Applying Ant Colony Algorithm and Neural Network Model to Color Deviation Defect Detection in Liquid Crystal Displays

Hong-Dar LIN and Chih-Hao CHIEN
Department of Industrial Engineering and Management
Chaoyang University of Technology
Taichung County, 41349, Taiwan (R.O.C.)

ABSTRACT

Thin Film Transistor Liquid Crystal Display (TFT-LCD) has excellent properties such as lower voltage to start and less occupied space if comparing with traditional Cathode-Ray Tube (CRT). But screen flaw points and display color deviation defects on image display exist in TFT-LCD products. This research proposes a new automated visual inspection method to solve the problems. We first use multivariate Hotelling T^2 statistic for integrating coordinates of color models to construct a T^2 energy diagram for inspecting defects and controlling patterns in TFT-LCD display images. An Ant Colony based approach that integrates computer vision techniques is developed to detect the flaw point defects. Then, Back Propagation Network (BPN) model is proposed to inspect small deviation defects of the LCD display colors. Experimental results show the proposed system can provide good effects and practicality.

Keywords: LCD defect detection, Multivariate T^2 statistics, Ant colony algorithm, Back propagation network, Small shift detection.

1. INTRODUCTION

Liquid Crystal Display (LCD) has excellent properties such as lower voltage to start and less occupied space if comparing with traditional Cathode-Ray Tube (CRT) but some problems related to color impurity in display of image quality exist in LCD products [1, 2]. The color impurity defects influence the display quality of LCD as the same as those of other's plane monitors. The reasons why the inspections of color impurity defects seldom be done automatically are: (1) comparisons of real colors and exhibit colors are difficult; (2) display brightness spread is unsettled and inestimable. Besides, the LCD surface inspections have stricter inspection specification since LCD production processes have more precise and innovative manufacturing techniques. It is not only difficult to find the defects by artificial inspection, but also easy to make wrong judgments due to human subjectivity and eye fatigues. Therefore, developing an automated inspection and process control system is needed to improve the quality of LCD products. It is necessary for monitors to have worthy trust properties of display. The display quality of colors not only has sufficient color purity but also emphases on the output reproducibility of precision and true colors. Because LCD display inspections have various standards of measurement in quality control at present, different image display quality comes from different manufacturing techniques and quality requirements. The color purity of monitor displays is easily affected by lighting conditions, environmental factors and subjective perception of human visual. How to ensure the reliability of LCD visual quality is an important problem that needs to be solved [3].

2. OVERVIEW OF RELATED WORKS

Two common defects, screen flaw points and display color deviations, often exist in TFT-LCD's. To detect these defects, this research proposes a new automated visual inspection method based on multivariate Hotelling T^2 statistic, Ant Colony algorithm, and Back Propagation Neural network (BPN) model.

Multivariate Quality Control Techniques
Multivariate control chart is originally used in multivariate process monitoring operation. The current multivariate control chart includes general multivariate control model and small shift detection of multivariate process. Lowry and Montgomery [4] propose that an univariate Shewhart control model can be extended to Hotelling Multivariate control chart. This chart can monitor many quality characteristics and consider relations among several variates. Mason *et al*. [5] provide a processing model of Hotelling T^2 statistic for monitoring batch process.

Two vectors of in-control mean μ and covariance matrix Σ are both unknown in Hotelling T^2 control chart. Therefore, it is usually necessary to estimate μ and Σ from a preliminary analysis with sample size n when the process is assumed to be in control. Suppose that m sample sets are available, *p* are quality characteristics, $\overline{x}_{jk}$ (j= 1, 2, …, p; k= 1, 2, …, m) are sample means and are independent and identical distributed. The average of the sample covariance matrices S is an unbiased estimate of Σ when the process is in control. If we replace μ with $\overline{\overline{x}}$ and Σ with S, the test statistic becomes:

$$T^2 = n(\overline{x} - \overline{\overline{x}})^T S^{-1} (\overline{x} - \overline{\overline{x}}) \qquad (1)$$

In this form, the procedure is usually called the Hotelling T^2 control chart [6]. When the μ and Σ are estimated to form a large number of preliminary samples (m≧20), it is customary to use UCL=$X^2_{\alpha,p}$ where α is significance level. If we use (m<20) preliminary samples, the control limits are as follows:

$$UCL = \frac{p(m-1)(n-1)}{mn-m-p+1} F_{\alpha, p, (mn-m-p+1)}\ ;\ LCL = 0 \quad (2)$$

Ant Colony Algorithm
Ant colony algorithm is a meta-heuristic based upon a nature metaphor concerning the collaboration and knowledge-sharing mechanism exhibited in ant colonies during their food-seeking process. Dorigo *et al.* [7, 8] introduces the model with the main characteristics: positive feedback, distributed computation, and the use of a constructive greedy heuristic. The positive feedback accounts for rapid discovery of good solutions, the distributed computation avoids premature convergence, and the greedy heuristic helps find acceptable solutions in the early stages of the search process.

The ant colony algorithm is commonly used in solving TSP (Traveling Salesman Problem) [7-8]. Given a set of n towns, the TSP can be stated as the problem of finding a minimal length closed tour that visits each town once. We call d_{ij} the length of the path between towns i and j; in the case of Euclidean TSP, d_{ij} is the Euclidean distance between *i* and *j*. An instance of the TSP is given by a graph (N, E), where N is the set of towns and E is the set of edges between towns (a fully connected graph in the Euclidean TSP) [7].

Let $b_i(t)$ be the number of ants in town *i* at time *t* and let $m = \sum_{i=1}^{n} b_i(t)$ be the total number of ants. And let $\tau_{ij}(t)$ be the intensity of trail on edge (*i*, *j*) at time *t*. Each ant at time *t* chooses the next town, where it will be at time *t*+1. At this point the trail intensity is updated according to the following formula [8]:

$$\tau_{ij}(t+n) = \rho \cdot \tau_{ij}(t) + \Delta\tau_{ij} \quad (3)$$

where ρ is the quantity such that $(1-\rho)$ represents the evaporation of trail between time *t* and *t*+n, the plus term is

$$\Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\tau_{ij}^{k} \quad (4)$$

where $\Delta\tau_{ij}$ is the quantity per unit of length of trail substance (pheromone) laid on edge (*i*, *j*). The quantity made by the *k*-th ant between time *t* and *t*+n is given by

$$\Delta\tau_{ij}^{k} = \frac{Q}{L_k} \quad \begin{array}{l} if\ kth\ ant\ uses\ edge\ (i,j)\ in\ its \\ tour\ between\ time\ t\ and\ t+n \end{array} \quad (5)$$

where *Q* is a constant and L_k is the tour length of the *k*-th ant. We call visibility η_{ij} the quantity $1/d_{ij}$. We define the transition probability from town *i* to town *j* for the *k*-th ant as

$$P_{ij}^{k}(t) = \frac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{k \in allowed_k} [\tau_{ik}(t)]^{\alpha}[\eta_{ik}]^{\beta}} \quad if\ j \in allowed_k \quad (6)$$

where $allowed_k = \{N - tabu_k\}$ and α and β are parameters that control the relative importance of trail versus visibility.

Back Propagation Network
Neural networks are structured by simulating human neural cells and have a number of artificial neurons to do learning, memory, recalling and parallel computing. The past researches show neural networks have good performance in process control [9, 10]. Smith [11] uses neural network models to inspect changes of processing means and variations. The processing features include original data, sample mean, range and standard deviation of a sample set. And a differentiate numerical model summaries forecast processing data in the future.

Back Propagation Network (BPN) model is presently representative of neural network models. The applications of BPN models are effective on diagnosis, prediction and classification. The learning rule of BPN model uses generalized delta rule. This rule applies descent algorithm to get most small squared sum for adjusted weights. When BPN model is learning, input data is processed that feed-forward calculate difference of network output and expected output and feed-back adjust weights to network. Learning cycles are repeated on neural network until the network gains convergence.

3. RESEARCH METHODS

This research first uses multivariate Hotelling T^2 statistic to integrate coordinates of color models and construct a T^2 energy diagram. Then, an Ant Colony based approach that integrates computer vision techniques tackles the flaw point defects. And the Back Propagation Neural network (BPN) model is applied to detect small deviations of the LCD display colors.

Multivariate Quality Control Techniques Applied to Machine Vision Systems
This research uses color coordinates of RGB, XYZ, Yxy, and L*u*v* models as multivariate quality features to calculate Hotelling T^2 statistics. Figure 1 shows the calculation procedures of T^2 statistics in color images. The T^2 statistic is described as variations of color purity. And we set T^2 statistic is equal to image gray levels.

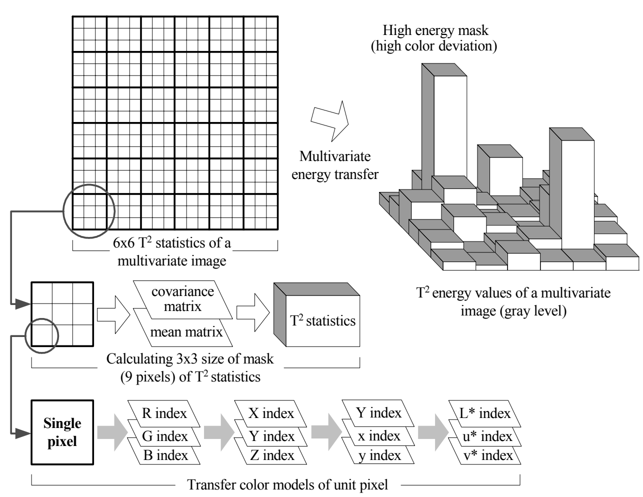

Figure 1. Calculations of T^2 statistics in color images

Multivariate image processing masks are used to calculate values of T^2 statistics. The masks are come from dividing an image into many image samples for setting sample set (m) and sample size (n). For example, an image of size 256 x 256 pixels can be divided into 51 x 51 image samples. Each image sample has 5 x 5 observations (pixels). The mean matrix ($\bar{X}$) and covariance matrix (S) of color coordinates in mask can be written as follows:

$$\bar{X} = \begin{bmatrix} \bar{M}_1 \\ \bar{M}_2 \\ \vdots \\ \bar{M}_k \end{bmatrix} \qquad S = \begin{bmatrix} S^2_{M_1} & S_{M_1M_2} \cdots S_{M_1M_k} \\ & S^2_{M_2} \quad \cdots S_{M_2M_k} \\ & \ddots \\ & \qquad S^2_{M_k} \end{bmatrix} \tag{7}$$

where $\bar{M}_k$ is the average of color coordinates (p) in all pixels of mask ($k=1, \ldots, p$). $S^2_{M_k}$ is the variance of color coordinates (p) in all pixels of Mask ($k=1, \ldots, p$). $S^2_{M_hM_k}$ is the covariance of color coordinates (p) among all pixels of mask ($h=1, \ldots, p, h \neq k$) ($k=1, \ldots, p$).

The transfer function of a multivariate model for color coordinates can be written as:

$$T^2 = n\left[M_{(i,j)} - \bar{X}\right]^T S^{-1}\left[M_{(i,j)} - \bar{X}\right] \tag{8}$$

where T^2 is the energy value of multivariate on color coordinates in mask, n is pixel number of mask, $M_{(i,j)}$ is the feature matrix of color coordinate in mask, $\bar{X}$ is the mean matrix of image features in mask and S^{-1} is the covariance matrix of image features in mask.

Ant Colony Algorithm Applied to Color Flaw Point Detection

In this research, we apply the explorations for the shortest paths of ant colony algorithm to the finding of the maximum T^2 statistics in multivariate processing masks. We use this concept and combine with computer vision techniques to detect color deviation defects in LCD inspection. Figure 2 describes the concept of the proposed ACPM method applied to flaw point detection.

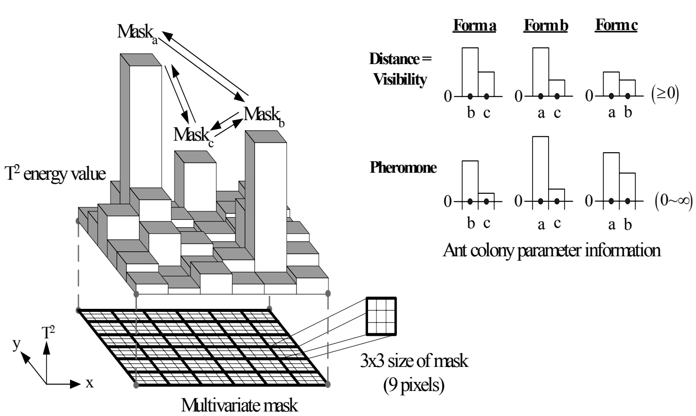

Figure 2. Concept description of the proposed ACPM method applied to flaw point detection

Parameter definitions of the proposed ACPM model are summarized as follows: O_i is a T^2 value of mask i in T^2 energy diagram; σ_{T^2} is a standard deviation of T^2 values in T^2 energy diagram; $t(O_i)$ is a suspected mask i with T^2 value more than 3 σ_{T^2} ; s_{ij} is a connected path strength between masks i and j; and ν_{ij} is a visibility between masks i and j. To proceed with the calculation of the ACPM model, some suspected masks $t(O_i)$ need to be sieved out by using following equation for reducing the complexity of algorithm computations and increasing model practicability:

$$t(O_i) = \begin{cases} 1 & \text{if } O_i > 3\sigma_{T^2} \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

After the suspected masks being sieved out, the connected path strength and visibility between masks i and j are:

$$s_{ij} = \left[O_i^2 + O_j^2\right]^{1/2}; \quad i, j = 1,2,\ldots n \tag{10}$$

$$\nu_{ij} = s_{ij}; \quad i, j = 1,2,\ldots,n \tag{11}$$

The ant colony algorithm could not perform well without pheromone evaporation. Pheromone decay is implemented by introducing a coefficient of evaporation ρ , $0 < \rho \leq 1$, such that the pheromone quantity from masks i to j in the E-th exploration is:

$$\tau_{ij}(E) = (1-\rho)\,\tau_{ij}(E-1) + \Delta\tau_{ij} \tag{12}$$

The changed pheromone amount between masks i and j is:

$$\Delta\tau_{ij} = \sum_{k=1}^{s} \Delta\tau_{ij}^k \tag{13}$$

where changed pheromone amount made by the k-th ant is:

$$\Delta\tau_{ij}^k = \begin{cases} \sqrt{t_j} & \text{if } (i,\ j) \in t(O_i) \text{ described by } Tabu_k \\ 0 & \text{otherwise} \end{cases} \tag{14}$$

The transition probability from masks i to j for the k-th ant in the E-th exploration is;

$$P_{ij}^k(E) = \begin{cases} \dfrac{\left[\tau_{ij}(E)\right]^\alpha \left[\nu_{ij}\right]^\beta}{\sum_{k \notin Tabu_k} \left[\tau_{ik}(E)\right]^\alpha \left[\nu_{ik}\right]^\beta} & \text{if } b \notin Tabu_k \\ 0 & \text{otherwise} \end{cases} \tag{15}$$

To locate the positions of flaw points, we define a percentage k% of energy values as a threshold to separate the masks with higher energy values. If Q_i is greater than the threshold $Q_{\%}$, the mask i is judged as a defect mask containing flaw points.

$$Q_i = \sum_{j=1,\, j\neq i}^{n} \tau_{ji}; \quad i = 1, 2, \ldots, n \tag{16}$$

$$Q_{\%} = k\% \sum_{i=1}^{n} Q_i; \quad i = 1, 2, \ldots, n \tag{17}$$

Back Propagation Network Applied to Color Small Shift Areas Detection

The BPN model is used to detect small shift deviation of multivariate quality data in this research. In previous section, we find and eliminate extreme defects by ACPM method. Then we uses T^2 statistics as the inputs of the neural network to describe total variations of color impurity, which is expected to apply training and testing of neural network for detecting small shift. To develop a quality control model for inspecting color impurity defects of the LCD, the BPN model is proposed in this research. A flow chart of this model applied to this research is described in Figure 3.

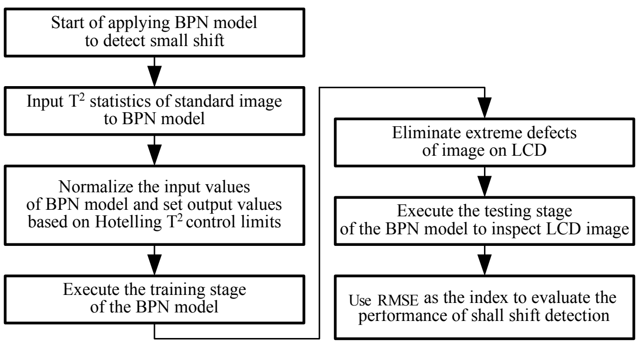

Figure 3. Procedures of BPN model applied to small shift areas detection

The proposed method applies several continuous T^2 statistics (m) in rows of an image as network input values. An image of size 256×256 pixels has 2601 T^2 statistics. The totals of input patterns of rows are 51 values of T^2 statistics. Each T^2 statistic can be judged as in-control or out-of-control. The m values directly affect detection results of the network. If m is too large, it will increase loads of calculations and affect detection of network. If m is too small, it will not exhibit defective features of an image. To make network input features describing color features of a testing image, this research uses T^2 statistics in standard images which are inputted to BPN model for training.

Network output unit is divided into in-control and out-of-control which 0 and 1 are used to represent. The determination of expected output result is based on control limits. If one or more T^2 statistics exceed the control limits, the patterns are out-of-control. The research uses Hotelling T^2 control limits ($m \geq 20$, $UCL = X^2_{\alpha,p}$) for the difference among m T^2 statistics in small shift detections of images. The input data are needed be scaled. We use linear transformations to set range of network input values between [0, 1] to avoid extreme values affect the results of network training.

The proposed experimental design is used to determine parameters of BPN, such as learning rate (η), training number, error and hidden layer nodes. We use random numbers of uniform distributions to set interconnected weights and biased weight vectors (θ) in which the numerical range between [-1, 1] for BPN training. The BPN processing unit is Sigmoid function that numerical range between [0, 1] is as follows:

$$f(x) = \frac{1}{1 + e^{-net_j}} \tag{18}$$

And standard energy function is used to calculate variation between expect output and network output.

$$E = \frac{1}{2} \sum_j (T_j - Y_j)^2 \tag{19}$$

The stop criterion of BPN is based on proposition of Hush and Horne [12]. They use recognized mean squares algorithm and learning number to set the parameters. Figure 4 shows the network structures of the proposed BPN model.

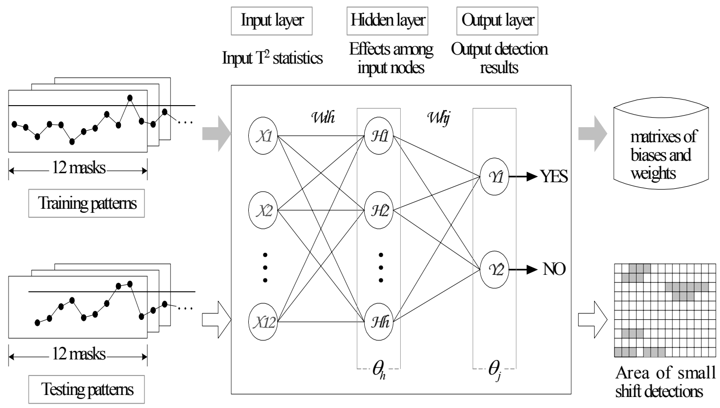

Figure 4. Network structure of the proposed BPN model

4. EXPERIMENTAL RESULTS

In our experiments, two phases of the color deviation defects of LCD are planed and conducted. In the first phase, the proposed ACPM method is implemented to detect the color flaw points of LCD images. In the second phase, the proposed BPN model is implemented to detect the color small shift areas. Four color coordinates of RGB, XYZ, Yxy, and L*u*v* models are input as the quality characteristics of the multivariate control and transform T^2 statistics to image with gray levels. Testing and training images include pure red, green, and blue images with small deviations of colors from a LCD display. The experimental data including sample image size, area image size, mask size, and sample numbers of color deviation defects are summarized in Table 1. To detect the color flaw points of LCD images, the ACPM method try to find higher T^2 statistics of suspected masks for locating the positions of flaw points. Table 2 lists the parameter setting of the proposed ACPM method.

To evaluate performance of the ACPM method for detecting flaw points under different color models, an evaluation index is defined as:

$$\gamma = \frac{\text{average of detected flaw points}}{\text{average of judgement errors}} = \frac{\#(1-\beta)}{\#(\alpha+\beta)} \tag{20}$$

The γ value is a relative ratio, representing the average value of detected flaw points per average of judgment errors. The judgment errors include statistical type I and II errors.

Table 1. Experimental data

Item	Description
Color classification	Pure red, green, blue
Sample image size	35 LCD screen images in each color (1024 x 768)
Area image size	5 area images (256 x 256 pixels) in each sample; Total 175 area images in each color
Mask size	3 x 3 pixels
Samples of color flaw points	15 LCD images in each color
Samples of color small shift areas	60 LCD images as training and testing samples in each color; 10 LCD image as standard images in each color

Table 2. Parameter setting of the ACPM method

Objective	Parameter setup	
Value control	Evaporation	
	0.5	
Sample setup	City number	Ant number
	Suspected masks	10
Probability calculation	α of ACPM	β of ACPM
	1	2
Stopping conditions	Explorations	Tolerance
	200	0.001
Determine flaw points	Threshold parameter $Q_{\%}$	
	0.7%,1%, 2%, 5%	

In the second phase, the BPN technique is implemented to detect color small shift areas of LCD images under different color models. We combine T^2 statistics and BPN model to establish a process control system of image quality for mean deviations of a multivariate process. The inputs of BPN model are twelve continuous T^2 statistics come from the 32 masks of each row of the standard image. The Hotelling T^2 control limits is divided into in-control and out-of-control of T^2 statistics in training outputs of BPN. If any T^2 statistic exceeds control limits, the area of image is out-of-control.

The parameter setting of BPN model used in this research is shown in Table 3. The testing results of BPN model is subjected to effects of many factors. Such as parameter settings, number of training samples, input features of network, mask size, and so on. The index RMSE (Root Mean Square Error) is used to evaluate the performance of the network. From the experimental results, we find that if the T^2 statistics are close to control limits will cause inspection errors due to insufficient training cycles of the network. Figures 5 and 6 are the results of pure green images without and with a flow point after proceeding with the developed defect detection process.

Table 3. Parameter setting of the BPN model

Patterns and parameter setting	
Training patterns	40 images (2/3)
Testing patterns	20 images (1/3)
learning rate	0.5
Cycles	1,000,000
Error value	0.01

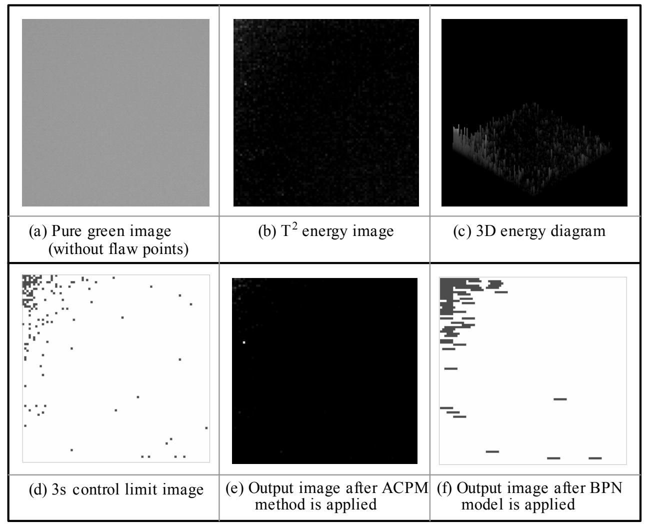

Figure 5. Results of a pure green image without flow points after proceeding with the developed defect detection process

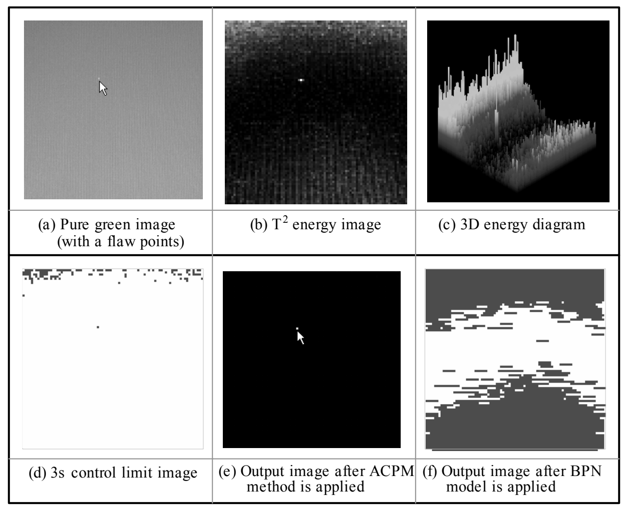

Figure 6. Results of a pure green image with a flow point after proceeding with the developed defect detection process

5. CONCLUSIONS

After conducting experiments of this research, the ACPM method with L*u*v* model can not only reduce error rates of color flaw point detection but also have a larger relative ratio (γ= 1.9733). The BPN technique with Yxy model has good effects of detecting color small shift areas and having lower RMSEs. This research contributes a solution to TFT-LCD common problems of color flaw points and color small deviation detections and offers a computer-aided detection and a process control system to meet the process and quality control request. In addition, the results of this research can be beneficial to enterprises that have similar process and quality control request.

6. ACKNOWLEDGEMENT

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