Defect Inspection in Low-contrast LCD Images Using Hough Transform-based Non-stationary Line Detection

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Abstract. In this paper, we propose a Hough transform-based method to identify low-contrast defects in unevenly-illuminated images, and especially focus on the inspection of mura defects in liquid crystal display (LCD) panels. The proposed method works on 1D gray-level profiles in the horizontal and vertical directions of the surface image. A point distinctly deviated from the ideal line of a profile can be identified as a defect one. A 1D gray-level profile in the unevenly-illuminated image results in a non-stationary line signal. The most commonly used technique for straight line detection in a noisy image is Hough transform (HT). The standard HT requires a sufficient number of points lying exactly on the same straight line at a given parameter resolution so that the accumulator will show a distinct peak in the parameter space. It fails to detect a line in a non-stationary signal. In the proposed HT scheme, the points that contribute to the vote do not have to lie on a line. Instead, a distance tolerance to the line sought is first given. Any point with the distance to the line falls within the tolerance will be accumulated by taking the distance as the voting weight. A fast search procedure to tighten the possible ranges of line parameters is also proposed for mura detection in LCD images.

Experimental results have shown that the proposed method can effectively detect various mura defects including spot-, line- and region-mura. It performs well for the test images containing non-textured and structurally-textured patterns in the unevenly-illuminated surfaces.

Keywords: Surface inspection; Defect detection; Hough transform; Mura; Liquid crystal display.

1. INTRODUCTION

In automated surface inspection, defects in uniform or non-textured surfaces can be easily identified if the local anomalies have distinct contrasts from their regular surrounding neighborhood. However, a defect in the low-contrast image is extremely difficult to detect when the defect shows no clear edges from its surroundings and the background presents uneven illumination. In this paper, we consider the task of automated visual inspection of low-contrast defects and, especially, aim at the mura defects in liquid crystal display (LCD) panels, where the material surfaces require uneven lighting to intensify the hardly visible defects.

"Mura" is one large category of defects found in LCD manufacturing. It is derived from the Japanese word for blemish. Mura is a local brightness non-uniformity that causes an unpleasant sensation to human vision (Taniguchi et al. 2006). According to the size and shape, the types of mura can be roughly classified as line-mura, spot-mura and region-mura. A line-mura is a narrow straight of brightness different from its surrounding neighborhood. A spot-mura is a small circular-shaped area defect. Region-mura is one of the most difficult defects to detect in terms of the automated surface inspection algorithms since the region-mura possesses a large area of a LCD image and shows smooth changes of brightness from its uneven-lighting, low-contrast neighborhood.

Figures 1(a1) and (a2) demonstrate two surface images of a defect-free LCD panel, in which (a1) and (a2) are, respectively, the macro-view (lower image resolution) and micro-view (higher image resolution) of the panel. Figures 1(b1) and (b2) illustrate the respective enhanced images of Figures 1(a1) and (a2) by linearly stretching the original gray levels between 0 and 255 for 8-bit displays. It can be seen from Figure 1(a2) that the micro-view of LCD
panel presents a textured background. It comprises horizontal gate lines and vertical data lines in the surface, and makes the sensed image a class of structural texture. Figures 1(a3) and (a4) present two defective LCD images that contain, respectively, a line-mura and a spot-mura on the surfaces. Figures 1(b3) and (b4) are the corresponding enhanced defect images of Figures 1(a3) and (a4). The enhanced images of both defect-free and defective surfaces show that the surface images are unevenly-illuminated and the defects present only smooth edge transition and low intensity contrast from the surrounding background. All these surface properties in images make the automated defect inspection task extremely difficult. This section first reviews the previous work on surface defect detection. It then describes the properties of the low-contrast mura in LCD images and the core of the proposed method to tackle the defect detection problem.

1.1 Review of Related Work

The requirement of defect detection in uniform surfaces has arisen in glass plates (Wilder 1989, Chao et al. 2008), sheet steel (Olsson and Gruber 1992), aluminum strips (Fernandez et al. 1993) and web materials (Brzakovic and Vujovic 1996). Defects in these uniform images can be effectively identified with simple statistical measures such as the mean and variance of gray levels. They can also be easily detected using simple thresholding or edge-detection techniques. The main target surfaces in the present paper involves low-contrast anomalies in an uneven lighting background, which invalidates the use of first-order statistics and thresholding and gradient methods to segment the defects.

The currently available surface inspection techniques for defect detection in low-contrast images are either only applicable for specific types of small mura defects such as line-mura and spot-mura, or very computationally intensive for large region-mura. Saitoh (1999) presented a machine vision scheme for the inspection of brightness unevenness in LCD panel surfaces. An edge detection algorithm was used to identify discontinuous points first. Then, a genetic algorithm was applied to extract the boundary of anomalous brightness region. Kim et al. (2004) studied the detection of spot-type defects in LCD panel surfaces. An adaptive multi-level thresholding technique is employed to detect abnormal line defects that are brighter or darker than the surrounding pixels. Zhang and Zhang (2005) presented a fuzzy expert system to detect point defects, line defects and region defects in TFT-LCD panels. The defects are measured by the features of intensity contrast, area, location, direction and shape. The choice of proper defect features and design of fuzzy rules are time consuming, and highly rely on the types and characteristics of defects in question. Lee and Yoo (2004) proposed a surface fitting approach to identify low-contrast region-mura in LCD panels. For each data pixel, they first used the modified regression diagnostics to roughly estimate the background region. The background region was further approximated by a low order polynomial to generate a background surface. The estimated background surface was then subtracted from the original image to remove the influence of non-uniform background and transform the segmentation problem into a simple thresholding one. This approach showed good detection results in the experiment. However, it is rather computationally intensive for background surface estimation.

By observing the horizontal or vertical scan lines of an unevenly-illuminated LCD image, the gray-level profile of a scan line shows the trend of a straight line. Due to the effect of uneven illumination in the surface image, the profile will not present a well-structured line. Rather, the gray-level profile can be considered as a non-stationary signal that shows an upward, downward or flat variation in direction. In this paper, we propose a Hough transform-based one-dimensional surface inspection scheme that can
detect both small- and large-sized mura defects of varying shapes in LCD panel surfaces.

Finding a line segment in a noisy non-stationary signal is a non-trivial problem. The most commonly used technique for straight line detection in a noisy image is the Hough transform (HT) (Hough 1962). The Hough transform for line detection in an image is based on a voting procedure which accumulates the number of points that lie on the same line of specific parameter values. For straight-line detection, the best straight line is estimated by the maximum counts of accumulator which corresponds to a pair of specific line parameters. The merit of HT that converts the difficult shape detection in the Cartesian space into simple peak detection in the parameter space will not be beneficial for non-stationary signals. The points deviated from a specific line, even with a minor distance to the line, will not be accumulated and the resulting peak is low and scattering. In this study, the standard Hough transform is not suitable to detect the linear trend of non-stationary gray-level profiles in low-contrast images.

The standard Hough transform has been popularly applied to straight line detection since Duda and Hart (1972) proposed the parameter-space transform method. It converts the Cartesian coordinate system \((x, y)\) to parameter space \((\rho, \theta)\) for a line equation
\[
x \cdot \cos\theta + y \cdot \sin\theta = \rho
\]
with \(\theta\) in the range of \(-\pi\) and \(\pi\). The transform creates the corresponding line equations, which intersect in the parameter space \((\rho, \theta)\). The accumulators count the number of intersection points and find a peak to decide a pair of specific parameter \((\rho, \theta)\) with respect to the line equation.

The Hough transform is a very costly algorithm in terms of computation time. The space complexity of the standard algorithm is determined by the number of accumulators in the parameter space, and the time complexity is determined by the total number of increments of parameter values. A number of speed-up algorithms for straight-line detection were developed to overcome the high computation load of the standard Hough transform. Bergen and Shvaytser (1991) described an efficient probabilistic algorithm with Monte-Carlo approximation to the Hough transform. The complexity of the proposed algorithm is independent of the input size. The proposed probabilistic steps involve randomly choosing small subsets of points, and have shown that the complexity can be further reduced by sampling small subsets of points that jointly vote for likely patterns. Rau and Chen (2003) used the principal axis analysis method to accelerate the extraction of straight lines and increase the accuracy of the detected lines. Duquenoy and Taleb-Ahmed (2006) proposed two Hough transform acceleration techniques, spatial under-sampling and anticipated maxima detection. The under-sampling technique was presented to find the best criterion derived from the observed stability of the peak position in the parameter space to stop the transform calculation. The anticipated maxima detection adaptively detects the maximum peak of accumulation in the parameter space to improve the estimated accuracy of peak detection. Furthermore, many a modified HT methods were also proposed to improve the accuracy of line parameter estimation based on the coarse-to-fine technique (Jiang et al. 1997, Li 1986, Illingworth and Kittler 1987). Niblack and Petkovic (1990) alternatively used filtering techniques in the Hough space to improve the estimation accuracy of line parameter values. Costa and Sandler (1988) presented a normalized parameter space to reduce the effect of noise points so that the accuracy of peak detection can be improved.

1.2 Surface Properties of LCD Images

By scanning the sensed 2D surface image horizontally or vertically, the 1D gray-level profiles crossing over faultless and defective surface regions will all have a global representation of straight line. Given a non-stationary gray-level profile with the trend of a straight line, the defect points on the gray-level profile can be detected by calculating the distance of each point to the best fitting line of the profile. If the distance of a point on the profile is distinctly far away from the fitting line, the point can then be declared as a defect one.

The currently available Hough transform methods focused on either improving accuracy of parameter values or accelerating computation time. The standard Hough transform may perform poorly for non-stationary gray-level profiles in a low-contrast, unevenly-illuminated image. Figure 2(a) demonstrates a textured LCD image, in which the dark mura defect is in the central bottom area. Figure 2(b) shows the gray-level profiles of two horizontal scan lines across defect-free (scan line 1) and mura (scan line 2) regions. Figure 2(c) shows the detection results of the standard Hough transform for the defective gray-level profile (scan line 2), in which the detected straight-line with the largest accumulation peak is depicted in the figure. Figure 2(d) presents an ideal straight line which makes the mura defect segment far away from the fitting line. The demonstration sample reveals that the standard voting procedure of the Hough transform is invalidated to find the line segment in a non-stationary gray-level profile.
In this study, a revised version of the Hough transform is proposed for line detection in non-stationary gray-level profiles. The standard Hough transform requires a sufficient number of points lying exactly on the same straight line at a given parameter resolution so that the accumulator will show a distinct peak in the parameter space to indicate the presence of a straight line. It fails to detect a line that has numerous points distributed around the vicinity of the line in a non-stationary signal. In the proposed Hough transform-based scheme, the distance tolerance of a point to the line sought is first given. Any point with the distance to the line falls within the tolerance will be accumulated as a function of the distance to the line sought. This approach allows the non-stationary points contribute to the accumulator in the voting processing. The proposed Hough transform with adaptive voting weight under a given distance tolerance can well detect the most possible line equation in a non-stationary gray-level profile. Any points on the gray-level profile that are distinctly far away from the fitting line can then be identified as defective ones. A fast search procedure that can tighten the possible ranges of the line parameters is also proposed by finding the global dominant line segment of all gray-level profiles in each scan direction. By recursively applying the proposed Hough transform method to all individual row and column gray-level profiles, the actual region of a mura defect can be presented in the 2D inspection image.

2. NON-STATIONARY LINE SEARCH

This section presents the proposed Hough transform scheme for line detection in non-stationary gray-level profiles. The proposed Hough transform-based scheme is described in subsections 2.1 and 2.2.

2.1 Proposed Hough transform scheme

In the proposed Hough transform scheme, the points that contribute to the vote do not have to lie exactly on a line. Instead, the distance tolerance $\varepsilon$ of a point to the line sought is first given. Any point with the distance to the line falls within the tolerance will be accumulated as a function of the distance of the function. Conversely, any point with the distance beyond the tolerance is discarded in the voting process. Highly non-stationary gray-level profiles require a larger distance tolerance $\varepsilon$, while more stable gray-level profiles use a smaller distance tolerance $\varepsilon$ for detecting the line equation.

Let the inspection image $f(x, y)$ be of size $M \times N$. For a given horizontal scan line $Y$, $Y = 0, 1, 2, \ldots, M - 1$, the row gray-level profile is denoted by $f_Y(x) = f(x, Y)$, $x = 0, 1, 2, \ldots, N - 1$. The coordinates of a point on the gray-level profile $Y$ of length $N$ is then given by $(x, f_Y(x))$, for $x = 0, 1, 2, \ldots, N - 1$. To simplify the notation, the gray-level $f_Y(x)$ is represented by $f_x$, i.e., the point on a gray-level profile is denoted by $(x, f_x)$. To calculate the distance between a point $(x, f_x)$ and a straight line, we can rewrite eq. (1) from the normal form to the slope-intercept form $f_x = mx + b$. That is,

$$f_x = \frac{-\cos \theta}{\sin \theta} x + \frac{\rho}{\sin \theta}$$

where $-\cos \theta/\sin \theta$ is the slope $m$, and $\rho/\sin \theta$ is the intercept $b$. Therefore, the distance from a point $(x, f_x)$ in the gray-level profile to the line with parameter values $(\rho, \theta)$ is calculated by

$$D(x, f_x | \rho, \theta) = \frac{-m \cdot x + f_x - b}{\sqrt{m^2 + 1}}$$

The distance $D(x, f_x | \rho, \theta)$ of a point $(x, f_x)$ is used to derive the voting weight in the accumulator, which is given by

![Figure 2: Two-dimensional and one-dimensional LCD images: (a) original LCD image containing a mura defect in the central bottom area; (b) gray-level profiles crossing over defect-free and mura regions; (c) straight line detected by the HT for the scan line 2 in (b); (d) expected straight line for the scan line 2 in (b).](image)
\[ W(x, f_x | \rho, \theta) = \frac{1}{1 + D^k(x, f_x | \rho, \theta)} \]  

where \( k \) is the exponent and is used to adjust the significance of a small change in distance \( D \). It is set at 3 in this study. Note that the weight \( W(x, f_x | \rho, \theta) \) is in the range between 0 and 1. A point lying exactly on the \( \rho - \theta \) line has a maximum weight of 1, whereas the weight is dramatically reduced to 0 as the point is far away from the line.

In order to accommodate the non-stationary nature of the gray-level profile, a point \((x, f_x)\) with distance \( D(x, f_x | \rho, \theta) \) less than a predetermined distance tolerance \( \varepsilon \) is considered as a point on the line with the voting weight defined in eq. (4). Hence

\[ W_x(x, f_x | \rho, \theta) = \begin{cases} 
1 & \text{if } D(x, f_x | \rho, \theta) < \varepsilon \\
0 & \text{otherwise} 
\end{cases} \]

The accumulator then adds the voting weight as

\[ A_x(\rho, \theta) = A_x(\rho, \theta) + W_x(x, f_x | \rho, \theta) \]

At the end of the voting process, the final line equation of the gray-level profile is, therefore, given by the maximum value of \( A_x(\rho, \theta) \), i.e.,

\[ (\rho^*, \theta^*) = \arg \max_{(\rho, \theta)} A_x(\rho, \theta) \]

A synthetic gray-level profile is generated to demonstrate the effectiveness of the proposed Hough transform that uses the distance as the adaptive weight to find a straight line within a given distance tolerance. Figure 3(a) shows the line detection result from the standard Hough transform for the synthetic non-stationary profile. The result indicates the linear trend of the profile cannot be precisely detected. In contrast, Figure 3(b) shows the line detection result from the proposed method. It well performs the detection of linear trend, regardless of the variation along the line.

In defect detection, the proposed Hough transform scheme is used to identify best fitting lines of the oscillated, non-stationary gray-level profiles in a low-contrast image. During the scanning procedure of an inspection image, each column (vertical) and row (horizontal) gray-level profiles are individually evaluated. Any point deviated distinctly from the fitting line is marked as a defect one. For an image of size \( M \times N \), we have to estimate \( M \) gray-level profiles of horizontal rows and \( N \) gray-level profiles of vertical columns in the image. The voting procedure of the proposed HT scheme for the points on the gray-level profile is based on the distance tolerance \( \varepsilon \), i.e., the points need not lie exactly on the line sought.

The standard HT needs only to evaluate all possible values of \( \theta \) in a small finite range, and then \( \rho \) can be calculated by using eq.(1). For the proposed HT method, the line equation (1) cannot be used to calculate the \( \rho \) value for given coordinates \((x, f_x)\) and \( \theta \) values. Therefore, the proposed Hough transform method must evaluate all possible combinations of both \( \theta \) and \( \rho \). This should result in a huge computational burden if all possible combinations of \((\rho, \theta)\) must be evaluated for every point on the gray-level profile. In order to make the proposed Hough transform applicable to defect detection in a manufacturing process, we present a fast selection process that finds the most possible ranges of \( \rho \) and \( \theta \) in the line equation. For a given inspection image, all row gray-level profiles in the image should have the similar trend of a straight-line shape with or without defects on the surface. It is also true for all column gray-level profiles in the image. The core idea for the constraints of \( \theta \) and \( \rho \) values is to evaluate the ranges from a profile map. The profile map is constructed by overlapping all row gray-level profiles (or column profiles) in the \( x - f_x \) plane (or the \( y - f_y \) plane). The most possible ranges of \( \theta \) and \( \rho \) will be extracted from this profile map. The detailed process for searching the ranges of line parameters \( \theta \) and \( \rho \) in the profile map is discussed in the following subsection.

2.2 Constraints on the Line Parameters \( \theta \) and \( \rho \)

The gray-level profiles of the same scan direction in a low-contrast image have approximately the same trend of a
line slope. We can therefore plot all gray-level profiles of the same scan direction on a map which has the gray-level (from 0 to 255 for an 8-bit display) in the vertical axis and the profile point number (0 ~ N -1 in the row and 0 ~ M -1 in the column) in the horizontal axis. Each row (or column) scan image will be overlapped in the x - f_y (or y - f_x) plane to form a profile map. Figure 4 illustrates an image f(x, y) of size M x N. It therefore involves M row profiles and N column profiles. The row profile map in the x - f_x plane is given by

\[ R(x, f_x(x)) = \{ (R(x, f_x(x)) \oplus B) \Theta B \} \]

where \( \oplus \) and \( \Theta \) denote, respectively the dilation and erosion operation, and B is a 3 x 3 structuring element. The binary closing operation smoothes the contour and removes isolated (extreme) points in the profile map. Since the majority of the row gray profiles has similar trend of a line slope, the upper contour \( \hat{R}_u(x) \) and lower contour \( \hat{R}_l(x) \) in the filtered profile map \( \hat{R}(x, f_y(x)) \) are basically identical in shape. In a given inspection image, the defect-free region is generally distinctly larger than the defective region. Therefore, the defect-free line segment in the upper contour \( \hat{R}_u(x) \) will be longer than any of the defective segments. We need only to identify the defect-free line segment from \( \hat{R}_u(x) \) and the possible \( \theta \) range can be easily determined from such a segment.

In this study, we use the fast Haar wavelet decomposition to detect the longest line segment in the upper contour \( \hat{R}_u(x) \) of the filtered profile map. The \( \theta \) range search procedure is proceeded as follows. The upper contour \( \hat{R}_u(x) \) in the filtered profile map \( \hat{R}(x, f_y(x)) \) is given by

\[ \hat{R}_u(x) = \max \{ f_y(x) \mid \hat{R}(x, f_y(x)) \}, \text{ for } x = 0, 1, 2, \ldots, M -1 \]

where \( H(i) \) are the high-pass coefficients of the Haar basis (Burrus et al. 1998), and are given by

\[ H(0) = \frac{1}{\sqrt{2}} \] \[ H(1) = -\frac{1}{\sqrt{2}} \]

\( \hat{d}_u(x) \) is the decomposed detail version of \( \hat{R}_u(x) \), which entails only the fine detail of the upper contour. Note that \( \hat{d}_u(x) \) has the same full length of the original upper contour \( \hat{R}_u(x) \) because the filtered 1D signal is not subsampled. Figure 5(a) illustrates the filtered horizontal profile map of an image, and Figure 5(b) presents its upper contour. Figure
5(c) shows the detailed version of \( \hat{R}_u(x) \) in the wavelet decomposition. In order to extract the dominant line segment that shows significantly linear trend in \( \hat{d}_u(x) \), a simple statistical process control limit is used to set up the threshold. This threshold can effectively detect the transition points (i.e., the points that show significant contour direction changes), and the maximum length between two neighboring transition points is then chosen as the dominant line segment of the gray-level profiles. The threshold is given by

\[
0 + \alpha \cdot \sigma_{\hat{d}(x)}
\]

It is expected that the mean of \( \hat{d}_u(x) \) should be zero, and \( \sigma_{\hat{d}(x)} \) is the standard deviation of the wavelet details. The control constant \( \alpha \) is set at 2 in this study.

Let \( L_{max} \) be the maximum length of continuous points starting from \( x_{start} \) and ending at \( x_{end} \) that fall under the control limit \( \alpha \cdot \sigma_{\hat{d}(x)} \) in the wavelet details \( \hat{d}_u(x) \). The dominant line segment in the upper contour \( \hat{R}_u(x) \) of the row profile map is now restricted within a range between \( (x_{start}, \hat{R}_u(x_{start})) \) and \( (x_{end}, \hat{R}_u(x_{end})) \), the principle angle \( \theta_r \) of all row gray-level profiles in the inspection image can then be estimated by

\[
\theta_r = \tan^{-1}\left(\frac{\hat{R}_u(x_{end}) - \hat{R}_u(x_{start})}{x_{end} - x_{start}}\right)
\]

(6)

Since the line direction of each row gray-level profile could be in the vicinity of the estimated principle angle, a small interval \( \Delta \theta \) is used to tolerantly restrict the search range of \( \theta_r \). The search range of line angle can now be tightly limited to \( \theta_r \pm \Delta \theta \). For mura detection in LCD surface images, the angle interval \( \Delta \theta \) is set at 1° owing to the accurate estimation of the principle angle. The angle search procedure described above can also be used to estimate the principle angle of the column profile map \( C(y, f_X(y)) \).

2.2.2 Range of \( \rho \)

We can now limit the search range of \( \theta \) angle for each gray-level profile from the profile map. The range of distance \( \rho \) from the line to the origin needs also to be restricted. For a given angle \( \theta_r \) in the row profile map, the range of distance \( \rho_x \) must be limited between upper contour \( \hat{R}_u(x) \) and lower contour \( \hat{L}_u(x) \). The lower contour \( \hat{L}_u(x) \) in the filtered profile map \( \hat{R}(x, f_Y(x)) \) is given by

\[
\hat{L}_u(x) = \min\{f_Y(x) \mid \hat{R}(x, f_Y(x))\}, \quad x = 0, 1, 2, \ldots, N - 1
\]

For the dominant line segment with starting point \( x_{start} \) and ending point \( x_{end} \) found in the subsection above, the search range of \( \rho_x \) can now be easily estimated from eq. (1). The upper limit \( \rho_{max} \) and lower limit \( \rho_{min} \) of parameter \( \rho_x \) are given by

\[
\rho_{max} = x_{end} \cdot \cos(\theta_x - \Delta \theta) + \hat{R}_u(x_{end}) \cdot \sin(\theta_x - \Delta \theta),
\]

\[
\rho_{min} = x_{start} \cdot \cos(\theta_x + \Delta \theta) + \hat{R}_u(x_{start}) \cdot \sin(\theta_x + \Delta \theta)
\]

The upper limit \( \rho_{max} \) and lower limit \( \rho_{min} \) have tightly limited the search ranges of parameter \( \rho_x \) from the dominant line segment. Figure 6 illustrates the proposed method to determine the search range of distance \( \rho \) in the...
row profile map. Once the search ranges of $\rho$ and $\theta$ are determined, the voting weight $W(x, f_x | \rho, \theta)$ in eq. (4) can be efficiently calculated.

### 2.2.3 Defect detection

Let $(\rho^*, \theta^*)$ be the estimated line parameter values of a row gray-level profile $Y$. A point $(x, f_x(x))$ in the gray-level profile $Y$ will be distinguished between defect and normal one by calculating the distance $D(x, f_x(x) | \rho^*, \theta^*)$ from point $(x, f_x(x))$ to the $\rho^*$ - $\theta^*$ line using eq. (3). If the distance $D$ is significantly large than a distance threshold, then the point $(x, f_x(x))$ is classified as a defect point. The simple statistical process control (SPC) is applied to set up the threshold. The control limit (i.e. threshold) used to identify defect points is therefore given by

$$
\mu_{\rho\nu} + \beta \cdot \sigma_{\rho\nu}
$$

where $\mu_{\rho\nu}$ is the mean and $\sigma_{\rho\nu}$ is the standard deviation of distance $D(x, f_x(x) | \rho^*, \theta^*)$ for all points on the gray-level profile $Y$. Note that the distance threshold is adaptively calculated for each individual gray-level profile.

In the experiment, the control constant $\beta$ is empirically given by 3 for all gray-level profiles. A defect point will be set at 1 (shown in black) if the distance larger than the control limit, while a defect-free one will be set at 0 (shown in white) in the resulting binary image. The detection result from the row gray-level profiles then appears as a binary image $B_{\rho\nu}(x, Y)$. That is

$$
B_{\rho\nu}(x, Y) = \begin{cases} 
1 & \text{if } D(x, f_x(x) | \rho^*, \theta^*) > \mu_{\rho\nu} + \beta \cdot \sigma_{\rho\nu} \\
0 & \text{otherwise}
\end{cases}
$$

Since the defect points detected in either row or column gray-level profiles are considered as defective pixels in the original 2D image, the final detection result of mura defects is given by the union of the two binary images

$$
B(x, y) = B_{\rho\nu}(x, y) \cup B_{\theta\nu}(x, y)
$$

where $B_{\rho\nu}(x, y)$ and $B_{\theta\nu}(x, y)$ are the resulting binary images from row and column gray-level profiles, respectively.

Compared with the standard Hough transform, the proposed Hough transform scheme gives a better straight-line detection for non-stationary profiles in unevenly-illuminated images. It can well detect the mura segment that is evidently deviated from the fitting line. By restricting the search ranges of the two line parameters in very tight limits based on the common linear trend of gray-level profiles in a given LCD image, the proposed method can efficiently detect the best fitting line. The computational burden can then be reduced significantly.

### 3. EXPERIMENT RESULTS

This section presents the experimental results on a number of low-contrast images which contain various mura defects in LCDs to evaluate the performance of the proposed defect detection scheme. The LCD images used for testing are categorized into micro- and macro-view samples. A micro-view (high-resolution) LCD image shows orthogonal data lines and gate lines on the panel, and results in a structural texture pattern on the surface. A macro-view LCD image gives a coarser resolution of the LCD surface, in which no texture is present on the surface. Both types of LCD images involve low-contrast mura defects in unevenly-illuminated surfaces. All of the test images are 200×200 pixels wide with 8-bit gray-levels. That is, a two-dimensional (2D) test image comprises 200 one-dimensional (1D) line images, each of the length 200 pixels, in both horizontal and vertical scan directions. All the test images conducted in the experiment are captured from real LCD panels.

In order to present the effectiveness of the proposed method, the final detection results shown in the figures are not refined with any post-processing operations to remove noise or connect blobs. The proposed algorithms were implemented on Intel Core 2, 1.87GHz CPU personal computer. In the experiment of macro-view LCD images, the mean computation time of the proposed method is 0.696 seconds including the detection of both row and column gray-level profiles in a 200×200 image.

In the subsequent experiments in subsections 3.1 and...
3.2, the distance tolerance \( \varepsilon \) is given by a constant 2. Because the principle angle can be well estimated using eq. (6), the angle interval width \( \Delta \theta \) is tightly set at 1° and the control constant \( \beta \) of the statistical control limit is set at 3 for defect detection. All the parameter values of \( \varepsilon \), \( \Delta \theta \) and \( \beta \) are the same for all test samples in the experiments.

### 3.1 Macro-View Mura Images With Uneven-Lighting Background

The LCD panel in a macro-view image shows no textured pattern, and presents only a surface with uneven illumination. Figure 7(a1) shows a faultless LCD surface image, and Figures 7(b1)-(e1) present four defect images containing white spot-mura (Figures 7(b1)), dark spot-mura (Figures 7(c1)), gravity-mura (Figures 7(d1)), and line-mura (Figures 7(e1)). Figures 7(a2)-(e2) show the respective enhanced images by linearly stretching the original intensities between 0 and 255 for an 8-bit display. In the proposed method, horizontal and vertical gray-level profiles are detected separately. Therefore, Figures 7(a3)-(e3) are the detection results \( B_s(x, y) \) from row gray-level profiles for the respective LCD images in Figures 7(a1)-(e1), and Figures 7(a4)-(e4) are the detection results \( B_c(x, y) \) from the column gray-level profiles. Figure 7(a5)-(e5) are the final detection results \( B(x, y) \) from the union of \( B_s(x, y) \) and \( B_c(x, y) \) in Figures 7(a3)-(e3) and 7(a4)-(e4). The proposed method can well detect local defects in unevenly-illuminated images for small mura sizes, such as spot- and line-mura. Even the hardly distinguishable gravity mura that contains a large area in the image is also reliably detected and the defective region is accurately segmented.

Semiconductor Equipment and Materials International (SEMI) defines a measurement index, called SEMU (SEMI Mura), to evaluate the quantitative value of mura based on the area and contrast. The SEMU is defined as (SEMI D31-1102 2005):

\[
\text{SEMU index} = \frac{|C|}{1.97S^{0.33} + 0.72}
\]

where \( C \) is the average contrast of mura with respect to its surrounding background (unit: \%); \( S \) is the surface area of mura being measured (units: mm\(^2\)). The SEMU index is low when the mura is small in size with a very low contrast from its surrounding background. Table 1 summarizes the SEMU values for the white-spot, dark-spot, gravity-mura and line-mura, respectively; (a2)-(e2) respective enhanced images; (a3)-(e3) detection results \( B_s(x, y) \) of row gray-level profiles; (a4)-(e4) detection results \( B_c(x, y) \) of column gray-level profile; (a5)-(e5) the union of \( B_s(x, y) \) and \( B_c(x, y) \).

<table>
<thead>
<tr>
<th>Mura</th>
<th>( C )</th>
<th>( S ) (mm(^2))</th>
<th>SEMU index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Figure 7(b1) white-spot</td>
<td>1.1632</td>
<td>391.33</td>
<td>1.1635</td>
</tr>
<tr>
<td>Figure 7(c1) black-spot</td>
<td>0.9434</td>
<td>308.00</td>
<td>0.9273</td>
</tr>
<tr>
<td>Figure 7(d1) gravity-mura</td>
<td>1.1827</td>
<td>5658.33</td>
<td>1.4185</td>
</tr>
<tr>
<td>Figure 7(e1) line-mura</td>
<td>1.0645</td>
<td>386.00</td>
<td>1.0607</td>
</tr>
</tbody>
</table>

This table shows that the SEMU indexes are only around 1 for the four hardly identifiable mura defects. The proposed method can reliably detect the low-contrast mura.

### 3.2 Micro-View Mura Images With Textured Background
Figure 8: Effects of textured LCD images with and without smoothing: (a) original image; (b) enhanced image of (a); (c) a row gray-level profile of (a); (d) a column gray-level profile of (a); (e) median filtering result of (a); (f) the corresponding row gray-level profile in (e); (g) the corresponding column gray-level profile in (e).

The micro-view LCD images under a higher image resolution show both a regular textured pattern and uneven-lighting background on the surface. All these increase the difficulty for mura detection in low-contrast images. Figure 8(a) shows the original gray-level image of a micro-view LCD panel that contains a region-mura on the left margin of the image. The enhanced image, as seen in Figure 8(b), clearly displays the textured pattern and the mura defect.

In the textured images (the data lines and gate lines on the LCD panel), the periodical data lines (or gate lines) generate large amplitudes in the periodic gray-level profiles, as seen in Figure 8(c) and (d). The oscillation increases the difficulty of line detection and also increases the computation loading since large interval widths of $\Delta \theta$ and $\Delta \rho$ are required. For a textured LCD image, we first used a $3 \times 3$ median filter to smooth the original LCD image so that the periodical texture pattern can be reduced. Figure 8(e) depicts the smoothing result of the LCD image in Figure 8(a). It can be seen from Figures 8(f) and (g) that the gray-level profiles with high amplitude oscillation in the original images have been effectively smoothed. The trend of a line shape is well preserved in the smoothed gray-level profiles and the interval widths $\Delta \theta$ and $\Delta \rho$ for the possible ranges of line parameters $\rho$ and $\theta$ can also be efficiently reduced to narrow intervals.

Figures 9(a1) and (b1) show two faultless LCD images and Figures 9(c1)-(f1) display four defective LCD images, in which the texture pattern and uneven-lighting background are present in the panel surfaces. The respective enhanced images in Figures 9(a2)-(f2) clearly display the texture patterns and the mura regions. Figures 9(a3)-(f3) are the detection results $B(x, y)$ from the row gray-level profiles, and Figures 9(a4)-(f4) are the detection results $B(x, y)$ of column gray-level profiles; (a5)-(f5) the union of $B(x, y)$ and $B_c(x, y)$.

In the experiments, the proposed Hough transform scheme has shown its efficacy to detect the low-contrast defects in an uneven background. It can well detect defects in both low-resolution and high-resolution images of LCD
panels. The same parameter setup of $\varepsilon$, $\Delta \theta$ and $\Delta \rho$ can be used for various inspection images.

**CONCLUSION**

The proposed method constructs separately two profile maps by overlapping the row and column gray-level profiles in an image to find the most possible ranges of the line parameters. This strategy can efficiently reduce the computational complexity of the proposed Hough transform process. The proposed method currently concentrates on one-dimensional gray-level profiles for the inspection of mura defects in LCD panel surfaces. It is believed that the proposed method can be applied in general for the inspection of arbitrary low-contrast, unevenly-illuminated surfaces. The proposed Hough transform scheme in its present form only considers non-stationary straight-line detection. It is worth to extend the proposed approach for defect detection in non-stationary curved profiles and non-stationary linear/curved surfaces.

**REFERENCES**


**AUTHOR BIOGRAPHIES**

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