Automatic Defect Inspection for LCDs Using Singular Value Decomposition

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Abstract - The purpose of this study aims at the use of machine vision for automatic surface inspection, in which defects are embedded in homogenously LCDs textured surfaces. The proposed method does not rely on local features of textures. It is based on a global image reconstruction scheme using the singular value decomposition (SVD). The singular values on the decomposed diagonal matrix represent different degrees of detail in the textured surface. By selecting proper singular values on the diagonal matrix and reconstructing the matrix with the selected singular values, we can eliminate regular, periodical patterns of the textured image, and preserve the anomalies in the restored image. Experimental results have shown that the proposed method is effective for detecting micro-defects in LCDs surfaces.

1. INTRODUCTION

Since Liquid Crystal Displays (LCDs) have many advantages in its full-color display capabilities, low power consumption, and small size, LCDs are becoming increasingly important in recently years. In order to guarantee the display quality of LCD flat panels, human operators visually inspect the TFT- array plate against prescribed standards. However, the manual activity of inspection could be subjective and highly dependent on the experience of human inspectors. In this paper, we propose an automatic visual system for LCD defect inspection.

A few automatic inspection systems or methodologies have been proposed in recent years for LCD manufacturing. Kido [7] presented a non-destructive, in-process inspection technique for partially completed active-matrix LCD panel and used surface reflection to sense optical changes and to generate maps showing the type and location of defects. Lin *et al.* [1] proposed a vision system to detect the degree of uniformity of light reflection using a light guide plate before the diffuser has been attached. They designed a bright spot search and statistical software for adjusting the parameters of the LCD light guide plate before manufacture. Kido *et al.* [8] proposed an optical charge-sensing method for testing and characterizing Thin Film Transistor (TFT) arrays. They used interface reflection to generate maps that show the type and location of line and point defects. Most of the existing methods of automatic optical inspection systems for TFT-array were based on conventional electrical methods and electro-optic modulator to detect the surface potential of a TFT-array [8]. But those methods can not be applied to detect the small defects on the surface directly.

In the TFT-array plate, defects could roughly classified into two parts [4]. One is called macro-defects including “MURA”, “SIMI” and “ZURE”. Macro-defects are large in size and, therefore, can be easily detected by human inspection. Another type of defects is called micro-defects including pinholes, fingerprints, particle and scrapes. Because the size of the micro defects are very small and can not be easily found by human eyesight, electrical methods and electro-optic modulator.

A TFT-array plate generally consists of TFT-array and Polimide film (PI film). It involves many horizontal gate lines and vertical data lines, and lines intersect to form right angles. The TFT-array plate surface can be treated as a structural texture in an image. Since the composition of TFT- array plate surface comprise horizontal and vertical elements, it can be classified as a structural texture in the image.

The textural feature of TFT-array plate surface is a homogeneous texture that consists of an arrangement primarily of horizontal and vertical elements appearing periodically on the surface. Few studies have utilized the structure characteristics of TFT-array plate to inspect the defects. Since singular value decomposition (SVD) involves horizontal and vertical basis functions, we use SVD-based image reconstruction technique to detect the micro-defects on the TFT-array plate surface.

The method of SVD was first proposed in 1970 and has been applied in a wide range of computer vision applications such as data compression, image restoration, and feature extraction [5,6]. A few studies have been done on using SVD for texture analysis in computer vision. Luo and Chen [3] utilized SVD strategy for texture discrimination. They used the proportion of dominant singular value of an image matrix as textures for texture discrimination and employed SVD-based algorithm for discriminating synthesized textures and natural textures. Xia *et al.* [2] proposed a method that combines SVD and gray-level co-occurrence matrix (GLCM) to extract textural features embedded in forest image. The aforementioned methods for texture analysis generally use singular values or singular vectors that derived from the textured images to characterize the textural features, and use those features to segment or classify textures. Different textures may need different singular values and singular vectors to describe the textural features. The feature extraction process for a best set of textural features is generally carried out by try-and-error, and may highly rely on human expertise.

SVD can be used to decompose an image and obtain

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a diagonal matrix. The ordered entries of the diagonal matrix are singular values. The main information of an image can be represented by the larger singular values. The other singular values with small magnitude provide detailed information of the image. For the application of image restoration, we can preserve only the larger singular values to reconstruct an image. In application of defect inspection, we can set the larger singular values to zero and preserve the smaller singular values to reconstruct an image. The background information will be eliminated and can be distinctly retained the defects in the restored image.

In this paper, we propose a global approach based on an image reconstruction scheme using singular value decomposition for inspecting micro- defects including pinholes, scrapes and fingerprints on the surface of TFT-array plates. A simple thresholding can then be used to discriminate between defective region and regular regions in the reconstructed image.

2. SVD IMAGE RECONSTRUCTION

2.1 TFT-Array Plate

A TFT-array plate generally consists of TFT-array and Polimide film (PI film). A TFT-array has horizontal gate lines on one plane and vertical data line on other plane. At each pixel, the gate of the TFT is connected to the gate line and the source is connected to the data line [8]. Fig. 1 shows a schematic of a typical single pixel. Since the TFT-array involves many horizontal gate lines and vertical data lines. The features of TFT- array surface will have horizontal and vertical structures. Since the PI film is coated in TFT-array and the color is nearly limpid, it does not change the texture on the TFT-array surface. The textural features of TFT-array plate surface will have orthogonal structure. It is shown in Fig. 2.

In a typical LCD manufacturing process, the cell assembly consists of adding a liquid crystal alignment layer to both the color filter plate and TFT array plate. Surface defects of the TFT array plate and color filter plate not only cause visual failure but also cause electrical failure to operate LCD panel. The defects embedded on the TFT- array plate surface are micro defects- pinhole, scrape and fingerprint. Those defects might not be easily detected by using conventional electrical and optical methods [1,7,8] to perform functional electrical test. In this paper, an automatic defect inspection method is proposed to inspecting the micro-defects including pinhole, scrape and fingerprint embedded in TFT-array plate surface.

2.2 Singular Value Decomposition

SVD is a very powerful tool in image restoration, power spectrum estimation and data compression. By considering an input image of size $N \times N$ as a matrix X of dimensions $N \times N$, the SVD can be applied to factor the X into

$$X = USV^T \tag{1}$$

where U is an orthogonal $N \times N$ matrix whose columns are the eigenvectors of XX^T, V is an orthogonal $N \times N$ matrix whose columns are eigenvectors of $X^T X$. S is a $N \times N$ matrix having non-zero entries only on the main diagonal. These non-zero entries are sort in descending order and called singular values (σ), where $\sigma_1 \ge \sigma_2 \ge ... \ge \sigma_p \ge 0$, where q =rank(X)

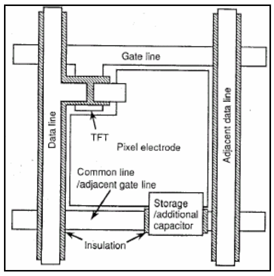

Fig.1. Schematic of a single pixel of a TFT-array[8].

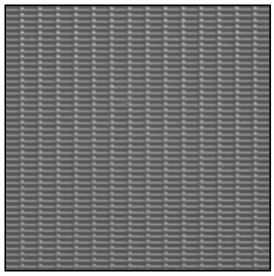
Fig. 2. A surface of TFT-array plate.

The singular values (σ) represent the energy of matrix X projected on each subspace. The singular values and their distribution which carry useful information about the content of X . The SVD is based on orthogonal bases for decomposing the matrix X . Each singular value preserves the varied orthogonal information of image features. It uses few singular values to describe the horizontal and/or vertical structures.

Fig. 3 show the artificial orthogonal and obliquely intersection lines image. Fig. 3(a1) shows an image containing intersection lines and Fig. 3(a2) shows an image reconstructed from σ_1 . Because the textural features of original image (a1) are well represented by orthogonal bases of SVD, the whole energy is concentrated in the first singular value. It can be seen that only reconstructed the first singular value can represent the original image (a1) very well. Fig. 3(a3) is an image reconstructed from σ_2 . It shows a white uniform image since the second singular value does not contain any energy of the original image. On the other hand, Fig. 3(b1) shows an image contained oblique intersection lines. The image reconstructed from λ_1 is shown on Fig. 3(b2). It can be observed that the feature image of the first singular value cannot sufficiently represent the original image (b1). Fig. 3(b3) shows the feature image of the second singular value. It consists of several rectangular blocks.

From Fig. 3, it can be observed that the method of SVD uses proper orthogonal bases to pile up the image. If the textural features of an image have orthogonal structure such as vertical/horizon lines, we use only a few singular values to describe the repetitive, periodical pattern. Conversely, if the textural features of the image are different from the orthogonal structure such as oblique lines, we need more number of singular values to approximate the original image. Therefore, the SVD is a very powerful method in extracting features from an image which has horizontal/vertical textural feature.

Since the textural feature of TFT-array plate surface has horizontal/vertical textural structure, we can use the SVD to represent the features of TFT-array plate and detect the defects.

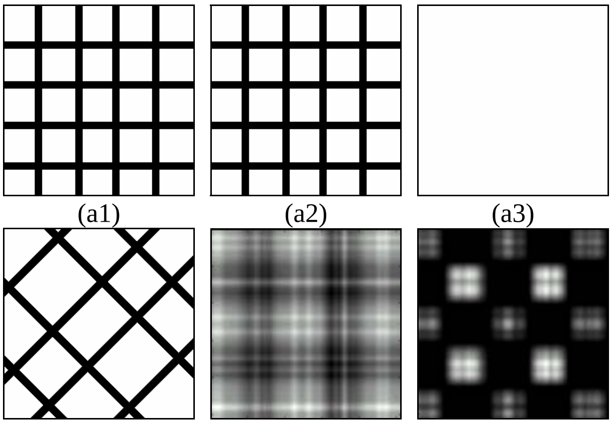

Fig. 3. (a1) The artificial horizontal/vertical intersection lines image; (a2) the reconstructed image from σ_1; (a3) the reconstructed image from σ_2; (b1) The artificial obliquely intersection lines image; (b2)-(b3) the reconstructed image from the first and the second singular values, respectively.

2.3 SVD for defect detection

In this study we use machine vision to tackle the problem of detecting micro-defects including pinhole, scrape and fingerprint which appear as local anomalies in TFT-array plates. The SVD has desirable properties of orthogonal bases to deal with the orthogonal textural feature of TFT-array surface. Therefore, the SVD-based image restoration technique is used to remove the orthogonal line patterns in TFT-array plate surfaces. We are then able to inspect for defects in the restored image.

The restoration technique proceeds as follows:

$$\hat{X} = \sum_{j=k+1}^{q} U_j S_j V_j^T \qquad (2)$$

where $\hat{X}$ is restored image, U_j and V_j are jth columns of U and V, respectively, S_j is jth singular value of S, k is the steady- state point of singular values, and q is the rank of the matrix X.

While using the SVD algorithm for defect detection, we first use Eq. (1) to decompose the image X and gain the singular values which represent the energy of image. Then we need to select the proper number of singular value which have sufficient information to represent the repetitive orthogonal structure features of TFT-array plate. We can eliminate regular, periodical and structural patterns of the TFT-array plate and preserve the anomalies in the restored image by setting the selected singular values to zero and reconstructing the image using Eq. (2). Higher energy corresponds to the main textural patterns of the image and lower energy provides detailed information of image.

Since the various images have different distributions of singular value. We can normalize singular values first and then use first–order difference of normalized singular values (NSV) perform the steady-state point more consistently. The normalization proceeds as follows:

$$\sigma_i' = \frac{\sigma_i - \mu_\sigma}{s_\sigma} \quad \text{for} \quad i = 1,2,...,q \qquad (3)$$

where q =rank(X), σ_i is the value of ith singular value, μ_σ is the mean of singular values and s_σ is the standard deviation of singular values.

The concept of first–order difference of NSV ($\Delta\sigma$), $\Delta\sigma_i = \sigma_i' - \sigma_{i+1}'$, is considered for determining the proper number of the singular values which can represent the background information. When the $\Delta\sigma_i$ at the specific singular value (σ_i) approximate to zero and decrease very smoothly after σ_i , this σ_i can be selected to be the steady-state point. All singular values, larger than the steady-state point are proper number for representing the repetitive orthogonal structure features.

After the proper number of singular value is selected, we can eliminate background information and preserve the defects. Eq. (2) is used to perform the restored image, in which the transformed region associated with the structural pattern becomes an approximately uniform gray-level region and the defects are preserved. Since the intensity variation in homogeneous regions is very small, we can use the simple statistical process control principle to set up the control limits for distinguishing defects from regular regions. The upper and lower control limits for intensity variation in the restored image are $\mu_f \pm k\sigma_f$, where k is a control constant; μ_f and σ_f are the mean and standard deviation of gray levels in the restored image $f(x, y)$. If a pixel with the gray level falls within the control limits, the pixel is classified as a homogeneous element. Otherwise, it is classified as a defective element.

3. EXPERIMENTAL RESULT

In this section, we present experimental results on a variety of micro-defects including pinhole, scrape and fingerprint on TFT-array plate surface to evaluate the performance of the proposed SVD defect detection method. All experimental are implemental on a personal computer using Matlab. The images are 256×256 pixels wide with 8-bit gray levels.

According to the proposed method, we need to select the proper number of singular values for inspecting the defects. It can be expected that the normalized singular value (NSV) of the first singular value ($\sigma_1^{'}$) dominate all other singular values, and the NSV of remaining singular values drop dramatically. It reaches a steady-state point that approximates to zero after a few number of NSVs. The steady-state point with $\Delta\sigma < 0.05$ can be used to distinguish the repetitive background and defects in the image. We can use the first-order difference of consecutive NSV ($\Delta\sigma_i$) to find the location of the steady-state singular value.

Fig. 4(a1), (b1) and (c1) show a TFT-array plate surface with three different patterns that contain pinhole, scrape and fingerprint. The restored image in Fig. 4(a2) shows that $\sigma_1 - \sigma_5$ are set to zero for the defective image with pinhole. It can be found that the periodic texture becomes an approximately uniform gray-level region and the abnormal pinhole is well persevered in the restored image. Fig. 4(b2) shows the restored result of defective image with scrape by setting $\sigma_1 - \sigma_8$ to zero. Fig. 4(c2) shows the restored image of Fig. 4(c1) by setting $\sigma_1 - \sigma_6$ to zero. It reveals that the fingerprint is distinctly enhanced in the restored image. Figs. 4 (a3)-(c3) depict the defect detection results of Figs. 4(a1)-(c1) as a binary image, respectively. It can be seen that the orthogonal texture patterns on the TFT-array plate surfaces are eliminated and defects are distinctly preserved.

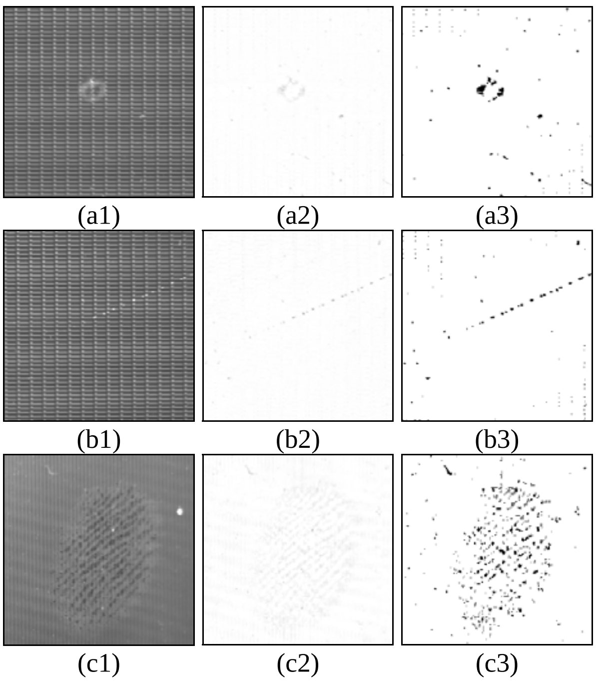

Fig. 4. (a1), (b1) and (c1) The defective images with pinhole ,scrape and fingerprint, respectively; (a2), (b2)and(c2) the restored images; (a3), (b3) and (c3) the resulting binary images for defect segmentation.

4. CONCLUSIONS

Surface defects on TFT-array plates not only cause visual failure, but result in electrical failure to operate LCD functionally. In this paper we have presented a global approach for automatic inspection of micro-defects including pinholes, scrapes and fingerprints on TFT-array plate surfaces. The proposed method does not rely on the conventional electrical and optical methods to perform functional test. It based on an image reconstruction scheme using the singular value decomposition. The SVD approach decomposes image into the eigenvalue-eigenvector factorization. By selecting proper number of singular values on the diagonal matrix and reconstructing the matrix with selected singular values set to zero, we can eliminate regular, periodical patterns of the textured image, and preserve the anomalies in the restored image.

In the experiments we have evaluated a variety of micro-defects including pinhole, scrape and fingerprint on TFT-array plate surfaces. The experimented results have concluded that 0.05 is a threshold which can be used for first-order difference $\Delta\sigma$ to find a steady-state singular value point. The steady-state point can determine proper number of singular values that represent the repetitive background information. The proposed SVD image reconstruction scheme has shown promising result for LCD micro-defect inspection.

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