AN AUTOMATED AND RAPID DEFECT INSPECTION ALGORITHM FOR FLUORESCENT PDP PATTERNS

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ABSTRACT

Plasma display panels (PDPs) represent the next generation of visual display in the new century. Relative to traditional CRTs, PDPs offer advantages such as providing clearer images and occupying less space. The quality control of the PDP in the production line is very important to minimize costs and maximize product quality. Although there are several different kinds of patterns that need to be inspected, this research will present algorithms used for fluorescent pattern inspection of PDPs. Here, a complete design and implementation of a sequence of algorithmic components necessary to identify fluorescent pattern PDP defects is described. A primary criterion is that the maximum time allowed for the entire analysis is only a few seconds, so each component must execute rapidly and efficiently.

1. INTRODUCTION

Over the past few years machine vision has consolidated its early promise and has become a vital component in the design of advanced manufacturing systems. An important application of machine vision – automated assembly line inspection – can be performed using vision systems employing dedicated algorithms. An obvious use of inspection is to check products for quality so that defective ones may be rejected or modified to satisfy a quality index. Also, one can measure specific parameters for each defect pattern to classify the cause of a particular defect. V-Technology is a high technology Japanese-based company with expertise in the field of plasma display panel (PDP) defect inspection instrumentation. This company is actively developing a colour PDP inspection system.

All colours can be created with the primary colours of red, green, and blue (RGB). This is called the additive colour property, and this process works for the mixing of primary colour sources emitting light. The red, green, and blue colours make up a colour space (or colour gamut) that can be represented by a cube. As a result, any colour image can be separated into those three channels. Figures 1 to 4 illustrate the RGB channels for a given fluorescent pattern PDP image. Note the defect near the centre of the image. The objective is to design robust algorithms for detection and assessment of such defects.

There are four design components necessary to achieve the overall goal of classifying defects in fluorescent pattern PDPs. These will be discussed in their order of implementation: (1) automatic binarization, (2) run length encoding for defect inspection, and (3) Fourier descriptor for blob analysis.

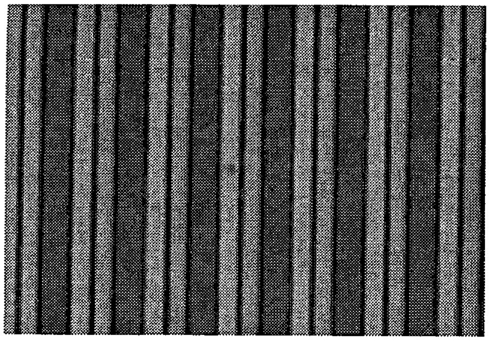

Figure 1 – Fluorescent colour PDP image.

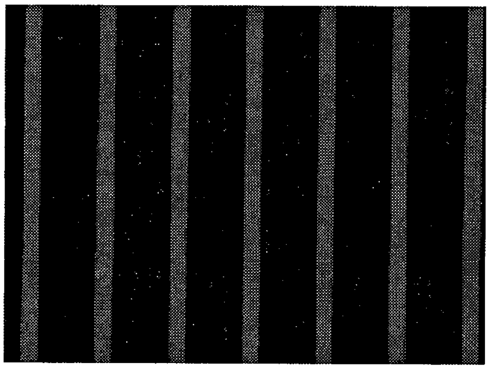

Figure 2 – Red component of Figure 1.

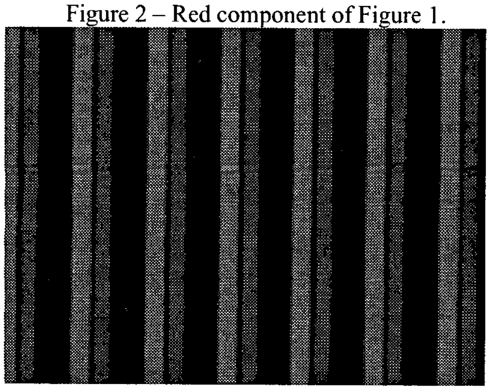

Figure 3 – Green component of Figure 1.

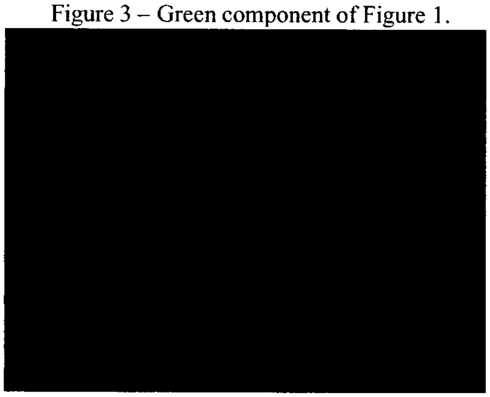

Figure 4 – Blue component of Figure 1.

2. METHODOLOGY AND TESTING

2.1. Automatic Binarization

Automatic binarization of the image is the basic method of image segmentation. The method introduced here is based on the cluster separation according to the maximum separability value for the threshold selection given the image histogram. The separability of the image cluster separation is defined in a continuous sense as:

$$\eta(t) = \frac{\sigma_B^2(t)}{\sigma_T^2}$$

where $\sigma_B^2(t)$ and σ_T^2 represent the variance of the two clusters and the image respectively. Since σ_T^2 is a constant for the image, the maximum of the $\eta(t)$ is based on the maximum of $\sigma_B^2(t)$. Briefly, the term $\sigma_B^2(t)$ can be represented discretely by a binary weighted function:

$$\sigma_B^2(k) = \omega_0(\mu_0 - \mu_T)^2 + \omega_1(\mu_1 - \mu_T)^2$$

$$N = \sum_{i=1}^{255} n_i \quad , \quad p_i = \frac{n_i}{N}$$

$$\omega_0 = \sum_{i=1}^{k} p_i \quad , \quad \omega_1 = \sum_{i=k+1}^{255} p_i$$

$$\mu_0 = \sum_{i=1}^{k} \frac{ip_i}{\omega_0} \quad , \quad \mu_1 = \sum_{i=k+1}^{255} \frac{ip_i}{\omega_1}$$

$$\mu_T = \sum_{i=1}^{255} ip_i$$

where:

Finally, the variance of the clusters can be expressed as:

$$\sigma_B^2(k) = \frac{\left[\sum_{i=1}^{k} in_i\left(1 - \frac{1}{N}\sum_{i=1}^{k} n_i\right) - \sum_{i=k+1}^{255} in_i \frac{1}{N}\sum_{i=1}^{k} n_i\right]^2}{N^2 \frac{1}{N}\sum_{i=1}^{k} n_i\left[1 - \frac{1}{N}\sum_{i=1}^{k} n_i\right]}$$

The k for which $\sigma_B^2(k)$ is maximum is the appropriate index as the threshold for binarization of the image. Figures 5 to 7 show representative results for the binarization of Figures 2 to 4.

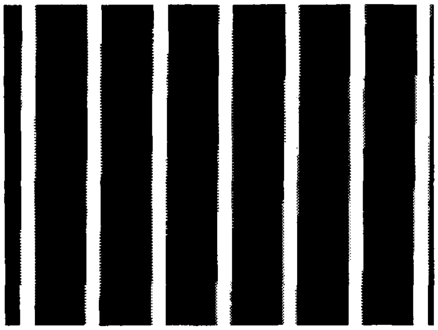

Figure 5 – Red binary image.

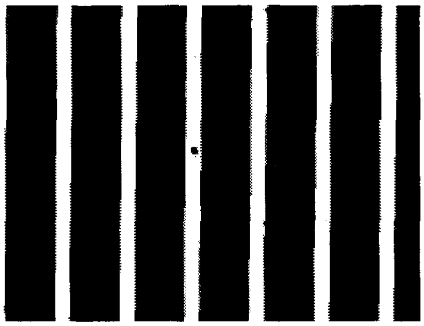

Figure 6 – Green binary image.

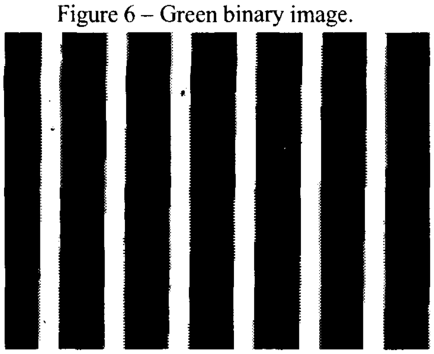

Figure 7 – Blue binary image.

2.2. Run length encoding for defect inspection

Run length encoding is a lossless entropy coding technique often used for image compression. Across each line of an image, pixel brightnesses are sequentially compared and grouped together into runs of identical brightness. The resulting compressed image data is composed of a series of paired brightness and run length values. Each brightness value represents the number of pixels in the run. For example, a run of 25 pixels with the same brightness of 176 would be coded as 176:25. The 25 original image bytes are replaced with two run length coded bytes.

The run length technique is used here to assist identification of any defects found in the binary image. A histogram can be formed that represents the total number of times a certain row count is made of one of the binary values. The x-axis of the histogram represents the total possible values for the given run length ie. it will range from zero to the number of columns in the image. Figures 8, 9, and 10 illustrate the process used to locate defects using run length coding. Since straight vertical lines are expected in this type of image, a defect-free image would have all the run length codes with approximately the same value. Rows which contain defects will have a different value in the histogram and this can be used to locate the defect for the given binary image. Figure 11 illustrates the combined result for the images in Figure 6, 7, and 8.

Figure 8 – Example original pattern.

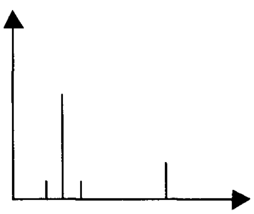

Figure 9 – Run length encoding histogram.

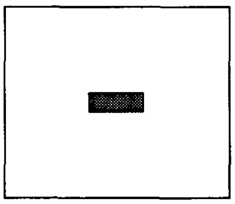

Figure 10 – Locating the defect.

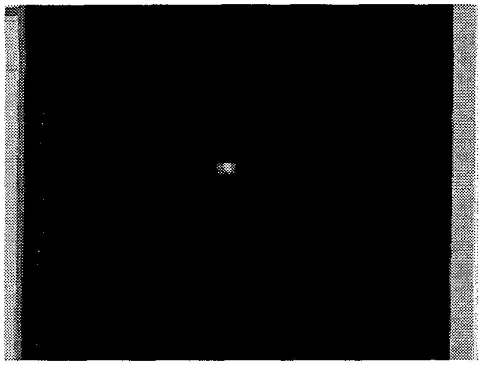

Figure 11 – Result for given images (RGB).

2.3. Fourier Descriptor for blob analysis

A quantitative means for extracting shape information for the resulting blobs in the given images is required. Many object shape measures exist and Fourier descriptors is a method that will be employed here. This technique creates concise object boundary representations using the Fourier transform. The resulting boundary description can be generated with an arbitrary range of accuracy from coarse to fine.

The Fourier descriptor method treats the (x, y) points of an object outline as a function and decomposes this relationship into values representing frequency components. These values are called the Fourier descriptors of the boundary. This process operates mathematically on an image very much like the Fourier transform. The frequency-transformed values (the Fourier descriptors) relate to the physical nature of the object boundary. The boundary representation described by Fourier descriptors can be a compact means for describing object boundary shape.

A mathematical model of the Fourier descriptor can be introduced as followings. We define C as the boundary of the region, which is the simple closed curve in the normal case. s is the arc length from the starting point b_0 to the movement point b in the curve C. S is the girth of the boundary curve C.

The coordinate $b(x(s), y(s))$ of the moving point b is both a function of (x, y) and a function of girth S. The intrinsic function of the curve can be expressed in the form of a complex number:

$$U(s) = x(s) + j\, y(s)$$

Since this is a periodic function ie.

$$U(s + S) = U(s) \text{ for } 0 < s < S$$

then setting $t = 2\pi s/S$ produces:

$$U(t) = x(t) + j\, y(t) \text{ for } 0 < t < 2\pi$$

where $U(t)$ is a periodic function with a period 2π. The Fourier expansion formula is:

$$U(t) = \sum_{-\infty}^{+\infty} P_n e^{jnt}$$

$$= P_0 + \sum_{n=1}^{\infty} (P_n e^{jnt} + P_{-n} e^{-jnt}) \quad \text{for } 0 < t < 2\pi$$

and the Fourier coefficients are defined as:

$$P_n = \frac{1}{2\pi} \int_0^{2\pi} U(t)\, e^{-jnt}\, dt \quad \text{for } n = 0, \pm 1, \pm 2, \ldots$$

The Fourier coefficients can be computed using the boundary chain code. In a digital image, the boundary contour of the region is often expressed by a 8 directional chain code $\{c_i = 0, 1, \cdots, 7\}$. Here, the chain is constructed along the curve in a counter-clockwise direction.

The girth of the curve is defined by:

$$S = \sum_{k=1}^{M} a_k$$

where

$$a_k = \begin{cases} 1 & \text{if } c_k \text{ is even} \\ \sqrt{2} & \text{if } c_k \text{ is odd} \end{cases}$$

so the P_n can be expressed as,

Color	ID	Area	girth	Xc	Yc	ΔX	ΔY
Red	Notice: There are no defects for red channel image						
Green	1	108	35.14	221.13	298.61	13	10
Blue	1	39	19.49	93.70	266.58	8	6
	2	7	5.83	103.90	67.24	3	3
	3	7	5.41	146.55	69.92	3	3
	4	7	5.83	439.17	58.00	3	3
	Unit: Pixels Area: defect area Girth: surround length of the defect Xc, Yc: FD center of the defect ΔX , ΔY : defect size						

Figure 12. Blob analysis results with the help of Fourier Descriptor method

$$P_n = \frac{1}{2n\pi j} \sum_{m=1}^{M} a_m \cdot \exp(j\left[\frac{\pi}{4} c_m - 2n\pi \frac{\sum_{k=1}^{m} a_k}{\sum_{k=1}^{M} a_k}\right])$$

The Fourier coefficients P_n have a relationship with the boundary chain code c_k , while a_k also only depends on c_k . Therefore, we can compute the Fourier coefficients with the help of the boundary chain code. P_0 defines the center position of the boundary curve. The coefficients P_n and the contour curve C have a relationship and correspond to each other. Figure 12 displays results.

3. SUMMARY

The described algorithm has been implemented in a real-world system for the purposes of characterizing defects in fluorescent PDP images. The technique has demonstrated robustness by successfully being applied to a wide variety of imagery captured in the analysis process.

The automatic binarization method can be used to segment any digital image into two regions. This technique requires no user parameters. Based on our experiments, the automatic binary method is successful in most cases for the PDP image, even when the images have very low contrast.

The run length encoding method is used successfully to identify the location of defect in the image. This algorithm has provided a consistent means to perform this task.

Fourier descriptor method is an appropriate method for blob analysis in binary image patterns. The computational speed is not as fast as some other methods, since the Fourier transformation must be performed. The slightly slower speed is not of critical concern due to the higher processing speeds available in today's host processors. In addition, the Fourier descriptive method generate features that uniquely identify the blobs of interest. method can give the detail information for blob analysis.

The algorithms such as Fourier descriptor method discussed in the report are available for V-Technology in standard C functions, but not for others. The run length encoding algorithm will be realized by hardware. The logical design here is also used for automatic defect classifications (ADC). The defect judgements or modifications also can be completed with the help of the algorithms discussed here.

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