

Defect detection in low-contrast glass substrates using anisotropic diffusion

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Abstract

In this research, we propose an anisotropic diffusion scheme to detect defects in low-contrast surface images and, especially, aim at glass substrates used in TFT-LCDs (Thin Film Transistor-Liquid Crystal Displays). In a sensed glass substrate, the gray levels of defects and background are hardly distinguishable and result in a low-contrast image. Therefore, thresholding and edge detection techniques cannot be applied to detect subtle defects in the glass substrates surface. The proposed diffusion method in this paper can simultaneously carry out the smoothing and sharpening operations. It adaptively triggers the smoothing process in faultless areas to make the background uniform, and performs the sharpening process in defective areas to enhance anomalies. Experimental results from a number of glass substrate samples including backlight panels and LCD glass substrates have shown the efficacy of the proposed diffusion scheme in low-contrast surface inspection.

1. Introduction

In this study, a machine vision approach is proposed for automatic surface inspection. In recent years image analysis techniques are being increasingly used to automate industrial inspection. In automatic surface inspection, one has to solve the problem of detecting small defects that appear as local anomalies in material surfaces. In this paper, we focus on the problem of surface inspection in low-contrast images and, especially, aim at glass substrates used in TFT-LCDs. In a glass substrate, the gray levels of defects and background are very similar and result in a low-contrast image. Therefore, using traditional surface inspection methods such as thresholding and edge detection are difficult to detect subtle defects in the glass substrate. Figure 1 presents two images of backlight panels, of which Figure 1(a) is a faultless backlight panel surface, and Figure 1(b) is a defective

one. It can be seen from Figures 1(b) that the defect is difficult to be found in the uniform background. It is hard to distinguish between defect area and faultless area in the low-contrast surface image. In order to visualize the tiny defects, the gray values of the backlight panel images are equalized between 0 and 255 for an 8-bit display. Figures 1(c) and (d) show the enhanced images of Figures 1(a) and (b), respectively. The enhanced defective image shows the defects clearly, but it also shows the non-uniformity of the light source. To solve these problems, one may need complex texture analysis techniques.

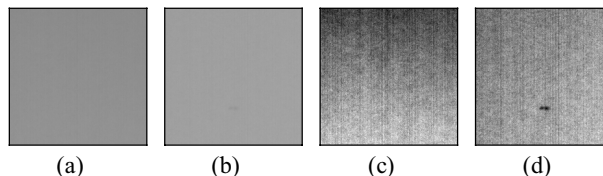


Figure 1. Surfaces images of backlight panels with low-contrast intensities: (a), (b) faultless and defective images; (c), (d) contrast-stretched images of (a) and (b), respectively.

Few researches have studied the defect detection in low-contrast images. Ngan et al. [1] developed an automated vision system for patterned fabrics and repetitive patterned textures. It combined wavelet transform and golden image subtraction to detect small-size and low-contrast defects. Their method requires a golden image for reference, so the detection performance is affected by environmental changes. Taniguchi et al. [2] proposed a detection method to identify low-contrast mura, which is defined as brightness unevenness on LCD panel surfaces. Their method used linear mapping to enhance images which is a kind of histogram equalization. However, in our application the low-contrast glass substrate images after linearly mapped may show the defects clearly, but they also create the non-uniformity of the background texture in a stretched image. The complex texture in the background makes the inspection task

more difficult in low-contrast glass substrates. Lee and Yoo [3] proposed a complicated data fitting approach for detecting regional defects of brightness unevenness in LCD panel surfaces. They first estimated the background surface of an inspection image using a low-order polynomial data fitting. Subtraction of the estimated background surface from the original image is then applied to find the threshold for binary segmentation. The resulting image is then post-processed by median filtering, morphological closing and opening to remove noise and refine the segmentation. The proposed method worked successfully to detect regional defects in low-contrast TFT-LCD surface images. However, it is very computationally intensive because the background surface must be estimated recursively by eliminating one pixel at a time throughout the entire inspection image.

In this paper, we propose an improved anisotropic diffusion scheme to tackle the problem of defect inspection in low-contrast surface image. Anisotropic diffusion was first proposed by Perona and Malik [4] for scale-space description of images and edge detection. The approach is basically a modification of the linear diffusion (or heat equation), and the continuous anisotropic diffusion is given by

$$\frac{\partial I_t(x, y)}{\partial t} = \text{div}[c_t(x, y) \cdot \nabla I_t(x, y)] \quad (1)$$

where $I_t(x, y)$ is the image at time t , div the divergence operator, $\nabla I_t(x, y)$ the gradient of the image, and $c_t(x, y)$ the diffusion coefficient. If $c_t(x, y)$ is a constant, equation (1) is then reduced to the isotropic diffusion equation, and is equivalent to convolving with a Gaussian function. The idea of anisotropic diffusion is to adaptively choose c_t such that intra-regions become smooth while edges of inter-regions are preserved. The diffusion coefficient c_t is generally selected to be a nonnegative function of gradient magnitude so that small variations in intensity such as noise or shading can be well smoothed, and edges with large intensity transition are distinctly retained.

In this paper, we propose an improved anisotropic diffusion model to detect defects in low-contrast surface images. The proposed method aims to enhance the difference between defects and the normal background using an improved diffusion model.

2. The improved diffusion model

2.1. The Perona-Malik anisotropic diffusion

Let $I_t(x, y)$ be the gray level at coordinates (x, y) of a digital image at iteration t , and $I_0(x, y)$ the original input image. The continuous anisotropic diffusion in eq. (1) can be discretely implemented by using four nearest neighbors and the Laplacian operator [4]:

$$I_{t+1}(x, y) = I_t(x, y) + \frac{1}{4} \sum_{i=1}^4 [c_t^i(x, y) \cdot \nabla I_t^i(x, y)] \quad (2)$$

where $\nabla I_t^i(x, y)$, $i = 1, 2, 3$ and 4 , represent the gradients of four neighbors in the north, south, east and west directions, respectively, i.e.,

$$\begin{aligned} \nabla I_t^1(x, y) &= I_t(x, y-1) - I_t(x, y) \\ \nabla I_t^2(x, y) &= I_t(x, y+1) - I_t(x, y) \\ \nabla I_t^3(x, y) &= I_t(x+1, y) - I_t(x, y) \\ \nabla I_t^4(x, y) &= I_t(x-1, y) - I_t(x, y) \end{aligned}$$

$c_t^i(x, y)$ is the diffusion coefficient associated with $\nabla I_t^i(x, y)$, and is considered as a function of the gradient $\nabla I_t^i(x, y)$ in the P-M model, i.e.,

$$c_t^i(x, y) = g(\nabla I_t^i(x, y))$$

For the sake of simplicity, $\nabla I_t^i(x, y)$ is subsequently denoted by ∇I . The function $g(\nabla I)$ has to be a nonnegative monotonically decreasing function with $g(0) = 1$ and $\lim_{|\nabla I| \rightarrow \infty} g(\nabla I) = 0$. The function $g(\nabla I)$ should result in low coefficient values at image edges that have large gradients, and high coefficient values within image regions that have low gradients. In the Perona-Malik anisotropic diffusion model, a possible diffusion coefficient function is given by

$$g(\nabla I) = 1/[1 + (|\nabla I|/k)^2] \quad (3)$$

where the parameter k is a constant, and must be fine-tuned for a particular application. Parameter k in the diffusion coefficient function acts as an edge strength threshold. If the k value is too large, the diffusion process will oversmooth and result in a blurred image. In contrast, if the k value is too small, the diffusion process will stop the smoothing in early iterations and yield a restored image similar to the original one.

Let $\phi(\nabla I)$ be a flux function [4] defined by

$$\phi(\nabla I) = g(\nabla I) \cdot \nabla I \quad (4)$$

A large flux value indicates a strong effect on smoothness. The classical P-M model only stops the smoothing process in image areas with large gradient magnitude. Therefore, it can not effectively enhance the target objects in a low-contrast image.

2.2. The proposed anisotropic diffusion model

In order to enhance the subtle defects effectively in low-contrast surface image, we incorporate the sharpening strategy in the classical diffusion model. The new diffusion model proposed in this study is

$$I_{t+1}(x, y) = I_t(x, y) + \frac{1}{4} \sum_{i=1}^4 [c_i^t(x, y) \cdot \nabla I_t^i(x, y)] - \frac{1}{4} \sum_{i=1}^4 [v_i^t(x, y) \cdot \nabla I_t^i(x, y)] \quad (5)$$

where the second term on the right hand side of eq. (5) is the classical diffusion term as in eq. (2), and the third term is the sharpening operator. In eq. (5), the sharpening diffusion coefficient function $v(\nabla I)$ has to be a nonnegative monotonically increasing function with $v(0) = 0$ and $\lim_{|\nabla I| \rightarrow \infty} v(\nabla I) = 1$. The function $v(\nabla I)$

should result in high coefficient values at image edge that have large gradient magnitudes, and low coefficient values within image regions that have low gradient magnitudes. In this study, $v(\nabla I)$ is defined as

$$v(\nabla I) = \alpha \cdot [1 - g(\nabla I)] \quad (6)$$

where α is the weight of sharpening coefficient function, and $0 \leq \alpha \leq 1$. It decides the degree of sharpness process.

Since the parameters α and k must be fine-tuned for a particular application, the following experiments are performed to find out the suitable values of α and k for the defect detection in backlight panels. Figure 2 shows the inspection results of the sample image in Figure 1(b) at various combinations of α and k . The number of iterations is set to 30 for all test images. When α is too small, a defect still cannot be enhanced in the resulting diffusion image, as seen in Figures 2(a)-(c). In contrast, when α is too large, the diffusion results in Figure 2(h) shows that the proposed diffusion

model will over sharpen the image. When k is overly large, the resulting images are severely smoothed. Not only the background area is smoothed, but also the shape of defect is lost, as seen in Figures 2(c), (f) and (i). When k is overly small and α is too large, the results in Figures 2(d) and (g) show that the diffusion process cannot restrain noise. These results do not succeed in the inspection of defects in backlight panel surfaces. Conversely, Figure 2(e) shows a good filtering result that enhances the tiny defect and removes noise at the same time. Thus, $\alpha=0.2$ and $k=1$ are suitable values to use in this study.

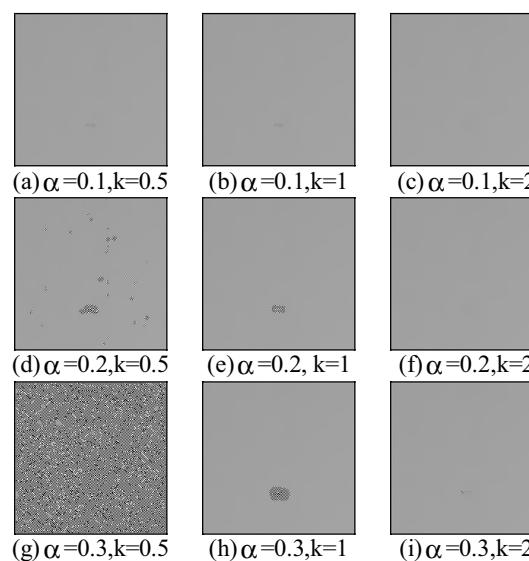


Figure 2. The diffusion results of the defective image in Figure 1(b) using various combinations of α and k .

3. Experimental results

In this section, we present experimental results from a number of glass substrates involving various low-contrast defects in images. The algorithms are implemented on a Pentium 4, 3G Hz personal computer using the Visual Basic language. The images were 200×200 pixels wide with 8-bit gray levels. The values of parameters α and k were set to a fixed value of 0.2 and 1, respectively. The number of iterations equals to 30 for all test images in the following experiments. Computation time of 30 iterations on a 200×200 image was 0.3 second. The test images in Figures 3(a)-(d) present one faultless and three defective backlight panel surface images. The results from the proposed diffusion model are shown in Figures 3(e)-(h). It can be seen that the shapes of defects are well enhanced in the filtered images. Figures 3(i)-(l) illustrate the simple thresholding results

of the filtered images in Figures 3(a)-(d) as binary images (using a 3-sigma statistical process control), where pixels with gray values falling outside the control limits are marked in black, and the ones falling within the control limits appear in white. The results reveal that the resulting image of the faultless backlight panel surface is uniformly white, and the defects in all three defective surfaces are correctly segmented in the binarized images.

Figure 4 demonstrates further the detection results of LCD glass substrate images. Figure 4(a) is a clear LCD image, and Figures 4(b)-(d) are three defective LCD images. The results from the proposed diffusion model are presented in Figures 4(e)-(h), which show that the tiny defect is distinctly enhanced. Figures 4(i)-(l) show the thresholding results using the 3-sigma control limits of the diffused images in Figures 4(e)-(h). The results also reveal that all local defects embedded in low-contrast surface images are effectively detected, and the resulting image of the clear surface image is uniformly white. The experiments have shown that the proposed diffusion scheme performs well in detecting subtle defects in low-contrast glass substrate images.

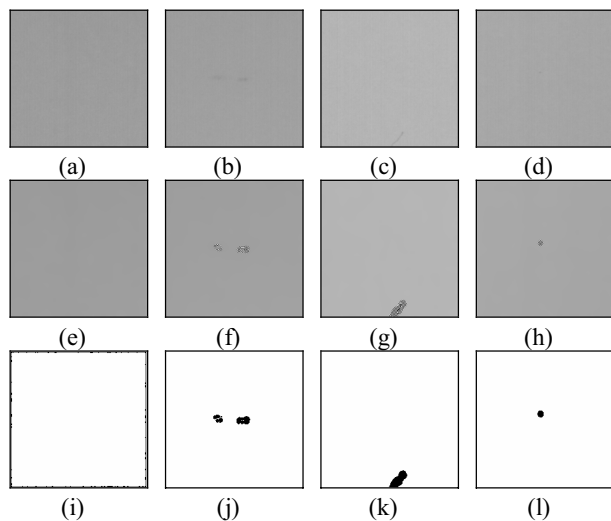


Figure 3. The diffusion results of backlight panel surfaces: (a)-(d) a faultless and three defective test images; (e)-(h) respective diffusion results at 30 iterations with $\alpha=0.2$ and $k=1$ for all samples; (i)-(l) the thresholding results.

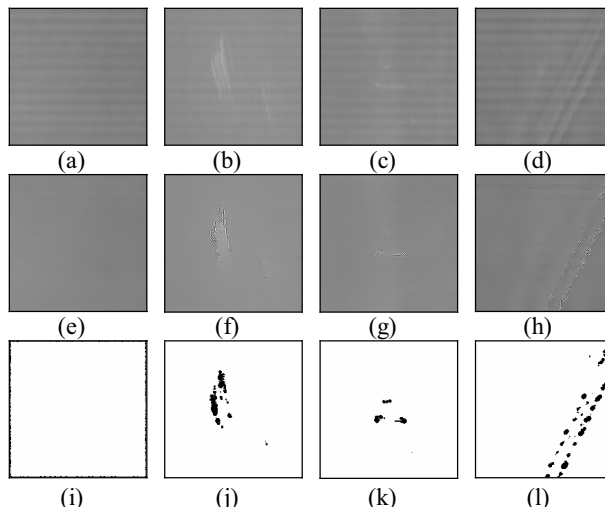


Figure 4. The diffusion results of LCD glass substrate surfaces: (a)-(d) a faultless and three defective test images; (e)-(h) respective diffusion results at 30 iterations with $\alpha=0.2$ and $k=2$ for all samples; (i)-(l) the thresholding results.

4. Conclusions

In this paper we have proposed an improved version of anisotropic diffusion scheme for detecting defects in low-contrast surface images and, especially, aim at glass substrates used in TFT-LCDs. Since the defects in low-contrast glass substrate surfaces are hardly-visible in defective areas, it makes the defect detection task extremely difficult. In order to enhance the subtle defects, the sharpening operator was incorporated in the proposed diffusion model. Experimental results have shown that the proposed anisotropic diffusion scheme can effectively remove background noises in faultless areas, and yet sharpen the anomalies in the filtered image of a low-contrast glass substrate.

References

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