OLED Panel Defect Detection Using Local Inlier-Outlier Ratios and Modified LBP

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Abstract

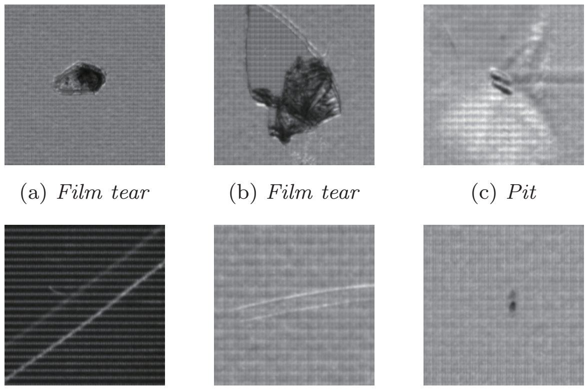
We present an automated system for detecting surface defects on OLED panels. These panels exhibit varying textures and patterns which complicates the defect detection process. These detection systems have to be highly accurate and reliable as even a small error in detection can cause huge losses. In this paper, we present a method for detection of OLED panel surface defects using a novel and simple set of features based on local inlier-outlier ratios and modified LBP. The proposed inlier-outlier vector is easy to compute and provides robust discrimination between defect and non-defect samples of micro defects such as scratches and spots which are missed by modified LBP, thus proving to be a good complement to the modified LBP vector. Next, we train a SVM classifier using the concatenation of inlier-outlier ratios and modified LBP features. In the experiments, we have evaluated our method on several defects like scratch, spot, stain and pit, and the results show that our method significantly outperforms methods which use only modified LBP approach with minimal increase in computational complexity.

1 Introduction

Due to various advantages of OLED displays like no motion lag, perfect viewing angle, razor sharp display of images, excellent brightness levels and low power consumption, they have become a seemingly ubiquitous part of our daily lives in the form of mobiles, televisions, monitors, smart watches, etc. However, a major disadvantage of these displays is their complex manufacturing process which results in a variety of surface defects on the panels. It is important that only high quality panels get shipped as a part of the product to ensure customer satisfaction. Hence, automated inspection of the panels becomes an important part of the manufacturing and assembly process.

Due to the manufacturing process, an OLED panel image consists of texture made of repetitive, equally spaced horizontal and vertical lines along with small complicated patterns. This background texture can vary based on the lighting conditions. The variation in texture, low contrast of the defect pixels and varying sizes of the defect regions impose huge challenges in detection of these defects.

Surface defects can be broadly categorized into macro defects and micro defects (Figure 1). Macro defects are large in size, come in irregular shapes and are characterized by high contrast. Micro defects are smaller in size and much more difficult to detect. In this paper, we propose a global approach for detecting macro and micro defects on OLED panels using local



(a) *Film tear* (b) *Film tear* (c) *Pit*

(d) *Scratch* (e) *Scratch* (f) *Spot*

Figure 1: Categorization of defects: *(a)-(c)Macro defects (d)-(e)Micro defects*

inlier-outlier ratios and modified LBPs with high accuracy. The proposed method consists of two steps. First, feature vector extraction from a set of training images. Second, training a support vector machine using the extracted feature vectors. The rest of the paper is organized as follows. Section 2 reviews the work related to the surface defect detection. Section 3 introduces the new feature vector and reviews modified LBP and training of SVM. Section 4 describes the implementation details and experiment results. Section 5 draws conclusion and results.

2 Related Work

Surface defect inspection has been extensively investigated by many researchers. Various solutions have been proposed for the problem of defect detection on LCD panels which are similar to OLED panels. Jiang et al. [1] applied analysis of variance and exponentially weighted moving average technique. They are not able to generalize to all types of defects. Many have approached the problem of defect detection as elimination of background texture ([2]-[5]). These methods are slow, require selection of threshold for binarization and do not work on defects which are aligned with the background texture. Tsai et al. [6] designed an optimal filter using independent component analysis. The filter was able to generate distinctive responses to defect pixels but it is not suitable for large defect regions and varying background textures. Recently, Gan et al. [7] proposed a defect inspection method by using active contour model to detect various types of defects effectively and achieves high performance in terms of inspection accuracy. However, this method is unable to handle textured surfaces.

Fabric defect detection is a related problem where

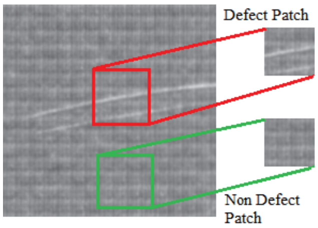


Figure 2: Modified LBP will not be able to distinguish between defect and non-defect patch.

lot of research is being conducted. A. Kumar [8] and Ngan et al. [9] introduce the problem of fabric defect detection and present a survey of fabric inspection methods. Tajeripour et al. [10] successfully applied modified LBP features defined by Ojala et al .[11] for detection of fabric defects.

3 Feature Extraction and Defect Classification

As stated earlier, Tajeripour et al [10] applied modified LBP and maximum likelihood classifier successfully on detection of fabric defects. The background texture in fabrics is similar to that of OLED panels and therefore we studied the application of modified LBP for OLED defect detection. In this section, we review modified LBP for OLED panels, introduce inlier-outlier ratio feature vector and training of a SVM classifier in the newly proposed feature space.

3.1 Modified LBP features

Local binary patterns have been extensively applied in texture analysis [11] and defect detection in textured fabrics [10]. LBP operator labels every pixel based on its neighborhood. The center pixel is compared with its neighbors and the resulting sign of the difference is used to generate a label. LBP operator is formally defined in [11] as:

$$LBP_{P,R} = \sum_{p=0}^{P-1} s(g_p - g_c)2^p, s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \quad (1)$$

where g_c is the gray value of the center pixel on which the LBP operator is applied, g_p is the gray value of the neighboring pixel in the p^{th} position.

The output of the LBP operator on a pixel generates a P bit binary number where P is the number of neighbors with which the center pixel is compared. Thus, the LBP code can take 2^P distinct values. The elimination of magnitudes renders the LBP operator gray scale invariant.

Ojala et al [11] proposed a modified version of LBP where they define a uniformity measure which is the number of transitions between 0's and 1's in the LBP code. Patterns having uniformity measure below a threshold U_T are labeled as uniform. The modified LBP is defined as follows:

$$LBP_{P,R}^{riur_T} = \begin{cases} \sum_{p=0}^{P-1} s(g_p - g_c) & \text{if } U \leq U_T, \\ P+1, & \text{otherwise} \end{cases} \quad (2)$$

The modified LBP is used to calculate the probability distribution of the co-occurrence of the center pixels label in its neighborhood. Each pixel gets a label value between *0* and *P+1* according to (2). Hence, the probability distribution will be calculated over these *P+2* values.

A drawback of this method is that modified LBP will be unable to distinguish between defective and non-defective patches for micro defects as shown in Figure 2. The primary reason being, modified LBP was defined [11] to represent texture rather than any anomalies in texture. Hence, we propose to augment the modified LBP feature with a set of local inlier-outlier ratios thereby catering to general category of defects including micro defects.

3.2 Local inlier-outlier ratios

A robust way to discriminate between the defect and non-defect patches for micro defects is to calculate the ratio of inlier pixels to outlier pixels (3a). For a given window patch that is being evaluated, the number of inlier pixels is the number of pixels similar to the gray level of the center pixel. The inlier-outlier ratio for a defective patch (patch containing defect pixel in the center) will be low relative to a non-defective patch (Figure 3). A pixel p is said to be similar to the center pixel if the gray level distance between the two is below a threshold th (3d).

$$D(p) = \frac{\#Inliers(th, W, g_p)}{\#Outliers(th, W, g_p)} \quad (3a)$$

where p is the center pixel of the patch W that is being evaluated, g_p is the gray level of the center pixel.

$$\#Inliers(th, W, g_p) = \sum_{g_p \varepsilon W} s(g_c, g_p, th) \quad (3b)$$

$$\#Outliers(th, W, g_p) = W_{size} - \#Inliers(th, W, g_p) \quad (3c)$$

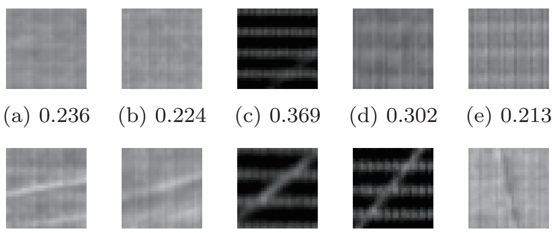
$$s(g_c, g_p, th) = \begin{cases} 1, \text{if } |g_c - g_p| \leq th \\ 0, \text{otherwise} \end{cases} \quad (3d)$$

It can be observed that deciding this threshold th can be cumbersome in case the gray level variance between the defect pixel and the non-defect pixel is very low. Hence, we form a vector of ratios for different thresholds which we call as local outlier ratio descriptors (4).

$$D(th_i) = \frac{\#Inliers(th_i, W, g_p)}{\#Outliers(th_i, W, g_p)} \; \forall \; th_i = 1x, 2x, ..., 127 \quad (4)$$

where x is the step value.

The computation of the absolute difference between the center pixel and its neighbor in (3d) ensures that



(a) 0.236 (b) 0.224 (c) 0.369 (d) 0.302 (e) 0.213

(f) 0.0215 (g) 0.027 (h) 0.045 (i) 0.059 (j) 0.038

Figure 3: Inlier-outlier ratio (3a) calculated at *th*=20 for *(a-e) non-defect patches and (f-j) defect patches*

29	27	33	54	89
77	71	62	88	87
28	29	98	30	28
82	98	79	74	80
64	38	29	28	30

(a)

69	71	65	44	9
21	27	36	10	11
70	69	0	68	70
16	0	19	24	18
34	60	69	70	68

(b)

i	0	1	2	3
th	1	33	65	97
Ratio Vector	0.08	0.31	0.67	0.92

(c)

Figure 4: Illustration of inlier-outlier ratio vector computation: *(a)5X5 neighborhood (b)Absolute difference between center pixel and its neighbors (c)Inlier-outlier ratio vector for th = 1 to 97 and step value x=32.*

the proposed feature vector is invariant to illumination changes. The computation of inlier-outlier ratio vector for a sample 5x5 patch is illustrated in Figure 4. Figure 5 demonstrates the descriptors' effectiveness in bringing out the discrimination between low contrast micro defect regions and non-defect regions. This vector of ratios (4) is augmented with modified LBP feature vector (2) for defect detection.

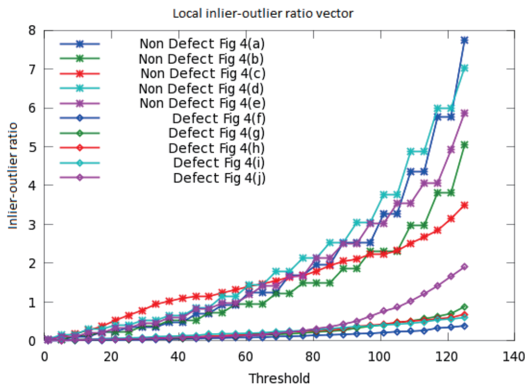


Figure 5: Local inlier-outlier ratio vector (calculated using (4) with x=4)for defect and non-defect patches shown in Figure 3.

3.3 Classification using SVM

Given a linearly separable labeled training dataset SVM classifier aims to find the hyperplane that maximizes the distance between the two classes [12]. SVM provides good generalization performance in high dimensional spaces and do not suffer from the problem of local minima. Local inlier-outlier ratio vector(4) is concatenated with modified LBP features(2) and are used for training a linear SVM classifier.

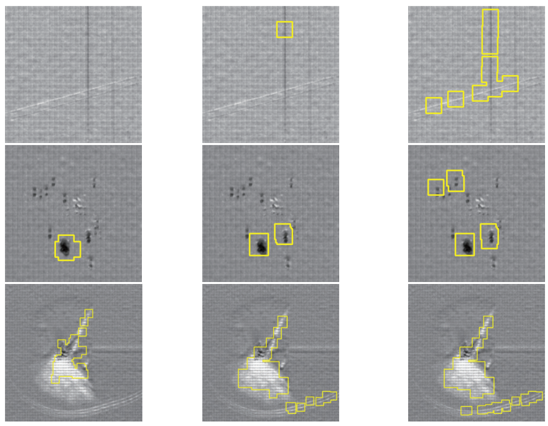
4 Experiments and Results

In this section we present the implementation details, dataset information, comparison of our results with other approaches and a detailed evaluation of our method in terms of accuracy and computations.

The implementation consists of two stages: training and testing. In the training stage, we crop defect and non-defect patches of size 25x25 from OLED panel images. We can choose smaller size for the patch. However, this will increase the number of computations. Increasing the patch size will reduce the capability of the algorithm in detecting smaller defects [10]. For each patch, we calculate modified LBP vector (2) and outlier ratio vector (4). The concatenation of these two vectors form the our final feature vector for each patch. These features along with the labels form our training dataset. We train a linear SVM using this dataset. In the testing stage, we run a scanning window (of size 25x25) on the test images with an overlap factor of 80%. We calculate the feature descriptor of each window/patch and pass it to the SVM classifier.

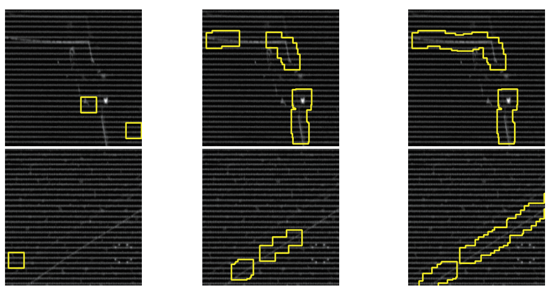
Table 1: Accuracy comparison.

Method	Dataset 1	Dataset 2
Modified LBP with maximum likelihood classifier [10]	55.26%	50.11%
Modified LBP with SVM	86.03%	83.62%
Proposed Approach	93.06%	90.76%



(a) (b) (c)

Figure 6: Detection results for dataset 1: *(a)Modified LBP with maximum likelihood classifier [10] (b)Modified LBP with SVM (c)Proposed method.*



(a) (b) (c)

Figure 7: Detection results for dataset 2: *(a)Modified LBP with maximum likelihood classifier [10] (b)Modified LBP with SVM (c)Proposed method.*

We trained a linear SVM classifier on two datasets with different background patterns and consisting of four types of defects: scratch, spot, pit and film tear. We used 2110 and 500 samples respectively from dataset 1 and dataset 2 for training. We evaluated the classifier on 148905 samples and 8605 samples from dataset 1 and dataset 2 respectively. During feature extraction phase, we used LBP windows of size 3x3, 5x5 and 7x7 for modified LBP. For inlier-outlier ratio vector, the threshold *th* was varied from 1 to 65 in steps of 4. The resulting concatenated feature vector dimension was 56(modified LBP) + 16(outlier ratio vector) = 72. We obtained a detection rate of 93% and 90% respectively on dataset 1 and dataset 2. We compared our method with modified LBP features [10] which uses maximum likelihood classifier and modified LBP features using SVM classifier. The results are tabulated in table 1 and demonstrated for dataset 1 and dataset 2 in Figure 6 and Figure 7 respectively.

We obtained significantly better results with minimal increase in the number of computations compared to modified LBP approach [10]. The calculation of outlier ratio vector requires 657 comparisons, 32 subtractions and 32 divisions for a detection patch size of 25x25 with *th* varying from 1 to 64 in steps of 4. In comparison, modified LBP vector computation requires 19952 comparisons, 54 divisions, 54 multiplications and 48 additions for detection window patch of 25x25 with LBP windows of size 3x3, 5x5 and 7x7.

We performed a detailed evaluation of our method by varying various parameters like dataset size, inlier-outlier ratio threshold values and inlier-outlier ratio vector length. We observed consistent performance for inlier-outlier threshold values and inlier-outlier ratio vector length. The ROC curves for modified LBP and our approach obtained by varying the training data size (Figure 8) demonstrate that the proposed method significantly outperforms the modified LBP with SVM approach.

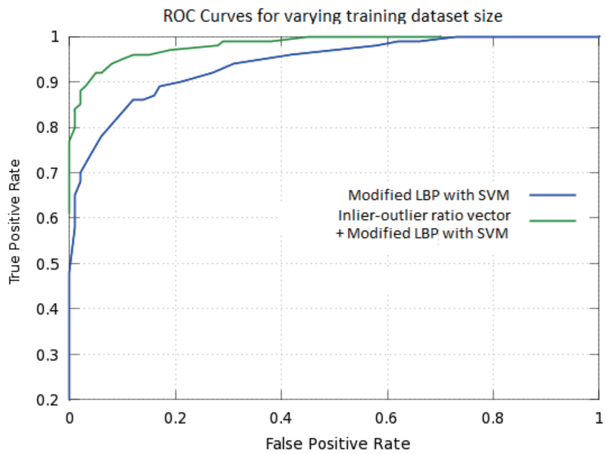


Figure 8: ROC Curve for varying training data size.

5 Conclusion

In this paper, we proposed a novel method of automatic detection of defects on OLED panels by training a linear SVM classifier using local inlier-outlier ratio vectors and modified LBP. Experiments with modified LBP revealed that though it works well with macro defects, it is not effective for micro defects like scratch and spot. Hence, we designed local inlier-outlier ratio vector to handle the micro defects. The combination of these two feature vector along with linear SVM resulted in a detection accuracy greater than 90% at the cost of only few extra computations compared to modified LBP approach. We would like to extend this approach to other textured surface defects like fabric and wood defects in the future.

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