Proceedings of the 17th World Congress
The International Federation of Automatic Control
Seoul, Korea, July 6-11, 2008

Region Mura Detection using Efficient High Pass Filtering based on Fast Average Operation

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Abstract: A Mura (also called "alluck") defect that causes local deterioration of colors or brightness on a LCD(liquid crystal display) panel is one of the critical issues in display manufacturing. In this paper, we propose mura detection method using frequency filtering. As a mean of frequency filtering to eliminate the low frequency background term, subtraction of the averaged image from the raw one is utilized. And a fast averaging algorithm has been devised for reducing computational costs. The validity and the performance of the proposed method is discussed through experimental studies on actual LCD panel mura defects.

1. INTRODUCTION

As FPD(Flat Panel Display) industries such as LCD, PDP mature and competition between manufactures stiffens, product quality becomes much more important. To meet the requirements of the defect-free product production, numerous automated inspection through optical and electrical methods are being applied during the manufacturing processes to detect the most critical defects.

A Mura is one of the major defects which affect the quality of FPD. "Mura" is a Japanese term meaning blemish and has become widely used in the industry to describe a large, non-uniform defects that range tremendously in size, shape and severity. [Ref.]

Mura inspection, despite being one of the major quality issues, still relies on human visual inspection in most manufacturing sites. However the inspection by a human operator is strongly dependent on the physical and psychological conditions of the individual, one can not guarantee the reliability of the results and may lead to difficulties in quality control.

On the other hand, Since the inspection automation helps overcome the limitation of human visual inspection and cuts down production costs, a lot of efforts is being made for mura inspection automation.

Researches on mura inspection has been conducted on the view point of two items. One is on the methodologies of detecting mura, and the other is quantification of the detected mura. That is, how to detect and how to measure mura defects.

One of the difficulties in detecting mura defects of LCD panel is discriminating mura from background non-uniformity. Non-uniformity of background results from various factors. The inherent characteristics of backlight illumination unit or inconsistent manufacturing processes can create the non-uniformity. It also can be originated from shading effect during image acquisition by the camera.

Fig.1(a) illustrates typical LCD mura defects. Since the background has a brightness gradient, it is not easy to separate mura from background by direct threshold method as shown in Fig. 1. (b) and (c).

In this paper, we describe a method for detecting mura defects under non-uniform background. Comparing to mura, background brightness changes macroscopically, thus we can utilize space frequency filtering. As the background has lower frequency band than that of a mura, it can be removed through high pass filtering. By removing the background, we can discriminate mura defects from the background.

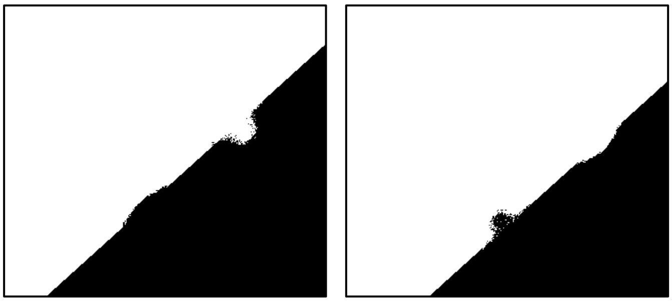
First, we propose a high pass filtering method using average subtraction, where mura dominant image can be achieved by the elimination of the non-uniform background. Then, fast

978-1-1234-7890-2/08/$20.00 © 2008 IFAC

10.3182/20080706-5-KR-1001.2299

averaging algorithm is discussed for improving the efficiency of the average operation.

(a) A typical image of Mura defect



(b) threshold 150 (c) threshold 100

Fig. 1. A typical issue in binarization of a mura image

2. MURA DETECTION USING FREQUENCY FILTERING

2.1 Mura Detection Approach

Efforts to discriminate mura from background non-uniformity have been made by a number of researchers. Lee and Yoo[Ref.] proposed the concept of background surface estimation. They applied a strategy of modelling polynomial surface minimizing estimation error. Although their strategy is viable, there were limitations when applied in practical use. Much processing time to create the polynomial model.

Wang and Ma[Ref.] extended the surface estimation strategy by adopting Haralick's recursive polynomial[Ref.] to reduce processing time. It successfully reduced processing time. But the method requires large memory resources, and should be amended to reduce memory consumption.

(a) High pass filtered image

(b) Thresholding and Detection

Fig. 2. Mura detection using high pass filtering based on average operation.

2.2 Frequency Filtering with Background elimination

As mentioned above, a mura can be discriminated from an image with non-uniform background by making use of its frequency characteristics. It is identical to calculating surface estimation with frequency filtering. As a mean of high-pass filtering to eliminate the low frequency background term, subtraction of the averaged image from the original one is proposed. Through the average operation, we can obtain a low frequency band image, i.e., a background image. Subtraction of this background image from original one produces the high pass filtered image.

Here, *A(x,y),* the average operation of an image *I(x,y)* within an area of *(2K + 1)(2K +1)* pixels is expressed as :

$$A(x,y) = \frac{\sum_{i=x-K}^{x+K} \sum_{j=y-K}^{y+K} I(i,j)}{(2K+1)\times(2K+1)} \quad (1)$$

Subtracting low freqency background Image *A(x,y)* from Image *I(x,y)*, high pass filtered image $I_{filtered}(x,y)$ is acquired.

$$I_{filtered}(x,y) = I(x,y) - A(x,y) + Bias \quad (2)$$

The frequency band which is passed varies with respect to the averaging sample size *(2K + 1)*. The greater *K* is , the broader the band which is passed, and the smaller *K* is, the narrower the band is passed.

Fig 2. illustrates the high pass filtered image of Fig. 1 (a), which shows that the mura defect dominates the final image, and therefore can be used as an effective way for mura detection.

2.3 Fast Average Operation

Although high pass filtering using subtraction of averaged image is possible, it is inappropriate for use(?) in practical applications as average operation is an expensive operation. In particular, processing time increases geometrically with the averaging size. Hence, a fast average algorithm is used for dramatically improving the efficiency of the average operation.

The objective is to minimize iterations in fast average algorithm.

For the sake of convenience, consider a 1-dimensional function *f(x)* and its average *A(x). A(x)* can be expressed in a similar form of Eq. (1) and it can be transformed as follows:

$$\begin{aligned} A(x) &= \frac{\sum_{i=x-K}^{x+K} f(i)}{(2K+1)\times(2K+1)} \\ &= \frac{\sum_{i=0}^{x+K} f(i) - \sum_{i=0}^{x-K-1} f(i)}{(2K+1)\times(2K+1)} \\ &= \frac{P(x+K) - P(x-K-1)}{(2K+1)\times(2K+1)} \end{aligned} \quad (3)$$

$$\begin{aligned} where, P(x) &= \sum_{i=0}^{x} f(i) \\ &= P(x-1) + f(x) \end{aligned}$$

Now, the iterative form has been changed to recursive form with simple operation. The summation table *P(x)* can be easily calculated by recursive operations. Average *A(x)* is obtained with summation table *P(x)*

The same approach is applied to a 2-dimensional image *I(x,y)* .

The 2-dimensional Summation Table *P(x,y)* is defined as follows:

$$P(x,y) = \sum_{i=0}^{x} \sum_{j=0}^{y} I(i,j) \quad (4)$$

Summation Table *P(x,y)* is in recursive form :

$$\begin{aligned} P(x,y) &= P(x-1,y) + P(x,y-1) \\ &\quad - P(x-1,y-1) + I(x,y) \end{aligned} \quad (5)$$

$$\begin{aligned} &with \quad x \geq 0 \; and \; y \geq 0, \\ &\quad P(-1,y) = 0 \; and \; P(x,-1) = 0 \end{aligned}$$

The Sum *S(x,y)* of image area from *I(x-K,y-K)* to *I(x+K,y+K)* is expressed as :

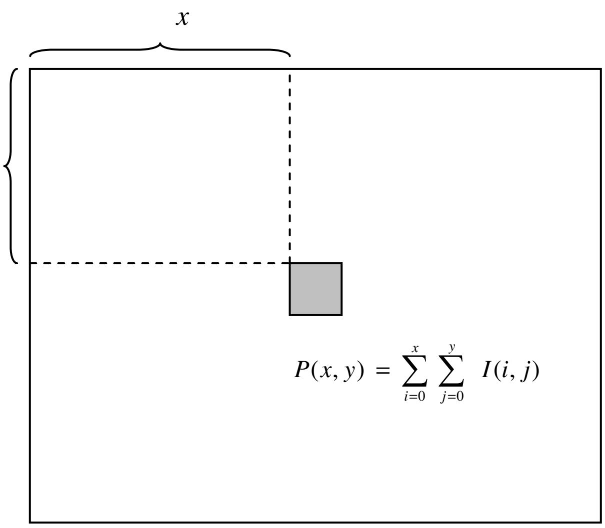
$$
\begin{aligned}
S(x,y) = \; & P(x+K, y+K) \\
& - P(x-K, y+K) \\
& - P(x+K, y-K) \\
& + P(x-K, y-K)
\end{aligned} \tag{6}
$$

Thus, Average *A(x,y)* becomes :

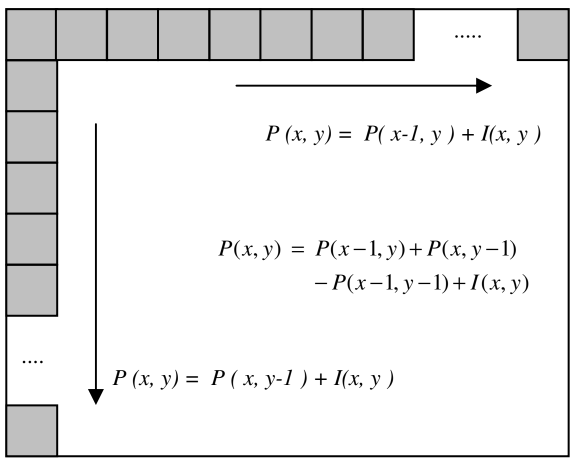
$$A(x,y) = \frac{S(x,y)}{(2K+1)\times(2K+1)} \tag{7}$$

Recursively calculated summation table *P(x,y)* make it possible to abbreviate iteration, and processing speed is improved remarkably

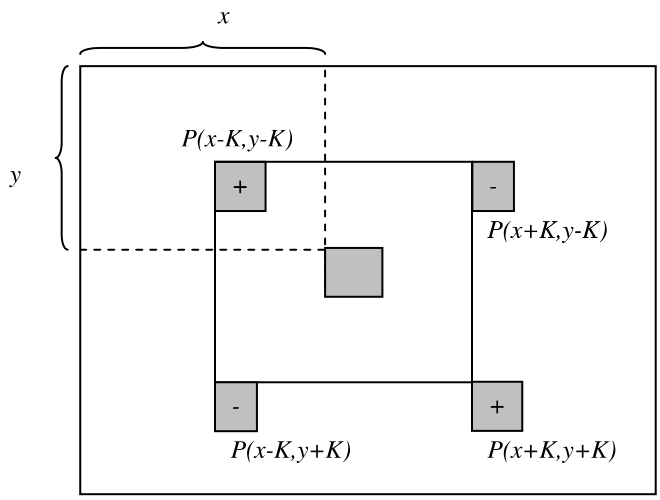
Fig 3. illustrates how fast average algorithm works.



(a) Summation Table



(b) Recursive Calculation of Summation Table



(c) Average Operation with Summation Table

Fig. 3. Fast Average Operation with Recursive Summation Table

2.4 Application to mura detection

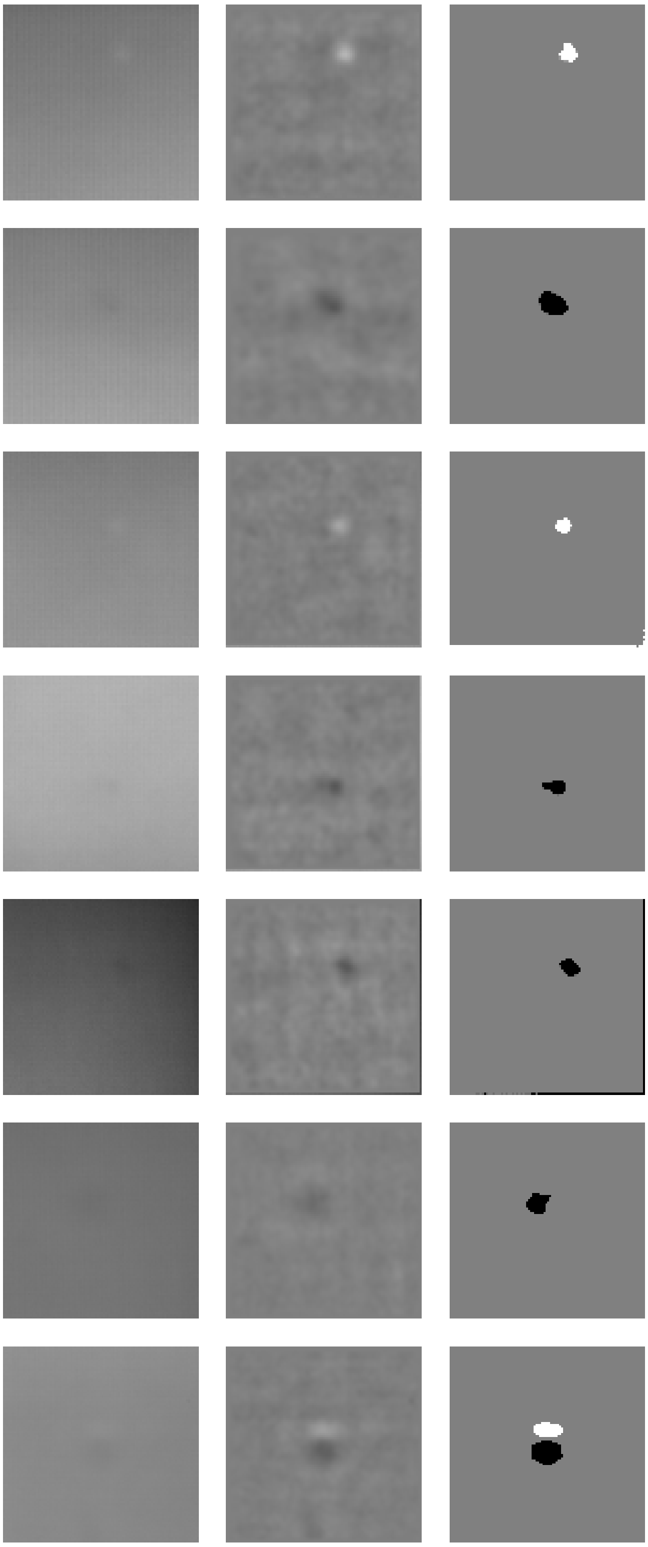
Fig 4. shows several examples of real mura detection.

For the experimental studies, 5 LCD TV modules with mura defects were collected and all the images were captured with a industrial CCD camera. The backlight illumination of the LCD modules was turned on and 4 patterns (gray, red, green, blue) were alternatively displayed on the LCD while images were captured.

7 images were selected from 20 captured images (5 LCD Modules and 4 patterns for each Module).

High pass filter based on average subtraction was applied to the image with size parameter set to 41 and bias parameter 128. Here, size refers to the average size and bias refers to the image background level after filtering (refer to Eq. (2)). Then for the visualization effect, the contrast was enhanced 200 %. The threshold level was set to bias + 10 and bias - 10.

The results show that the proposed frequency filtering can be an effective way to detect mura in an image with non-uniform background.



(a) (b) (c)

Fig. 4. Detecting real mura examples on LCD panels

(a) Mura image (b) High-pass filtered image (c) Detected mura.

2.5 *Performance*

Table 1 compares the performance of the average operation with fast average operation. It is found that fast average operation is 1600 times faster than average operation, which can be considered sufficient for industrial applications.

Method	Elapsed Time (msec)
Average Operation	8410
Fast Average Operation	50
Image Size : 1024 x 1024	
Averaging Size : 41 x 41	
CPU : Intel Centrino 1.6 GHz	
Language : C++	

Table 1. Performance Comparison.

3. CONCLUSIONS

As a mean of mura detection method in a non-uniform background, high pass filtering has been proposed. Furthermore, a fast averaging algorithm using recursive summation table was utilized to improve the high pass filtering performance. In actual mura detection tests, it is found that the proposed method is applicable for mura detection and has sufficient performance for industrial applications.

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