



Enabling Artificial Intelligence as Input Variable Control to Prevent Package Thickness Related Defect in Compression Molding

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Authors' contributions

This work was carried out in collaboration between both authors. Author EDP designed the study, performed the statistical analysis, wrote the protocol and first draft of the manuscript analyses and managed the literature searches. Author EPB managed the analyses of the study and execution of the experiments. Both authors read and approved the final manuscript.

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ABSTRACT

This paper aims to identify the causes of package thickness related defects in compression mold process. Related defects include wrong package thickness, exposed wire and/or die and mold bleed out.

There are three scenarios why package thickness problem is encountered in compression molding. These include wrong mold recipe selected against the actual lot, wrong lot loaded against the current recipe loaded and product input to mold having irregularities such as presence of stray die or damage on strip side rails and end rails. Applying artificial intelligence (AI) the mold machine to detect all abnormalities identified at input and prevent it from proceeding to molding.

Applying AI was able to eliminate occurrence of all package thickness related defects and machine related downtimes.

Keywords: *Artificial intelligence; compression mold; camera scan; laser scan.*

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1. INTRODUCTION

Compression molding is a recent development in IC packaging assembly wherein granule type mold compound is used to encapsulate product. Strip completed wirebond will be scanned for the total chip count on the strip then the machine will compute the amount of granule to dispense to meet the package thickness requirement [1].

The granule will then be transferred to the bottom mold tool with release film as its carrier. With strip at dead bug orientation on the top mold tool, bottom tool will move upward to compress mold compound to the strip until the desired package thickness is met as shown in Fig. 1 [2].

The critical process step is the die scan as this dictates the package thickness of the product. There are two types of die scan in compression mold, laser scan and camera scan. Laser scan is used to count the number die for big die size

while camera scan is used for smaller die size. Die scan will cover the scanning of the entire strip die active area only and does not include end rails and side rails. An actual strip and actual die scan result is illustrated below in Fig. 2.

1.1 Package Thickness Related Issues

Misprocessing of wrong lot or wrong recipe is being prevented by die scan depending on the die configuration data registered to the product recipe. It will recognize a different die size or wrong die stack height if product loaded is not same as the recipe. The recent new products have same die configuration data and the only difference between products is the package thickness requirement as illustrated in the Fig. 3 below. If the product with low package thickness requirement will be run using higher package thickness recipe it will continue die scan without error since same die configuration and vice versa.

COMPRESSION MOLD PROCESS

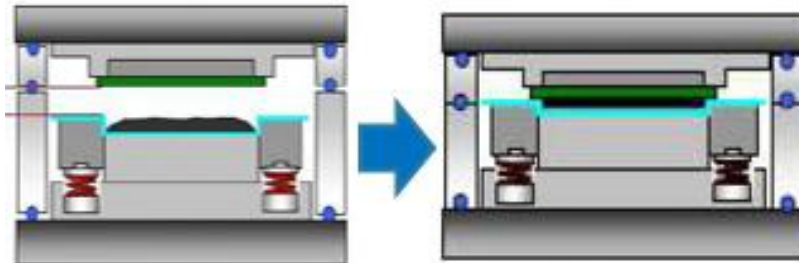


Fig. 1. Compression mold process

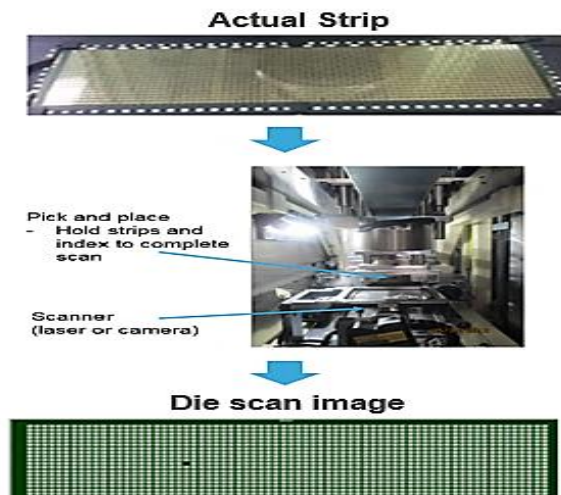


Fig. 2. Actual strip and scanned image of machine

Another issue of wrong package thickness is when there is discrepancy on incoming product from wirebond. If there is presence of stray die it will affect the planarity of the mold tool and cause mold compound to escape the clamping line. Damage strip that is extending to the mold active area will cause mold compound to leak during compression. For both cases, bleed of mold compound will lower the compound volume to meet the thickness requirement. At worst case, expose die and expose wire defect will be induced due to low package thickness as shown in Fig. 4.

process of the products which has multiple stack die.

For damage strip, based from the comparison of the different products highest occurrence are those with dual pass at diebond and wirebond for product B and E. Multiple pass processes has higher risk of occurrence of damage strip. For stray die, curing is only performed after the last die attach process thereby fly-off of die on lower die levels is possible. It can also be noted that lower occurrence for products with higher strip thickness for product A and D. Lower strip thickness is more susceptible to damage even with slight machine jamming. Below is the comparison of the different products in Table 1.

Current improvements on stray die and damage strip are still being worked on but will take time to improve due to complexity of the material and

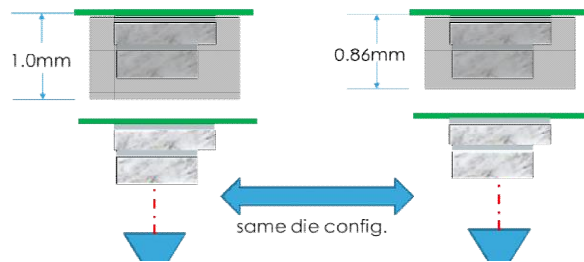


Fig. 3. Same die configuration with different package thickness

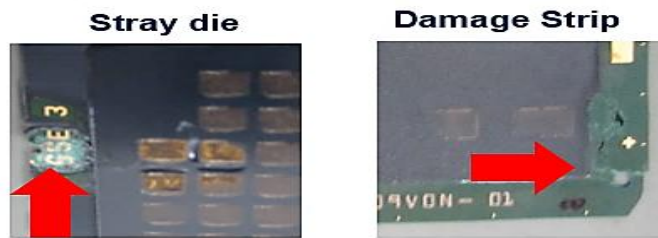


Fig. 4. Actual stray die and damage strip resulting to expose die and wire

Table 1. Process and material comparison between products

	Product A	Product B	Product C	Product D	Product E
Substrate damaged contribution?	4%	47%	18%	2%	21%
DB/WB Dual pass?	-	Yes	-	-	Yes
Substrate Thickness?	0.2mm	0.13mm	0.13mm	0.18mm	0.13mm
Rank in damaged?		1 st	3 rd		2 nd

1.2 Package Thickness Related Defect Performance

Package thickness related defects in compression mold has an average monthly ppm of 106ppm in 2018 as shown in Fig. 5.

Bleed of mold compound will clog the vacuum lines of the mold tool that will require pull-out affecting productivity. Base from 2018 downtime trend, there is an average downtime of 28 hrs per month as shown below in Fig. 6.

1.3 Current Mold Package Thickness Misprocessing Controls

Current control to prevent misprocessing of wrong program or wrong lot loaded includes posting on machine package thickness requirement per product as shown in Table 2.

Each lot is checked if lot traceability via traveler or runcard, actual strip and machine recipe are

tally prior loading the lot to the machine as shown below in Fig. 7.

If lot has strip abnormality like damage strip or stray die at front of line (FOL), a tag shown below in Fig. 8 is attached to the lot as traceability to assess if strip can be processed or yielded off prior mold.

It is required to perform mold package thickness measurement at 1 strip per lot using a micrometer to ensure that there will be no escape of wrong package thickness. It is stated in the production work instruction.

1.4 Enabling Artificial Intelligence in Compression Mold

For misprocessing due to wrong recipe or wrong lot loaded, die scan field of vision was extended to include side rails and end rails as shown in Fig. 9.

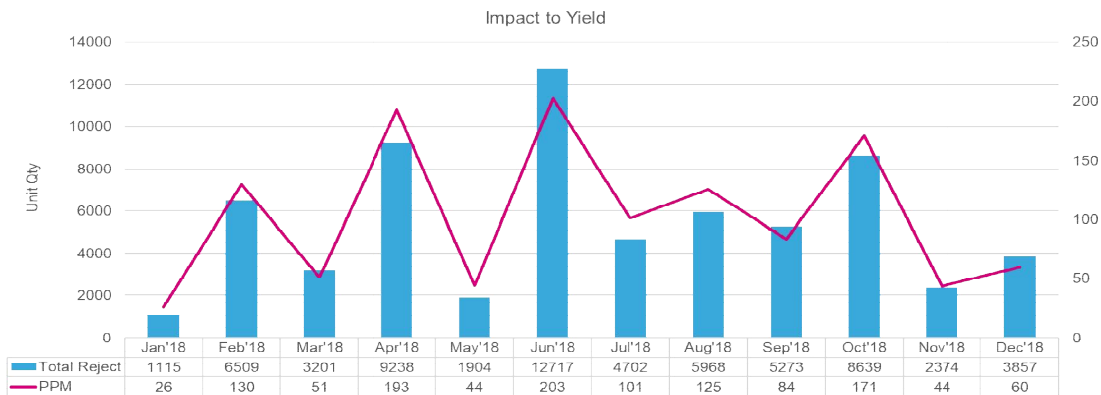


Fig. 5. Package thickness related defects trend in 2018

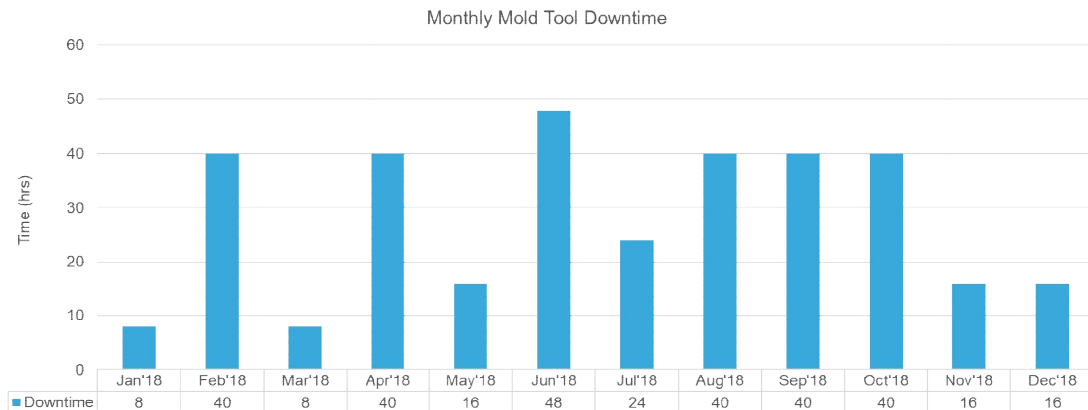


Fig. 6. Monthly downtime trend

Table 2. Compression mold package thickness matrix

Device name	Package description	Mold cap thickness (mm)	LF/Substrate thickness (mm)	Package thickness (mm)
ACCELEROMETER	LLGA 3X3X1.0 16L-FOR SENSOR	0.785	0.20	0.942-1.027
GYRO	LGA 4X4X1 16L LEAD PITCH 0.65 mm	0.785	0.20	0.942-1.027
GYRO DIS	LLGA 3X3X1.0 16L-FOR SENSOR	0.785	0.20	0.942-1.027
KITKAT	VFLGA 3X3X1 22L	0.855	0.13	0.942-1.027
ORA ET LABORA	TFLGA 3.5X3X1 24L	0.855	0.13	0.97-1.027
VULCANO	VFLGA 2X2X1 12LD	0.785	0.13	0.95-1.0
ARGENTERA	VFLGA 2X2X0.86 12LD	0.70	0.13	0.78-0.86
ARGENTERA	LGA 2X2X0.7 12LD	0.54	0.13	0.62-0.70
ARGENTERA	VFLGA 2X2X0.7MM 14LD	0.54	0.13	0.64-0.70
ALCANTARA	LLGA 3X3X1.0 16L	0.84	0.13	0.92-1.0
OGGIONO	VFLGA 3X3X0.86	0.70	0.13	0.78-0.86
SEOUL	VFLGA 3X3X0.86 16L	0.70	0.13	0.78-0.86
SUWON/SWAN	VFLGA 2.5X3X0.86 12LD	0.70	0.13	0.78-0.86
GROHMANN	VFLGA 2X2X0.86 12LD	0.70	0.13	0.78-0.86
COL	WFQFPN 4X4X.075 COL 20L 0.5P	0.55	0.20	0.70-0.80
NEWTON	WFLGA 2.3X2.3X0.7 16L	0.53	0.13	0.61-0.70
STARK	LGA 2X2X0.7 12 LEADS	0.53	0.13	0.61-0.70
COL	UFDFPN 1X1X0.6 6L P0.5	0.35	0.155	0.50-0.60
COL	VFDFPN 1.0X1.0X0.38 4L PITCH 0.6	0.25	0.13	0.34-0.40
COL	UFQFPN 1.5X1.5X0.55 8L PITCH 0.5	0.40	0.125	0.42-0.55
SALIX/NOBLE/ WILLOW/OAK	XFBGA7X4.2X0.47 87 0.5 PITCH 0.22BALL	0.20	0.13	0.28-0.38
SALIX	UFBGA 5X7X0.60 117 0.5P	0.27	0.13	0.38-0.45

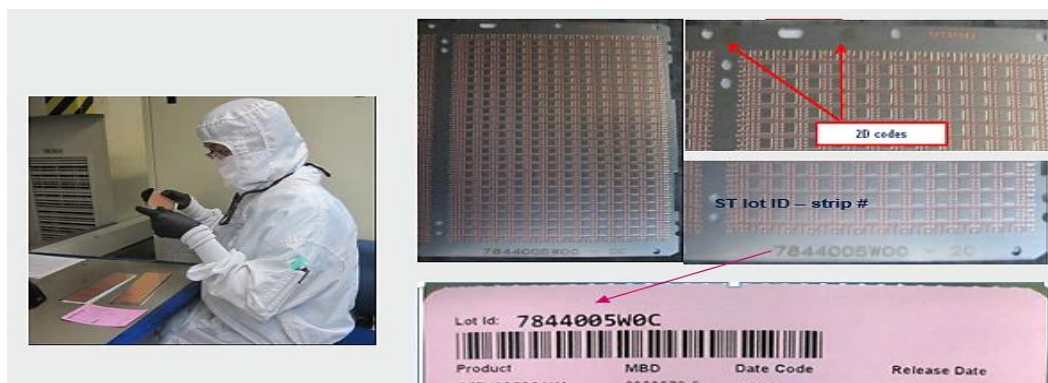


Fig. 7. Lot, Run card and machine cross check

Leadframe Damaged/Manually Handled Strip Tag			
Failure:	<input type="checkbox"/> Leadframe damaged	<input type="checkbox"/> Manually handled strip	
ST Lot ID:			LEMS no. _____
Process/Strip no:	<input type="checkbox"/> Diebond 1	<input type="checkbox"/> Wirebond/_____	
	<input type="checkbox"/> Diebond 2	<input type="checkbox"/> Plasma (<input type="checkbox"/> DB: <input type="checkbox"/> WB: <input type="checkbox"/> Mold)	
	<input type="checkbox"/> Diebond 3		
	<input type="checkbox"/> Interposer	<input type="checkbox"/> Molding/_____	

Fig. 8. Tag used to identify FOL strip abnormality

The innovative idea is to be able to recognize the unique alpha numeric material code of the product on the strip end rail through optical character recognition (OCR). Content will be cross-checked with the material code that is stored in the recipe selected. If match the process will resume until all strips of the lot was checked for otherwise machine will prompt an error and stop the machine.

For the damaged strip or stray die, side rails and end rails will be scanned either by camera or laser to check for presence of this abnormalities by comparing it to the image or contour of a good. If detected it will prompt an error and stop the machine.

1.5 Review Related Literature

To have better understanding of the key enabler of the poka-yoke detection of the unique 8 alphanumeric strip material code, literature review on various optical recognition techniques will be tackled. Optical character recognition is a promising technology that is used to convert the letters or words written using hand into a digital format. It is a common method of digitizing printed texts so that they can be electronically edited, searched, stored more compactly, displayed on-line. Optical Character Recognition consists of various stages includes preprocessing, Classification, Post-Acquisition, Pre-Level processing, Segmented Processing, Post-Level processing, Feature Extraction.

As usual the image is acquired initially, then it is preprocessed and segmented. During the segmentation the character lines are separated. Enumeration of character lines in a character image is essential in delimiting the bounds within which the detection can precede. Next step in segmentation is to separate the characters. Once the characters are separated the features are extracted. To implement the feature extraction process, Image to matrix mapping processing used. This process is converting the images to a 2D matrix. Next step is to train the system. Training gives the system capability to take the decision to do the task efficiently and it will give a better result in an unpredicted environment. The proposed system used the Multi-Layer Perceptron Learning Algorithm. This method uses pyramid like structure for the learning purposes. This method can be utilizing not only for the learning purposes but also for the classification purposes. Applying the learning process algorithm within the multilayer network architecture, the synaptic weights and threshold are updated in a way that the classification/recognition task can be performed efficiently. These synaptic weights are important for the iteration purposes. During the iterations the weights are got updated to some integer value. So in order to recognize an object its feature data is feed to the network input layer and produced an output vector. The error is

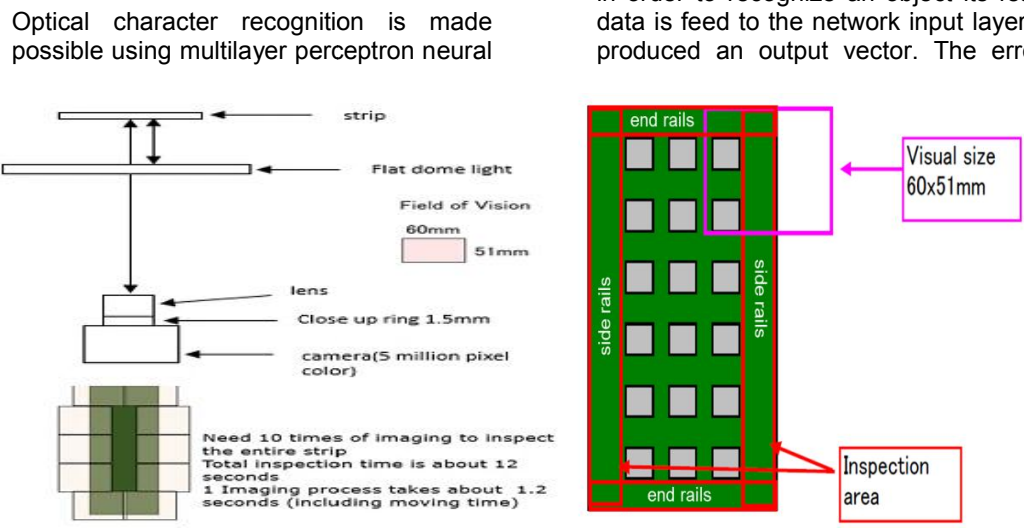


Fig. 9. Die scan illustration

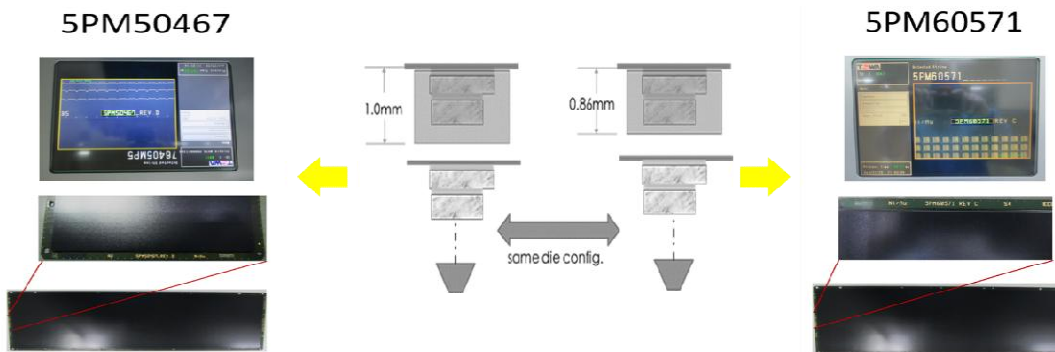


Fig. 10. Optical character recognition of material code

calculated now by the output and by using the target output. By analyzing the output one can determine the character of the recognition rate. The proposed system achieves 91.53% accuracy for the isolated character and 80.65% accuracy for the sentential case character [3].

Optical character recognition using template matching and back propagation algorithm is implemented. Template matching is one the most common method used in optical character recognition techniques. It is mainly used as a feature extraction technique. Its simplicity for the implementation makes it more popular. Correlation is one other name that holds for the template matching. In this method each individual character pixel matrix was used and they are suitable for the feature extraction. A correlation function R is used in the test data set and the resultant is the stored in the database. The character with highest correlation value is selected as the best match for that character. Back propagation algorithm that uses reverse mechanism to find the error and it reduces the error by propagating it backwards. It is based on the error correction. The problem that is found after the grouping was unidentified letters exist. These unidentified letters will appear as character that leads to an erroneous result. The character recognition using this method gives a highest accuracy rate.

Research was made to understand the object recognition of camera scan in reference to the detection of stray die and damage strip which focuses on technique of enhancing image resolution. The paper does not involve any enhancement of current camera object recognition but

rather on enlarging the field of vision to detect object on the area of concern. However, this will be part of the recommendation to increase the camera accuracy [4].

Although object recognition using deep neural networks have reported remarkable performance, they have usually assumed that adequate object size and image resolution are available, which may not be guaranteed in real applications. This proposes a framework for recognizing objects in very low resolution images through the collaborative learning of two deep neural networks: Image enhancement network and object recognition network. The proposed image enhancement network attempts to enhance extremely low resolution images into sharper and more informative images with the use of collaborative learning signals from the object recognition network. The object recognition network with trained weights for high resolution images actively participates in the learning of the image enhancement network. It also utilizes the output from the image enhancement network as augmented learning data to boost its recognition performance on very low resolution objects. Proposed method improved the image reconstruction and classification performance through experiment.

Laser scan performance was compared to camera scan in the detection of stray die and damage strip wherein relevant study was performed to its applicability to object detection [5].

Low-cost 3D imaging, particularly by using laser detection and ranging (LIDAR), is important for applications such as object

recognition, surface mapping, and machine vision. Conventional time-of-flight LIDAR uses a scanned laser to obtain the intensity and range of targets, which requires a narrow bandwidth of illumination and high-speed synchronizers. A non-scanning prototype of a pulse-width-free 3D LIDAR which combines single-pixel imaging and diffractive optical elements, for the first time to our knowledge. Compressive sensing techniques are used to measure echo pulses from the target and reconstruct the intensity map of the target scene. Diffractive optical elements are also applied to generate structured illumination and the depth map of the target scene can be obtained from laser spot extraction. The simulation results are presented to verify the effectiveness of the proposed prototype as well as illustrate its superiority where traditional 3D imaging methods are unavailable or limited. This novel prototype has advantages of low cost and flexible structure at wavelengths beyond the visible spectrum and will be highly interesting for practical applications [6].

2. MATERIALS AND METHODS

2.1 Materials

The products that will be used as vehicle to validate die scan upgrade for wrong recipe and wrong lot loaded will cover all the possible scenario. Three lots having 20 strips each from three different products with different package thickness requirement were chosen. Product A is different in configuration to Product B and C which have same die configuration. Product A and C have same mold cap thickness requirement while strip thickness is different across products. The key characteristic of the products to discriminate each other is the

unique material code. Details are shown below in Table 3.

Actual strips with stray die and damage were prepared to simulate if machine can detect these abnormalities during die scan. Location of the abnormalities covers both end rails and side rails. For stray die, different size of die was used to test detectability.

2.1.1 Die scan software upgrades

The detection of the unique 8 alphanumeric characters on the substrates end rails will be tested if can be recognize by the die scan software upgrade as shown in Fig. 11.

The content will be compared to the content registered on the recipe of the product under test. If content is the same machine will continue processing while if not it will trigger an error and stop the machine as shown in Fig. 12.

Another software that was developed was for the detection of presence of stray die and damage strip on the end rails and side rails. It will be tested on two different scan technique, laser scan and camera scan.

For camera scan, image recognition of the presence or absence of stray die and damage strip will be detected by comparing the pixel difference of the bad strip to the reference good strip as shown in Fig. 13.

Another detection technique is via laser scan which scan the height of the surface and compare it with the height that was thought for good strip. If there is deviation in height either higher or lower the machine will prompt an error and stop machine. The testing will be done for stray die and damage strip for both side rails and end rails location as shown in Fig. 14.

Table 3. Evaluation matrix for wrong recipe/wrong lot

Device name	Package description	Mold cap thickness (mm)	Strip thickness (mm)	Package thickness (mm)	Material Part No
Product A	LLGA 3x3x1.0 16L	0.785	0.20	0.942-1.027	5PM18525
Product B	VFLGA 2x2x0.86 12L	0.70	0.13	0.78-086	5PM60571
Product C	VFLGA 2x2x1.0 12L	0.785	0.18	0.95-1.0	5PM50467

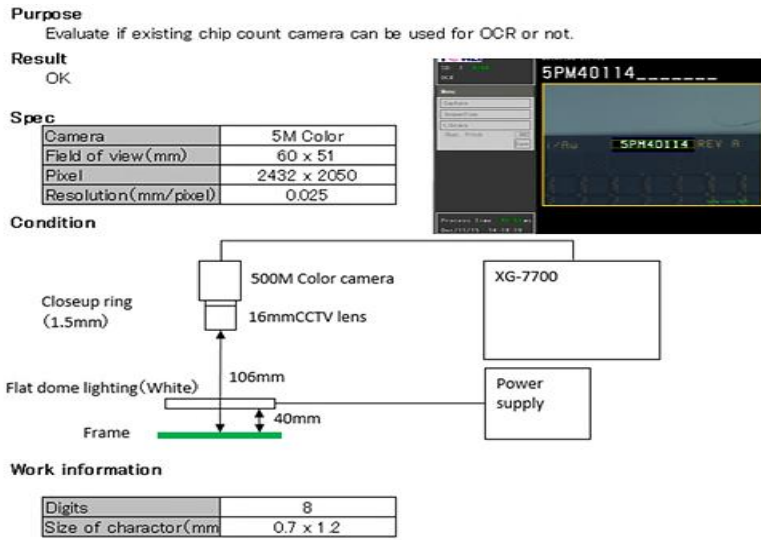


Fig. 11. Camera scan schematic and actual scanned image

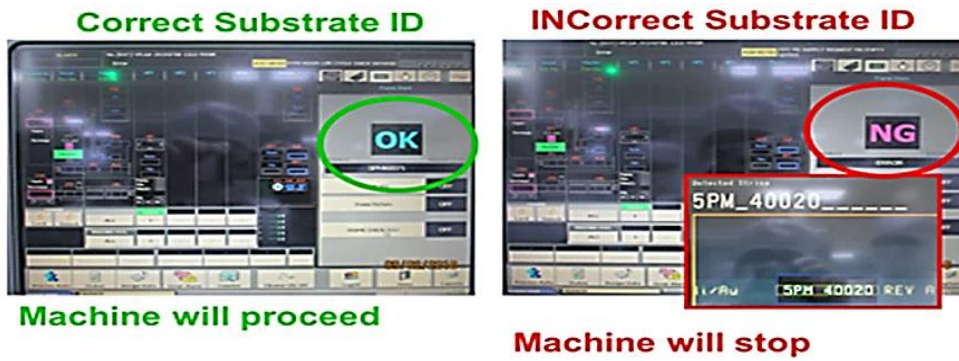
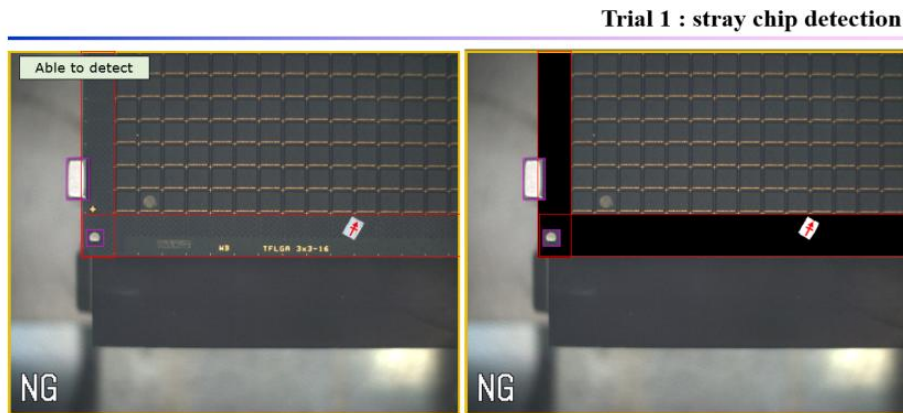


Fig. 12. Machine screen for material code detection



Able to detect the stray chips which locates at out of mold area
Set the PPV chuck and the holes of strips as exceptional area

To detect the color of the stray chips
To detect the stray chips based on the size of white area

(a)

Trial 2 : broken strips

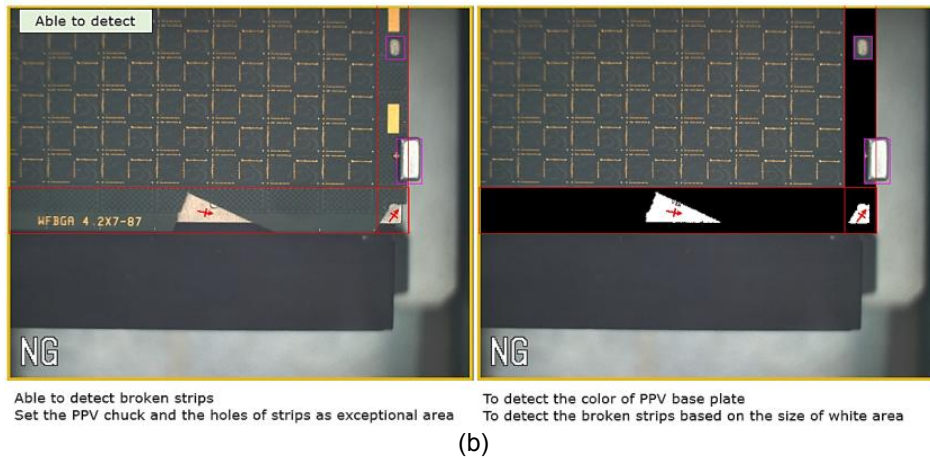


Fig. 13. Scan detection image (a) stray die actual view, (b) damage strip actual view

2.2 Procedure

Test will be conducted to compare the effectiveness of the two die scan upgrade namely material code recognition and stray die and damage strip detection.

For material code detection, camera will be tested if it can accurately recognize material code for different products. The challenge is to detect for all alphanumeric font size, style and orientation. The upgrade will be tested for

consistency of detection strip to strip by adding 20 strips with wrong material code inserted in random. Details as shown in Table 4.

For the stray die and damage strip, a comparison of between laser scan and camera scan accuracy to detect the defect will be tested. Actual strip with different appearance and size of defects on both end rail and side rail will be tested if die scan can accurately detect. For stray die samples with varying die size will be tested to check its sensitivity in Table 5.

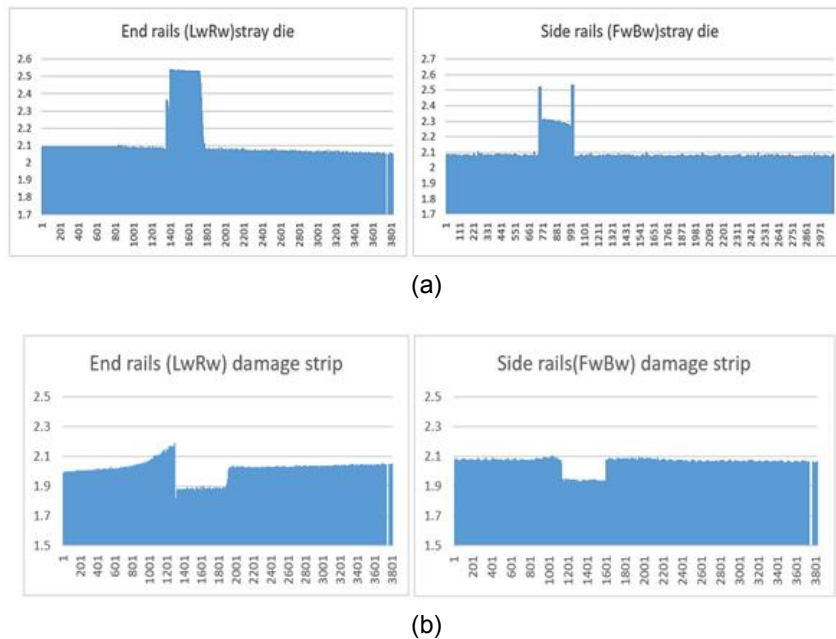


Fig. 14. Laser scan height chart for end and side rail (a) stray die height (b) damage strip

Table 4. Material code detection experiment design

Device name	Package description	Material code	No. of good strips	No. of wrong material code
Product A	LLGA 3x3x1.0 16L	5PM18525	20	10 (5PM60571)
Product B	VFLGA 2X2X0.86 12L	5PM60571	20	10 (5PM50467)
Product C	VFLGA 2X2X1.0 12L	5PM50467	20	10 (5PM18525)

Table 5. Stray die/ damage broken detection experiment design

Scan technique	Stray die size (mm)	Damage/Broken
Camera	2x2	Chip
Camera	3x3	Crack
Laser	2x2	Chip
Laser	3x3	Crack

3. RESULTS AND DISCUSSION

3.1 Test for Material Code Detection

Based from the results of the experiment for software upgrade to detect material code per product there is a 100% detection of all the strip for all three products tested. Both the good and the wrong material code was successfully detected as shown in the graph in Fig. 15.

Based from the result, high level of accuracy was achieved wherein all the strips process for all products under test is matched including the detection of the additional 10 strips with wrong material code.

3.2 Test for Stray Die and Damage/Broken Strip

To validate which between camera scan and laser scan is more effective in detecting stray die and damage strip, a two proportion test was conducted to compare its detectability.

For stray die, a Chi square test was conducted to compare the difference is scan accuracy between laser and camera scan using two different die size used for current products. At 95% confidence level, with a Pvalue of 0.0003 there is a significant difference in the scan accuracy between camera scan and laser scan as shown in Fig. 16.

Based from the result, camera scan can consistently detect presence of stray die even at small die size as pixel recognition is still significant to camera threshold. Laser scan accuracy is reduced as the die size is reduced as it cannot discriminate the difference of the height

from the base of the substrate rail due variation in height and planarity against its threshold.

For damage strip detection, camera scan and laser scan will again be compared against detection accuracy using two different damage strip signature, chip which is a portion of the strip is missing and the other is a crack as shown in Fig. At 95% confidence level, with a Pvalue of <0.0001 there is a significant difference between camera scan and laser scan as shown in Fig. 17.

Camera scan has better accuracy in detecting damage strip as compared to laser scan with same reason as stray die detection. However, the accuracy of detection degrades as the signature of damage is change from a highly visible chip on strip to line crack on the strip.

3.3 Implementation Status and Results

The software upgrade for detection of wrong recipe/wrong lot detection is 100% complete (3/3 machines) with no occurrence recorded starting 2019 to date.

The software upgrade for detection of stray die and damage/broken strip has passed beta test and is scheduled for machine installation.

3.4 Recommendation

It is recommended to further develop the detection capability for future scenario that material code is the same for two products, but package thickness requirement is different. Current activities involve adding additional codes per product through substrate engraving and include these codes to the 8-digit alphanumeric code to discriminate one from the other.

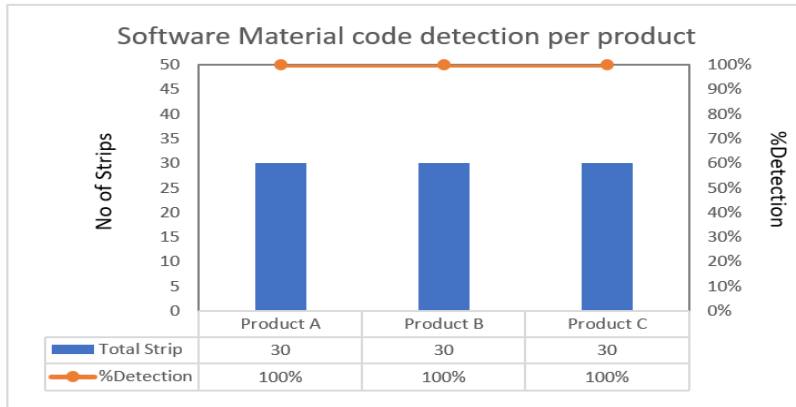


Fig. 15. Two proportion test of software upgrade between products

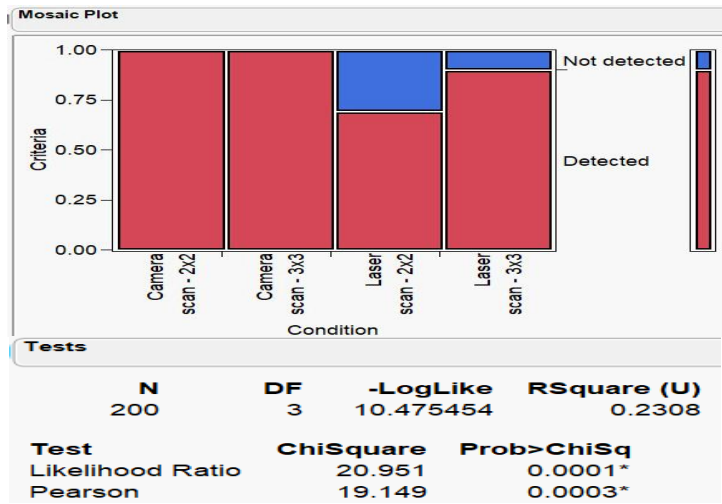


Fig. 16. Chi square test between camera scan and laser scan for stray die

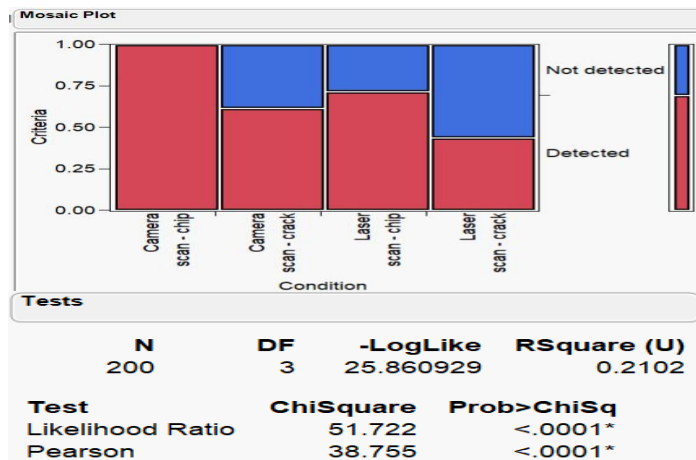


Fig. 17. Chi square test between camera and laser scan for damage strip

As future study, higher resolution camera can also be evaluated to increase detection accuracy specifically for crack signature of damage substrate and stray die with smaller die size than the one used in this study.

Improvement for stray die and damage strip should be pursued as the project on aims to improve detection of the defects and prevent it from being molded to prevent quality and downtimes. If strip cannot be reworked it will still result to yield loss.

4. CONCLUSION

It can be concluded that current camera in die scan can be used as an optical character recognition (OCR) to identify the 8 unique alphanumeric material code and use it to detect wrong product against the stored content in the loaded recipe.

Camera scan is more accurate in detecting stray die as compared to laser scan on the die size evaluated. It is also more accurate in detecting damage strip with chip signature as compared laser scan. This is due to the sensitivity of the laser scan to the substrate height variation to differentiate with stray die and/or damage strip. Camera scan is not dependent on this factor and uses pixel count as reference to detection.

DISCLAIMER

The products used for this research are commonly and predominantly use products in our area of research and country. There is absolutely no conflict of interest between the authors and producers of the products because we do not

intend to use these products as an avenue for any litigation but for the advancement of knowledge. Also, the research was not funded by the producing company rather it was funded by personal efforts of the authors.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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