DEFECT INSPECTION OF PATTERNED TFT-LCD PANELS USING A FAST SUB-IMAGE BASED SVD

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ABSTRACT
Thin Film Transistor Liquid Crystal Displays (TFT-LCDs) have become increasingly attractive and popular as display devices. In this paper, we propose a machine vision approach for automatic inspection of micro defects in patterned TFT-LCD surfaces. The proposed method is based on a global image reconstruction scheme using singular value decomposition (SVD) that involves orthogonal bases. A partition procedure, which separates the input image into non-overlapping sub-images, is utilized to reduce the computation time of SVD. Taking the pixel image as a matrix, the singular values on the decomposed diagonal matrix represent different degrees of information from the TFT-LCD image. By selecting the dominant singular values that represent the repetitive orthogonal-line texture of the TFT-LCD surface and reconstructing the matrix by excluding the dominant singular values, the reconstructed image effectively removes the background texture and distinctly preserves anomalies. In the experiments, we have evaluated a variety of TFT-LCD micro defects including pinholes, scratches, particles and fingerprints at different image resolutions. The experimental results reveal that the proposed method is effective and efficient for micro defects inspection of TFT-LCD panels.

Key Words: Petrinets, Computer Integrated Manufacturing, Automatic Inspection, TFT-LCD Panels, Defect Inspection, Quality Inspection, Machine vision.
1. INTRODUCTION

Flat-panel displays have become increasingly important in recent years. They can be used as monitors for notebook and personal computers, and as viewfinders for handheld devices such as cellular phones and PDAs. Thin Film Transistor Liquid Crystal Displays (TFT-LCDs) are particularly attractive due to their full-color display capabilities, low power consumption and lightweight. In order to ensure the display quality and improve the yield of LCD flat panels, the inspection of defects in the TFT-LCD panels becomes a critical task in manufacturing. Human visual inspection and electrical functional tests are the most commonly used methods for LCD defect detection. However, manual inspection is a time consuming and tiresome task. The manual activity of inspection could be subjective and highly dependent on the experience of human inspectors. In this paper, we propose a computer vision-based defect detection scheme for TFT-LCD inspections.

Surface defects of a TFT-LCD panel not only cause visual failure but also cause electrical failure to the panel. Appearance defects on TFT-LCD panels can be roughly classified into two categories, macro and micro defects (Nakashima 1994). Macro defects include “MURA”, “SIMI” and “ZURE”. “MURA” means unevenness of a TFT-LCD panel. “SIMI” mean stains on a TFT-LCD panel. “ZURE” means misalignment of a TFT-LCD panel. Micro defects include pinholes, fingerprints, particles and scratches. The macro defects appear as high contrast regions with irregular sizes and shapes. They are generally large in size and, therefore, can be easily detected by human inspectors. However, sizes of micro defects are generally very small. They can not be found visually by human inspectors or detected with electrical methods. The proposed method in this paper especially focuses on the inspection of micro defects by utilizing the structural features of TFT-LCD panels.

Regarding automatic inspection systems for TFT-LCDs, several electrical and optical based inspection techniques have been developed for LCD manufacturing (Kido et al. 1995, Hawthorne 2000). Most existing automatic inspection systems for LCDs are based on conventional electrical methods to detect the surface potential. Those electrical methods work well for functional verification of a TFT panel. They can only be accomplished after the fabrication is completed. In-process inspection may not be possible with the functional test approach.

A few vision-based techniques that use pattern-matching algorithms were developed for LCD inspections (Sokolov and Treskunov 1992, Nakashima 1994). The existing vision-based techniques generally need a pre-stored reference image for comparison. This requires a large volume of data for reference and precise environmental controls such as alignment and lighting.

In the LCD manufacturing process, perpendicular data and gate conductive lines are patterned onto the glass substrate. A TFT-LCD panel contains horizontal gate lines on one
plane and vertical data lines on the other plane. A thin film transistor is located at each intersection of the data and gate lines. Figure 1 shows the schema of a single pixel of a typical TFT-LCD panel (Kido et al. 1995). Since the geometrical structure of a TFT-LCD panel surface involves the horizontal and vertical elements, it can be classified as a structural texture in the image. The textural feature of a TFT-LCD panel surface results in a homogeneous image that consists of an arrangement primarily of horizontal and vertical lines appearing periodically on the surface. The textured image of a TFT-LCD panel is shown in Figure 2. The problem of defect detection in TFT-LCD panel surfaces can now be considered as a texture analysis problem in image processing. In this study, we propose an image reconstruction scheme based on singular value decomposition (SVD) to detect micro defects including pinholes, scratches, particles and fingerprints in TFT-LCD panel surfaces.

Singular value decomposition was first proposed in the 1970s and applied in a wide range of computer vision applications such as image hiding (Chung et al. 2002, Liu and Tan 2001), image restoration (Ibrahim et al. 1998, Kamm and Nagy 1998), and image compression and reconstruction (Popesuc et al. 2001, Wei et al. 2001, Selivanov and Lecomte 2001, Hoge et al. 2001). By considering an image as a matrix, the SVD is used to decompose the image and then obtain a diagonal matrix and two orthogonal matrices of the singular vectors. The ordered entries of the diagonal matrix are singular values. The global information (or the approximation) of the image can be represented by a few singular values of large magnitude. The remaining singular values of small magnitude provide detailed information of the image.

A few studies have been done with the use of the SVD for texture analysis in image processing. Luo and Chen (1994) utilized the SVD for texture discrimination. They used the proportion of two dominant singular values of an image matrix as the textural feature to discriminate textured images. Kvaal et al. (1998) used the SVD for feature extraction from an image of bread. The distribution of logarithms of singular values of an inspection image was used as the textural feature to classify the sensory porosity of wheat baguettes. The aforementioned SVD-based methods for texture analysis generally use singular values or singular vectors to characterize the textural features. Then complicated classifiers were used to segment or classify textures. However, different textures may need different textural features to describe the textural patterns. The feature extraction process for a best set of
textural features is generally carried out by trial and error, and may highly rely on human expertise.

The SVD is based on orthonormal bases for decomposing a matrix (Petrou and Bosdogianni 1999). It is well suited for representing the structural features of a TFT-LCD panel that comprises orthogonal gate lines and data lines. In this paper, we propose a global approach that uses an SVD-based image reconstruction technique for inspecting micro defects in TFT-LCD panels. The larger singular values retain the global information of the repetitive structural pattern of a TFT panel. The smaller singular values are associated with local anomalies in the TFT panel. In the application of TFT-LCD defect inspection, we can set the larger singular values to zero and preserve the smaller singular values to reconstruct the image. The background texture will be removed and anomalies can be distinctly enhanced in the reconstructed image accordingly.

Since the SVD process for an image of large size is extremely time-consuming (Orti and Orti 1998), a partition procedure is considered to reduce the SVD computation time. The proposed partition procedure separates an image into non-overlapping sub-images. The sub-images are used in place of the complete input image so that the computational load of the SVD in a small matrix can be greatly improved. The size of partitioned sub-images not only affects the SVD computation time but also influences the results of defect detection. In order to find the proper sub-images size which can most effectively and efficiently detect the micro defects in TFT-LCD surfaces, the effect of changes in a sub-image size under varying image resolutions is thoroughly evaluated in this study.

The proposed method does not rely on textural features to detect local anomalies, nor does it require a reference image for comparison. It alleviates all limitations of the feature extraction and template matching methods. By considering an input image as a matrix, the partition procedure is first performed to separate the matrix into non-overlapping sub-images of a fixed size. Then, the SVD process individually decomposes each partitioned sub-image into the eigenvalue-eigenvector factorization. To reconstruct each sub-image, we first use an effective procedure that can automatically select the proper number of larger singular values to represent the repetitive, orthogonal structure features of the TFT-LCD pattern in the sub-image. Next, we set the selected singular values to zero and reconstruct each sub-image. Finally, a combined image of all restored sub-images shows the complete reconstructed image of the original TFT-LCD panel image. For a faultless TFT-LCD image, the reconstruction process will result in a uniform image. For a defective TFT-LCD image, the anomalies will be preserved and the periodical patterns will be eliminated in the reconstructed image. The statistical process control principle can then be used to set up the control limits (i.e., the threshold) for distinguishing between defective regions and uniform regions in the reconstructed image.
2. THE DEFECT DETECTION SCHEME

2.1 Singular Value Decomposition

Consider an input image of size \( M \times N \) as a matrix \( X \) of dimensions \( M \times N \), where \( M \geq N \). It is possible to represent this image in the \( r \)-dimensional subspace, where \( r \) is the rank of \( X \), and \( r \leq N \). The SVD is a factorization of the matrix \( X \) into orthogonal matrices (Strang 1998),

\[
X = USV^T
\]

where \( U \) is an \( M \times r \) matrix and consists of the orthonormalized eigenvectors of \( XX^T \);

\( V \) is an \( N \times r \) matrix and consists of the orthonormalized eigenvectors of \( X^TX \);

\( S \) is an \( r \times r \) diagonal matrix consisting of the “singular values” of \( X \), which are the nonnegative square roots of the eigenvalues of \( X^TX \). These singular values, denoted by \( \sigma_i \), \( i = 1, 2, ..., r \), are sorted in non-increasing order, i.e., \( \sigma_1 \geq \sigma_2 \geq \cdots \geq \sigma_r \geq 0 \).

The SVD is based on orthonormal bases for decomposing the matrix \( X \) (Petrou and Bosdogianni 1999). The singular values represent the energy of matrix \( X \) projected on each subspace. The singular values and their distribution carry useful information about the contents of \( X \). For an image containing an orthogonal structural pattern, only a very few larger singular values will dominate, and yet all others have magnitudes close to zero. Figure 3 shows an artificial image and its corresponding ten largest singular values. The artificial image in Figure 3(a) comprises horizontal and vertical lines patterns. It can be seen from Figure 3(b) that the first (the largest) singular value \( (\sigma_1) \) dominates all other singular values.

![Figure 3. (a) Artificial orthogonal-lines image; (b) plot of the corresponding ten largest singular values.](image)

2.2 SVD-Based Image Reconstruction

In this study, we use machine vision to tackle the problem of detecting micro defects including pinholes, scratches, particles and fingerprints. The defects break the regularity of line structures, and appear as local anomalies in TFT-LCD panels. The SVD has desirable properties of orthogonal bases to deal with the orthogonal textural feature of patterned TFT-LCD panel surfaces. Therefore, the SVD-based image reconstruction technique is used to remove the orthogonal line patterns in TFT-LCD panel surfaces.
As shown previously, singular values of larger magnitude represent a global approximation of the original image. Singular values of smaller magnitude provide the local, detailed information of the image. We can select the proper number of larger singular values to represent the global, repetitive textural pattern of the image. The background texture can then be removed by reconstructing the image without the use of dominant singular values. With this approach, we do not have to define various quantitative features for different types of defects. The proposed SVD-based image reconstruction scheme simply eliminates all TFT-LCD repetitive horizontal and vertical patterns. The remains in the reconstructed image can then be easily identified as defects in the TFT-LCD panels.

The image reconstructed by excluding the selected dominant singular values is given by

$$\hat{X} = \sum_{j=k+1}^{r} U_j \sigma_j V_j^T$$

where $\hat{X}$ is the reconstructed image, $U_j$ and $V_j$ are $j^{th}$ column vectors of $U$ and $V$, respectively; $\sigma_j$ is $j^{th}$ singular value of $S$; $k$ is some selected number of singular values, and $r$ is the rank of the matrix $X$. Note that $\sigma_j$'s are sorted in increasing order such that $\sigma_{j+1} < \sigma_j$.

In the defect inspection application, the proposed defect detection scheme sets $k$ largest singular values (from $\sigma_1$ to $\sigma_k$) to zero and preserves the smaller singular values to reconstruct the image. The background texture of periodical line patterns will be effectively removed and any anomalies will be distinctly preserved in the reconstructed image.

Figure 5 shows again the artificial image containing an orthogonal-line pattern and its reconstructed images. Figure 5(b) shows the reconstructed image by excluding the largest singular value $\sigma_1$. It can be seen that solely setting $\sigma_1$ to zero cannot sufficiently eliminate the background texture in the reconstructed image. Figure 5(c) demonstrates the reconstructed image by excluding both $\sigma_1$ and $\sigma_2$ simultaneously. We can observe that the result is approximately a uniform white image. All structural lines are effectively removed. Note that the image in Figure 5(a) is a well-structured, noise-free orthogonal line pattern. From the reconstruction results in Figures 5(b)-(c), it also becomes apparent that the minimum required number of singular values for the removal of any orthogonal line pattern is two.

![Figure 5](image_url)

**Figure 5.** (a) Artificial orthogonal-lines image (the original image); (b) reconstructed image excluding $\sigma_1$; (c) reconstructed image excluding both $\sigma_1$ and $\sigma_2$. 
2.3 Selecting the Proper Number of Singular Values

When using the SVD for defect inspection application, the most important task is to select the proper number (i.e., the parameter $k$ in Eq. (2)) of singular values for the representation of background texture in the TFT-LCD image. In order to find the cut of $\sigma_k$, which has $\sigma_1, \sigma_2, \cdots, \sigma_k$ best representing the global approximation and $\sigma_{k+1}, \sigma_{k+2}, \cdots, \sigma_r$ representing the details of the TFT-LCD image under inspection, the original magnitude of each singular value should be normalized. The normalization of $\sigma_i$ proceeds as follows:

$$\sigma_i' = \frac{\sigma_i - \mu_{\sigma}}{s_{\sigma}}, \quad i = 1, 2, \ldots, r$$

(3)

where $\sigma_i'$ is the $i^{th}$ normalized singular value, $\sigma_i$ is the $i^{th}$ singular value, $\mu_{\sigma}$ is the mean and $s_{\sigma}$ is the standard deviation of all singular values for a given image.

Let the zero crossing point for a set of non-increasing singular values $\sigma_1, \sigma_2, \cdots, \sigma_r$ occur between $\sigma_i'$ and $\sigma_{i+1}'$, where $\sigma_i' \geq 0$ and $\sigma_{i+1}' < 0$. From Equation (3), we can find that the zero crossing point ($\sigma_i'$) of an image represents the averaged energy point of the image. The point (i.e., $\sigma_{i+1}'$) before the zero crossing point can be used as a simple criterion to classify the singular values into two groups. If the magnitudes of normalized singular values are larger than $\sigma_i'$, the energy of the corresponding singular values represents the global approximation of the image. The remaining singular values then contain the detailed information of the image. Therefore, based on the zero-crossing criterion $\sigma_{i+1}'$, the proper number of singular value $k$ is $i-1$; i.e., $\{\sigma_1, \ldots, \sigma_i\}$ are the singular values representing the background texture, and $\{\sigma_{k+1}, \ldots, \sigma_r\}$ are the singular values representing the details of the image.

2.4 SVD in Partitioned Sub-images

Computational inefficiency is the major disadvantage of the use of SVD in machine vision applications. Given an image of size $M \times N$, where $M \geq N$, the computational complexity of SVD is $O(M^2 \times N)$ (Bingham and Heikki, 2001). SVD computation time increases with image width. In order to reduce the cost of computing SVD, a partition procedure is further applied in this study.

The partition procedure is to separate the input image $X$ of size $M \times N$ into non-overlapping sub-images $g_{xy}$, each of size $m \times n$,

$$X = [g_{xy}]$$

(4)

for $x = 1, 2, \ldots, \frac{M}{m}$; $y = 1, 2, \ldots, \frac{N}{n}$. Notice that $m$ and $n$ are the factors of $M$ and $N$, respectively.
With the partition procedure that divides an original image of size \( M \times N \) into \( \frac{M}{m} \times \frac{N}{n} \) sub-images, the computational complexity of SVD for each sub-image of size \( m \times n \), where \( m \geq n \), is dramatically reduced to \( O(m^2 \times n) \).

The distribution of singular values is affected by the size of partitioned sub-images. The partition procedure only separates an input image into \( \frac{M}{m} \times \frac{N}{n} \) non-overlapping sub-images. Therefore, the structural pattern and image resolution of each sub-image is identical to its original image. Since the size of each sub-image is smaller than the original input image, the number of singular values of each sub-image is less than that of the original image. The selected number of singular values used to represent the background texture of the sub-images is reduced as the sub-image size decreases. That is, the proper number of singular values \( k \) for each sub-image decreases when the sub-image size decreases.

Figure 6(a) shows a faultless TFT-LCD panel image of 256\( \times \)256 pixels size. Figures 6(b)-(e) show the plots of the corresponding ten largest normalized singular values of Figs 6(a) in four sub-image sizes of 256\( \times \)256, 128\( \times \)128, 64\( \times \)64 and 32\( \times \)32 pixels, respectively. Note that the normalized singular values presented in the plots are the averaged normalized singular values (\( \overline{\sigma_i} \)) of all partitioned sub-images in the input image. That is,

\[
\overline{\sigma_i} = \frac{1}{D} \sum_{x=1}^{M/m} \sum_{y=1}^{N/n} \sigma_i(x,y)
\]

where \( \sigma_i(x,y) \) is the \( i^{th} \) normalized singular value for sub-image \( g_{xy}, \ x = 1,2,\ldots,M/m, \ y = 1,2,\ldots,N/n \), and \( D = \frac{M}{m} \times \frac{N}{n} \).

The same zero-crossing selection rule is also applied to the averaged normalized singular values \( \overline{\sigma_i} \) for the input image with partitioned sub-images. Prior to the inspection, a faultless TFT-LCD panel surface is used as a training image, and the proper number of singular values \( k \) is selected by setting \( k = i - 1 \) for \( \overline{\sigma_i} \geq 0 \) and \( \overline{\sigma_{i+1}} < 0 \).
Figure 6. TFT panel image and the plots of its corresponding ten largest normalized singular values in various sub-image sizes: (a) TFT-LCD panel image; (b)-(e) sub-image sizes of 256x256, 128x128, 64x64 and 32x32, respectively.

Table 1. Averaged normalized singular values (\(\bar{\sigma}_i\)) of the image in Figure 7(a) in various sub-image sizes.

<table>
<thead>
<tr>
<th>Singular value ((\bar{\sigma}_i))</th>
<th>256x256</th>
<th>128x128</th>
<th>64x64</th>
<th>32x32</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>15.866</td>
<td>11.180</td>
<td>7.845</td>
<td>5.460</td>
</tr>
<tr>
<td>2</td>
<td>1.313</td>
<td>0.858</td>
<td>0.530</td>
<td>0.268</td>
</tr>
<tr>
<td>3</td>
<td>0.440</td>
<td>0.192</td>
<td>0.052</td>
<td>-0.064</td>
</tr>
<tr>
<td>4</td>
<td>0.173</td>
<td>0.018</td>
<td>-0.081</td>
<td>-0.158</td>
</tr>
<tr>
<td>5</td>
<td>0.084</td>
<td>-0.031</td>
<td>-0.100</td>
<td>-0.175</td>
</tr>
<tr>
<td>6</td>
<td>0.033</td>
<td>-0.052</td>
<td>-0.109</td>
<td>-0.184</td>
</tr>
<tr>
<td>7</td>
<td>0.001</td>
<td>-0.060</td>
<td>-0.115</td>
<td>-0.186</td>
</tr>
<tr>
<td>8</td>
<td>-0.020</td>
<td>-0.067</td>
<td>-0.119</td>
<td>-0.189</td>
</tr>
<tr>
<td>9</td>
<td>-0.023</td>
<td>-0.071</td>
<td>-0.123</td>
<td>-0.191</td>
</tr>
<tr>
<td>10</td>
<td>-0.029</td>
<td>-0.074</td>
<td>-0.125</td>
<td>-0.192</td>
</tr>
</tbody>
</table>

As seen in Figures 6(b)-(e), we need to use more numbers of singular values to represent global information when using larger sizes of sub-images to partition the input image. Conversely, if the sub-image size is small, only a few singular values are required to describe the background texture. Table 1 summarizes the averaged normalized singular values of the TFT-LCD panel images in Figure 6(a) at various sub-image sizes. It can be seen from the table that we need to select the first six singular values to represent the global approximation when the sub-image size is 256x256. As the sizes of sub-images decrease, the numbers of singular values selected for sub-image sizes 128x128 and 64x64 are reduced to three and
two, respectively. Since the minimum required number of singular values is two for an orthogonal-line patterned image (as discussed in Figure 5), \( k = 2 \) is used in place of \( k = 1 \) for the \( 32 \times 32 \) sub-image size.

### 2.5 The Effect of Changes in Sub-image Size

In the SVD image reconstruction scheme for defect detection, we first use the partition procedure (i.e., Eq. (4)) to separate the input image \( X \) of size \( M \times N \) into non-overlapping sub-images \( g_{xy} \) of size \( m \times n \). Eq. (1) follows to decompose each sub-image and obtain a set of singular values. Then, we select a proper number of dominant singular values that describe the repetitive structural pattern in the sub-images. Eq. (2) follows to reconstruct each sub-image. Finally, the whole reconstructed image proves to be a combined image of all reconstructed sub-images.

As mentioned, the proper number \( k \) is obtained by the zero-crossing criterion of the averaged normalized singular values. The minimum required proper number \( k \) is 2 since the background texture of a TFT-LCD surface image is orthogonal. For a given image resolution and sub-image size, the proper number \( k \) selected from a faultless TFT-LCD image in the training process is used for all sub-images.

Also as discussed previously, a smaller sub-image size can dramatically increase computational efficiency. However, it may not effectively detect defects in TFT-LCD surfaces when the size of the sub-image is overly reduced. As an example, Figure 7(a) depicts a defective TFT-LCD image containing a pinhole in a fine resolution of 60 pixels/mm. As shown in Figures 7(b)-(d), we can find that the resultant region associated with the background texture of the TFT-LCD panel becomes approximately uniform and the pinhole defect is well preserved in the reconstructed images. The partitioned sub-images of sizes \( 256 \times 256 \), \( 128 \times 128 \) and \( 64 \times 64 \) pixels along with their selected numbers of singular values all perform well to detect the pinhole defect.

However, it can be seen from Figure 7(e) that the pinhole defect is severely blurred, although better uniformity of the background texture is generated with the use of a small sub-image size of \( 32 \times 32 \) pixels. Therefore, the sub-image of size \( 32 \times 32 \) is overly reduced for the TFT-LCD image at a fine resolution of 60 pixels/mm.

### 2.6 Statistical Process Control for Segmentation

The proposed SVD image reconstruction scheme will make a faultless TFT-LCD surface become approximately uniform, and distinctly preserve anomalies in the reconstructed image. The intensity variation in the background region is very small in the reconstructed image, compared with that in the defective area. We can therefore use the statistical process control principle to set up the control limits for distinguishing defects from the uniform region. The
upper and lower control limits for intensity variation in the reconstructed image are 
\[ \mu_f \pm t \cdot s_f , \]
where \( t \) is a control constant; \( \mu_f \) and \( s_f \) are the mean and standard deviations of grey values in the whole reconstructed image \( f \), and. If a pixel with its gray value falls within the control limits, the pixel is classified as a homogeneous element of the background region. Otherwise, it is classified as a defective element.

3. EXPERIMENTAL RESULTS

In this section, we present experimental results from a variety of micro defects including pinholes, scratches, particles, and fingerprints in TFT-LCD panel surfaces to evaluate the performance of the proposed defect detection scheme. The experiments were conducted on a Pentium 4-1.8 GHz PC. The test images are 256×256 pixels wide with 8-bit gray levels.

3.1 Detecting scratch, pinhole and particle defects

The averaged normalized singular values from various sub-image sizes of the faultless image at a fine resolution of 60 pixels/mm (Figure 8(d1)) are the same as those summarized in Table 1. Note that the pinhole, scratch and particle defects can only be detected in images of fine resolution. The proper numbers of singular values \( k \) are determined by the zero-crossing criteria. They are 3, 2 and 2 for sub-image sizes of 128×128, 64×64 and 32×32, respectively, based on the resulting statistics in Table 1.

Figure 8 shows the reconstructed results from the sub-image size of 64×64. Figures 8(a1)-(d1) show the defective images and their faultless versions of the TFT panel surfaces. Figures 8(a2)-(d2) show whole reconstructed images by setting the first three largest singular values (i.e., \( \sigma_1, \sigma_2 \) and \( \sigma_3 \)) of each sub-image to zero. In the defective images of Figures 8(a2)-(c2), it can be found that the repetitive, structural texture becomes an approximately uniform gray-level region and the abnormal defects of scratch, pinhole and particle are well enhanced in the restored images. As seen in Figure 8(d2), the restored image of the faultless surface is approximately a uniform gray-level image. Figures 8(a3)-(d3) show the defect
3.2 Detecting Fingerprint Defects

Table 2 summarizes the averaged normalized singular values of the faultless image at a coarse resolution of 20 pixels/mm (Fig. 9(b)) in various sub-image sizes. Note that the fingerprint defect can only be observed in images of coarse resolution. It can be observed from Table 2 that the proper numbers of singular values selected for sub-image sizes of $128 \times 128$, $64 \times 64$, $32 \times 32$ and $16 \times 16$ pixels are 3, 2, 2 and 2, respectively, based on the zero-crossing criterion.

Figure 9 shows the reconstructed results of the defective image under the coarse image resolution at various sub-image sizes. The control constant $t = 4$ is also used for binary detection results of Figures 8(a2)-(d2) as binary images. The control constant $t = 4$ is used for all test images in the binarization process. For defective images, the orthogonal texture patterns in the TFT panel surfaces are sufficiently eliminated and defects are well segmented. For the faultless TFT-LCD surface image, the resulting binary image is uniformly white and no defect is claimed in the resulting image. Based on the detection results from Figures 8, the sub-image of size $64 \times 64$ can efficiently and effectively detect scratch, pinhole and particle defects at the fine image resolution of 60 pixels/mm.
segmentation. Figures 9(c1)-(c3) show that the fingerprint defect is well preserved in the restored images from sub-image sizes of 128×128, 64×64 and 32×32, respectively. However, Figures 9(c4) reveal that the fingerprint detected from the small sub-image of size 16×16 is much scattered. A sub-image size smaller than 32×32 cannot reliably detect a fingerprint defect in an image at the coarse resolution of 20 pixels/mm. Based on the detection results from Figures 9, we can find that the sub-image of size 32×32 can efficiently and effectively detect fingerprints at the coarse image resolution of 20 pixels/mm. An experiment has also shown that the detection results of the faultless version at the coarse resolution are uniformly white images, regardless of the sub-image sizes.

Table 2. Averaged normalized singular values (σᵢ̅) of the coarse resolution image of 20 pixels/mm in various sub-image sizes.

<table>
<thead>
<tr>
<th>Singular value (σᵢ̅)</th>
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<th>32×32</th>
<th>16×16</th>
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<td>-0.047</td>
<td>-0.035</td>
<td>-0.254</td>
</tr>
</tbody>
</table>

(a) (b) (c1) (c2) (c3) (c4)
3.3 Computation Time of the Proposed Method

In order to evaluate the computational efficiency of the proposed method, the computation times for a whole input image of $256 \times 256$ at various partitioned sub-image sizes are collected in Table 3. It can be seen from the table that the computation time decreases as the size of the sub-image is reduced. The computation time for the whole image of $256 \times 256$ takes 1.51 seconds. It is dramatically reduced to 0.2 seconds for the same image with a sub-image size of $64 \times 64$ in the detection of scratch, pinhole and particle defects. For fingerprint detection at the coarse resolution, the computation time for the $256 \times 256$ image with a sub-image size of $32 \times 32$ is only 0.17 seconds. Given an image of $256 \times 256$, the computation times from sub-images of sizes $32 \times 32$ and $16 \times 16$ are 0.17 and 0.16 seconds, respectively. The savings in computation time are relatively insignificant. In the consideration of processing effectiveness, the minimum partitioned sub-image size for micro-defect detection in TFT-LCD panels should not be less than $32 \times 32$.

4. CONCLUSIONS

In this paper, we have presented a global approach for automatic visual inspection of micro-defects in patterned TFT-LCD surfaces. The proposed method does not rely on the conventional feature extraction methods to detect defects. It is based on an image reconstruction scheme using singular value decomposition. In order to speed up the computation of SVD, we partition an input image into non-overlapping sub-images. Given an input image of size $M \times N$ ($M \geq N$), and a sub-image of size $m \times n$ ($m \geq n$), the

Table 3. Total computation times for various sub-image sizes

<table>
<thead>
<tr>
<th>Sub-image size</th>
<th>Computation time (sec.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$256 \times 256$</td>
<td>1.51</td>
</tr>
<tr>
<td>$128 \times 128$</td>
<td>0.28</td>
</tr>
<tr>
<td>$64 \times 64$</td>
<td>0.20</td>
</tr>
<tr>
<td>$32 \times 32$</td>
<td>0.17</td>
</tr>
<tr>
<td>$16 \times 16$</td>
<td>0.16</td>
</tr>
</tbody>
</table>

*Note: This is a total computation time for a whole image of $256 \times 256$. 

Figure 9. Reconstructed results of a fingerprint image from various sub-image sizes: (a)-(b) defective image with fingerprint and its faultless image; (c1)-(c4) restored images from sub-image sizes $128 \times 128$, $64 \times 64$, $32 \times 32$ and $16 \times 16$ pixels, respectively; (d1)-(d4) respective binary images of (c1)-(c4).
computational complexity can be dramatically reduced from $O(M^2 \times N)$ of an entire input image to $O(m^2 \times n)$ of each sub-image in a total of $\frac{M}{m} \times \frac{N}{n}$ sub-images.

The SVD approach is used to decompose each sub-image into eigenvalue-eigenvector factorizations. It selects a proper number of singular values on the diagonal matrix of each sub-image, and reconstructs the image without the use of the dominant singular values. The resulting image then removes global repetitive gate lines and data lines of a TFT-LCD image. The experiments showed that a sub-image size of $64 \times 64$ is effective and efficient enough to detect the scratch, pinhole and particle defects in TFT-LCD surfaces at the fine image resolution. A $32 \times 32$ sub-image size is reliable and computationally attractive to detect fingerprint defects at the coarse image resolution.

REFERENCES


