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The application of clustering analysis for the critical areas on TFT-LCD panel

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Abstract

For thin film transistor-liquid crystal displays (TFT-LCD) factories in Taiwan, yield performance had become as an important competitiveness determinant during the competitive environment. As we known, the market for LCDs has grown at over 20% on average per annum and the downward pricing trend had also promoted LCD applications. However, only few studies were proposed to address the related issues for process analysis in TFT-LCD industry from the viewpoint of systems. Particularly, the defect status (i.e. abnormal position) on TFT-LCD panel may represent the clustering effect when there are many defect counts on it. Hence, performing the clustering analysis for those abnormal positions will be an important issue to be addressed in TFT-LCD process. In this study, we will propose an approach incorporating fuzzy adaptive resonance theory (Fuzzy ART) and stepwise regression techniques to achieve such process analysis. Besides, an illustrative case owing to TFT-LCD manufacturer at Tainan Science Park in Taiwan will be applied to verifying the rationality and feasibility of our proposed procedure.

Keywords: Process analysis; Liquid crystal displays (LCDs); Fuzzy adaptive resonance theory (Fuzzy ART); Stepwise regression

1. Introduction

During the past several years, the market for LCDs has grown at over 20% on average per annum. The speculative demand increase has driven capacity expansion, especial at Taiwan (Su, Yang, & Wang, 2004). The price for LCD products is significantly reduced due to both the technology maturity and ample manufacturing capacity. The downward pricing trend further promotes LCD applications. Generally, LCDs can be divided into three major products including TN (twisted nematic), STN (super twisted nematic) and TFT (thin film transistor). The most widely used LCD for high information content display is the TFT-LCD. In the TFT-LCD each picture pixel is controlled using a thin film transistor. The TFT-LCD panel has a sandwich structure (Singer, 1994) consisting of two glass plates with liquid-crystal material in between. The bottom substrate is the TFT array. The top substrate is the color filter plate.

The manufacturing technology, capital investment and industrial infrastructure can be viewed as three key factors affecting LCD industry competition (Su et al., 2004). For most TFT-LCD manufacturers, the optimum allocation of resources is the important issue to be addressed. The ability to improve yield in the manufacturing process is an important competitiveness determinant for LCD factories due to the significant yield loss ranging from 5% to 25%. In order to survival during the competitive environment, how to mine the useful information from the "know how" or "domain knowledge" of manufacturing process will be an important issue to all TFT-LCD manufacturers. How to keep the knowledge about the effect on yield or yield loss for the possible process parameters will be also another importance issue. Besides, the defect status (i.e. abnormal position) on a panel may represent the clustering effect when there are many defect counts on it (it is graphically depicted in Fig. 1). Hence, performing the

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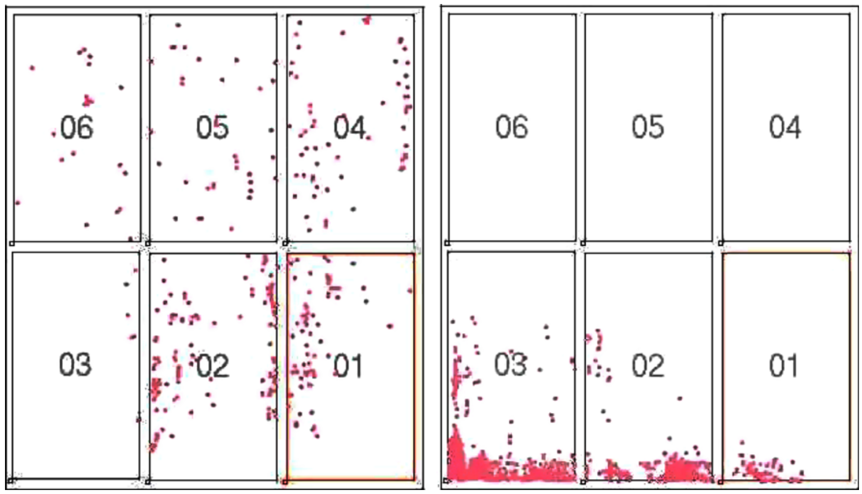

Fig. 1. The dispersion sample diagram for the defect (abnormal position) on a glass.

clustering analysis for those abnormal positions will be an important issue to be addressed in TFT-LCD process. From the considerations mentioned above, we will propose an approach to address such issues. Besides, in this study, an illustrative example owing to TFT-LCD manufacturer at Tainan Science Park in Taiwan will be also chosen to demonstrate the rationality and feasibility of the proposed approach.

2. Fuzzy adaptive resonance theory (Fuzzy-ART)

The behavior in fuzzy adaptive resonance theory (Fuzzy ART) lends itself well to simple geometrical interpretation owing to an internal representation of category prototypes as hyperrectangles in the input space. As for the category choice process, by which Fuzzy ART always responds the same way to a familiar input: it recalls the smallest hyperrectangle containing this input (Georgiopoulos, Fernlund, Bebis, & Heileman, 1996). Hyperrectangle overlaps have been argued to be an inconvenience if categories are mutually exclusive (Simpson, 1993). In order to learn intersecting and overlapping categories, a neural network must be capable of repressing previously known categories while it forms new ones. In other words, it must be able to make temporary abstraction of previous knowledge. The generalization would allow the learning of the tulips category first, and the flowers category next, whereas discrimination would allow the reverse. In the case of Fuzzy ART, increasing the value of a network parameter called vigilance allows formation of new, more specific categories intersecting broad ones that are already known. The network is thus capable of discrimination. However, reducing the same parameter value does not yield generalization. This is due to the predilection of Fuzzy ART for the smallest hyperrectangle containing the input. To avoid a category proliferation problem that could otherwise occur (Moore, 1988), Carpenter, Grossberg, and Rosen (1991) recommend input normalization by a procedure called complement coding. Letbe an M-dimensional vector $(a_1, a_2, \ldots, a_M)$, where $0 \leqslant a_i \leqslant 1$. The complement coded input I is obtained as $I = (a_1, a_2, \ldots, a_M, 1 - a_1, 1 - a_2, \ldots, 1 - a_M) = (a, a_c)$. Assign to each category j a vector $w_j = (w_{j1}, w_{j2}, \ldots, w_{j2M})$ of adaptive weights. Each category is initially uncommitted, and its weights are initialized to one. The functionality of Fuzzy ART may be described as a three-step algorithm (Carpenter et al., 1991):

Step 1. Category choice: upon presentation of an input I, a choice function T_j is computed for each category j. The norm operator $|\cdot|$ is defined as $|x| = \sum_{i=1}^{2M} \wedge |x_i|$, the symbol $\wedge$ denotes the fuzzy AND operator, that is, $x \wedge y = (\min(x_1, y_1), \ldots, \min(x_{2M}, y_{2M}))$, and α is a user-defined parameter, $\alpha > 0$. The category J for which the choice function is maximal, that is, $T_j = \max\{T_j, j = 1, 2, 3, \ldots\}$ is chosen for the vigilance test.

Step 2. Vigilance test: the similarity between w_J and I is compared to a parameter ρ called vigilance, $0 \leqslant \rho \leqslant 1$, in the following test:

$$T_j = \frac{|I \wedge w_j|}{\alpha + |w_j|} \tag{1}$$

If the test is passed, then resonance occurs and learning takes place. If the test is failed, then mismatch reset occurs: the value of T_j is set to -1 for the duration of the current input presentation, another category is chosen in Step 1, and the vigilance test is repeated. Categories are searched, that is, chosen and then tested, until one that meets (1) is found. This category is said to be selected for I. It is either already committed or uncommitted, in which case it becomes committed during resonance.

Step 3. Resonance: resonance makes reference to the internal dynamics of the neural network as it pays attention to the vector $(I \wedge w_J)$. During resonance, the weight vector w_J of the selected category I is updated according to the equation

$$w_J^{(\mathrm{new})} = \beta(I \wedge w_J^{(\mathrm{old})}) + (1-\beta)w_J^{(\mathrm{old})} \tag{2}$$

where β is a learning rate parameter, $0 \leqslant \beta \leqslant 1$. What is learned is not the input I itself, but rather an attended weight vector $(I \wedge w_J^{(\mathrm{old})})$: Fuzzy ART thus learns prototypes, rather than exemplars. The special case $\beta = 1$ is called fast learning and is assumed throughout this work. Once resonance is finished, a new input may be presented, and the three-steps repeated.

3. The proposed approach

From the purposes mentioned in Section 1, two issues were addressed as the parameter effect and clustering analysis. As for the parameter effect, the statistical techniques can provide the useful tools to resolve it. Stepwise model-building techniques for regression designs with a single dependent variable had been described in numerous sources (e.g., see Darlington, 1990; Hocking, 1996; Lindeman, Merenda, & Gold, 1980; Morrison, 1990; Neter, Wasserman, & Kutner, 1985; Pedhazur, 1982; Stevens, 1986; Younger, 1985). The basic procedures of Stepwise model-building will involve: (1) identifying an initial model; (2) repeatedly altering the model at the previous step by adding or removing a independent variable (or process parameters) in accordance with the "stepping criteria"; (3) terminating the search when stepping is no longer possible given the stepping criteria, or when a specified maximum number of steps has been reached. And, it will be chosen in this study.

As for the clustering analysis, it will be the core function to the proposed approach. Fuzzy-ART will be chosen in this study due to the characteristic, which is the new cluster can be created when the comparison of similarity degree for the particular element will exceed the cutoff value (i.e. the vigilance value), will lead to Fuzzy-ART to be suitable for the real clustering analysis than Self-Organizing Mapping (SOM) techniques (Carpenter et al., 1991; Georgiopoulos et al., 1996). The proposed process analysis will be represented as two phases as follows:

3.1. Phase 1. Screening out the sensitive position (or critical area) by using statistical test and stepwise regression techniques

Generally, a TFT-LCD glass can divide the surface into several panels according to the requirement of specification. Each panel will be performed via the same TFT-LCD manufacturing processes. The probability of defect (or abnormal position) will not be the same, i.e. the distribution of defect is not a Uniform distribution, and it may be summarized as there are some particular causes (e.g. the equipment operation conditions) to be happened. Hence, we can make the necessary analysis to mine are there any critical areas on a panel? In order to make such analysis, we discussed with the senior engineers to initially divide a panel into a 6×6 matrix. That is, total thirty six areas are formed on a panel. According to probability philosophy, if the defect is randomly happened, the probability value of any area on a panel will obey a Uniform distribution. Restated, we can take necessary statistical test, e.g. a distribution fitness test (or χ^2 test), to verify it. That is, we can make a hypothesis as follows:

$$\begin{aligned} &H_0\text{: the defect count on a panel will obey a}\\ &\qquad\text{Uniform Distribution.}\\ &H_\mathrm{a}\text{: the defect count on a panel can not obey a}\\ &\qquad\text{Uniform Distribution.}\end{aligned} \tag{3}$$

The statistic will have the following formula:

$$\chi_0^2 = \sum_{i=1}^{n} \frac{(o_i - e_i)^2}{e_i} \tag{4}$$

where, o_i will denote the actual defect count on i-th area; e_i will represent the ideal defect count obeying the Uniform distribution on i-th area. Then, we can take the χ_0^2 value to compare with the cutoff value $\chi^2_{\alpha,v=n-1}$. If the judgment is to reject H_0, we can obtain the conclusion as "the defect count on a panel will not significantly obey a Uniform distribution". That is, the sensitive position (or critical area) will exist. Next, we can take the yield to be the output variable and the thirty-six defect counts to be input variables, and the stepwise regression technique will be performed again (The detailed procedure can be referred to (SPSS, 2000)). Finally, the potential critical areas on a panel can be mined via stepwise regression technique.

3.2. Phase 2. Verify the possible clustering effect on the critical layer by using Fuzzy-ART and statistical paired comparison

After the critical areas on a panel being obtained, we can make a subsequent analysis from the viewpoint of defect clustering. From the real manufacturing process, we can find out the clustering effect of the defect (abnormal position) count maybe exist on glass surface (an illustrative example in Fig. 1), especial for the critical areas. In order to verify the existence of the clustering effect for those critical areas on a panel, we can apply Fuzzy-ART technique to perform the clustering analysis. That is, we can compute the defect count of those critical areas before and after performing the clustering analysis. Then, we will meet a problem with the paired comparison. Hence, we can apply the paired t-test to verify the hypothesis of "the clustering effect does not exist" according to the total defect count on those critical areas before clustering analysis and after clustering analysis. The corresponding assumption will be given as follows:

H_0: clustering effect does not exist. (i.e. the $\mu_D = 0, \mu_D$ will denote the difference between the average defect count of those critical areas after and before clustering analysis, $\mu_D = \mu_{\text{after clustering}} - \mu_{\text{before clustering}}$)

H_a: clustering effect does exist. (i.e. the $\mu_D < 0$.) (5)

The detailed procedure to perform *t*-test can be referred to SPSS 12.0 (2000). The mined information can improve the focus of the manufacturing control and the practitioners can pay more attentions to the significant processes or manufacturing layer.

4. Illustrative example

A TFT-LCD manufacturer's data at Tainan Science Park in Taiwan will be taken as an example to demonstrate our proposed procedure. The case of data are collected from AOI inspection and array electrical measurement of Array manufacturing which section is the most complex and precise during TFT-LCD manufacturing process. Hence, we will focus on such case. After discussing with the senior engineers (Hsieh & Lu, 2006), we found out that the AOI inspect in ITO layer will be an important manufacturing layer for TFT-LCD process. And, the engineers would like to check if there are any particular causes to lead the affection on yield. Hence, we will directly address such manufacturing layer. Then, we will perform the necessary analysis depending on the proposed procedure as follow:

Phase 1. Screening out the sensitive position (or critical area) by using statistical test and stepwise regression techniques.

A hypothesis will be assumed as follows:

H_0: the defect count on a panel will obey a Uniform Distribution.

H_a: the defect count on a panel can not obey a Uniform Distribution.

In order to make the analysis, the thirty-six area on a panel can be graphically depicted in Fig. 2. An example of defect count on a panel will be given as Table 1. Then, we will process the statistical test. We collect data recorded from 10 glasses. That is, totally sixty panel data were collected. The ideal defect count obeying a Uniform distribution will be listed in Table 2, where the ideal defect count

6	31	32	33	34	35	36
5	25	26	27	28	29	30
4	19	20	21	22	23	24
3	13	14	15	16	17	18
2	7	8	9	10	11	12
1	1	2	3	4	5	6
	1	2	3	4	5	6

Fig. 2. The designed area on a panel.

Table 1
The actual defect count on a panel

6	21	56	24	30	6	56
5	49	29	16	20	15	115
4	30	62	43	97	8	35
3	69	37	31	6	6	60
2	31	30	21	2	17	23
1	43	38	39	39	27	34
	1	2	3	4	5	6

based on a Uniform distribution can be computed as (total defect count)/(total area count) = 35.13889. Next, the computation procedure of statistics according to Eq. (4) will be given as Table 3.

Finally, we can get the statistic $\chi_0^2 = 583.9771$ by using Excel 2003. It significantly exceeds the cutoff value (43.77–55.76) and the judgment is made to reject H_0. That is, the distribution of defect count on a panel does not obey a Uniform distribution. Hence, we can make the detailed analysis to find out the critical area on a panel.

Next, we can take the yield to be the output variable and the thirty-six defect counts to be input variables, and the stepwise regression technique will be performed. For simplifying the operation, we will employ SPSS 12.0 to perform the necessary analysis. Fig. 3 will graphically depict the stepwise procedure and Fig. 4 will list the result of SPSS 12.0, the final chosen model includes about eight critical area with the sequence (area 21 → area 2 → area 27 → area 30 → area 36 → area 26 → area 4 → area 6). About 90% variation can be explained by such model. That is, the

Table 2
The ideal defect count on a panel

6	35.13889	35.13889	35.13889	35.13889	35.13889	35.13889
5	35.13889	35.13889	35.13889	35.13889	35.13889	35.13889
4	35.13889	35.13889	35.13889	35.13889	35.13889	35.13889
3	35.13889	35.13889	35.13889	35.13889	35.13889	35.13889
2	35.13889	35.13889	35.13889	35.13889	35.13889	35.13889
1	35.13889	35.13889	35.13889	35.13889	35.13889	35.13889
	1	2	3	4	5	6

Table 3
The computation of statistics

6	5.689087	12.38474	3.530984	0.751537	24.16339	12.38474
5	5.467743	1.072486	10.42426	6.522288	11.54205	181.5025
4	0.751537	20.53336	1.758652	108.9049	20.96023	0.000549
3	32.6298	0.098573	0.487505	24.16339	24.16339	17.58948
2	0.487505	0.751537	5.689087	31.25272	9.363395	4.193434
1	1.758652	0.23296	0.424264	0.424264	1.885134	0.036913
	1	2	3	4	5	6

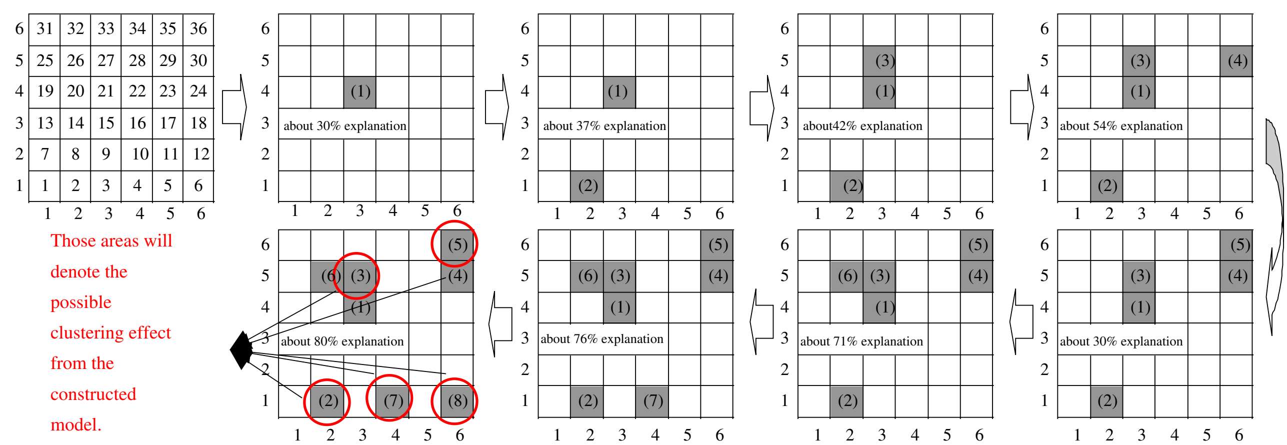

Fig. 3. The stepwise procedure for the critical area on a panel.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.550[a]	.303	.297	15.40937
2	.615[b]	.378	.367	14.61714
3	.660[c]	.435	.420	13.99066
4	.746[d]	.557	.541	12.44897
5	.829[e]	.688	.674	10.48833
6	.855[f]	.731	.717	9.78323
7	.881[g]	.776	.762	8.95648
8	.903[h]	.816	.803	8.16161
9	.920[i]	.846	.833	7.50484
10	.952[j]	.907	.898	5.86266
11	.965[k]	.931	.924	5.06889
12	.974[l]	.949	.943	4.37271
13	.982[m]	.965	.960	3.66329

Fig. 4. The stepwise result after performing SPSS 12.0.

critical areas on a panel will be mined by using the proposed approach.

We can construct the linear yield model by taking the stepwise regression again, and the constructed model will be given as follows:

$$\text{Yield} = -0.974 * \text{defect count}_{\text{area } 21} + 0.27 * \text{defect count}_{\text{area } 2} + 0.621 * \text{defect count}_{\text{area } 27} - 0.968 * \text{defect count}_{\text{area } 30} + 1.225 * \text{defect count}_{\text{area } 36} - 0.589 * \text{defect count}_{\text{area } 26} + 0.261 * \text{defect count}_{\text{area } 4} + 0.21 * \text{defect count}_{\text{area } 6}.$$

From the constructed model, we can find out that the defect count on critical area 2, 4, 6, 27 and 36 will denote a positive correlation with yield. Restated, the larger defect count will lead to a larger yield. It can not be acceptable case for the issue of yield analysis. Hence, the engineers would like to check the clustering effect to be existed or not.

Phase 2. Verify the possible clustering effect on the critical layer by using Fuzzy-ART and statistical paired comparison.

Next, we will perform the subsequent analysis to verify the clustering effect to be existed or not. The Fuzzy-ART technique will be taken into perform the clustering analysis. Herein, the important parameter to set for Fuzzy-ART is the vigilance value. After discussing with the practitioners, we will take vigilance value to be 0.7 due to that too larger value or too smaller value will lead to a bias for making judgment. We take Fuzzy-ART technique to perform clustering analysis for all five critical areas on the sixty panels. And the partial data about the defect count after and before clustering will be given as Table 4. Then, we take the paired t-test to test the hypothesis "null hypothesis H_0: clustering effect does not exist ($\mu_D = 0$); alternative hypothesis H_a: clustering effect does exist ($\mu_D < 0$)" and the judgment is made as "reject the null hypothesis H_0" (the analysis result can be listed in Table 5). Restated, the average defect count after clustering analysis is significantly less than the average defect count before clustering. From the findings, we can make a rational and feasible conclusion as that the clustering effect for abnormal position on LCD-TFT glass will exist. Then, the engineers can pay more attention to eliminate the possible causes to make the abnormal position clustering.

The engineers can apply the proposed approach to collect the useful information for another product. An expert system can be then constructed for the manufactured TFT-

Table 4
The partial data of defect count before clustering, after clustering and the difference

No. of panel	No. of critical area	Before clustering	After clustering	Difference	Total defect count before clustering	Total defect count after clustering
1	2	6	2	4	24	6
1	4	8	2	6		
1	6	1	1	0		
...	...					
60	27	4	1	0	18	5
60	36	2	2	0		

Table 5
The t-test result for the paired comparison

	Before clustering	After clustering
Average	3.05	1.266666667
Variance	28.01440678	1.317514124
Observation	60	60
Parson correlation	0.628272455	
Asumed mean	0	
Dgree of freedom	59	
t-Value	2.965500994	
$P(T <= t)$ single tail	$0.002178089 \ll 0.01$	
Critical value: single tail	1.671091923	
$P(T <= t)$ two tails	0.004356179	
Critical value: two tails	2.000997483	

We can obtain the result of "Reject H_0".

LCD products. The practitioners can search out the related process knowledge or analysis from such expert systems.

5. Concluding remarks and recommendations

To establish the expert system for TFT-LCD manufacturers will be important project, especial for that it will be viewed as the core of the process analysis. In this study, we proposed an approach to demonstrate how to construct the core of the process analysis and the rationality and feasibility also be represented. The advantage of the proposed procedure can be summarized as:

(1) The critical area on a panel of the glass can be mined via the proposed approach. After the critical areas being obtained, the engineers can pay their attention to them via the necessary process control or equipment monitoring.
(2) We analyzed the possible clustering effect with respect to the abnormal position (or defect) on LCD-TFT glass and a complete data mining procedure is also proposed in this study. It will be viewed as a good reference for the future analysis.
(3) As for TFT-LCD products, the practitioners can apply the proposed approach to construct their core of expert systems. And, the application system can be re-designed according to the real requirements.

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