Adaptive Pixel Defect Correction

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1. Introduction

Although the number of pixels in image sensors has been increasing exponentially, production techniques have only been able to linearly reduce the probability that a pixel will be defective. The result is a rapidly increasing probability that a sensor will contain one or more defective pixels. A defective pixel can destroy the perceived quality of the images from a sensor. Defects in sensors using a Bayer color filter array are especially hard to correct. Sensors with more than a few defects are often discarded after production. To reduce the cost of image sensor production, defect correction algorithms are needed that allow the utilization of sensors with bad pixels. We present a relatively simple defect correction algorithm, requiring only a small 7 by 7 kernel of raw data from a sensor with a Bayer color filter array, that effectively corrects a wide variety of defect types.

2. Requirements for algorithm

Our interest lies in correcting defects in image sensors using the Bayer color filter array. To be practical, the algorithm should:

- be independent of other in-camera algorithms.
- utilize Bayer image data.
- require a small amount of memory.
- correct most types of defects with minimal visual error.

3. Useful natural image properties

Development of an algorithm that is computationally efficient and visually pleasing requires exploiting the properties of natural images. By using these properties, we can achieve improved results, particularly in high-frequency image regions, without the use of higher-order interpolation methods.

Our algorithm targets sensors used in pictorial imaging. The human visual system uses complex spatial differencing mechanisms that emphasize edges. We will minimize errors where the human visual system is most sensitive by using the large spatial color correlation inherent in nearly all pictorial images shown in Figure 1.

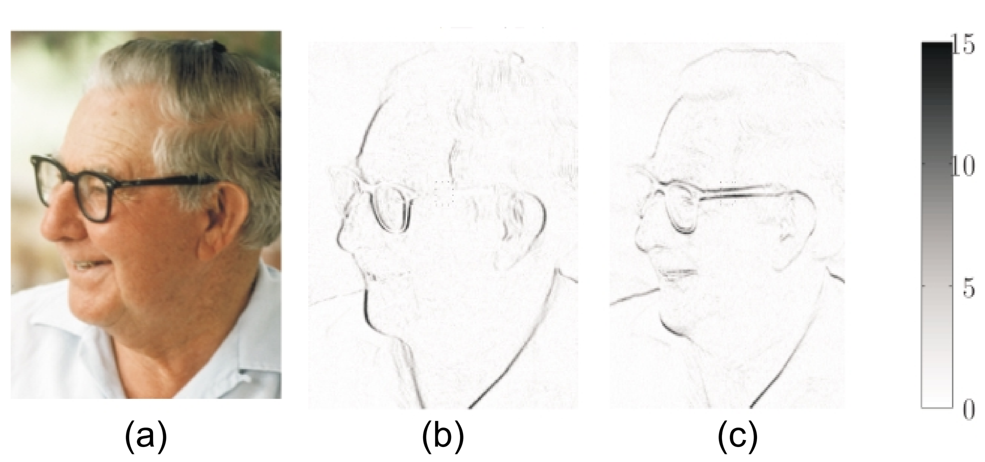


Fig. 1. Demonstration of high color correlation. The horizontal gradient of (a) is computed for the red, green, and blue color channels. The standard deviation of the R-G-B gradients at each given spatial position is displayed in (b). Light values indicate high color correlation. The standard deviation of the vertical gradients are shown in (c). The figures show that there is almost perfect color correlation *in the edge direction* for high frequency regions. Low frequency regions have nearly perfect correlation in any direction.

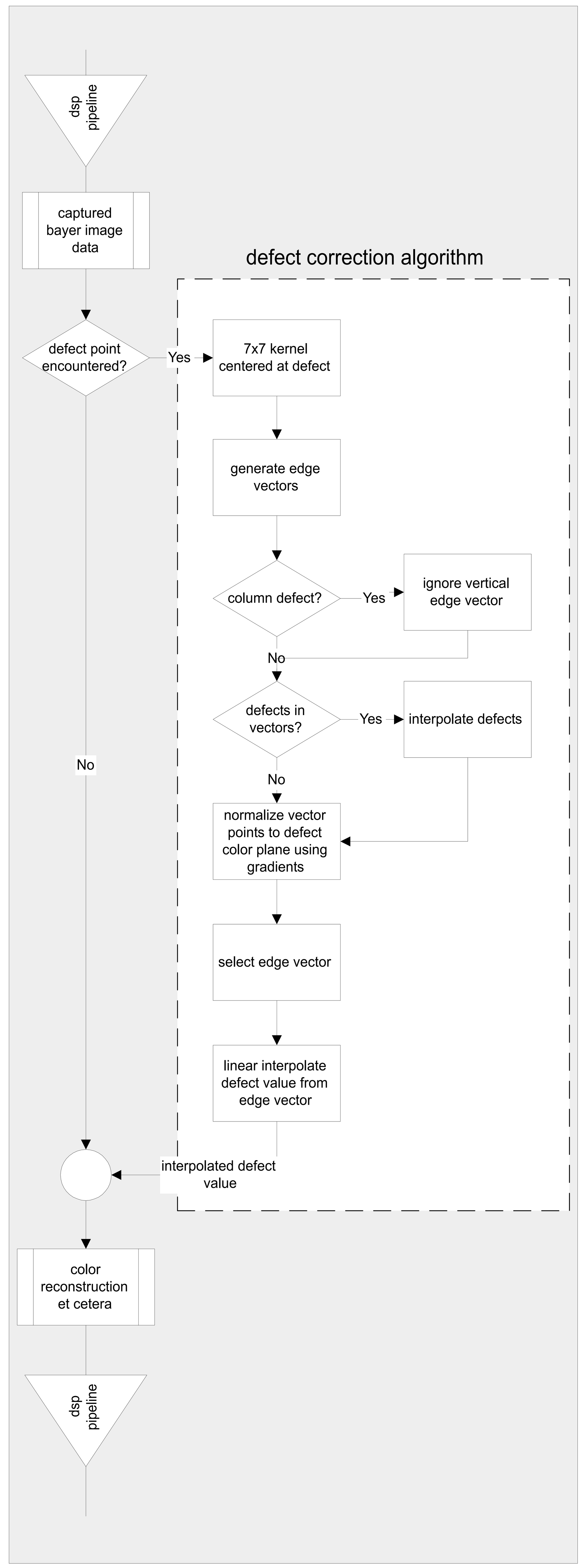
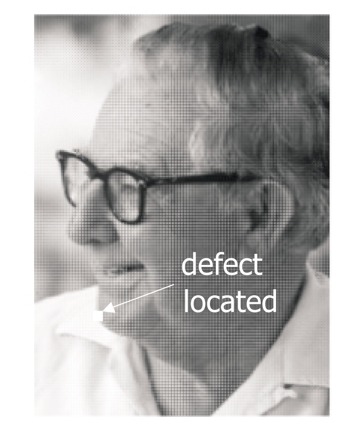


Fig. 2. Flow diagram of algorithm.

4. Algorithm details

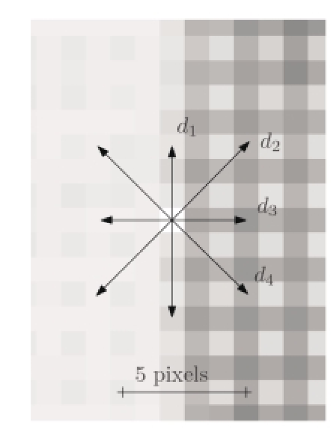
To correct a defective pixel, the algorithm carries out the steps outlined in Figure 2 as follows:



I. input image

I. Given an input Bayer sampled image, the correction algorithm is initiated when a defect location is encountered.

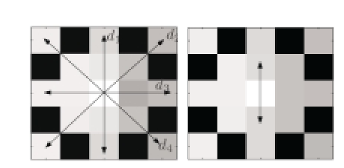
The algorithm is limited to a 7 x 7 kernel of data.



II. Bayer data with edge vectors in 7 x 7 kernel around defect

II. The 7 x 7 kernel is broken up into 4 different edge direction vectors: vertical, positive diagonal, horizontal, and negative diagonal.

If any defects exist in the vector data these defects are corrected using a linear interpolation.



III. Uncorrelated data (left) is correlated (right), edge is found

III. Directional derivatives are used to correlate nearest good pixel data to same color plane as defect.

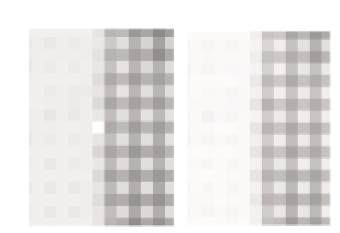
The edge direction is determined from the correlated data.

IV. The defect value is estimated using neighboring correlated pixels in a weighted average based on their alignment to the edge direction. The estimated pixel value $\hat{a}$ is:

$$\hat{a}[m_0, n_0] = \sum_i \xi_i \left(\frac{d_i[-1] + d_i[+1]}{2} \right).$$

$$\xi_i = \left(1 - \frac{\delta_i^k}{\sum_i \delta_i^k}\right) / (I-1).$$

$$\delta_i = |d_i[-1] - d_i[+1]|.$$



IV. Defect value (left) is estimated and replaced (right)

Where $d_i[\pm 1]$ is a neighboring correlated pixel in a given vector direction. The constant k can be adjusted to modify the algorithm's sensitivity to the edge direction. The number of vectors in use is I.

5. Experimental results

To measure the abilities of the proposed algorithm, defects were implanted into a zone plate target and then corrected. This allowed analysis of the algorithm's behavior at frequency ranges from zero to the Nyquist frequency. For comparison, the same tests were conducted with the one-dimensional (1-D) averaging algorithm proposed by van der Sidje (2002).

Figure 3 illustrates that the proposed algorithm has a significantly smaller error in correction for frequencies slightly beyond 3/16 cycles per pixel. Furthermore, Table 1 shows that the proposed algorithm provides marked improvements for all five defect types tested.

As a worst case scenario, Figure 4 illustrates the algorithm's ability to correct a sensor with every fourth column defective.

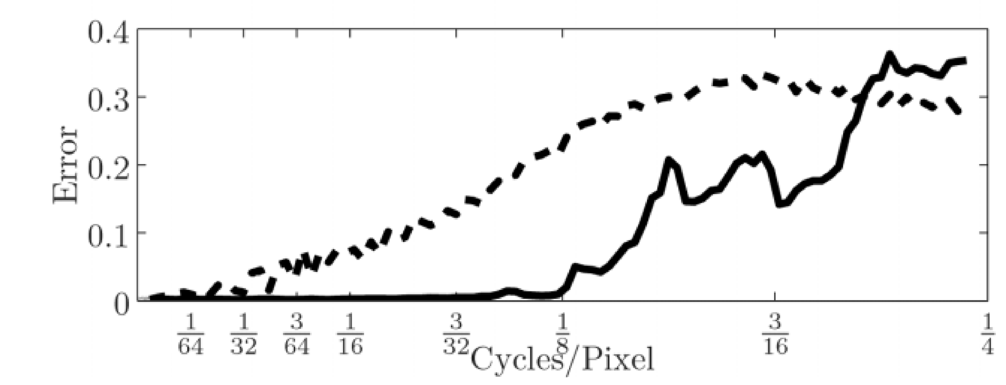


Fig. 3. Comparison of adaptive algorithm's error (solid line) in correcting single pixel defects versus the 1-D algorithm (dashed line).

Table 1. Average maximum frequency that each algorithm can correct 100% defects with mean error <10%.

	Max Frequency (cycles/pixel)		
Defect Type	Adaptive Edge	1D	Improvement*
single pixel	0.140	0.075	1.87x
2 × 2 cluster	0.130	0.070	1.86x
3 × 3 cluster	0.070	0.042	1.67x
single column	0.130	0.063	2.01x
double column	0.094	0.047	2.00x

Fig. 4. Image sensor with massive column defects uncorrected (left) versus image corrected with proposed algorithm and color reconstructed (right).

6. Conclusions

The experimental results have shown that the proposed adaptive defect correction algorithm is capable of correcting defects in image regions with frequencies up to twice that of the 1-D algorithm (Table 1). Furthermore, the algorithm requires only a small data kernel and operates independently of other in-camera algorithms by using raw Bayer data to produce corrected Bayer data.

References

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