ABSTRACT

To promote product quality of TFT-LCD in mass manufacturing, development of an automatic defect inspection system to replace human inspection is required. In this paper, we use machine vision for automatic inspection and present several research results for TFT-LCD defects inspection and classification. For MURA defects inspection, Jiang et al. (2003) proposed to use ANOVA and EWMA control charts for detecting non-uniformity areas in a panel, and to design a weighted index mask matrix for MURA defects classification. For Micro defects, including pinholes, scratches, particles and fingerprints on the surface of TFT panels, Lu and Tasi (2004) proposed a global approach that uses an SVD-based image reconstruction technique. In the experiment, we have evaluated a variety defects including MURA, pinholes, scratches, particles and fingerprints on TFT panel surfaces, and the result reveals that the proposed methods are effective for LCD defects inspection.

Key Words: LCD, Defects inspection, Statistical methods
using electrical methods. Lu and Tsai (2004) proposed a global approach for automatic micro defects visual inspection on TFT-LCD panels.

Generally, automatic inspection systems for LCDs use optical, electrical based or vision-based approaches. Several electrical or optical based inspection techniques have been developed for LCD manufacturing (Lin et al (2001), Jeff (2000), Chen et al (2000), Kido (1992) ). Most existing automatic inspection systems for LCDs are based on conventional electrical methods that detect the surface potential. Electrical methods work well for functional verification of a TFT panel; however, they can only be performed after product fabrication is completed. In-process inspection is not yet applicable to the functional test approach.

There is not much research in the literature related to TFT-LCD defect inspection using vision-based approaches. Lin et al. (1998) established a fast image segmentation technique for inspecting the defects on a TFT-LCD spacer. The fuzzy set theory was used to determine the threshold value for image segmentation. A set of specially designed operation masks was applied to abstract the features on a spacer. Huang and Lin (2001) suggested using Houng’s transformation technique to calibrate the positional accuracy of a TFT-LCD. Saiton (1999) developed a machine vision system for inspecting TFT-LCD brightness unevenness. The author first used an edge detection algorithm to detect discontinuous points that included brightness unevenness and noise pixels. A generic algorithm was then applied for detecting the brightness unevenness defects. Sokolov and Treskunov (1992) developed an automatic vision system for the LCD final output check. For defect detection, they compared the brightness distributions between a reference TFT-LCD image and a test image. The existing vision-based techniques generally need a pre-stored reference image for comparison. Moreover, the techniques for TFT-LCD inspection focus mainly on final appearance checks for defects such as nap or dark/bright spots after product fabrication is completed.

We used machine vision for automated inspection and present several research results for TFT-LCD panel surface defect inspection and classification. For macro MURA defects, we propose an ANOVA and EWMA control chart to detect the non-uniform areas in a panel. A weighted index mask matrix is designed for MURA defect classification. For Micro defects, including pinholes, scratches, particles and fingerprints on the surface of TFT panels, we propose a global approach that uses a Singular Value Decomposition (SVD)-based image reconstruction technique.

2. RESEARCH METHODS AND RESULTS

In this section, we present several research results for TFT-LCD panel surface defect inspection and classification using machine vision. The research results for surface defects include MURA, pinholes, scratches, particles and fingerprints.

2.1. Macro Defects Inspection

MURA is one of the macro defects. MURA defects indicate uniformity in a TFT-LCD panel. The MURA defects appear as areas in which the color (or gray) is different from other areas in the panel (see Figure 1). These defects could appear with a different color background and might occur due to uneven exposure or other steps in the manufacturing process.

A major difficulty in TFT-LCD panel MURA defect inspection is that a good quality image is difficult to obtain using a regular CCD camera because the CCD camera’s gray level resolution is limited. Therefore, a CCD camera cannot be used for TFT-LCD inspection. In this work, a luminance meter, a light sensitive device, was used to measure the panel surface brightness values. The proposed method for inspection and classification uses the following procedure:
Step 1. Panel surface information measurement

A BM-5A was used to measure the luminance level of a defined area on a TFT-LCD panel. Because Mura defects less than 5 cm$^2$ is usually ignored in the field, a 15” TFT-LCD panel was divided into 16 by 9 blocks at 4.28 cm$^2$ each. Five sub-areas with 1000 pixels each were measured in each block. The five sub-areas were the four corners plus center locations. A 15” TFT-LCD has $1024 \times 768 = 786432$ pixels. This is equivalent to 5461 pixels in each of the 144 blocks. The luminance meter measures the luminance value by collecting a 200 pixels data area. Five sub-areas with 1000 pixels of data were collected. This meant that 92% of the pixels were measured in each block. This data collection plan was thought sufficient to detect Mura defects on a TFT-LCD panel under the common specification.

<table>
<thead>
<tr>
<th>GAP Mura</th>
<th>Surrounding GAP</th>
<th>Half-moon GAP</th>
<th>Tr GAP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-uniform exposure</td>
<td>Non-uniform side angle exposure</td>
<td>Red color GAP</td>
<td>Non-uniform CF color</td>
</tr>
</tbody>
</table>

Figure 1. Common non-uniformity display defects in a TFT-LCD.

Step 2. MURA Defects detection

For MURA defect detection, we adopted ANOVA techniques. The ANOVA was used because the non-uniformity problem between panels is not an issue. The major concern is the non-uniformity (e.g., Mura defects) existing within a given panel. Therefore, this technique could be used to identify areas that are significantly different from other areas in a panel. While applying ANOVA on the 144 data blocks, residual analysis was conducted to check the normality, equal variance and independence assumptions. A set of statistical tests was conducted to serve as a reference for accepting the three assumptions. The Kolmogorov-Smirnov test, Bartlett and Durbin-Waston tests were used to test normality, equal variance and independence, respectively (Ryan 1997). The ANOVA result box plots for the tested normal panel are shown in Figure 2(a). It can be observed that under the 95% confidence level, the 144 data blocks have no significant differences. An LCD panel with Mura defects was selected for the same procedure. The ANOVA result box plots for the tested data are shown in Figure 2(b). Under the 95% confidence level at least one block has luminance values significantly different from the other blocks.

Figure 2. (a) Box plot for the LCD panel without Mura defects; (b) Box plot for the LCD panel with GAP Mura defects

Step 3. Defects position detection

In this study, the control chart concept was used for detecting the Mura defects, shown as non-uniform luminance on an LCD panel. The measurement data from the 144 blocks was
plotted onto the control chart. Because the luminance variation might be slight, the EWMA control chart was selected for this study. The EWMA detection ability is affected by the parameters $k$ and $\lambda$. As a common practice, $k$ is set as 3. The $\lambda$ was determined using the trial and error method. One normal and one defective LCD (with Mura defects) panels were used to determine the $\lambda$ value. The Mura position of the defective panel is shown in Figure 3.

**Step 4. Defects position detection**

In this study, the control chart concept was used for detecting the Mura defects, shown as non-uniform luminance on an LCD panel. The measurement data from the 144 blocks was plotted onto the control chart. Because the luminance variation might be slight, the EWMA control chart was selected for this study. The EWMA detection ability is affected by the parameters $k$ and $\lambda$. As a common practice, $k$ is set as 3. The $\lambda$ was determined using the trial and error method. One normal and one defective LCD (with Mura defects) panels were used to determine the $\lambda$ value. The Mura position of the defective panel is shown in Figure 3.

![Figure 3. Position of the GAP Mura of an LCD panel](image)

The detection rate is highest when $\lambda$ is 0.8 from the experiment result. Therefore, $\lambda$ was set at 0.8 in this study. The resulting EWMA control charts are shown in Figure 4.

![Figure 4. EWMA control charts for normal and Mura LCD panels (for $\lambda=0.8$)](image)

When $\lambda=0.8$, the blocks were detected as abnormal through the EWMA control chart: 28, 29, 41, 42, 43, 44, 45, 46, 56, 57, 58, 59, 60, 61, 62, 63, 64, 74, 75, 76, 77, 78, 91, 92, 93, 94. The area is in agreement with the area shown in Figure 3.

**Step 5. Defects Classification**

For defect classification, because the area, size and position of the defects is an important factor for TFT-LCD quality, a weighted index mask matrix (WIMM) was designed for MURA defect classification criterion. The WIMM is given by
And, define of the classification index (CI) is given by

\[ CI = \sum_{i=1}^{16} \sum_{j=1}^{9} w_{ij} x_{ij}, \]

where \( w_{ij} \) be the \( i \)th row and \( j \)th column value of WIMM, \( x_{ij} \) be a defect position deflection result of MURA from step 3.

According to the experiment result and discussion, TFC-LCD Mura defects can be classified into four categories for: A level, B level, C level and D level. Table 1 shows the classification levels and Figure 5 shows the classification results.

**Table 1. Classification level statement**

<table>
<thead>
<tr>
<th>Classification level</th>
<th>Classification index</th>
<th>Statement</th>
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<tbody>
<tr>
<td>A</td>
<td>1 – 15</td>
<td>Far Small</td>
</tr>
<tr>
<td>B</td>
<td>16 – 30</td>
<td>Far Large</td>
</tr>
<tr>
<td>C</td>
<td>31 – 45</td>
<td>Near Small</td>
</tr>
<tr>
<td>D</td>
<td>over 46</td>
<td>Near Large</td>
</tr>
</tbody>
</table>

**Figure 5.** The classification image result for MURA defects: (a) level A defects; (b) level B defects; (c) level C defects; (d) level D defects.
2.2. Micro Defects Inspection

Because the geometric structure of a TFT panel surface involves repetitive horizontal and vertical elements, it can be classified as a structural texture in the image. In this study, we used machine vision to address the problem of detecting micro defects including pinholes, scratches, particles and fingerprints which appear as local anomalies in TFT panels (see figure 6).

The SVD-based image reconstruction technique is used to remove the orthogonal line patterns in TFT panel surfaces. For defect detection purposes, the SVD-based image reconstruction scheme simply eliminates all repetitive horizontal and vertical patterns in TFT panels. The image reconstructed from the selective singular values is given by

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

where $\hat{X}$ is the reconstructed image, $U_j$ and $V_j$ are $j$th column vectors of $U$ and $V$, respectively; $k$ is some selected number of singular values; $\sigma_j$ is $j$th singular value of $S$ and $r$ is the rank of the matrix $X$.

![Figure 6. Four defective images: (a) pinhole; (b) scratch; (c) particle; (d) fingerprint](image)

When using the SVD image reconstruction scheme for defect detection, the proper number ($k$) of singular values must be selected. In the defect inspection application, the proper number of larger singular values is set to zero and the smaller singular values are preserved to reconstruct the image. The background texture will be removed and the defects will be preserved if they exist. In this study, the proper number $k$ was determined by the difference between two adjacent singular values $\sigma_j$ and $\sigma_{j+1}$. To find the proper threshold value and accommodate various images, the singular values for each image under inspection must be normalized. Figure 7(a) represents an artificial structural image that contains two scratch defects. Figure 7(b) shows the plot of the marginal gain for the normalized singular values in the image in Figure 7(a). For Figure 7(b), the proper number 4 should be excluded for image reconstruction. Once the proper number of singular values is selected, we can eliminate the background texture and preserve the defects by excluding the first $k$ largest singular values. The reconstructed image in Figure 7(c) shows that the resultant region associated with the repetitive line pattern becomes approximately uniform and the local scratch anomalies are well preserved in the reconstructed image. Since the intensity variation in the background region is very small in the reconstructed image, we can 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 given by $\mu_X \pm t s_X$, where, $\mu_X$ and $S_X$ are the mean and standard deviation of gray levels in the restored image $\hat{X}$; and $t$ is a control constant.

In TFT panel manufacturing, the size of a micro defect is generally small with respect to the entire sensed image. We set the control constant to $t = 4$, which corresponds to 93.75% for pixels falling within the control limits. If the gray level of a pixel falls within the control limits, the pixel is classified as a homogeneous element in the background region. Otherwise,
it is classified as a defective element. Figure 7 (d) depicts the defect detection result from Figure 7 (c) as a binary image. It shows that the two scratches in the original image are correctly presented in the resulting binary image.

Figures 8(a1), (b1), (c1) and (d1) show the defect images from the TFT panel surfaces in Figure 6(a-d). Figure 8(a2) shows the reconstruction result from setting the first five largest singular values to zero for the pinhole defective image with (Fig. 8(a1)). It can be found that the repetitive structural texture becomes an approximately uniform gray-level region and the abnormal pinhole is well enhanced in the restored image. Figures 8(b2) and (c2) show the reconstruction results from the defective images with scratches (Fig. 8(b1)) and particles (Fig. 8(c1)) from setting the first eight and first four singular values to zero, respectively. The figures also reveal that the scratch and particle defects are well preserved in the restored images. Figure 8(d2) illustrates the restored image in Figure 8(d1) from setting the first six singular values to zero. The fingerprint is also distinctly enhanced in the restored image. Figures 8(a3)-(d3) show the defect detection results from Figures 8(a1)-(d1) as binary images, in which the control constant $t = 4$ was used for all test images. It can be seen that the orthogonal texture patterns on the TFT panel surfaces are eliminated and the defects are distinctly preserved.

![Figure 7](image7.png)

**Figure 7.** The artificial orthogonal image with scratch defects: (a) the original image; (b) the plot of the marginal gain of normalized singular values; (c) the restored image; (d) the resulting binary image for defect segmentation.

![Figure 8](image8.png)

**Figure 8.** (a1)-(d1) The defective images with pinholes, scratches, particles and fingerprints, respectively; (a2)-(d2) show the respective restored images; (a3)-(d3) the resulting binary images for defect segmentation.
3. CONCLUSION

In this study machine vision was used for automated inspection. Several research results for TFT-LCD surface defect inspection and classification were presented.

For macro MURA defects, we proposed ANOVA and EWMA control charts to detect non-uniform panel areas. A weighted index mask matrix was designed for MURA defect classification. The advantages of the proposed procedure are: (1) the proposed method uses equipment currently used for other purposes. Additional equipment is therefore not needed. (2) Defective LCD panel determination is more objective compared with naked eye inspection. (3) The defect type, location and size can be readily obtained. This information can be provided to manufacturing for process improvement. The proposed procedure was limited to 15” LCD panels as produced by a local manufacturer.

For Micro defects, including pinholes, scratches, particles and fingerprints on the TFT panel surfaces, we proposed a global approach that uses an SVD-based image reconstruction technique. The proposed method does not rely on the conventional electrical and feature extraction methods to detect defects. By selecting the proper number of singular values on the diagonal matrix and reconstructing the image without using the selected singular values, we can eliminate global repetitive patterns in the structurally textured image and preserve local anomalies in the reconstructed image. In these experiments, we evaluated a variety of micro defects including pinholes, scratches, particles and fingerprints on TFT panel surfaces. The proposed SVD-based machine vision scheme showed promising results for TFT panel micro defects inspection.

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