공학석사학위논문

TFT-LCD 결함 분류 공정에서의 K-Means Clustering 을 이용한 라벨링 자동화 성능 향상에 대한 연구

Improvement of Labeling Performance using

K-Means Clustering in TFT-LCD Defect Classification Process

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Abstract

Improvement of Labeling Performance using K-Means Clustering in TFT-LCD Defect Classification Process

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The paper focuses on the improvement of defect classification for a TFT-LCD by enhancing labeling performance. Defects occur in the manufacturing process of TFT-LCD, which have to be repaired or disposed depending on the size and type, thereby lowering the productivity. Defects are detected through optical systems and image

processing algorithms. Machine learning algorithms are used to classify the detected defects, and information gathered from the process provides feedback. The process requires an initial input of labeled defects that is crucial to the later learning process. Any faulty inputs given at the initial stage are consequential to impede a proper learning process.

I propose a method for effectively labeling defects using a k-means clustering algorithm to solve this problem. Previous research only used features that can be visually confirmed. I argue that adding the values obtained by passing kernel over the defect data in addition to visually confirmed features. Using this feature, we could better classify defects that were not previously classified. Experimental defect data occur during the TFT-LCD process.

Keyword : TFT-LCD, Defect, Classification, Labeling, K-Means Clustering, Features, Kernel

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Symbols Description

Δu	Cycle of the pattern in the frequency domain
Δx	Cycle of the pattern in the signal domain
r	Deletion amount in the frequency domain
$I(x, y)$	Brightness value of (x, y) in the image
N_x	Number of longitudinal pixels
F_y	Power spectrum
t	Time domain
ξ	Frequency domain
S	Cluster in k-means clustering
μ	Center of cluster
W	Kernel value
n_{in}, n_{out}	Input, output pixel to kernel

Chapter 1. Introduction

1.1. Study Background

As Thin Film Transistor – Liquid Crystal Display (TFT-LCD) industry rapidly develops, process control has become increasingly important for productivity [1]. Defects occurring during the TFT-LCD manufacturing process lower productivity, mounting additional processes to classify defects then to be either discarded or repaired depending on its size and type. Defects are detected through optical systems equipped with image processing algorithms, which use machine learning algorithms with a feedback mechanism. The classification process requires a labeling process. Since the labeling process is classified according to the characteristics of defects in a state where the answer is not set in advance, it requires a learning method different from the algorithm used in the subsequent learning.

Defects are labeled by a person or a machine. In this process, defects are characterized and classified according to their characteristics. In the previous research, only characteristics that can be used to classify defects were used for visual confirmation [2]. Since the defect image data are automatically detected through image processing algorithms, an error occurs when labeling. Learning from mislabeled data is like studying with the wrong answer, so there is a

problem that the learning rate and the accuracy of the algorithm used for classifying increase, but fail to classify defects well.

We have selected new features that can be used in the defect labeling process. New features can be used to classify defects and improve labeling accuracy. As a result, the learning and classification performance of defects can be improved. That will help LCD industry.

Fig 1.1. TFT-LCD defect classification process diagram

1.2. Purpose of Research

This paper focuses the improvement of labeling performance by diversifying features of defect images of TFT-LCD. I devise the kernel for using features reflect image itself. The kernel uses a filter to extract a characteristic of an image, compresses the image through several filters, and uses final values as a feature for classification. First, I used the results of the research used in Convolutional Neural Network (CNN) using the kernel for identifying characteristics of the image for the size, in addition to the value of the kernel used in previous research [3].

Chapter 2. Defects and features

2.1. Existing defect detection methods and limitations

Optical inspection and image processing algorithms are used for detecting defects in TFT-LCD processes. In a manual process, a defect can be picked up, only if there is a visible defect on the part. In an automatic process, defects are detected by image processing algorithms, and defects are detected according to the characteristics of the image defined by algorithms.

The automated process using algorithm is inhibited by following problems. First, defects are often cut off during the pattern removal procedure. A TFT-LCD has a pattern, which is removed by using a Fast Fourier Transform (FFT) method and a band-pass filter. After the image data of the signal domain is converted into a frequency domain by a FFT method, the band-pass filter is used to remove the frequency of the specific part by removing the pattern [7], [11]. When patterns are removed, defects existing on the pattern are no longer detectable, Defects crossing the pattern are cut off. To solve this problem, I propose a morphological operation, “Closing”. But the operation does not guarantee to establish a closing parameter for all defects, thus it can leave a truncated defect.

Secondly, uneven lighting in imagery affects the effectiveness of detection. Current industry uses a line scan camera to collect defect data, but the light source used is a circle-type instead of a line-type. Therefore, the image is darkened at the edges, and the distance centering on the light center area. Due to the light unevenness, the pattern is not completely erased during FFT, and there are problems in adjusting the threshold value in binarization. I propose to use a Gaussian filter in the light center area to solve problems of light unevenness.

The third problem is the problem of controlling the binarization threshold by 'Ghost' [12] generated during FFT. The 'Ghost' phenomenon refers that the image overlaps up, down, left, and right image signal moving from 'signal domain → frequency domain → signal domain'. To solve this problem, I propose to experimentally determine the optimal value of the frequency domain filter parameters and thresholds used for binarization. Expected results are to overcome the ghost phenomenon, while the binarization threshold optimized for removing the ghost may remain as a problem due to the exclusion of the defect regions with the relatively bright edge portion in binarization.

2.2. Defects

In a TFT-LCD manufacturing process, defects are caused by alien substances or scratches during transfer. Defects can be categorized into following types, particle, pinhole, and scratch. The particle type is caused by an alien substance is stuck in the deposition process. The pinhole type is a defect in which the relevant part is not deposited by the alien substance, and the scratch type is a defect caused an external impact during transport. Each defect has different characteristics as shown in Fig 2.1. below.

Fig 2.1. Major TFT-LCD defects

2.3. Features

As we have seen in Fig 2.1., respective type of defects has different visible characteristics, and they can be visually distinguished. In algorithms, these visually obtainable information is often referred as ‘Feature’, which are divided into three categories.

The first category is size. Each type of defects represents a different size. For example, particles are generally smaller than the other types. And the number of white pixels in the detected defect image is pinhole.

The second category of features is brightness. Each type has different brightness. Particles contain solely dark areas. Pinholes show a contrasting brightness between inside and outside. Scratch displays uneven brightness because many parts are cut by patterns.

The third category of features is shape. The particle and pinhole types have high rectangularity, and the scratch type mostly has a large aspect ratio and eccentricity.

Defects can be classified by using features related to size, brightness, shape. Based on previous research, this paper used the following features for classifying defects.

Features related to size

- Size of defects
- Merging number
- Average size
- Relative DX, DY
- Length and Size of contour

Features related to brightness

- Transparency
- Mean
- Median
- Standard deviation
- Max
- Min

Features related to shape

- Area ratio
- Rectangularity
- Eccentricity
- Compactness

However, since this paper aims at automatic detection and classification, the same problem as in 2.1. occurs. Therefore, it is difficult to classify defects simply by applying visually distinctive features.

Chapter 3. Distinction methods

3.1. Defect detection using image processing algorithm

I use a Fast Fourier Transform (FFT) method and filtering in the frequency domain to detect defects occurring during the TFT-LCD manufacturing process.

FFT is an operation that performs Fourier transform more efficiently. The conventional Fourier transform requires the operation of $O(n^2)$, but the FFT requires only the operation of $O(n\log n)$. Fourier transform is the process of decomposing a function of time into a frequency component. The function of the time domain becomes a complex function of the frequency domain through the Fourier transform. The magnitude of this complex function represents the amount of the frequency component, and angle represents the phase difference. The Fourier transform is expressed as follows:

$$X(\xi) = \int_{-\infty}^{\infty} x(t)e^{-2\pi i t\xi}dt\,, \xi: \mathbb{R} \to C$$

After converting to the frequency domain through FFT, the display pattern part excluding defects is removed through the filtering process. The band-pass filter is used, and the deletion interval is as follows [11]:

$$\mathrm{F_y}(u) = 0, for\ u_i^* - r \le u \le u_i^* + r, i = 1, 2, \dots, n.$$

$$\Delta \mathrm{u} = \frac{\mathrm{N_x}}{\Delta \mathrm{x}}, r = 3$$

The image is then brought back into the signal domain by an inverse Fourier transform. The inverse Fourier transform is expressed by the following equation:

$$\mathrm{x(t)} = \int_{-\infty}^{\infty} X(\xi) e^{2\pi i t \xi} d\xi$$

The data imported into the signal area again is emphasized through the binarization. The binarization proceeds as follows:

$$\mathrm{I(x,y)} \begin{cases} 0, if\ I(x,y) < threshold \\ 255, if\ I(x,y) \ge threshold \end{cases}$$

3.2. K-Means Clustering

I use a k-means clustering algorithm [5] to classify defects that are not labeled before. The k-means clustering is an unsupervised or self-learning algorithm in machine learning methods. Unsupervised learning is not given an answer, in contrast to supervised learning when answers are given [8].

A K-means clustering algorithm clusters input data into a number of clusters. More specifically, given N number of D-dimensional input data sets, the k-means clustering algorithm classifies N input data into K sets that maximize cohesion among data in each set. This algorithm is divided into two processes, first is to determine the number K of clusters, and second is the clustering process to group the data.

First is the selection of K. As the name suggests, the choice of K is important in learning algorithms. Improper choice of K results in appropriate clustering of the data. Among several available methods of selecting K the most commonly used methods are the elbow [9] and silhouette method [10]. The elbow method is a method to focus on a change of the result by the increase of the number of clusters. The silhouette method is to observe the degree of coupling of data by the increasing number of clusters.

The following is the clustering process. During data clustering, the sum of distances between the cluster center and data is minimized. The mathematical formula is as follows:

$$\underset{s}{\operatorname{argmin}} \sum_{i=1}^{k} \sum_{x \in s_i} \|x - \mu_i\|^2$$

And this algorithm is performed in the following manner.

a) The initial center is k, which is randomly extracted from the input data.

$$\mu_1, \mu_2, \dots, \mu_k \in \mathbb{R}^n$$

b) Calculate Euclidean distances from the center k to each data, and cluster data, which has the smallest distance.

$$S_i^{(t)} = \left\{ x_p : \left| x_p - \mu_i^{(t)} \right|^2 \leq \left| x_p - \mu_j^{(t)} \right|^2 \forall j, \ \dots 1 \leq j \leq k \right\}$$

c) Recalculate centers of each clusters using the average value of clusters.

$$\mu_i^{(t+1)} = \frac{1}{\left| S_i^{(t)} \right|} \sum_{x_j \in S_i^{(t)}} x_j$$

d) Repeat steps b~c until the clusters are no longer change.

3.3. Kernel

The 'kernel' refers to a small matrix used in an image-processing field and plays a role in detecting image's characteristics through blurring, sharpening, edge detection, and etc. The kernel and image are convoluted. According to the kernel size and internal value, convoluted values are different.

The convolution operation performed is as follows:

$$\begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix} * \frac{1}{16}\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix} = \frac{1}{16} * (a + 2b + c + 2d + 4e + 2f + g + 2h + i)$$

Chapter 4. Experiment & Evaluation

4.1. TFT-LCD defects for experiment

Images obtained by the optical system and the image converted through the Fourier transform, filtering, and binarization are as follows.

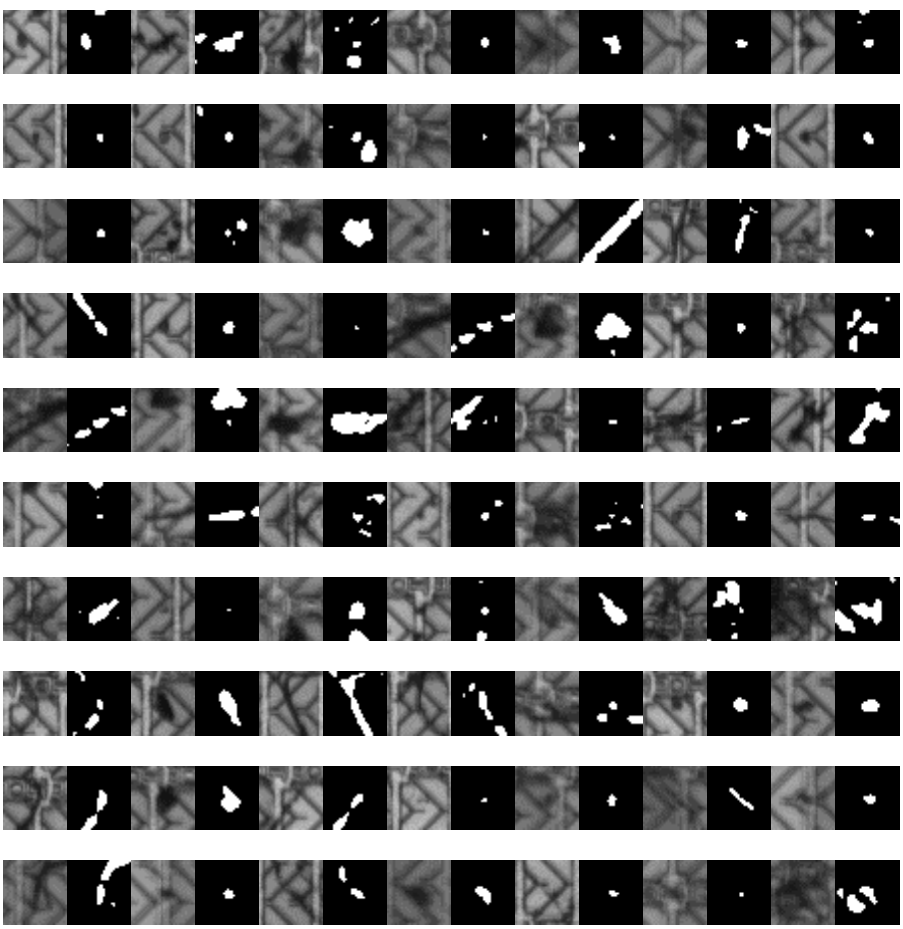


Fig 4.1. Detected defects

TFT-LCD defects used in the experiment are in Fig 4.1. As mentioned above in 2.1., there are three kinds. Each is a particle, a pinhole, and a scratch. The defect data is a 32x32 image, and there are approximately 400 defects per each type. When learning and classifying all the data, the training set and the test set has to be separated. We used the test set to verify clusters, which clustering with the algorithm.

	Training Set	Test Set	Total
Particle	290	125	415
Pinhole	280	121	401
Scratch	292	126	418
Total	862	372	

Table 4.1. Defect data used in experiments

4.2. Define K in K-Means Clustering

In the experiment, the K value was fixed at 3 because three types of defects were classified. In order to validate whether the data used in the experiments are correct, we used elbow method. The reason we used elbow method is we already have an answer for all of the data.

K is increased from 1 to 8 and the values are examined. When k is 3, there is almost no change in performance. So, k was chosen as 3. We classify three types of defects, therefore we have verified by the elbow method that k is 3.

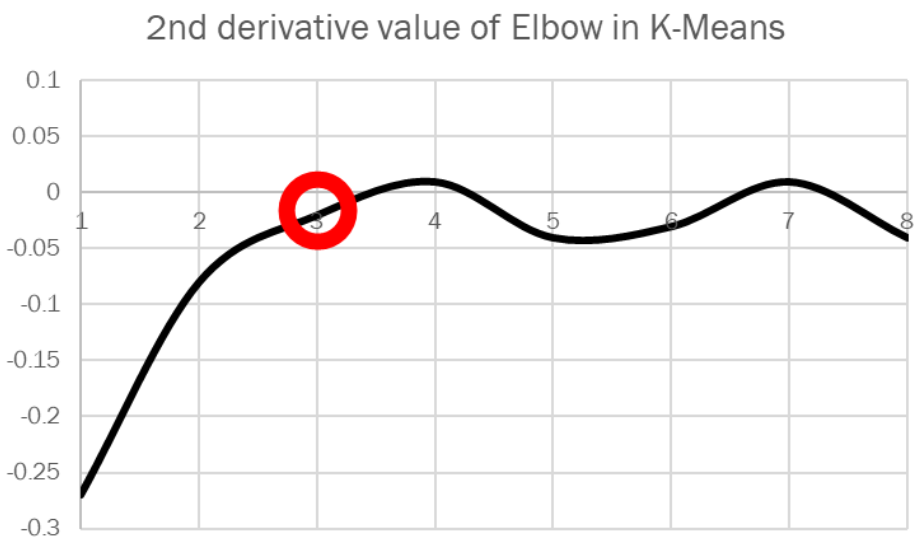
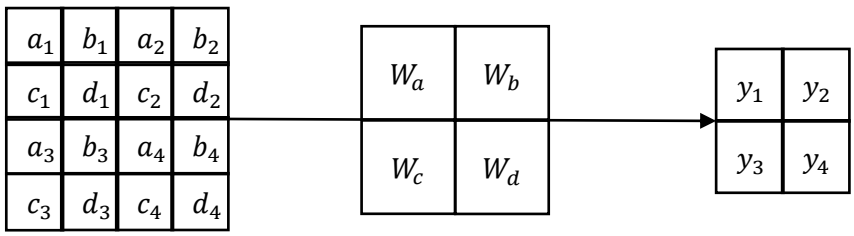


Fig 4.2. Result of elbow method

4.3. Define Kernel

When configuring the kernel, we have to select the size and value. First is size selection. We used square images and used the smallest square kernel (2x2) to minimize image loss. 2x2 kernel works in the following manner.



$$y_j = \sum_i i_j * W_i \ (i = a, b, c, d, \ j = 1,2,3,4)$$

Fig 4.3. Kernel used in experiments

The following is the kernel internal value selection. There is a study by Xavier that selects kernel values according to the number of input and output pixels during the study of the kernel. The kernel values are within a certain range and all values are simulated in order to find the best value among values.

$$\mathrm{W} \sim \mathrm{U}\left[-\sqrt{\frac{6}{n_{in} + n_{out}}}, \sqrt{\frac{6}{n_{in} + n_{out}}}\right]$$

W_a	W_b	W_c	W_d	Performance
0.206	1.000	0.402	0.392	0.933
−0.654	0.688	−0.802	−0.986	0.917
−0.426	0.998	0.232	−0.618	0.901
0.068	−0.402	−0.832	−0.884	0.900
0.848	0.978	0.406	0.260	0.883
0.804	0.976	0.890	0.040	0.883

⋮

Table 4.2. Kernel value selection

4.4. Results

For the labeling performance test, we used data from 4.1. We used a k-means clustering algorithm for the labeling, and the features used were size, brightness, shape, and kernel.

The results are better than when using only the features that can be visually confirmed.

	Using existing features (%, number)	Adding kernel features (%, number)
Particle	97.6% (122)	99.2% (124)
Pinhole	47.9% (58)	72.7% (88)
Scratch	88.9% (112)	96.0% (121)
Total	78.5%	89.5%

Table 4.3. Labeling performance evaluation result

Chapter 5. Conclusion

I propose suggested solutions for the improvement of the labeling performance, which is the step of naming defects in the TFT-LCD defect classification process. The research improves the detection of three types: particles, pinholes, and scratches. Each type exhibits different characteristics, which are visibly identifiable. Using these features alone, the process had a limited result.

I utilized features of the image itself for labeling by adding features using the kernel. Labeling used k-means clustering, an unsupervised learning among machine learning. When using k-means clustering, k and features must be determined. Features used were described above and we used the internal evaluation method, elbow method for selecting K.

The experiment presents enhanced results when these additional features are applied. Extracting features of the image itself, performance of the labeling process can be improved, which has the implication to the later learning and classification process leading to a higher accuracy.

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Abstract

TFT-LCD결함 분류 공정에서의 K-Means Clustering을 이용한 라벨링 자동화 성능 향상에 대한 연구

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본 논문에서는 디스플레이 결함 분류 공정에서의 라벨링 정확도 향상에 대해 연구를 하였다. TFT-LCD 제조 공정 중 결함이 발생하는데, 이렇게 발생한 결함은 크기와 종류에 따라 수리해서 사용하거나 폐기해야 하므로 생산 수율을 낮추는 원인이 된다. 공정 중 결함 발생을 줄이기 위해 발생한 결함을 광학계와 영상처리 알고리즘을 통해 탐지하고 머신러닝 알고리즘을 통해 탐지한 결함을 분류하고 공정에 피드백을 준다. 탐지한 결함을 분류하는 과정에서 결함을

학습하고 분류하는데 학습 이전에 결함에 이름을 붙여주는 라벨링 작업이 필요하다. 사람이나 기계가 결함을 라벨링 하는데 이때 오류가 발생하면 결함이 제대로 학습되지 않기 때문에 공정에 제대로 된 피드백을 줄 수 없다.

이 문제를 해결하기 위해 k-means clustering 방법을 이용해 효과적으로 결함을 라벨링 하는 방법을 고안하였다. 기존 연구에서는 라벨링 시 결함의 특징을 이용해 분류하는데 이때 시각적으로 확인할 수 있는 특징만을 이용했다. 본 논문에서는 시각적으로 확인할 수 있는 특징 이외에 결함 데이터에 kernel 을 통과시켜 얻은 값을 영상의 특징으로 추가했다. 이 특징을 이용해 기존에 분류하지 못했던 결함을 더 잘 분류할 수 있게 되었다. 실험 데이터는 TFT-LCD 공정 중 발생한 결함을 이용했다.