A ROBUST SEQUENTIAL APPROACH FOR THE DETECTION OF DEFECTIVE PIXELS IN AN IMAGE SENSOR

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ABSTRACT

Large image sensors usually contain some defects. Defects are pixels with abnormal photo-responsibility. As a result they often generate outputs different from their adjacent pixel outputs and seriously degrade the visual quality of the captured images. However, it is not economically feasible to produce sensors with no defects for rendering images. A limited number of defects are usually allowed in an image sensor as long as the defective outputs can be corrected with post signal processing techniques. In this paper we present a robust sequential approach for detecting sensor defects from a sequence of images captured by the sensor. With this approach no extra non-volatile memory is required in the sensor device to store the locations of sensor defects. In addition, the detection and correction of image defective outputs can be performed efficiently in a computer host. Experimental results of this approach are reported in the paper.

1. INTRODUCTION

A fabricated solid state image sensor, such as CCD or CMOS sensor, usually contains some defects. Defects are pixels with abnormal photo-responsibility [1]. As a consequence they often produce outputs different from their neighboring-pixel outputs, and seriously degrade the overall visual quality of the captured images. However, due to the complexity of a sensor fabrication process, the occurrence of such defects is hard to prevent. To have a profitable manufacturing yield, a limited number of defects are usually allowed in an image sensor as long as the defective outputs within each captured image can be corrected with post signal processing techniques. Conventionally, the defects within each fabricated sensor are identified with some test procedures performed under a controlled environment. The locations of the defects are recorded and then transferred to some non-volatile memory in the sensor device (e.g., digital camera, scanner, etc.). The size of the memory space required for storing the locations of these defects depends upon the size of the sensor array and the maximum number of defects allowed in a sensor. For example, approximate 2000 bits (250 bytes) memory space is needed to store, with a simple bit-packing scheme, the locations of up to 100 defects of a megapixel sensor (i.e., sensor with $\approx$ 1000 x 1000 pixels). In addition to an increase in the production cost of sensor devices, a great amount of data handling is also required to transfer the locations of sensor defects into the devices during sensor assembly. An alternative way of using image sensors with defects is to consider the defective outputs within each captured image as noises. Without knowing their exact locations, the defective outputs are usually corrected by applying a noise reduction function over the entire image. However, most of the effective noise reduction algorithms are computationally intensive and normally provide some low-pass filtering effects. As a result, the function not only conceals the defective outputs but also reduces the overall image sharpness, which is a precious image quality to sacrifice.

In this paper, we present a robust sequential approach for detecting the defective pixels in an image sensor from a sequence of images captured by the sensor. The contents of the images are assumed not to be known a priori. With our proposed approach, both the defect detection and correction algorithms can be implemented with software and run in a computer host. Since the result of the defect detection, such as a location map of the defective pixels, can be stored as a file in the host, no extra memory space is required in the sensor device to store the defect locations. After the defect location map has been generated, the defective outputs in each captured image can be promptly corrected according to the outputs of their functional neighboring pixels. Furthermore, as only the defective outputs are modified, the overall image sharpness can be well preserved.

The rest of this paper is organized as follows. Section 2 briefly describes some common types of sensor defects. Section 3 reviews some properties of a sequential probability ratio test procedure based on which the proposed sensor defect detection algorithm is designed. A pixel attribute, *minimum neighboring-pixel difference*, and the characteristics of its values measured from both functional and defective pixels are introduced in section 4. In section 5, we propose a robust sequential algorithm for detecting sensor defects using a sequence of images whose contents are not known a priori. Experimental results are reported in section 6 to demonstrate the efficacy of the proposed approach. In section 7, we conclude.

2. SENSOR DEFECTS

Sensor defects are results of fabrication errors such as impurity contamination and silicon dislocation. According to its location, a

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sensor defect can be classified as a point defect (an isolated defective pixel), a cluster defect (a group of contiguous defective pixels) or a column/row defect (a column/row of contiguous defective pixels) [1]. In this work, we are interested in detecting three common types of point defects: *stuck high*, *stuck low* and *abnormal sensitivity* defects. A stuck high defect is a pixel that always has a very high or near to full scale output. On the other hand, a stuck low defect always has a very low or near to zero output. An abnormal sensitivity defect is a pixel that produces an output different from the output of a functional pixel by more than a certain amount or percentage when both are exposed to the same light condition. These point defects are usually allowed in an image sensor since their defective outputs can be readily corrected according to the outputs of their functional neighboring pixels. However, to avoid changing the outputs of functional pixels when correcting the defective outputs, the locations of sensor defects need to be known a priori. In the next section, we shall describe a sequential decision rule based on which our proposed algorithm for detecting sensor point defects is developed.

3. SEQUENTIAL PROBABILITY RATIO TEST

A sequential probability ratio test (SPRT) [2][3] is an optimum decision rule for identifying one out of the two underlying hypotheses from a sequence of observations. Specifically, an SPRT over a sequence of observations $\mathbf{y} = (y_1, y_2, \ldots, y_n)$ is the decision rule given by

$$\delta_n(\mathbf{y}) = \begin{cases} H_1, & \Lambda_n(\mathbf{y}) \geq \mathcal{B} \\ H_0, & \Lambda_n(\mathbf{y}) \leq \mathcal{A} \\ \text{take another observation}, & \text{otherwise} \end{cases} \quad (1)$$

which accepts hypothesis H_1 if the likelihood ratio, $\Lambda_n(\mathbf{y}) \equiv \mathbf{P}_1(\mathbf{y})/\mathbf{P}_0(\mathbf{y})$, is above a pre-defined threshold $\mathcal{B}$; accepts hypothesis H_0 if the likelihood ratio is less than a threshold $\mathcal{A}$; otherwise continues taking observations until either one of the thresholds $\mathcal{A}$ and $\mathcal{B}$ is attained; where the decision thresholds $(\mathcal{A}, \mathcal{B})$ satisfy the condition $0 < \mathcal{A} < 1 < \mathcal{B} < \infty$, while $\mathbf{P}_0$ and $\mathbf{P}_1$ are the probability density functions of the observations under the two underlying hypotheses H_0 and H_1, respectively.

The properties of an SPRT have been extensively investigated in the field of statistical signal processing [2][3]. Some of the properties that are useful in designing our proposed defect detection algorithm are summarized here. Let $\mathcal{N} = \min\{n : \Lambda_n(\mathbf{y}) \notin (\mathcal{A}, \mathcal{B})\}$ be the random number of observations required to make a decision. A well-defined SPRT has the following properties: **I**) *Finite Decision Time:* Wald showed in [2] that Prob$(\mathcal{N} < \infty) = 1$. Namely, a decision can always be made with an SPRT decision rule as long as the two underlying hypotheses are statistically discernible and an enough number of observations are available; **II**) *Reliability:* Let α = Prob$(\delta_{\mathcal{N}}(Y_1, Y_2, \ldots, Y_{\mathcal{N}}) = H_1|H_0)$ and β = Prob$(\delta_{\mathcal{N}}(Y_1, Y_2, \ldots, Y_{\mathcal{N}}) = H_0|H_1)$ be the false detection probability and miss detection probability of an SPRT decision rule, respectively . According to *Wald's approximations rule* [4], an arbitrary target error-probability performance level (α, β) can be achieved, approximately, by setting the decision thresholds as

$$\mathcal{A} = \beta/(1-\alpha) \quad \text{and} \quad \mathcal{B} = (1-\beta)/\alpha \quad (2)$$

Notice that the decision thresholds $(\mathcal{A}, \mathcal{B})$ are chosen independently of the probability densities $\mathbf{P}_0$ and $\mathbf{P}_1$ of the two hypotheses; **III**) *Optimality:* Consider the expectations $E(\mathcal{N}|H_0)$ and $E(\mathcal{N}|H_1)$ as the average number of observations required to make a decision under each respective hypothesis. The SPRT decision rule is optimal in the sense that any other decision rule with the same error-probability performance (α, β) would require, in average, more observations to make the decision. This result is known as Wald-Wolfowitz theorem [3].

Although an SPRT decision rule can make a decision in some optimum sense as described above, it requires the probability densities of the two underlying hypotheses to be known accurately to a certain extent. Furthermore, while the average number of observations required to make a decision is finite with probability one, it can be very large to be of no practical use if the probability densities of the two hypotheses overlap with each other to a large extent. In the next section, we introduce a pixel attribute whose values measured from functional and defective pixels are statistically discernible, and describe methods for estimating the probability densities of this pixel attribute from the images observed.

4. MINIMUM NEIGHBORING-PIXEL DIFFERENCE

In this section we consider a pixel attribute, *minimum neighboring-pixel difference* (MND), which will be used to sort out the defective pixels from the functional pixels in an image sensor . The MND value of a pixel (i, j) under examination is defined as

$$y(i,j) \overset{\triangle}{=} \min_{(m,n)\in G(i,j)} \{|I(i,j) - I(m,n)|\} \quad (3)$$

where $G(i, j)$ denotes the locations of the pixels within a neighboring support around pixel (i, j), $I(i, j)$ is the output of pixel (i, j) and $I(m, n)'s$ are the outputs of the neighboring pixels. The support of neighboring pixels around each pixel of interest can be properly selected for different types of sensors. Figure 1 shows some example supports of neighboring pixels (shaded regions) around a pixel in a monochrome sensor and a sensor with Bayer color filter array pattern. To assist the following discussion, we denote the output of the neighboring pixel with the minimum difference from the output of pixel (i, j) as $z(i, j)$, i.e., $y(i, j) = |I(i, j) - z(i, j)|$. To simplify the notation, from now on we will also suppress the location of the pixel under examination.

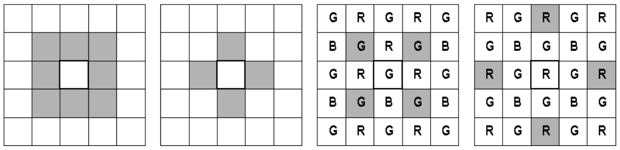

Figure 1: Four example supports of neighboring pixels (shaded regions) around a pixel (central pixel) in monochrome sensor (left two) and sensor with Bayer color filter array pattern (right two).

Let $p_F(y)$ be the probability density function (pdf) of the MND value measured from a functional pixel in an observed image. In order to model the pdf $p_F(y)$, we make the two following assumptions. First, at least one of the neighboring pixels of any functional pixel in the image is functional. Second, the MND values measured from all the functional pixels in the image can be considered as realization of a stationary and ergodic random process. These assumptions imply that the pdf $p_F(y)$ of a functional pixel is statistically equivalent to the distribution (or histogram) of the MND values measured from all functional pixels in the image, and furthermore the pdf $p_F(y)$ is independent of the outputs of the neighboring pixels, i.e., $p_F(y|z) = p_F(y)$. As the content of a general scene is highly spatially correlated, the pdf $p_F(y)$ would normally has a significant peak near the zero MND value and decreases rapidly when the MND value becomes large. From our findings, the pdf $p_F(y)$ of each observed image can be well approximated by a discretized Gamma distribution, given as

$$p(y) = \frac{1}{c}\int_{y}^{y+1} \frac{\lambda^{\alpha} x^{\alpha-1} e^{-\lambda x}}{\Gamma(\alpha)}\, dx \quad \text{for} \quad y = 0, 1, \ldots, L \tag{4}$$

with $0 < \alpha \leq 1$, where y is the measured MND value, $\Gamma(\alpha)$ is the Euler's gamma function defined as $\Gamma(\alpha) = \int_0^{\infty} x^{\alpha-1} e^{-x}\, dx$ for positive α, L is the maximum possible MND value, and scalar c is a normalization factor that makes $p(y)$ a legitimate density function [5]. The parameters α and λ can be computed as $\lambda = m/\sigma^2$ and $\alpha = m^2/\sigma^2$, where m and σ^2 are the mean and variance of the MND values measured from all the functional pixels in the image. Since a usable sensor normally contains a very small number of defective pixels (for example, 100 $\sim$ 200 defective pixels in a megapixel sensor) and the MND values of the defective pixels are bounded within the pixel output range, they can be considered as negligible outliers in estimating the pdf $p_F(y)$. Therefore, the pdf $p_F(y)$ of a functional pixel can be approximated very well by the normalized histogram, or the discretized Gamma density function with parameters α and λ, computed from the MND values measured from all pixels (both functional and defective) in the image.

To model the MND pdfs of different point defects, we assume that none of the neighboring pixels of a defective pixel is defective. Although this constraint appears somewhat strict, it is not an unreasonable assumption given that each usable sensor has only a very small number of defects. Sensors with defects which do not satisfy this assumption can be sorted out after the fabrication. Now, suppose $f_{SL}(\cdot)$ and $f_{SH}(\cdot)$ are the output pdfs of stuck low and stuck high defects inferred from existing data. According to equation (3), the MND pdf of a stuck low or stuck high defect, given that the output of its minimum difference neighboring pixel is z, can be expressed as

$$p_X(y|z) = \begin{cases} f_X(z+y) + f_X(z-y) & y \neq 0 \\ f_X(z) & y = 0 \end{cases} \tag{5}$$

where $X = SL$ or SH denotes the stuck low or stuck high defect. Similarly, let $f_{AS}(\cdot)$ be the pdf of an abnormal sensitivity defect whose output is $r \times 100\%$ different from its minimum difference neighboring-pixel output. The MND pdf of an abnormal sensitivity defect, given that the output of its minimum difference neighboring pixel is z (where $z \neq 0$), can be approximated as

$$p_{AS}(y|z) = \begin{cases} \frac{1}{z}\left[f_{AS}(y/z) + f_{AS}(-y/z)\right] & y \neq 0 \\ f_{AS}(0) & y = 0 \end{cases} \tag{6}$$

Hence, with the assumption that the pdfs $f_{SL}(\cdot)$, $f_{SH}(\cdot)$ and $f_{AS}(\cdot)$ can be determined from a set of existing data, we are able to obtain the MND pdfs of different types of defects after the outputs of their minimum difference neighboring pixels have been known. Our experience shows that the MND pdfs of these point defects are usually very distinguishable from the MND pdf of a functional pixel.

5. THE PROPOSED DETECTION PROCEDURE

Having a pixel attribute whose pdfs measured from functional pixels and defective pixels are statistically discernible, we can now formulate the detection of sensor defects from a sequence of images as a sequential probability ratio test. Let H_0 be the hypothesis saying that the pixel under examination is well functional and H_1 be the hypothesis saying that the pixel is a certain type of point defect of interest. For each pixel, by assuming that its MND values measured from different images are independent of one another, the SPRT rule for determining whether a pixel is defective after observing n images is equivalent to comparing the accumulated log-likelihood ratio, given as

$$\mathcal{L}_n(\mathbf{y},\mathbf{z}) = \sum_{1\leq k\leq n} \log \frac{p_1^k(y_k, z_k)}{p_0^k(y_k, z_k)} = \sum_{1\leq k\leq n} \log \frac{p_1^k(y_k|z_k)}{p_0^k(y_k)} \tag{7}$$

to two decision thresholds $(\mathcal{A}', \mathcal{B}')$ which are chosen to meet a desired error-probability performance according to a logarithmic form of equation (2). In equation (7), the property $p_0^k(y_k|z_k) = p_0^k(y_k)$ of the MND pdf of a functional pixel (discussed in Section 4) has been used to obtain the second equality; y_k and z_k are the MND value and the output of the minimum difference neighboring pixel, respectively; $p_1^k(y_k|z_k)$ is the MND pdf of a certain type of point defect as defined in (5) and (6); and k is the number of the image being processed.

Since the MND pdf under each hypothesis is only an estimate probability density, the likelihood ratio defined in (7) could be very sensitive to errors in the estimate pdfs, especially for those observations where the log-likelihood ratio, $l_k(y_k, z_k) = \log\left[p_1^k(y_k|z_k)/p_0^k(y_k)\right]$, becomes unbounded, i.e., when $p_1^k(y_k|z_k) \gg p_0^k(y_k)$ or $p_1^k(y_k|z_k) \ll p_0^k(y_k)$. One way to improve the robustness of the detection procedure is by limiting the range of the log-likelihood ratio obtained from each observation in equation (7) as

$$g\left(l_k(y_k, z_k)\right) = \begin{cases} c'' & l_k(y_k, z_k) > c'' \\ l_k(y_k, z_k) & c' \leq l_k(y_k, z_k) \leq c'' \\ c' & l_k(y_k, z_k) < c' \end{cases} \tag{8}$$

where c' and c'' are two proper limiting constants that satisfy $-\infty < c' < 0 < c'' < \infty$. In fact, the decision rule with this limiting log-likelihood ratio is an optimum decision rule if the actual MND pdf under each hypothesis can be modeled as a mixture of the estimate MND pdf and a small but arbitrary contaminating pdf [4]. Generally, we consider the decision rule with the accumulated log-likelihood ratio given by

$$\mathcal{L}_n(\mathbf{y},\mathbf{z}) = \sum_{1\leq k\leq n} w(z_k) \cdot g\left(l_k(y_k, z_k)\right) \tag{9}$$

where $g\left(l_k(y_k, z_k)\right)$ is defined in (8) and $w(z_k)$ is a weighting function which depends on the minimum difference neighboring-pixel output z_k as well as the type of the defect to be detected. The reason of incorporating such a weighting function is that it is easier to detect a specific type of defect from observations where the minimum difference neighboring-pixel outputs fall under a certain intensity range. For instance, a stuck high defect is easier to be detected when the outputs of its neighboring pixels are small. Similarly, it is easier to detect stuck low and abnormal sensitivity defects from high intensity image regions. As an example, one could set the weighting function for detecting stuck high defects as $w(z_k) = \mathbf{1}\,(z_k \in [0,b])$, where $\mathbf{1}(\cdot)$ is an indicator function that takes the value 1 if its argument is true and 0 otherwise. Note that this is nothing but only the observations with the minimum difference neighboring-pixel outputs below a certain value b will be used to determine whether a pixel is a stuck high defect.

We now describe the proposed procedure for detecting sensor defects. In our setting, each type of defect is detected separately. A binary decision map, which indicates whether or not a decision has been made on each pixel, is initialized to all zero before the detection starts. The images are then processed one after another. While processing an image, for each pixel if the accumulated log-likelihood ratio of any defect types falls outside the pre-selected decision thresholds $(\mathcal{A}', \mathcal{B}')$, its corresponding location in the decision map is set to 1, i.e., a decision is made. If the accumulated log-likelihood ratio is above the threshold $\mathcal{B}'$, the pixel is considered to be defective and its location is recorded in a sensor defect map. For each observed image, the detection procedure processes only those pixels which cannot be classified from the previous images. Therefore, the number of pixels required to be processed decreases rapidly as the number of the processed images increases. When there is no more input image, or the number of the processed images exceeds a certain limit, or the number of the unclassified pixels drops below a certain threshold, the procedure is terminated by declaring that all the unclassified pixels are defective, or only those unclassified pixels with terminal accumulated log-likelihood above a new threshold, say zero, are defective.

6. EXPERIMENTAL RESULTS

In this section, we report the experimental results of the proposed sensor defect detection procedure. A sequence of gray-scale images, 20 in total, were used in the experiments. The contents of the images include human portrait, outdoor, indoor, low key, and high key scenes. All the images have size 640 x 480 pixels and 8 bits output per pixel. Three different types of point defects (50 for each type) discussed in this paper were embedded in the images. In each image, the outputs of stuck low defects were uniformly selected from intensity range [0, 20]. Similarly, the outputs of stuck high defects were uniformly selected from intensity range [230, 255]. For each abnormal sensitivity defect, we first decided its abnormality r, where $0.15 < |r| < 1$, with some random probability. Then, its output in each image was set to a value that is $r \times 100\%$ different from the output of one randomly selected neighboring pixel. The 8-connected neighboring-pixel support shown in Figure 1 was used in the experiments. Figure 2 shows the percentage of the unclassified pixels versus the number of the processed images. We can see that the decisions on most pixels can be made after only a few images have been processed. Table 1 reports the numbers of both false detection and miss detection in identifying different types of defects after all the images have been processed. For example, out of 307200 (640 x 480) pixels, the 50 stuck low defects were successfully detected and 55 non-stuck low pixels were incorrectly classified. It should be noted that most of the false detection in identifying stuck low or stuck high defects are actually due to the other two types of defects. Combining the results of the detection of different types of defects using OR operation (i.e., a pixel is classified defective if it is identified as a stuck low, or stuck high, or abnormal sensitivity defect), all the defects were successfully detected by the proposed procedure with only 3 false detection, as shown in Table 1.

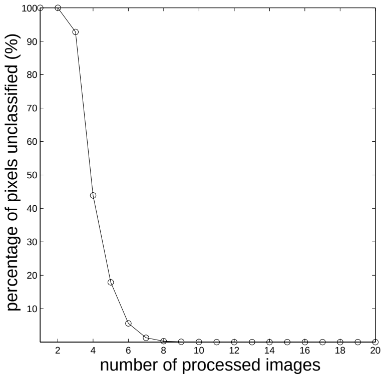

Figure 2: Percentage of the pixels which have not been classified versus the number of the processed images.

Defect	**miss-detection #**	**false-detection #**
Stuck low	0	55
Stuck high	0	78
Abnormal sensitivity	0	3
Combine results using OR	0	3

Table 1: The numbers of miss detection and false detection in classifying stuck low, stuck high, abnormal sensitivity defects and the combination (using OR operation) of the detection results.

7. CONCLUDING REMARKS

We have proposed a robust sequential approach for detecting different types of sensor defects using a sequence of images whose contents are not known a priori. In the approach, a pixel attribute, *minimum neighboring-pixel difference*, is measured from each pixel to sort out the defective pixels from the functional pixels. To reduce the impact due to the errors in estimating the pdfs of the pixel attributes measured from different types of pixels, robust detection techniques are engaged to enhance the performance of the detection procedure. Our experimental results show that most of the sensor point defects can be detected by the proposed procedure with only a very small number of false detection. The detection methodology can be readily extended to identify other types of sensor defects by considering different pixel attributes and appropriate neighboring-pixel supports. For example, to identify sensor cluster defects with at most k contiguous defective pixels in each cluster, we can define the pixel attribute as the value of the k^{th} minimum neighboring-pixel difference (in an ascending order) and select a neighboring-pixel support that contains at least k pixels.

8. REFERENCES

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