Yield Enhancement in BGA Substrates and Packaging

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Abstract
The growing use of high density interconnect (HDI) substrates in the microelectronics packaging industry has brought along a broad range of yield issues. Many of these issues are associated with surface defects in the interconnect terminals and solder mask areas of the finished substrates. Detecting such defects requires a different set of capabilities than that of traditional Automated Optical Inspection (AOI) tools used for in-process inspection. These differences result in particular from the surface integrity specifications of the interconnect terminals, and the subjectivity of defect severity. This paper presents examples of defects and discusses inspection capabilities required to detect and classify them correctly. It examines the factors affecting detection capability and false alarms, and proposes a simplified method for system performance evaluation and setup optimization.

Introduction
The use of organic substrates as chip carriers is growing rapidly. It is forecasted to exceed, dollar-wise, the usage of lead frames by 2005. This trend is predominant in high lead count BGA and chip-scale (CSP) packages. Those high density packages are sensitive to surface defects on their interconnect pads, in addition to conductivity defects such as short and open circuits. Manual inspection, which has been the norm for lower density substrates, can no longer cope with the complexities and fine features of the new type.

Although the manufacture of HDI substrates utilizes PCB technologies, the inspection of finished HDI products requires a different set of capabilities than that of traditional AOI equipment:

- PCB technology and materials are widely used in HDI substrates manufacturing
- Surface final inspection is essential for finished HDI products

Finished product vs. In-Process Inspection
Defect type variety and appearance are results of their originating stage along the PCB production line. There are different requirements when validating the output of each production stage. In-process AOI is performed after the inner layer copper etching stage and after outer layer pressing and drilling. Its task is to detect defects that are related to electrical conductivity of the circuit. In-process AOI algorithms strive to isolate copper from laminate for checking design rules violations, shape deformation and short / open circuits in the conductive lines. It does not attempt to identify surface defects. Moreover, in-process AOI is designed to ignore surface anomalies, since oxidation and fingerprints on bare copper traces do not impact their conductivity.

In contrast, Automated Finished Product Inspection hunts primarily for defects in surfaces of interconnect pads. Flaws in gold plated or solder mask areas, which later interface with the wirebond, flip-chip bump or solder ball, might degrade the reliability of that interconnect. Partial plating, scratches and other defects may allow the assembled system to pass even burn-in test, but fail prematurely in its service life. The task of finished product inspection is to spot failure-causing defects, while ignoring insignificant irregularities the production line prior to shipment. The finished product is presented to the inspection system after cleaning, controlled drying and electrical testing (ET). (See Figure 1.) It is too late for rework so extra care must be taken when automatically handling the delicate finished substrates. Finished HDI substrate inspection hunts for a large variety of defects, each with its own characteristics and appearance. The defects are found on gold pad area, solder mask (SM) areas and even in vias. The surface inspection system has to deal with cases like metal surface quality (gold, OTC), metal on metal (odd plating) and metal under SM cases. Here the isolation of real defects from their valid backgrounds is a different story in compare with AOI. Traditional AOI systems cannot cope with such tasks since they are designed for different missions:

- Traditional AOI – in process inspection - looks for design rule violation of conductive lines
- Finished product inspection looks for interconnect surface defects resulting from process quality and/or handling issues

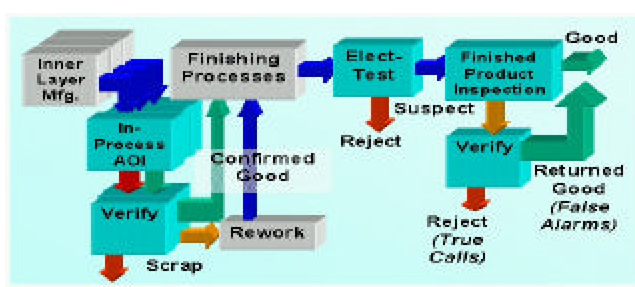


Figure 1 - AOI and Finished Product Inspection Along the Production Line

The Challenge of Inspecting Finished HDI Products
Visual inspection used to rely heavily on human inspectors for checking both in-process panels and finished products. Even today human inspectors still make

the final judgment. This is done at the verification stations that receive the sorted output of the surface inspection machines.

Correlating the type, size and appearance of a defect to its impact on interconnect reliability is not straightforward. Therefore, classifying surface defects is subject to a multitude of qualitative, as well as quantitative criteria. In many cases, a surface defect may be accepted by one inspector and rejected by another.

The ideal inspection system should be able to implement such qualitative criteria to effectively replace the human operator. For this end, the system should first be capable of differentiating all types of surface defects from their background. Then it should have the intelligence to qualify them by their significance according to preset rules:

- Subjective judgment due to uncertainty in defect reporting due to non-deterministic defect description in specs and variety of defect appearances
- Inspection machine performance relies upon detection sensitivity and defect classification capabilities

Examples of Finished Product Inspection

The main difference between in-process AOI and finished product inspection can be seen in Figures 2 and 3. Figure 2 shows an 'open circuit' in an HDI layer trace. The basic approach to detecting such defects is to have good differentiation between copper and laminate, while ignoring oxidation and discoloration. All copper areas usually have the same criteria for defect detection, since we are looking for conductive continuity (short/open) and copper integrity (shape conformity, pin holes, nicks). The marked 'open' should be reported while other oxidized areas could be ignored.

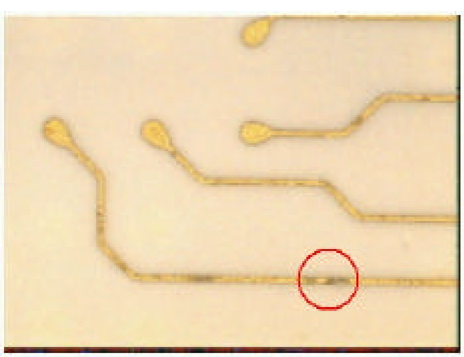


Figure 2 - AOI Inspection of HDI layer

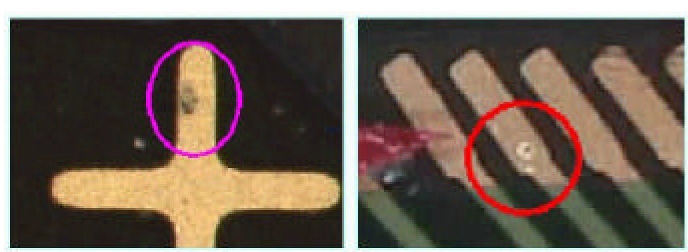
Figure 3 shows several discolored areas on a PBGA substrate for wire bonding interconnect. The impact on interconnect reliability presented by the stains on the 'fingers' (wirebond pads) is much greater than that of the ones on the fiducial (alignment mark) and power line, although the latter is much larger. In this case, even a single appearance of such defect indicates a systemic process problem in gold plating, so it should be reported regardless of where it appears.

Figure 3 - Defects on PBGA Gold Surface

Rejection criteria vary not only by the type and location of a given defect, but also by the nature of the application or the interconnect technology used. Fine pitch wire bonding pads are more sensitive than flip-chip pads, due to the larger interface area and subsequent reflow operation. The latter are more sensitive than the solder mask lands that later secure the BGA balls (Figure 5). Figure 4a shows a nodule in the fiducial. Figure 4b shows a dent in the wirebond pad. While demanding applications may consider both critical defects, other application may accept a minor defect in a non-functional area such as a fiducial, but reject a similar defect in the interconnect zone.

The challenge is even more complicated in 3D gold defects. Here there is no color differentiation from the background. Examples for such defects are shown in Figure 5 and 6 Note the surface differences between particles and valid gold. Increasing light intensity or detection sensitivity will only lead to missing the defects or false alarms on the valid gold, respectively. Reliable detection of such defects requires enhanced illumination techniques and dedicated algorithms:

- The complexity of detecting surface defects is due to their characteristics and variety of appearance



(a) **(b)**

Figure 4 - Local Dents in Fiducial and WB pad

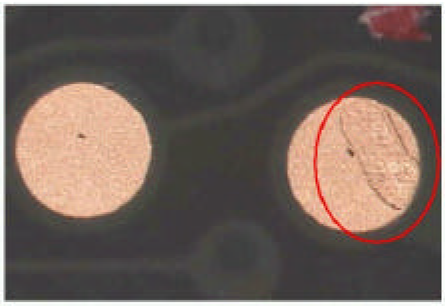


Figure 5 - 'Baby Shoe' Mark in Ball Pad

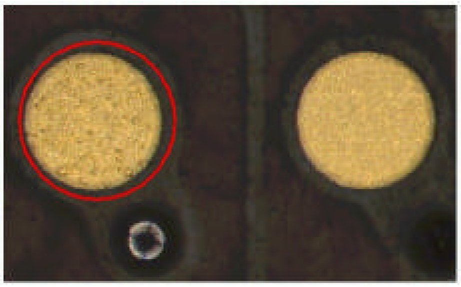


Figure 6 - Gold Ball Pad Granulation

Basic Mechanism of Automatic Inspection System

A typical inspection system includes an advanced machine vision system that is fed with images from a camera. The basic units described in Figure 7 have a key role in 'picking' the right defects and providing reliable reports on defects that exceeded the rejection criteria.

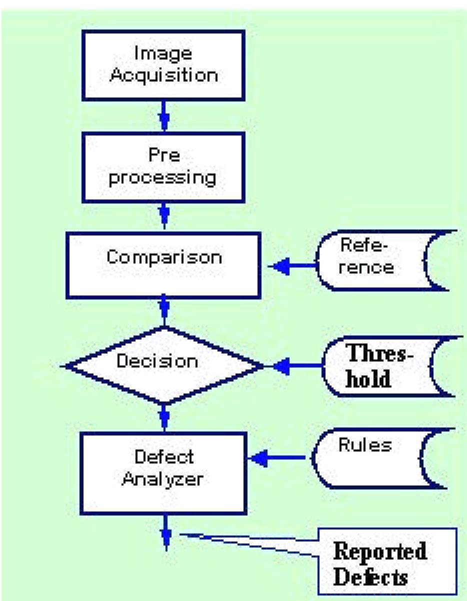


Figure 7 - Schematic Diagram of a Typical Inspection System

- Image Acquisition – the optics and electro-optical circuitry that translates optical image into digital data ready for processing.
- Image Pre-processing – Manipulates and prepares the image for comparison with the reference.
- Comparison Engine – Applies algorithms to compare the processed image data against a reference. Reports the degree of mismatch, or 'Score'.
- Decision Engine – provides a Pass / Fail decision based on user setup ('Thresholds Levels') and rules.
- Defect Analyzer – Marks the inspected image as 'Suspected Defect', classifies it based on user rule set, and forward data with coordinates for further verification and statistical process control (SPC):
  - ☞ Advanced inspection system: detection followed by classification

False Alarms and Missed Defects

The comparator engine described above reports the score of mismatch between image data and reference. If that score is higher than a preset level (Threshold), the system marks a defect. But where should this threshold be set, and how can the user confirm that the system detects accurately?

One popular method is to run test batches that contain known defects and known good products through the system, and log its 'Pass / Fail' reports against the known data. We can attempt to adjust the threshold level until we get the system to correctly identify all the products.

In most practical cases we will find that there are always some defect the system misses, and some good products it declares defect. As we change threshold setting the count of one decreases, but the other rises. There seem to be an inherent trade-off between the two detection errors.

To understand this trade-off, let us imagine that we can read the score at the comparison engine (see Figure 7). We would expect all the 'known good' products to receive a near-zero score, as they are supposed to be identical to the reference. In reality, inherent process variations in dimensions, reflectivity and color results in a range of score, from zero to a certain low value. Similarly, the 'known defects' should receive high scores, indicating their deviation from the reference, but practically are spread along a wide range. Plotting the distribution of scores received by each population looks typically like Figure 8, with the 'known good' plotted in green and the 'known defects' in red. The overlap between the 'known good', and 'known defect' populations is a natural outcome of the variability mentioned above, as well as of performance limitations of the image acquisition and processing subsystems. The goal of the system developer is to increase the separation between the two populations, to enable accurate detection.

Optimizing Threshold Setup

Naturally, we would like to set the system such that it will identify correctly all the 'known defects'. For that purpose, we would set the threshold below the lowest score of that population, giving the system maximum detection ability. However, at that point many 'known good' products will be falsely identified as defects. We refer to those as 'false alarms'. Moving the threshold up would indeed reduce the occurrence of false alarms, but leave many 'known defect' undetected. We relate to them as 'missed defects'.

Accepting some overlap as a given, we would set the threshold at the score level where the occurrence rate of both false alarms and missed defects is minimal. This level is the intersection point of the two distribution curves.

We can express the goal of minimizing the combination of false alarms and missed defects rates mathematically:

– Let *FA* be the number of False Alarms, or the area of known good products above the threshold.
– Let *MD* be the number of Missed Defects, or the area of known defects below the threshold.
– Let *TC* be the number of Total Calls, or the area of both Known Defects and False Alarms above the threshold.
– Let *KD* be the number of Known Defects
– Let *DI* be our Detection Index, representing the combination of false alarm and missed defects rates in a given situation. $DI = \left(1-\frac{FA}{TC}\right)\left(1-\frac{MD}{KD}\right)$

It is easy to see that as the values of false alarms and missed defects decrease, *DI* approaches 1. Figure 8 shows *DI* plotted on the secondary axis, against threshold setting along the score axis. Note that *DI* peaks when the threshold is set at the intersection 'sweet spot'. This fact allows us to use *DI* for setting the threshold, requiring no access to the score or plotting distribution curves.

There may be cases or products where manufacturers emphasize avoiding missing defects, while tolerating more false alarms, or vice versa. The consideration is driven by the cost of failure resulting from missing a defect, versus the cost of a false alarm. While this discussion is beyond the scope of this article, it is important to note that the intersection 'sweet spot' can usually be used as a starting point.

Using these tools, one can compare the performance of inspection system using a specific setup. The higher the value of the *DI*, the better the detection conditions are since the system provides a better separation between the defects and the valid surface: (See figure 9.)

- There is a tradeoff between false alarms and missed defects
- The *DI* function is a useful tool in locating the 'sweet spot'
- *DI* indicates the limits of system performance

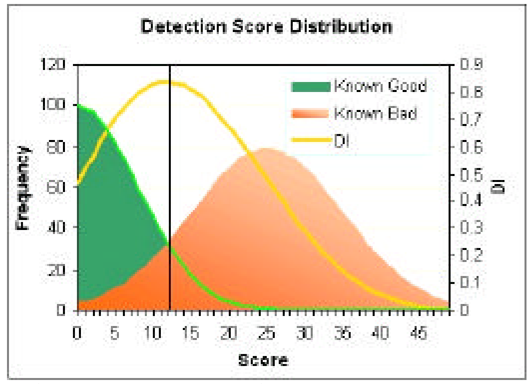


**Figure 8 - *DI* comparison Between Systems **

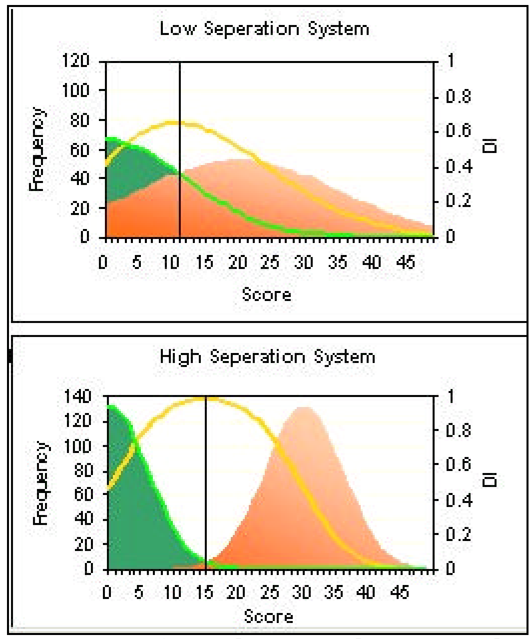


Figure 9 - Detection Index Examples: Low and High Separation Systems

Simplified Evaluation Method

Using test batches requires the collection of rather large quantities of tested products, including good material. It also consumes time that could otherwise be allocated to production.

Following is a simplified method based on direct data provided from a production standard inspection and verification setup.

Using *DI* calculation during normal production runs offers an attractive alternative. Recording the number of false alarms *(FA)* from the verification station and total calls *(TC)* from the inspection tool itself, we can easily calculate their ratio *(FA/TC)* and obtain the 'true alarm rate' factor *(1-FA/TC)*. The missed defects *(MD)* value is usually available as a statistic from the QA sampling inspection of pre-shipment products. We can substitute for *KD* the sum *(CD+MD)* of confirmed defects *(CD)* from the verification station and statistical MD, to obtain the value for *(1-MD/KD = 1-MD/(CD+MD))*. A more accurate estimate can be derived from sampling QA inspection prior to optical inspection. There we obtain a statistic for the total number of defects (*TD*) per batch – or the inherent production yield. The term for detection ability changes to $1-\frac{TD-CD}{TD}$.

The *DI* equation in its practical form is then:

$$DI = (1-MDR)(1-FAR) = \left(1-\frac{TD-CD}{TD}\right)\left(1-\frac{FA}{TC}\right)$$

We have shown in this section that the inspection performance of a given system on a given application can be represented graphically, as the separation between known good and known defect populations. This separation along the score line indicates the system ability to minimize the combination of false alarms and missed defects. This performance can also be represented mathematically as Unified Detection Index (*DI*). The best performance is obtained when the threshold is set at the cross point of the distribution curves, and that where *DI* reaches a maximum. Figures 9 shows the separation and corresponding *DI* curves for different systems:

- Systems can be compared using pragmatic procedures
- The *DI* value is universal and helps to compare systems
- When comparing systems, their setup has to be first optimized
- The *DI* function is useful for optimizing machine setup

Figure 10 illustrates some common data sources for evaluation.

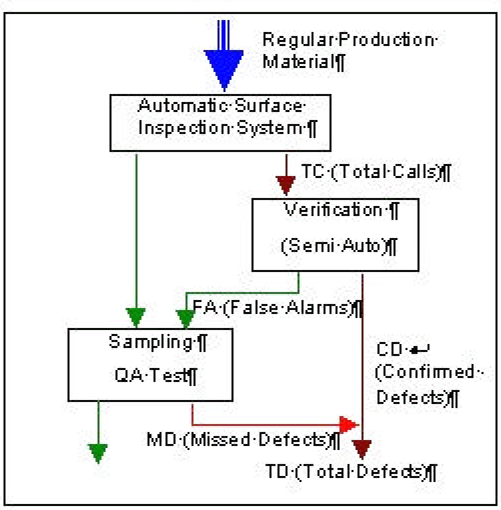


Figure 10 - Data Sources for Simplified Evaluation Method

Improved Systems for higher *DI*

What actually affects the *DI* of a system and how it can be improved?

Better tune up of the different system inspection stages and/or system modification will provide the goal for improved performance.

- Optics front end and improved design will affect the separation between the surface and the defects. Image improvement can be achieved also by using optimized optics that provides effective magnification and image resolution.
- Pre-processing improvement will increase the detection ability of the system that is less miss detection (lower MDR). Changing setup parameters will do the same on existing systems. Here the detection thresholds define the MDR factor.
- Smarter Machine Vision analysis with more accurate decision criteria will insure fewer false calls (lower FAR). Smart setup combination of rejection criteria on a given system will provide lower FAR as well. Nowadays, additional smart vision mechanisms are being developed for the latest generation of Final Inspection machines such as smart defect classification and adaptive filtering. Advance programming methods and techniques are used such as non-linear statistical processing, artificial intelligence (AI) and learning machines (SVM – Support Vector Machine):
  - Machine design and setup capabilities affect the MDR and FAR

The Development in Optical Inspection – History & Future (trends)

The first generation of surface final inspection systems had quite a poor *DI* due to high false alarms. There were actually AOI systems ported to the final inspection role while using traditional AOI techniques. They detected most of the defects but had little ability to filter or reject noncritical ones. Since the performance of such systems was not better than human inspectors, many HDI manufactures kept manual visual inspections.

A few years ago, a second generation of machines appeared in the market. At that time, the system manufactures were more aware of customers' special needs. Their designs were more oriented toward surface final inspection tasks and they provided better performances. Their missed defects rate were reduced, as well as the unacceptable false alarms rate of the previous generation. Yet, the setup was defined using classical parametric approach so the dilemma because where to locate the detection and decision thresholds. Lately, new models of Finished Product Inspection machines appeared in the market with better total *DI* characteristics. These are the pioneers of the use of advanced machine vision algorithms for defect analysis and classification. Their FAR and MDR are much more acceptable and competitive compared to human inspector. Here automatic machines with steady high performance can replace or reduce dramatically the inspection manpower at the QA departments. In *DI* terms, we can say that the 1st generation of inspection systems suffered from relatively low Figure Of Merit (FOM) that limited of their achievable performance (*DI*). The following generations had improved FOM so better performance could be provided.

Returning to our *DI* graph (Figure 11), we can draw the FOM factor as the upper limitation of the performance for each tested machine. The *DI* cannot exceed the FOM:

- Each generation of final inspection machine provides better *DI* with higher FOM
- First generation machines: ported AOI systems, detection with high far
- Second generation machines: tailored systems, better detection with classification
- Third generation machines: improving defect classification, learning machines

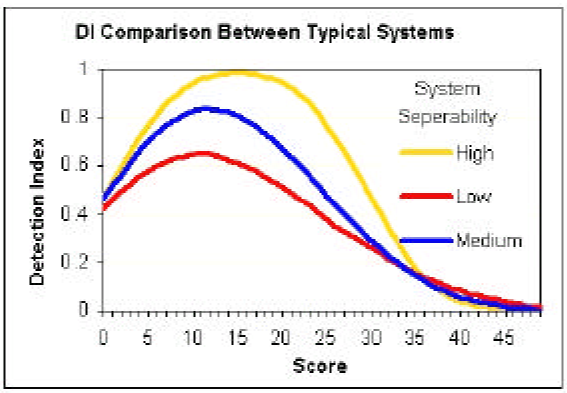


Figure 11 - DI Comparison Between Systems

Conclusions & Summary

There is an emerging need for reliable Automatic Finished Product Inspection systems for the HDI substrates production line. Since surface defects have many visual appearances, smart machine vision algorithms are to be used. In the past 5 years, different generations of inspection machines were introduced to the market but only the most recent advanced ones, could provide acceptable Detection Abilities with reasonable False Alarms rate. Pragmatic test procedures can be used when evaluating or comparing such inspection machines.

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