct_G* component realized the correction algorithm for channel G. *Bwlabel* component realized the connected component labeling. *Bayes* component realized the correction algorithm for the labeled data. *Top* component realized the whole process.

Figure 6(a-d) shows the visual results of figure 1. The saturated regions of man's forehead, nose and the face are composed of 1-channel of G and 2-channel of R & G, and 3-channel saturated pixels, the experiments of our results shows that the saturated region are restored more naturally.

Table 1 Resource of the Component used in FPGA

Componet	total logic elements	combinational logic register	dedicated logic registers	embedded multiplier 9-bit elements	total memory bits	Fmax (MHz)
mean	2.9k	1.8k	2.4k	0	21	202.3
variance	9.3k	6.4k	6.8k	12	1.8k	204.6
S	14.2k	9.1k	13.0k	74	1.7k	152.2
Z	2.5k	1.8k	1.7k	0	653	145.4
μ	4.2k	2.5k	3.9k	44	548	168.8
calexp	8.1k	5.4k	6.7k	60	6.1k	117.9
corret_G	14.8k	9.8k	12.3k	104	7.3k	110.3
Bayes	84.9k	55.4k	71.1k	422	49.4k	110.3
Bwlabel	1.2k	1.0k	748	0	19.3k	118.3
Top	86.1k	56.4k	71.9k	422	68.8k	110.2

(a) Saturated image ***(b) Zhang's result*** ***(c) Xu's result*** ***(d) Our result***

Figure 6 Comparison between the proposed result and other methods

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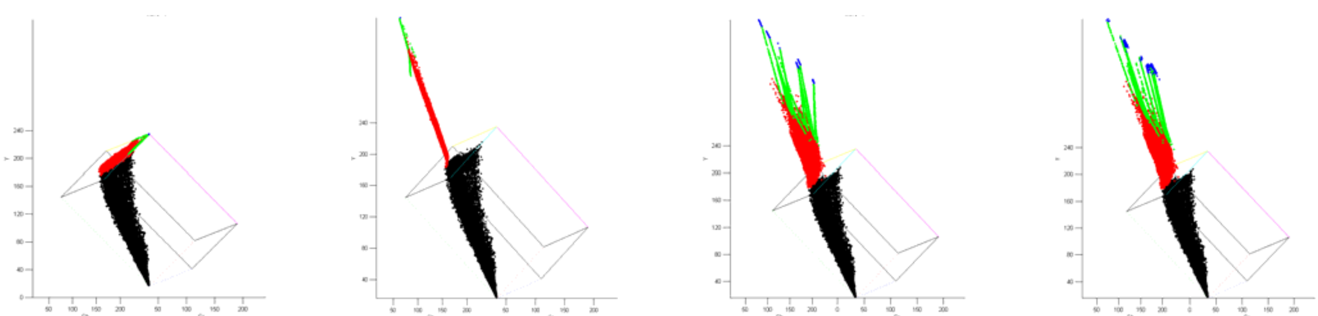
(a) Covering saturated pixels result (b) Result of Matlab fixed (c) Result of hardware implementation (d) Difference figure

Figure 7 Comparison between Matlab fixed and hardware implementation

(a) Saturated image (b) Zhang's result (c) Xu's result (d) Our result

(e) Saturation local zoom (f) Zhang's local zoom (g) Xu's local zoom (h) Our local zoom



(i) Cb-Cr-Y view of (a) (j) Cb-Cr-Y view of (b) (k) Cb-Cr-Y view of (c) (l) Cb-Cr-Y view of (d)

Figure 8 Comparison between the proposed result and other methods

During our experiment, the maximum difference between the matlab fixed image and the hardware implementation fixed image is 1 in 12 bits RAW data. Figure 7(b-c) compare the visual difference. Figure 7(d) represents the difference of two results in RAW data format, and the absolute sum of the difference is 2773.

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Figure 8(a) shows an overexposure image in a sunny day, the saturated pixels change the relative RGB values and results in magenta artifacts. If not handled carefully, saturated pixels can lead to image artifacts as in Figure 8(b), where the details and texture blurred. After the hardware implementation using our proposed algorithm, the blue and white T-shirt kept the original colors, while there are magenta artifacts when using Zhang [1], or Xu's [2] method. When zooming the nose area, it can be found that almost all of the original information has been restored in our result. In the YCbCr color space in Figure 8(i-l), the red, green and blue points represent 1-channel, 2-channel and 3-channel saturation pixels respectively. We can see that the green point in Figure 8(j) according to Zhang's method just has a straight line. In Figure 8(k), according to Xu's method, green point is too dispersive. However, in Figure 8(l), according to our method, we can find that green point increased the values according to the equations (3).

The method is not only suitable for the character but also for the nature landscape. Figure 9(a) shows a pillar losing some texture in the direct sunlight. Through our method, the details of pillar are restored very well.

(a) Saturated image ***(b) Marking saturated pixels result*** ***(c) Our result***

Figure 9 *Comparison between the proposed result and clipping result*

Experiment results show that the proposed method is more effective in correcting two or three color channels saturation. However, it is not very accurate to describe the distribution of each channel in RAW data as normal distribution. We are looking for more accurate distribution to solve this problem.

4. Conclusion

Focusing on RAW image, a rapid hardware implement algorithm for correcting two or three color channels saturation is proposed. It is more effective in correcting for the 2-channel and 3-channel saturation compared with the reference algorithm [1-2]. The algorithm proposed in this paper can be considered applying to camera in a real time processing.

5. Acknowledgement

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