Automated defect inspection of light-emitting diode chips using neural network and statistical approaches

Hong-Dar Lin

Department of Industrial Engineering and Management, Chaoyang University of Technology, 168 Jifong E. Rd., Wufong Township, Taichung County, 41349, Taiwan
TEL: 886-4-2332-3000 Ext.4258; FAX: 886-4-2374-2327
E-mail: hdlin@cyut.edu.tw

Abstract

This research explores the automated visual inspection of surface blemishes that fall across two different background textures in a light-emitting diode (LED) chip. Water-drop defects, commonly found on chip surface, impair the appearance of LEDs as well as their functionality and security. Automated inspection of a water-drop defect is difficult because the blemish has a semi-opaque appearance and a low intensity contrast with the rough exterior of the LED chip. Moreover, the blemish may fall across two different background textures, which further increases the difficulties of defect detection. The one-level Haar wavelet transform is used to decompose a chip image and extract four wavelet characteristics. Then, wavelet-based neural network (WNN) and wavelet-based multivariate statistical (WMS) approaches are proposed individually to integrate the multiple wavelet characteristics. Finally, the back-propagation algorithm of WNN and $T^2$ test of WMS individually judge the existence of water-drop defects. Experimental results show that both of the proposed methods achieve above 95% and 92% detection rates and below 7.5% and 5.8% false alarm rates, respectively.

Keywords: Defect inspection, LED chip, Wavelet characteristics, Neural network model, Multivariate statistical analysis.
1. Introduction

A light-emitting diode (LED) is a semiconductor device that emits visible light when an electric current passes through the semiconductor chip. Compared with incandescent and fluorescent illuminating devices, LEDs have lower power requirement, higher efficiency, and longer lifetime. Typical applications of LED components include indicator lights, LCD panel backlighting, fiber optic data transmission, etc. The basic structure of an LED consists of the light emitting semiconductor chip, a lead frame where the chip is actually placed, and the encapsulation epoxy which surrounds and protects the chip. Figure 1 shows the basic LED structure and an LED product. To meet consumer and industry needs, LED products are being made in smaller sizes, which increase difficulties of product inspection.

Surface defects impair the appearance of LED chips as well as their functionality and security. As inspecting surface defects by human eyes is ineffective and inefficient, this research aims to develop an automated vision system for detecting one common type of surface blemishes of LED chips, water-drop defects formed by the steam generated during the production process. Automated inspection of a water-drop blemish is difficult because the blemish has a semi-opaque appearance and a low intensity contrast with the rough exterior of the LED chip. With a width of 12.6 µm, an LED chip comprises an aluminum-
pad (bonding pad) in the central area and a metal oxide semiconductor (emitting area) in the outer area, as shown in Fig. 2 (a). Texture of the central area has a random pattern while that of the outer area has a uniform appearance. A water-drop defect may fall across the two areas of significantly different textures, which further increases the difficulties of defect detection. Figure 2 (b) and (c) display the LED chip images with water-drop blemishes of different shapes.

Figure 2 should be here

Inspection of surface defects has become a critical task for manufacturers who strive to improve product quality and production efficiency (Huang, 2007; Wen, & Tao, 1999). Defect detection techniques, generally classified into the spatial domain and the frequency domain, compute a set of textural features in a sliding window and search for significant local deviations among the feature values. Siew et al. (1988) applied the co-occurrence matrix method, a traditional spatial domain technique, to assess carpet wear by using two-order gray level statistics to build up probability density functions of intensity changes. For another spatial domain example, Latif-Amet et al. (2000) presented wavelet theory and co-occurrence matrices for detection of defects encountered in textile images and classify each sub-window as defective or non-defective with a Mahalanobis distance.

As to techniques in the frequency domain, Tsai and Hsiao (2001) proposed a multi-resolution approach for inspecting local defects embedded in homogeneous textured
surfaces. By properly selecting the smooth sub-image or the combination of detail sub-images in different decomposition levels for backward wavelet transform, regular, repetitive texture patterns can be removed and only local anomalies are enhanced in the reconstructed image. Tsai and Wu (2000) adopted Gabor transform to determine three texture features (scale, frequency and orientation) and use Gabor energy differences to discriminate defect locations. Also, Lin and Ho (2005) developed a novel approach that applies discrete cosine transform based enhancement for the detection of pinhole defects on passive component chips.

Regarding defect detection applications in the electronic industry, Lin and Chiu (2006) used multivariate Hotelling $T^2$ statistic to integrate different coordinates of color models for MURA-type defect detection on Liquid Crystal Displays (LCD), and applied ant colony algorithm and back-propagation neural network techniques to develop an automatic inspection procedure. Lu and Tsai (2004) proposed a global approach for automatic visual inspection of micro defects such as pinholes, scratches, particles and fingerprints. The Singular Value Decomposition (SVD) adopted by Lu and Tsai suits the need for detecting defects on the TFT-LCD images of highly periodical textural structures. Furthermore, in the recent decade, many vision systems have been developed for the inspection of surface defects on semiconductor wafers (Maruo et al., 1999; Shankar, & Zhong, 2005, 2006). For instance, Fadzil and Weng (1998) implemented a vision inspection system that achieves a 90% probability of accurately classifying defects, scratches, contamination, blemishes, off center defects, etc. in the encapsulations of diffused LED products.

The aforementioned techniques perform well in anomaly detection, but most of them do not detect defects with the properties of water-drop blemishes. This research has been
motivated by the need for an efficient and effective technique that detects semi-opaque and low-intensity-contrast water-drop defects falling across two different background textures.

2. Proposed Methods

To detect water-drop defects of LED chips, this research adopts the one-level Haar wavelet transform to conduct image transformation and extract wavelet characteristics. We apply the wavelet-based neural network and multivariate statistical approaches to integrate multiple wavelet characteristics and then develop the back-propagation algorithm of neural network model and $T^2$ test of multivariate statistical analysis to individually judge the existence of water-drop defects in LED chip images.

2.1. Wavelet decomposition and characteristics

Wavelet transform provides a convenient way to obtain a multi-resolution representation, from which texture features can be easily extracted. The merits of using wavelet transform include local image processing, simple calculations, high speed processing and multiple image information (Arivazhagan, & Ganesan, 2003; Bashar, Matsumoto, & Ohnishi, 2003). The Haar wavelet transform is one of the simplest and basic wavelet transformations (Gonzalez, & Woods, 2002). A standard decomposition of a two-dimensional image can be done by first applying the 1-D Haar wavelet transform to each row of pixel values, treating these transformed rows as if they were themselves an image, and then performing another 1-D wavelet transform to each column. The Haar transform can be computed stepwise by the mean value and half of the differences of the
tristimulus values of two contiguous pixels. Based on the transfer concept of the 1-D space, the Haar wavelet transform can process a 2-D image of \((M \times N)\) pixels in the following way:

Row transfer:

\[
\begin{align*}
    f_s(i, j) &= \frac{f(i, 2j) + f(i, 2j+1)}{2}, \\
    f_s(i, j+\left\lfloor\frac{N}{2}\right\rfloor) &= \frac{f(i, 2j) - f(i, 2j+1)}{2}, \\
    \text{where } 0 \leq i \leq (M-1), 0 \leq j \leq \left\lfloor\frac{N}{2}\right\rfloor - 1, \text{ is Gauss symbol.}
\end{align*}
\]

Column transfer:

\[
\begin{align*}
    f_c(i, j) &= \frac{f(i, 2j) + f(i, 2j+1)}{2}, \\
    f_c(i+\left\lfloor\frac{M}{2}\right\rfloor, j) &= \frac{f(i, 2j) - f(i, 2j+1)}{2}, \\
    \text{where } 0 \leq i \leq \left\lfloor\frac{M}{2}\right\rfloor - 1, 0 \leq j \leq (N-1).
\end{align*}
\]

In the above expressions (Eq. (1)), \(f(i, j)\) represents an original image, \(f_s(i, j)\) the row transfer function of \(f(i, j)\), and \(f_c(i, j)\) the column transfer function of \(f_s(i, j)\). As \(f_c(i, j)\) is also the outcome of the wavelet decomposition of \(f(i, j)\), the outcomes of a wavelet transform can be defined as:

\[
\begin{align*}
    A(i, j) &= f_c(i, j); \\
    D_1(i, j) &= f_c(i, j+\left\lfloor\frac{N}{2}\right\rfloor); \\
    D_2(i, j) &= f_c(i+\left\lfloor\frac{M}{2}\right\rfloor, j); \\
    D_3(i, j) &= f_c(i+\left\lfloor\frac{M}{2}\right\rfloor, j+\left\lfloor\frac{N}{2}\right\rfloor); \\
    \text{where } 0 \leq i \leq \left\lfloor\frac{M}{2}\right\rfloor - 1, 0 \leq j \leq \left\lfloor\frac{N}{2}\right\rfloor - 1.
\end{align*}
\]

One level of wavelet decomposition generates one smooth sub-image and three detail sub-images that contain fine structures with horizontal, vertical, and diagonal orientations. An image is decomposed by wavelet transform into one approximation sub-image \((A)\) and three detail sub-images \((D_1, D_2 and D_3)\). These four sub-images, each of which has a size of \((M/2 \times N/2)\) pixels, form the wavelet characteristics.

2.2. Wavelet-based Neural Network Approach

The wavelet-based neural network (WNN) approach decomposes an image of \((M \times N)\) pixels into a set of sub-images, each of which has a size of \((m \times n)\) pixels and is a wavelet processing unit. The original image has \(g \times h\) (i.e. \(M/m \times N/n\)) wavelet processing units.
For each wavelet processing unit, the wavelet transform can be applied to the region of \((m \times n)\) pixels to obtain four wavelet characteristics \(A, D_1, D_2\) and \(D_3\) through calculations. This research uses the MLP (Multi-Layer Perceptron) neural network with back-propagation algorithm (Kameyama et al., 1998; Kang, & Park, 2000; Chen, & Liu, 2000) to detect defective regions containing water-drop blemishes. We use the four wavelet characteristics as the inputs of the neural network model to identify the regions with water-drop defects. The four wavelet characteristics describe the surface variations of gray level uniformity.

The proposed method uses four wavelet characteristics of a wavelet processing unit as the input values of the MLP neural network model. If the size of a wavelet processing unit is 2x2 pixels, an image of 256 x 256 pixels will have 16,384 sets of wavelet characteristics. Each set of the wavelet characteristics can be judged as in-control or out-of-control. The output layer of the network uses 0 and 1 to represent the in-control and out-of-control decisions. The data of input patterns must be scaled first. The linear transformation is used to set the range of the input values between \([0, 1]\) to avoid extreme values from affecting the network training results.

Some parameters of the network model, such as learning rate \((\eta)\), training number, errors, and number of hidden layer nodes, need to be carefully set to achieve good model performance. Uniformly distributed random numbers which range between \([-1, 1]\) are used to set interconnected weights and biased weight vectors \((\theta)\) for the training patterns of the model. Sigmoid function is used in the model and the numerical range is between \([0, 1]\).

\[
f(x) = \frac{1}{1 + e^{-\text{net}_j}} \quad (3)
\]

The standard energy function below is used to calculate the variation between expected output and network output.
\[ E = \frac{1}{2} \sum (T_j - Y_j)^2 \] (4)

The stop criterion of the proposed model is based on the proposition of Hush and Horne (1993), who used methods of Root Mean Square Error and fixed learning cycles to set the parameters. Figure 3 shows the network structures of the proposed model.

---

2.3. Wavelet-based Multivariate Statistical Approach

The wavelet-based multivariate statistical (WMS) approach decomposes an image of \((M \times N)\) pixels into a set of sub-images, each of which has a size of \((m \times n)\) pixels and is a multivariate processing unit. The original image has \(g \times h\) (i.e. \(M/m \times N/n\)) multivariate processing units, each of which can be further decomposed into \(a \times b\) wavelet processing units. For each wavelet processing unit, the wavelet transform can be applied to the region of \((m/a \times n/b)\) pixels to obtain four wavelet characteristics \(A, D_1, D_2, D_3\) through calculations. The multivariate statistic \(T^2\) integrates the multiple wavelet characteristics into a \(T^2\) value for each multivariate processing unit. This \(T^2\) value can be regarded as a distance value of a multivariate processing unit. The larger the \(T^2\) statistic value, the more distinctive the region is from the normal area. Thus, the more easily the region can be judged as defective.

The proposed wavelet based approach assumes that the size of a multivariate processing unit is \(4 \times 4\) (i.e. \(m \times n\)) pixels and the size of a wavelet processing unit is \(2 \times 2\) (i.e. \(a \times b\))
pixels. One multivariate processing unit will have 2 x 2 (i.e. \(m/a \times n/b\)) wavelet processing units. That is, four wavelet processing units \(C(x_a, y_b)\) can be defined as one multivariate processing unit \(M(x, y)\), where \(a\) and \(b\) are integers and \((1 \leq a, b \leq 2)\). The corresponding spatial coordinates of \(C(x_a, y_b)\) are a square with size 2 x 2 pixels from \(f(4 \times x + a, 4 \times y + b)\) to \(f(4 \times x + a + 1, 4 \times y + b + 1)\). Thus, one \(M(x, y)\) includes four \(C(x_a, y_b)\), which are \(C(x_1, y_1)\), \(C(x_1, y_2)\), \(C(x_2, y_1)\) and \(C(x_2, y_2)\). One \(C(x_a, y_b)\) can be decomposed by wavelet transform to obtain one approximated characteristic \(A(x_a, y_b)\) and three detail characteristics \(D_1(x_a, y_b)\), \(D_2(x_a, y_b)\) and \(D_3(x_a, y_b)\).

The calculation formulas of a multivariate control procedure (Hotelling, 1947; Lowry, & Montgomery, 1995; Montgomery, 2005) can be rewritten as Eqs. (5) to (10) to represent a multivariate process of images.

\[
\bar{X}_{M(x, y)} = \left[ \frac{1}{a \times b} \sum_{i=1}^{a} \sum_{j=1}^{b} X_{C(x_i, y_j), p} \right]_{p=1} \tag{5}
\]

\[
\bar{X} = \left[ \frac{1}{g \times h} \sum_{i=0}^{g-1} \sum_{j=0}^{h-1} \bar{X}_{M(i, j), p} \right]_{p=1} \tag{6}
\]

\[
S^2_{M(x, y), p} = \frac{1}{a \times b - 1} \sum_{i=1}^{a} \sum_{j=1}^{b} \left( X_{C(x_i, y_j), p} - \bar{X}_{M(x, y), p} \right)^2 \tag{7}
\]

\[
S_{M(x, y), p,q} = \frac{1}{a \times b - 1} \sum_{i=1}^{a} \sum_{j=1}^{b} \left( X_{C(x_i, y_j), p} - \bar{X}_{M(x, y), p} \right) \left( X_{C(x_i, y_j), q} - \bar{X}_{M(x, y), q} \right) \tag{8}
\]

\[
S_c^2 = \frac{1}{g \times h} \sum_{i=0}^{g-1} \sum_{j=0}^{h-1} S^2_{M(i, j), p} \tag{9}
\]

\[
S_{p,q} = \frac{1}{g \times h} \sum_{i=0}^{g-1} \sum_{j=0}^{h-1} S_{M(i, j), p,q} \tag{10}
\]

where \(X_{C(x_i, y_j), p}\) is the \(p\)-th image characteristic of a wavelet processing unit \(C(x_i, y_j)\); \(\bar{X}_{M(x, y)}\) is the mean matrix of image characteristics in a multivariate processing unit \(M(x, y)\).
$\bar{X}_{M(i,j),p}$ is the mean value of the $p$-th image characteristic of $M(i, j)$; $S_{p}^{2}$ is the variance of the $p$-th image characteristic of $M(x, y)$; $S_{p,q}$ is the covariance of the $p$-th and the $q$-th image characteristics of $M(x, y)$. The multivariate matrices used in this research can be expressed as follows:

$$X_{C(x_{a}, y_{b})} = \begin{bmatrix} A(x_{a}, y_{b}) \\ D_{1}(x_{a}, y_{b}) \\ D_{2}(x_{a}, y_{b}) \\ D_{3}(x_{a}, y_{b}) \end{bmatrix}, \quad \Sigma_{M(x,y)} = \begin{bmatrix} A(x_{a}, y_{b}) \\ D_{1}(x_{a}, y_{b}) \\ D_{2}(x_{a}, y_{b}) \\ D_{3}(x_{a}, y_{b}) \end{bmatrix}_{4 \times 4} \quad (11)$$

Normal texture images are used to estimate the parameters of standard texture characteristics. The sample mean matrix $(a \times b)$ and the sample covariance matrix $(S)$ describe the properties and relations between normal and defect images. The $\bar{X}$ and $S$ are defined as:

$$\bar{X} = \begin{bmatrix} \bar{A} \\ \bar{D}_{1} \\ \bar{D}_{2} \\ \bar{D}_{3} \end{bmatrix}_{4 \times 1}, \quad S = \begin{bmatrix} S_{A}^{2} & S_{A,D_{1}} & S_{A,D_{2}} & S_{A,D_{3}} \\ S_{D_{1},A} & S_{D_{1}}^{2} & S_{D_{1},D_{2}} & S_{D_{1},D_{3}} \\ S_{D_{2},A} & S_{D_{2},D_{1}} & S_{D_{2}}^{2} & S_{D_{2},D_{3}} \\ S_{D_{3},A} & S_{D_{3},D_{1}} & S_{D_{3},D_{2}} & S_{D_{3}}^{2} \end{bmatrix}_{4 \times 4} \quad (12)$$

where $S_{p}^{2}$ is the sample variance of the $p$-th wavelet characteristic of an image; $S_{p,q}$ is the sample covariance of the $p$-th and the $q$-th wavelet characteristics of an image.

The $T^{2}$ statistic value of the multivariate processing unit $M(x, y)$ of a testing image can be defined as:

$$T^{2}_{M(x,y)} = a \times b \left[ \bar{X}_{M(x,y)} - \bar{X} \right] S^{-1} \left[ \bar{X}_{M(x,y)} - \bar{X} \right] \quad (13)$$
where \( a \times b \) is the number of wavelet process units in a multivariate processing unit. 

\( \overline{X}_{M(x,y)} \) is the mean matrix of image characteristics in the multivariate processing unit of a testing image. The \( \overline{X} \) and \( S \) are respectively the mean matrix and the covariance matrix of image characteristics of a normal image. The control limits are as follows:

\[
UCL = \frac{p(m-1)(n-1)}{mn - m - p + 1} F_{\psi, p, (mn - m - p + 1)}
\] (14)

where \( F \) is a tabulated value of the \( F \) distribution at the significance level of \( \psi \).

3. Experimental procedures and results

Experiments are conducted on real LED chips provided by a local manufacturing company of high quality LED chips in Taiwan to evaluate the performance of the proposed approaches. We test 210 LED images, of which 60 have no defects and 150 have various water-drop defects. The training patterns and testing patterns equal to two-third and one-third of the total images, respectively. All experiments are implemented on a Pentium IV personal computer with 2.6GHz CPU and 512 MB RAM; and all programming is done in the C language.

To maximize the number of LED chips on a wafer, every chip is located very close to its neighboring chips. As the carrier plate moves to have the image of the next chip captured, the movement might cause the CCD to deviate from its original position and the image capturing device to vibrate. Thus, the images of all the chips might be captured with slight differences. That is, not all the chips are located in the exactly same positions in their individual images. As a result, two areas are needed for each image to specify the locations of two different background textures in which water-drop defects may possibly exist. The
LED emitting area and bonding pad need to be separated first and then individually apply the proposed methods to detect defects. Figures 4 and 5 present the procedures of detecting defects on emitting area and bonding pad in a defective LED chip, respectively.

In the outer area of an LED chip is an emitting area which contains uniform texture. Since wavelet transform can process images of rectangular shapes, a specially made background must be added to convert the different shape region into a rectangular one. Thus, we change gray levels of the area falling outside the outer area to the average gray level of normal chip images in Fig.4 (b). With such a manipulated background, we not only obtain a rectangular region for wavelet transform but also minimize the affect non-emitting region. Once the mixed image is transformed into the wavelet domain, the non-emitting region will not interfere in the feature extraction of the emitting region. Similarly, this procedure is also applied to defect detection on LED bonding pad except additionally taking median filtering operation. In the central area of an LED chip is a bonding pad which contains statistical texture with random particles like pepper noises. The more similar the gray levels of the particles on bonding pad and the water-drop defect, the more difficult it is to distinguish the defect and the random particles. The median filter (Jain, Kasturi, & Schunck, 1995) is used to smooth the particles on the random texture. The mask of size 11 x 11 pixels is capable of smoothing all the random particles in the testing.
samples, as shown in Fig. 5 (b). Then, the filtered images are conducted the gray level changes of the area falling outside the central area for the same purpose described in Fig.4 (b).

For precisely presenting the locations of water-drop defects, we found the most appropriate size of a wavelet processing unit is 2 x 2 pixels in wavelet transformation. The input patterns of the WNN model, each including four wavelet characteristics, are obtained from the 16,384 sets of a testing image. The testing results of the WNN models can be affected by many factors, such as parameter settings, number of training samples, input patterns of network, and so on. After conducting various experiments, we find that the best parameter settings of the WNN model for water-drop defect detection of bounding area are: 1) number of hidden layers = 1; 2) number of hidden layer nodes = 6; 3) learning rate = 0.5; 4) momentum = 0.5; and 5) iteration cycles = 40; and those of the WNN model for emitting area are: 1) number of hidden layers = 1; 2) number of hidden layer nodes = 3; 3) learning rate = 1; 4) momentum = 0.5; and 5) iteration cycles = 10. The index RMSE (Root Mean Square Error) is used to evaluate the performance of the network models. The RMSE indices of the two WNN models with the given parameter settings are 0.063 and 0.074 for the bounding area and emitting area, respectively.

For the proposed WMS approach, we found the most appropriate size of a multivariate processing unit to be 4 x 4 pixels after conducting various experiments. At this size, this method achieves the best performance considering the sample training time, the recognition time of the testing period, the size of the defect area and other factors in the multivariate processing.
To verify the performance of the proposed methods, we compare the results of our experiments against those provided by professional inspectors. Figure 6 shows partial results of detecting water-drop defects by the Otsu method (Otsu, 1979), the proposed WNN and WMS approaches, and the professional inspector, individually. The WNN and WMS methods detect most of the water-drop defects while the Otsu method misses some defect regions. The performance evaluation indices, \( (1-\alpha) \) and \( (1-\beta) \), are used to represent correct detection judgments; the higher the two indices, the more accurate the detection results. Statistical type I error \( \alpha \) suggests the probability of producing false alarms, i.e. detecting normal regions as defects. Statistical type II error \( \beta \) implies the probability of producing missing alarms, which fail to alarm real defects. We divide the area of normal region detected as defects by the area of actual normal region to obtain type I error, and the area of undetected defects by the area of actual defects to obtain type II error.

The average detection rates \( (1-\beta) \) of all testing samples by the three methods are, respectively, 86.2% (Otsu method), 92.4% (WMS), and 95.3% (WNN). The proposed wavelet based neural network and multivariate statistical approaches have higher detection rates than does the traditional method applied to LED chip images. The WNN and WMS methods excel in its ability of correctly discriminating water-drop defects from normal regions.

Figure 6 should be here
As the decision threshold value changes, so do its false alarm rate ($\alpha$) and detection rate ($1-\beta$), both of which are used to describe the performance of a test according to hypothesis testing theory (Montgomery, & Runger, 1999). When various decision thresholds (Eq. (14)) are used, their pairs of false alarm rates and detection rates are plotted as points on a Receiver Operating Characteristic (ROC) curve. The two ROC curves of the WMS approach and four points of the WNN approach and the Otsu method for bonding pad and emitting area are presented in Fig. 7, whose upper-left corner indicates a 100% detection rate and a 0% false alarm rate. The more the ROC plot approaches the upper-left corner, the better the test performs. In industrial practices, a more than 90% detection rate and a less than 10% false alarm rate are a good rule of thumb for performance evaluation of a vision system. Accordingly, the proposed WMS and WNN approaches, with their ROC plots closer to the upper-left corner, outperform the traditional method.

More specifically, the WNN method has higher defect detection rate and the WMS method has lower false alarm rate if we compare the two proposed approaches. When the major concern of detection is on the area of erroneously detected defects, the WMS method is the best choice because it has the lowest false alarm rate. On the other hand, if the focus is on the accurate areas of the detected defects, the WNN method should be applied because of its higher accuracy in detecting real defect areas.

----------------------------------------------------------------------------------------------------------------------------------------

Figure 7 should be here

----------------------------------------------------------------------------------------------------------------------------------------
4. Conclusions

This research applies wavelet-based neural network and multivariate statistical approaches to detect water-drop defects that fall across two different background textures of LED chips. The proposed approaches use the back-propagation network algorithm and multivariate $T^2$ test to judge the existence of water-drop defects through multivariate processes of combining image characteristics from wavelet decomposition of local image blocks. Experimental results show that the WNN and WMS approaches achieve above 95% and 92% detection rates and below 7.5% and 5.8% false alarm rates in detecting water-drop blemishes across two different background textures, respectively. As indicated in the ROC curve analysis, the WNN and WMS approaches have lower false alarm rates and better detection rates than does the Otsu method. Regarding the directions for future research opportunities, the proposed approach can be extended to detection of semi-opaque and low-contrast image defects falling across two different background textures, such as abnormal region inspection in medical images, defect detection of electronic components, and so on.

Acknowledgments

This study was partially supported by the National Science Council of Taiwan (R.O.C.), Project No. NSC 95-2221-E-324-034-MY2.

References


Fig. 1 (a) basic LED structure, (b) LED product

Fig. 2 LED chip images (a) LED chip without defect; (b) and (c) LED chips with water-drop defects of different shapes

Fig. 3 Network structure of the proposed wavelet-based neural network approach
Fig. 4  The procedure of detecting defects on LED emitting area: (a) separate the outer area of an LED chip; (b) change gray levels of the area falling outside the outer area; (c) apply the proposed method to detect defects.

Fig. 5  The procedure of detecting defects on LED bonding pad: (a) separate the central area of an LED chip; (b) take median filtering on the central area; (c) change gray levels of the area falling outside the central area; (c) apply the proposed method to detect defects.
Fig. 6  Partial detection results of the Otsu, WMS, WNN methods and the professional inspector

<table>
<thead>
<tr>
<th>By Otsu method</th>
<th>By WMS method</th>
<th>By WNN method</th>
<th>By inspector</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1.png" alt="Image" /></td>
<td><img src="image2.png" alt="Image" /></td>
<td><img src="image3.png" alt="Image" /></td>
<td><img src="image4.png" alt="Image" /></td>
</tr>
<tr>
<td><img src="image5.png" alt="Image" /></td>
<td><img src="image6.png" alt="Image" /></td>
<td><img src="image7.png" alt="Image" /></td>
<td><img src="image8.png" alt="Image" /></td>
</tr>
</tbody>
</table>

**Fig. 7** ROC plots of the Otsu, WMS, and WNN methods

- **Detection Rate (1-β)**
- **False Alarm Rate (α)**

- ▲ WMS (bonding pad)
- ▸ WMS (emitting area)
- ○ Otsu (bonding pad)
- × Otsu (emitting area)
- ★ WNN (bonding pad)
- ★ WNN (emitting area)