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A fast algorithm for detecting die extrusion defects in IC packages

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Abstract. In this paper, we present a fast method for the detection of die extrusion defects in IC packages. The optical and lighting set-up as well as the details of the algorithm used for the isolation and detection of die extrusion defects are presented. Our algorithm basically involves the use of optimal filters for the detection of linear features and other feature enhancement techniques. This paper also addresses implementation issues including speed, effectiveness, and robustness.

Key words: IC package inspection – Die extrusion defects – Linear feature extraction – Feature enhancement

1 Introduction

In semiconductor manufacturing, machine vision plays an important role in automatic inspection of the IC chips (Rao 1996). The main automated inspection processes in IC manufacturing include mask and reticle inspection, in-process pattern inspection, and final chip inspection for quality control (Dom and Brecher 1995). Among the many types of IC package defects, die extrusion defects are gaining attention as IC packages get thinner (Marrs 1996).

The die extrusion defect is a result of the incorrect mounting of the die on the lead frame. It occurs after the molding process and appears as a faint outline of the die on the package surface as shown in Fig. 1a. The two faint linear features, one horizontal and the other vertical, represent the defect. The vertical linear features are disjointed due to the reflectance characteristics of the package surface that increase the difficulty of detecting the die extrusion defect.

As with other IC package defect inspection problems, the central issues are fast, robust detection and differentiation from other defects. In this paper, we propose a fast and robust algorithm to detect die extrusion defects. First an optimal filter for wide linear features extracts the defect features in the image of the IC package. The filter is designed such that it responds positively to linear features, while effectively filtering noise. The minimum response of defect features is used as a threshold to generate the binary image. A decision as to whether the die extrusion defect exists is then made by analyzing the resulting binary image. Noise removal filters and practical considerations related to the industrial settings are also discussed in this paper.

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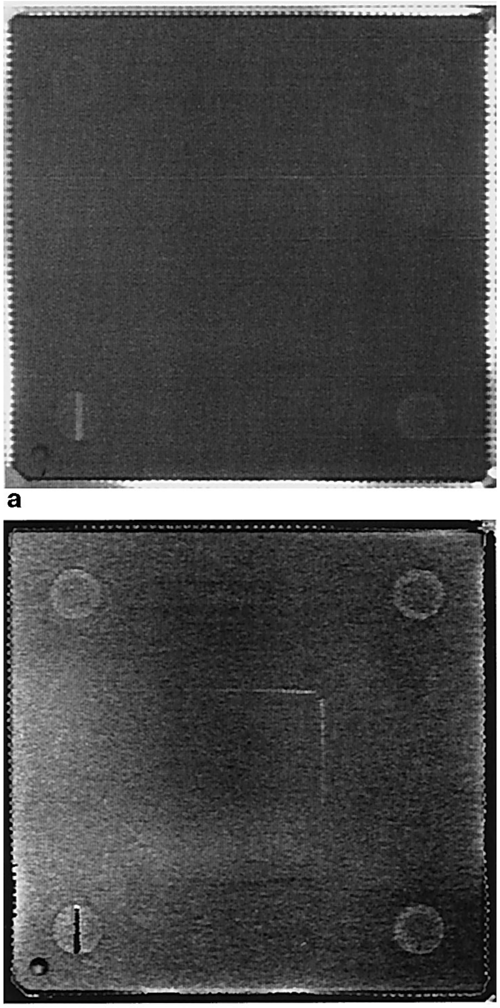
2 Obtaining a good image of the defect

Getting a good image is the first but difficult step in every inspection problem. Many different lighting systems, including circular and rectangular LED arrays, on-axis diffuse illuminators and square continuous diffuse illuminators with different kinds of illumination sources have been tried for this inspection objective. The uniform diffuse illuminator had the best effect among these illumination systems because of the diffuse reflectance characteristics of the IC package. However, the image obtained using the uniform diffuse illuminator suffers from background noise and does not provide sufficient contrast for direct analysis. The die extrusion defect is not easily discernible and the only sign of the defect is the faint outline of the die. The ring LED light is a good alternative for the more expensive square continuous diffuse module, although it only provides limited uniformity. Figure 1a and other unprocessed images in this paper are obtained with the LED ring illuminator. The size of the linear features in the image containing the die extrusion defect depends on the resolution of the imaging system. The thickness of the linear features under consideration is no larger than five pixels when the image of the whole IC package is 768×572 pixels. The $N_x \times N_y$ central portion of the image of the IC package is the region containing the die, i.e., the region where the die extrusion defect may exist.

Figure 1b is the contrast-stretched version of the unprocessed image of the IC package surface of Fig. 1a. The background noise, which is clearly visible in Fig. 1b, is due to the reflectance of the IC package surface and uneven lighting, and is large enough to hinder detection of the desired linear features associated with the die extrusion defect. Several filters are applied to remove the background noise. The Gaussian smoothing filter (Jain et al. 1995) was found to be not suitable, because it blurs the defect features significantly



a

b

Fig. 1a. IC package with the die extrusion effect; **b** contrast-stretched version of **a** which clearly shows the background noise

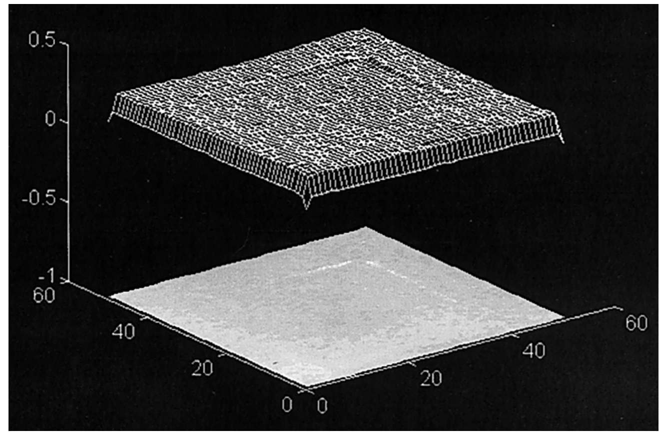


Fig. 2. 3D profile of the central portion of Fig. 1 (i.e., region of interest) after noise removal

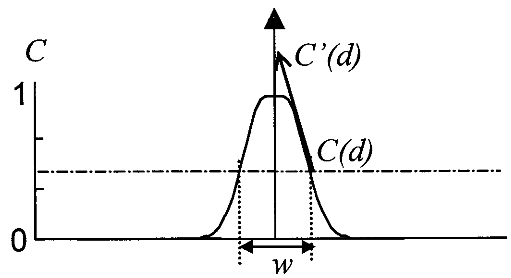


Fig. 3. 1D linear model with width w

as it reduces the noise. An appropriate filter is one based on anisotropic diffusion methods (Perona and Malik 1990; Saint-Marc et al. 1991) that determine the smoothing effect upon the local characteristics of the image. Such filters can adaptively smooth the image, while preserving the discontinuities at same time. The median filter can be combined with this kind of filter to remove the discontinuities caused by impulse noise. Figure 2 shows the 3D profile of the smoothed $N_x \times N_y$ central portion (i.e., region of interest) of Fig. 1a that is obtained using a noise filter based on the anisotropic diffusion method and a median filter. It is evident from this profile that the background in the filtered image becomes more even, while the original discontinuities are preserved. However, the contrast between the defect features and the background in the filtered image is still too small for direct analysis. Noise removal using the above-mentioned filters is a computationally intensive process and it is for this reason that the original image with noise is directly used in this inspection problem. More robust methods are thus necessary and one solution is to use feature enhancement that is more related to specific defect characteristics.

3 Extracting the defect features

Petrou proposed a model (Petrou 1993) for wide linear features and an optimal convolution filter according to Canny's three basic criteria for convolution filters (Canny 1986), i.e., signal-to-noise ratio (SNR), locality and minimal false response. The resulting 1D even filter is based upon the desired linear model illustrated in Fig. 3, where $w = 2d$ is the thickness of linear feature and $C'(d)$ is the gradient magnitude of $C(d)$ which satisfies $C(d) = 1/2\,C(0)$.

For 2D images, the linear features in an image U are detected using two orthogonal convolution filters based on following equation:

$$V = \max(U * f_x, U * f_y)\,, \tag{1}$$

where f_x is the 1D filter for linear features, $f_y = f_x^T, V$ is the resulting filtered image and "$*$" denotes the convolution operator. We applied this optimal filter for wide linear features to extract those faint features associated with die extrusion defect. Table 1 shows some convolution filters that represent several possibilities for the linear features that are determined by parameters s and d. The value of d is the estimated distance from the center of the linear feature to position x where the *pixel value* or *intensity* $I(x)$ satisfies:

$$I(d) = 1/2\,[I(0) + I(b)]\,, \tag{2}$$

where $I(0)$ is the intensity at the center of linear feature and $I(b)$ is the background intensity, which can be estimated as the average of several pixels that are well away from the center. s is estimated from the slope at d, $I'(d)$ such that $s \approx 2I'(d)[I(0) - I(b)]^{-1}$.

Table 1. The filters for linear features

Filter parameters			f_x
d	s	Size	1D even convolution filter for linear features
1	2	9	−0.161566, −0.467645, −0.3283, 0.453369, 1.0082, 0.453369, ...
1.2	2.5	11	−0.000887151, −0.246026, −0.501423, −0.277114, 0.526635, 0.99763, 0.526635, ...
2	2	15	−0.0878158, −0.30447, −0.485243, −0.493876, −0.233317, 0.296116, 0.808807, 0.999595, 0.808807, ...
2	3	15	0.0173986, −0.184069, −0.412764, −0.487315, −0.268737, 0.287266, 0.632964, 0.83051, 0.632964, ...

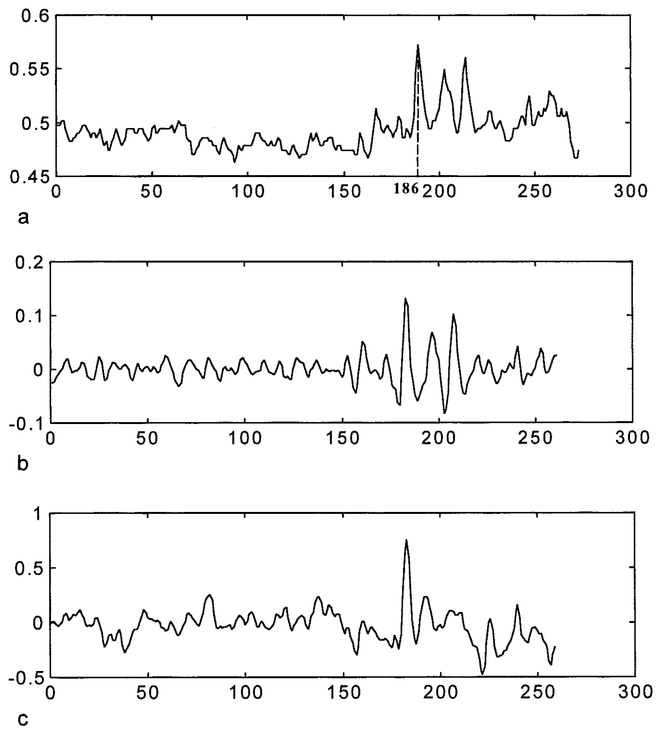


Fig. 4a. A horizontal line of the IC package image that contains the vertical linear feature at position 186; **b** the response of the filter based on Eq. 1 to **a**; **c** the response of the filter based on Eq. 5 to **a**

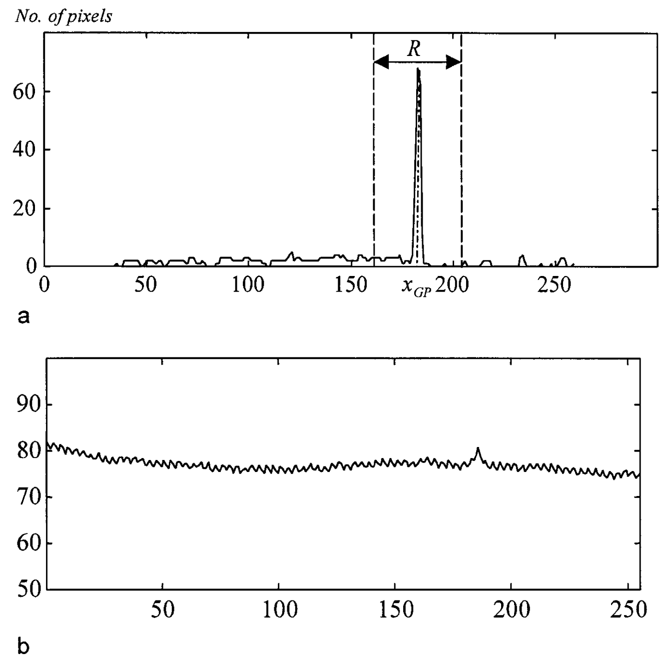


Fig. 5a. The vertical projection profile of the ROI after enhancement; **b** The vertical projection profile of ROI (before enhancement)

The convolution filters in Table 1 are designed based on the corresponding values for d and s. The larger the value of d, the larger the size of the filter, which results in more computations at each pixel. Further details about the filter computation are available in Petrou (1993).

In addition to 1D parameters of wide linear features, 2D characteristics of linear segments such as length and direction can be incorporated into the above filters as

$$V = \max\left(U * F\,,\ U * F^T\right)\,, \tag{3}$$

where $F = f_x * G_{m\times l}$ and $G_{m\times l}$ is the mask corresponding to length l and direction $\theta\left(45^0 \leq \theta \leq 135^0\right)$ of the linear feature. For example, a mask for a linear segment of length 5 and in a 60^0 direction is:

$$\begin{bmatrix} 1 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 1 \end{bmatrix}_{5\times 3} .$$

As the features of our interest are almost vertical or horizontal, the incorporated filter has the following simple form:

$$F_x = \begin{bmatrix} f_x \\ \vdots \\ f_x \end{bmatrix}_{l\times k} = f_x * \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix}_{l\times 1} , \tag{4}$$

so that the response of the convolution filter becomes

$$V = \max\left(U * F_x\,,\ U * F_y\right)\,, \tag{5}$$

where $F_y = f_x^T * [1\dots1]_{1\times l}$. Comparing with Eq. 1, Eq. 5 requires l extra operations for each pixel that result in significant enhancement of the desired features and good suppression of noise as illustrated by Fig. 4. While Fig. 4b was obtained using the information in Fig. 4a only, Fig. 4c was obtained using information of the neighboring l horizontal lines. Clearly, the length parameter in the F_y filter reinforces the response at the defect position and comparatively reduces the response at other points by averaging the responses of the vertical neighbors. As another result of this averaging effect, the segmented or discontinuous vertical linear feature can appear connected. F_x is similarly used to enhance horizontal features.

4 Obtaining the binary image for identifying the defect

After enhancing the features, the $N_x \times N_y$ region of interest of the intensity image is thresholded to obtain a binary image

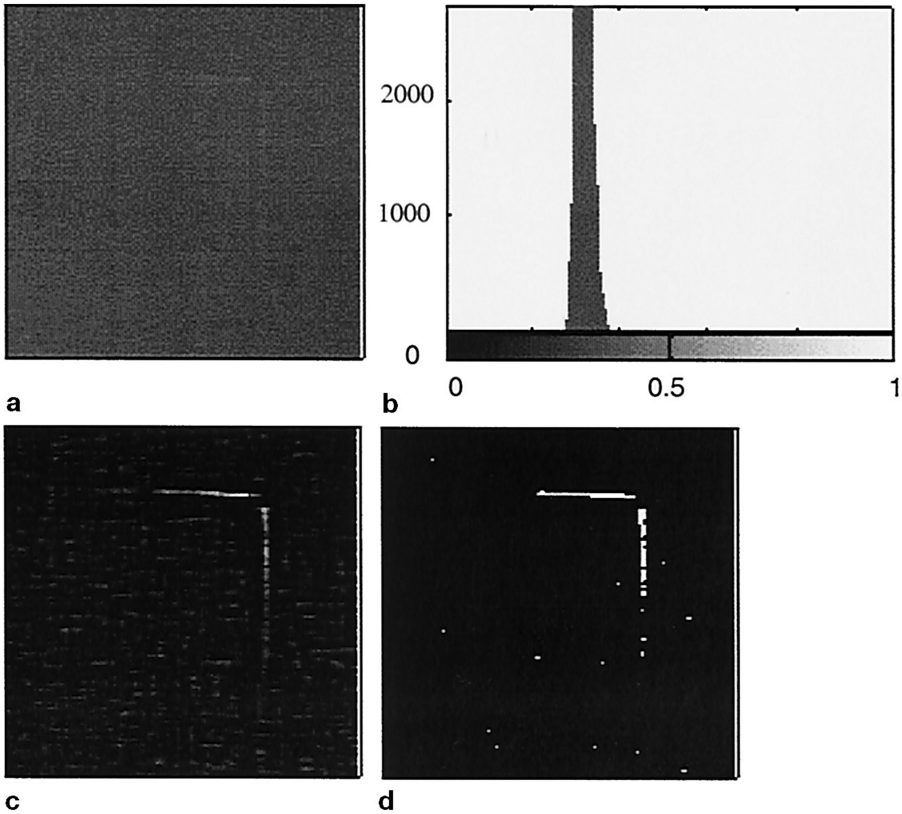


Fig. 6a. The original image; **b** the histogram of **a**; **c** response of the convolution filter based on Eq. 5; **d** the resulting image after thresholding

for further analysis. Two factors are considered in the threshold procedure. First is the selection of pixels that produce a large feature filter response, which are defined as those intensities that are among the top $100w\left(N_x^{-1}+N_y^{-1}\right)$ %. The second factor is to exclude pixels that are less than a defined minimum acceptable value, which we defined to be $2\Delta I(l-m)$, where ΔI is the minimum difference of the intensity between the desired linear features and background, l is the length of the linear feature and m is the number of pixels of disconnection. A good estimate of $(l-m)$ is $1/4l$, which represents large gaps between the linear segments.

5 Defect identification

The final step in an inspection process is to determine the existence and location of the defects (if any). General pattern detection methods based on normal Hough transform are robust and can be used for various types of patterns including the linear patterns of various orientations, but they are computationally intensive (Illingworth and Kittler 1987; Atiquzzaman 1992). The line-fitting algorithm (Haralick and Shapiro 1992) can compute the line parameters in an image but involves an initial labeling process. For fragmented linear features, the line-fitting algorithm requires preprocessing procedures to assign the same label to the fragmented linear segments. Other shape recognition methods such as chain code or polyline representations (Jain et al. 1995) assume continuity, and so such methods are prone to noise and are not robust.

Our algorithm utilizes the defect characteristics to reduce the amount of computations and to achieve a robust result. In the die extrusion problem, the defect features are linear in vertical and horizontal directions. By evaluating the projections in these two directions, a decision can be made about the presence of a linear feature in a particular direction by analyzing the distribution about the global peak x_{GP}. Figure 5a shows the vertical projection profile of the region of interest (ROI). The linear feature-enhancing effect of our algorithm is clearly evident when Fig. 5a is compared with the vertical projection profile of the ROI in the unprocessed image shown in Fig. 5b. Thus, the detection of the defect features by direct projection profile analysis of the original unprocessed image will be much more difficult than that of the enhanced version. Moreover the enhancement is pretty robust, since only the specified linear features are enhanced, while other defects such as scratches would not affect the projection analysis unless these other defects are also linear in nature.

There are two criteria to identify a linear feature. First, the variance σ^2 in region R (defined as $[x_{GP}-0.1N_x\,,\,x_{GP}+0.1N_x]$) about x_{GP} must be less than $2w$, otherwise the peak is not distinct enough to represent a line. Second, the number of pixels at x_{GP} must be greater than a threshold to isolate the peak due to the linear feature from noise. The threshold can be set as $l\times x\times n$ where $l\times w$ is the number of pixels that a linear segment contains and n is minimum number of segments that a line contains. The horizontal projection profile is similarly analyzed to determine the presence of the horizontal lines.

6 Discussion and concluding remarks

Our algorithm is a pixel-based algorithm and is therefore computationally intensive. The amount of computations can be reduced by reducing the amount of computations per pixel and the number of pixels that need to be processed (Kahn et al. 1990). Long integers were used in Eq. 5 instead of the float type. The error of such an approximation is negligible compared with the enhancement effect of the defect features and results in much faster operation. The number of pixels that need to be processed can be reduced by excluding the irrelevant pixels. Pixels with very small gradient magnitudes are considered to be noise pixels and can be excluded from further processing. As the gradient magnitude histogram for most images is approximated by an exponentially decreasing function, even a very low threshold can eliminate a large portion of the image from further processing.

Our algorithm successfully detected the die extrusion defects in samples provided by Texas Instruments (Singapore). The resolution of the captured images was 2.1 mils/pixel and the defect detection was accomplished in about 1.2 s using a Pentium 166 computer. Figure 6d clearly shows the enhanced die extrusion defect despite the low contrast (Fig. 6b) of original image in Fig. 6a (which is a $256{\times}256$ sub-image of Fig. 1a). The enhanced image of Fig. 6c is obtained using the filter with settings d = 1.2, s = 2.5 and l = 11. Although there is still some noise, the features of interest are highly enhanced. Filters with other parameter settings shown in Table 1 also provide good results, since the linear characteristics of those filters are similar. The die extrusion defect is easily and quickly located by analyzing the x and y profiles of Fig. 6d, the binary image obtained after the thresholding procedure.

In our algorithm, the vertical and horizontal linear characteristics of the defect are utilized to reduce the computation and to isolate defect features. When the package image is such obtained that the defect feature is not horizontal or vertical, one possible solution is to check the orientation of the IC package first and rotate the ROI of the package image to the desired direction before application of the above algorithm.

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References

1. Atiquzzaman M (1992) Multi-resolutional Hough Transform – an efficient method of detecting patterns in images. IEEE Trans Pattern Anal Mach Intell 11:1090–1095
2. Canny John (1986) A computational approach to edge detection. IEEE Trans Pattern Anal Mach Intell 11:679–698
3. Dom BE, Brecher V (1995) Recent advances in the automatic inspection of integrated circuits for pattern defects. Mach Vision Appl 8:5–19
4. Haralick RM, Shapiro LG (1992) Computer and Robot Vision. Addison-Wesley, Reading, Mass
5. Illingworth J, Kittler J (1987) The Adaptive Hough Transform. IEEE Trans Pattern Anal Mach Intell 5:690–698
6. Jain R, Kasturi R, Schunck BG (1995) Machine Vision. McGraw-Hill, New York
7. Kahn P, Kitchen L, Riseman EM (1990) A Fast Line Finder for Vision-Guided Robot Navigation. IEEE Trans Pattern Anal Mach Intell 11:1098–1102
8. Marrs LG, Amkor Electronics Inc. (1996) Trends in IC Packaging. Electron Packaging Prod 8:24–30
9. Perona P, Malik J (1990) Scale Space and Edge Detection Using Anisotropic Diffusion. IEEE Trans Pattern Anal Mach Intell 7:629–639
10. Petrou M (1993) Optimal convolution filters and an algorithm for the detection of linear features. IEE Proc Commun Speech Vision 5:331–339
11. Rao AR (1996) Future directions in industrial machine vision: a case study of semiconductor manufacturing applications. Image Vision Comput 14:3–19
12. Saint-Marc P, Chen J-S, Medioni G (1991) Adaptive Smoothing: A General Tool for Early Vision. IEEE Trans Pattern Anal Mach Intell 6:514–529

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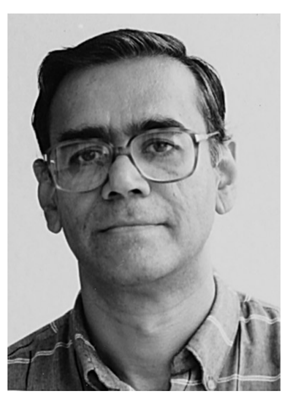

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