## Fast Search Algorithms for IC Printed Mark Quality Inspection<sup>1</sup>

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### Abstract

This paper presents an effective and general purpose search algorithm for alignment, and we applied it to IC printed mark quality inspection. The search procedure is based on normalized cross correlation, and we improve the method with hierarchical resolution pyramid, dynamic programming, subpixel accuracy, multiple target search, and automatic model selection. The proposed search method can be applied to general visual inspection.

The IC printed mark includes a logo pattern and characters. Due to the alignment error of the inspection machine, the mark can be rotated or translated. Main printing error of an IC mark is shown in Figure 1 [1].

We develop the teaching and inspection function, optimize the system, and test it on an IC inspection machine. Our algorithm achieves high accuracy, reliability, and repeatability with high speed for industrial requirement and works well on field test of various IC products.

			_
a	ABC - 1234	ABC - 1234	ı
с	ABC - 1234	ABC - 1234	ŀ
e	ABC - 1234	3C - 123	1
g	480 - 1234	A80 - IS84	ŀ
i	ABC 4234	ABC - 1234	

Figure 1: Main IC printed mark errors: (a) good, (b) smeared, (c) scraped, (d) double print, (e) broken, (f) missing ink, (g) bad contrast, (h) misprinted, (i) partial bad contrast, and (j) mis-orientation.

### 1 Introduction

Integrated Circuits (IC) are the fundamentals of computer and electronic industry. Mask exposure and defect inspection in wafer fabrication process and IC printed mark inspection, pin inspection, or die bonding in chip packaging all require high precision alignment. We develop the fast alignment algorithm to match a 128×128 pattern in a 640×480 field of view; the computing time is within 50 to 70 ms, and the locating accuracy can achieve subpixel accuracy.

Normalized Correlation Search (NCS) is the best linear method to solve 2D image matching [6], but traditional image correlation is computationally inefficient. We use the hierarchical pyramid strategy and a dynamic programming method to improve the speed and keep the excellent reliability and accuracy of NCS.

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Two fiducial marks are used to solve the image rotation [2]. Tolerance of about  $\pm 10^{\circ}$  is acceptable for NCS due to its excellent matching ability and reliability. After accurate alignment, optical verification can be easily achieved by image difference. The inspection method is divided into two main steps: the teaching step and the inspection step. During teaching step, we focus on complete functions for teaching on various kinds of IC printed marks. On the other hand, during inspection step, we focus on inspecting speed and accuracy for industrial requirement.

## 2 Background

Based on the nature of the IC printed marks, we can use horizontal projection to segment each printed line and vertical projection to segment each printed character.

Minimizing within-group variance method [5] is used to get a proper binarizing threshold for segmenting the printed mark and the background of an IC chip. We assume each the foreground part and the background part to be Gaussian distribution, and the best threshold t will minimize the within-group variance  $\sigma_w^2(t)$ . The difference threshold for inspection can be automatically calculated by the two mean values  $\sigma_1$  and  $\sigma_2$ .

Due to the image rotation and alignment error of the inspection mechanism, some edge noise will remain after image difference. Morphological opening will eliminate the noise and preserve the defect pixels.

Normalized cross correlation [4] matches a pattern to an image with the correlation coefficient  $\mathbf{r}(u,v)$  scaled in the range -1 to 1; independent of translation and linear shifting and scaling of gray intensity. The correlation coefficient is defined as follows:  $\mathbf{r}(u,v)$  =

$$\frac{\sum_{i=0}^{m} \sum_{j=0}^{n} \left[ \mathbf{I}(i+u,j+v) - \overline{\mathbf{I}} \right] \left[ \mathbf{M}(i,j) - \overline{\mathbf{M}} \right]}{\sqrt{\sum_{i=0}^{m} \sum_{j=0}^{n} \left[ \mathbf{I}(i+u,j+v) - \overline{\mathbf{I}} \right]^{2} \sum_{i=0}^{m} \sum_{j=0}^{n} \left[ \mathbf{M}(i,j) - \overline{\mathbf{M}} \right]^{2}}}$$

## 3 Fast Search Algorithms

#### 3.1 Introduction

General purpose fast search algorithm which accuracy, functionality, reliability, repeatability, and speed are satisfied at the same time is an important topic in computer vision. Normalized cross correlation is our main idea to perform general purpose matching, and we will improve the speed and enhance the ability by the dynamic programming and the resolution pyramid method.

By hierarchical sub-sampling of the pattern and search image, we get two sets of resolution pyramid images. By full search on the smallest sub-sampling image, we reduce the global search space. After getting the global matching point, we perform one or more local search on the finer resolution image layer near the neighborhood. Repeating this approach, we can get the accurate matching point of the original image. We can enhance this method by oversampling the image to get the subpixel accuracy and sorting the matching scores in descending order to get multiple matching targets.

### 3.2 Dynamic Programming to Speed-Up Normalized Cross Correlation

Referring to Equation 1, we can simplify the computation and apply the dynamic programming (D.P.) method as Equation 2. Seven main terms constitute the correlation equation. The three terms about the pattern image  $\mathbf{M}$  can be computed in the preprocessing step. The three terms about the search image  $\mathbf{I}$  can be computed once by the dynamic programming method in the pre-processing step. The dominating term of the correlation of the pattern and the search image is of the complexity  $O(m \times n \times w \times h)$ .

The original normalized correlation  $\mathbf{r}(u, v)$  needs a square root computation and ranges between -1 and 1. We discard the inverse matching and define the new correlation factor  $\mathbf{CF}(u, v) = \max(\mathbf{r}(u, v), 0)^2$ . By avoiding the square root of a floating number, we get better performance. The dynamic programming approach to reduce the computation of the correlation is shown in Figure 2, we sum up pixels and con-

struct the table step by step.

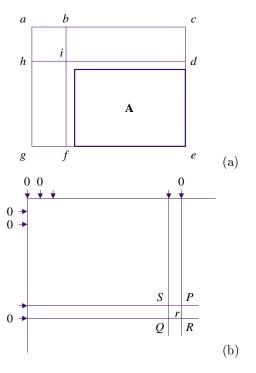


Figure 2: (a) Use D.P. table to compute the sum of pixels of a specific area.  $\mathbf{A} = aceg - abfg - acdh + abih = e - f - d + i$ . (b) The construction of the D.P. table. R = P + Q - S + r.

$$\begin{array}{l} min = \text{minimum } (pwidth, \ pheight); \\ \text{if } (min < 12) \ RLayer = 1; \\ \text{else if } (min < 24) \ RLayer = 2; \\ \text{else if } (min < 48) \ RLayer = 3; \\ \text{else if } (min < 96) \ RLayer = 4; \\ \text{else if } (min < 192) \ RLayer = 5; \\ \text{else if } (min < 384) \ RLayer = 6; \\ \text{else } RLayer = 7; \\ \end{array}$$

Table 1: The pseudo code that decides RLayer from pwidth and pheight.

## 3.3 Resolution Pyramid/Hierarchical Search

Resolution pyramid or hierarchical search can preserve almost all excellent properties of NCS. To achieve fast search, we need image sub-sampling; on the other hand, to search accurately, we need image over-sampling. We use the average of four pixel values as the sub-sampling pixel. With proper coding technique, we can achieve the work quickly. We sort these pattern and search image layers to a pyramid structure. The number of layers is adjustable and depends on the pattern and the search image sizes. The global search is performed only on the coarse layer, and the local search and subpixel search are on the finer layers. Each sub-sampling layer speeds-up the coarse search by the factor of  $2^4 = 16$ .

$$\mathbf{r}(u,v) = \frac{\sum_{i=0}^{m} \sum_{j=0}^{n} \mathbf{I}(i+u,j+v) \mathbf{M}(i,j) - \left(\sum_{i=0}^{m} \sum_{j=0}^{n} \mathbf{I}(i+u,j+v)\right) \left(\sum_{i=0}^{m} \sum_{j=0}^{n} \mathbf{M}(i,j)\right)}{\left[\sum_{i=0}^{m} \sum_{j=0}^{n} \mathbf{I}(i+u,j+v) - \left(\sum_{i=0}^{m} \sum_{j=0}^{n} \mathbf{I}(i+u,j+v)\right)\right] \left[\sum_{i=0}^{m} \sum_{j=0}^{n} \mathbf{M}^{2}(i,j) - \left(\sum_{i=0}^{m} \sum_{j=0}^{n} \mathbf{M}(i,j)\right)\right]}$$

where  $\mathbf{N}=m\times n$ . With the dynamic programming table, computing pixel sum of any specific area requires only two subtractions and one addition. The table is easy to compute at the pre-processing step before search.

We decide the number of layer based on the smaller value of the width and height of the pattern image, as shown in Table 1. The boundary value of the table is calculated from Table 2. We force the image width to be even for ease of computation.

min	RLayer	pwh	min	RLayer	pwh
1-8	1	2,4,6,8	80-95	4	10
9-11	1	10	96-127	5	6
12-15	2	6	128-159	5	8
16-19	2	8	160-191	5	10
20-23	2	10	192-255	6	6
24-31	3	6	256-319	6	8
32-39	3	8	320-383	6	10
40-47	3	10	384-511	7	6
48-63	4	6	512-639	7	8
64-79	4	8	640-767	7	10

Table 2: The calculation of the layer boundary where pwh means the pattern width or height in the top layer.

COARSE		coarse search only
_SEARCH		
SEARCH_ONE		search for one target
_FAST		with early jump out
SEARCH_ONE	nCoarseTarget = 3	search for one target
	nSearchTarget=1	exactly and robustly
SEARCH_MN		coarse search
	nCoarseTarget=10	for 10 targets
		and fine search
	nSearchTarget = 5	for 5 targets
		among them
SEARCH_MC		coarse search
	dCoarseMinCF = 0.2	for $CF > 0.2$
		and fine search
	dSearchMinCF = 0.5	for $CF > 0.5$
		among them
AUTO_SEARCH	dCoarseMinCF=0.2	automatic search,
	nCoarseTarget = 10	the default
	dSearchMinCF = 0.5	parameters are used

Table 3: Multiple target search methods and parameters.

## 3.4 Multiple Target and Subpixel Search

It is easy to extend the resolution pyramid method to achieve 0.5 or 0.25 subpixel accuracy by oversampling the image by bi-linear interpolation. In our miltiple target and multiple level pyramid search, proper threshold value for both the coarse search and the fine search is needed as shown in Table 3.

## 3.5 Automatic Search Model Detection

The automatic detection of search model is an important function in automatic alignment solution. We can design the model selection algorithm according to the search method. We select the model using the top sub-sampled layer to get the better and robust result. We define the input and output of the model detection algorithm as follows. The inputs are the pattern width, pattern height, and the search range. The outputs are the positions of the best model candidates sorted in the descending order.

We design the model selection algorithm by calculating the *position score* for local uniqueness and the *uniqueness score* for global uniqueness [3]:

position  $score = variance \ score \times (1 - max8CF)$ 

 $uniqueness\ score = 1 - secondCF$ 

Because the correlation score is between 0 and 1, 1-max8CF represents the local position uniqueness and 1-secondCF represents the global uniqueness. The scene contrast is also important information for model candidate selection, so the  $variance\ score$  will be taken into consideration. For the ease of computing, we define the  $variance\ score$  by the difference of the highest gray level and the lowest gray level of the model candidate.

# 4 IC Printed Mark Quality Inspection

#### 4.1 Introduction

The IC printed mark includes a logo pattern and characters. Due to the alignment error of the inspection machine, the mark can be rotated or translated. The inspection procedure includes the teaching step and the inspection step. After teaching, the system will perform horizontal and vertical projections to segment each character and logo to be a *sub-feature* [2]. Sub-feature is the basic unit of the difference inspection. We choose two *fiducial marks* from the sub-features as the search pattern for alignment.

Due to the alignment error, edge noise will remain after pattern difference. Morphological opening will eliminate the edge noise, and we count defect proportion of each sub-feature and compare it with the acceptance threshold to accept or reject this chip. Reliability, repeatability, false alarm rate, and misdetection rate will be used to adjust the algorithm and parameters. The inspection time is critical and affects industrial implementation.

### 4.2 The Alignment of IC Image

We can use two fiducial marks to detect IC rotation as shown in Figure 3. Choosing good fiducial marks is important and related to correlation performance. During inspection, we search for the two fiducial marks to calculate the translation and rotation of the inspected image. Then we rotate back the inspected part of the image and perform pattern difference.



Figure 3: Two fiducial marks to detect IC translation and rotation. The fiducial marks are the bold rectangles, and the search ranges are the thin rectangles.

### 4.3 Teaching and Inspection

The teaching and inspection process is shown in Figure 4. The inspection time is critical for industrial application, but it is related to many conditions such as the hardware, the size of the inspected area, and the inspection parameters. Table 4 shows the approximate time profile of our inspection procedure on a personal computer with Pentium 200 MMX CPU. Figures 5 shows the good IC and the inspection result of a defective IC.

### 5 Conclusion

In this paper, we have proposed a new, efficient, and general purpose grayscale fast search algorithm, and

	the inspection steps	time (ms)
1.	grab image	50
2.	search for two fiducial marks	50
3.	clip and rotate the image	30
4.	perform pattern difference	10
5.	perform opening	80
6.	count defect, accept/reject	20
	total	240

Table 4: The approximate time profile of inspection.

we applied it to IC printed mark quality inspection. Our method achieves high accuracy, reliability, and repeatability with high speed for industrial requirement and works well on field test of various IC products.

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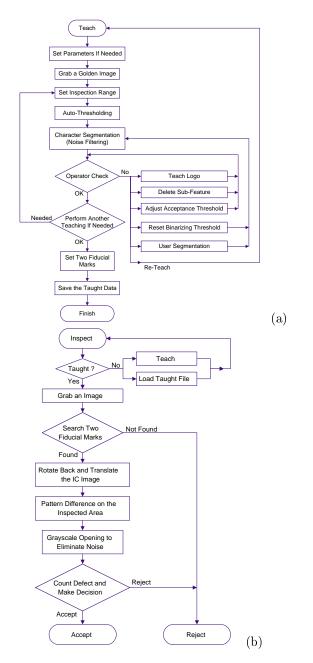


Figure 4: (a) The teaching and inspection process. (b) The inspection process.

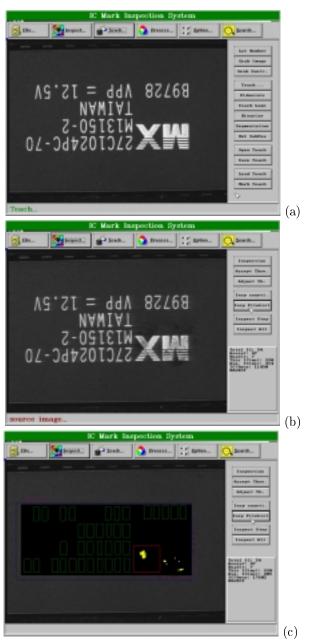


Figure 5: (a) The good IC image. (b) Test image of defective IC. (c) Inspected result of the defective IC.