

**AUTOMATIC DEFECT DETECTION SYSTEM
FOR
LEADFRAME INSPECTION**

by

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**Thesis submitted in fulfillment of the
requirements for the degree of
Master of Science**

**University Science Malaysia
April 2004**

ACKNOWLEDGEMENT

I would like to express my deepest gratitude to my supervisor Associate Professor Dr. Mani Maran Ratnam, for his tremendous guidance, advice, support, assistance and encouragement throughout my Master of Science programme.

I would also like to thank my co-supervisor Associate Professor Dr. Lim Chee Peng, for his help and support. I am also grateful to AKN Sdn. Bhd. for providing their leadframes for this research.

I am grateful to my loving parents Dr. R. Bhuvanesh and Hansa Bhuvanesh for their unfailing love, support and understanding throughout the years.

I would like to express sincere thanks to the University Science Malaysia and to the School of Mechanical Engineering, for providing the necessary facilities for this research. I also express my sincere appreciation to the Dean Dr. Zaidi Bin Mohd Ripin, Deputy Dean for Research and Development Dr. Zainal Alimuddin Bin Zainal Alauddin and Deputy Dean Dr. Zulkifly Bin Abdullah.

Last but not the least, I would like to thank my colleagues Vithyacharan and Arshad, who provided the encouragement, help and motivation in the research. Also special mention must be made of Mr. Ashamuddin, Mr. Rosnin and other technical staff for their co-operative and friendly attitude.

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ABBREVIATIONS

ADC	Automatic Defect Classifier
AVI	Automatic Visual Inspection
CAD	Computer Aided Design
CCD	Charge Coupled Device
COG	Centre of Gravity
COGs	Centres of Gravity
CCIR	International Radio Consultative Committee
DCF	Digital Conversion Format
ELF	Etched Leadframes
GUI	Graphical User Interface
IC	Integrated Circuit
NTSC	National Televisions Systems Corporation
PC	Personal Computer
PCB	Printed Circuit Board
RAM	Random Access Memory
ROI	Region of Interest
RS 170	Raster Scan 170
SOIC	Small Outline Integrated Circuit

ABSTRACT

Defect detection and classification are important for both product quality assurance and process improvement in the manufacturing industry. Machine vision systems offer several beneficial features such as consistency, accuracy and round the clock repeatability. This thesis presents the results of the development and implementation of such a machine vision system to automate the inspection of leadframes. Inspection of stamping defects and slugmark defects are the focus of this research. Stamping defects are caused due to improper stamping which primarily comprise of irregularities in meeting geometrical specifications and material removal. Whereas slug mark defect is caused by the stamping tool leaving an undesirable indentation on the leadframe after stamping. In this respect, several algorithms have been developed to inspect improper stamping not only for the critical internal leads but also the entire leadframe including the outer railing which contains the pilot holes. The proposed method follows three steps to evaluate the quality of the product. The first step consists of capturing images of the leadframe to be inspected. Next, using mathematical morphological processing, the image is subtracted from a defect free template image. The last step is to mark the location and display the defects. The proposed algorithms were tested on a variety of leadframes, and the experimental results are presented. The algorithms were extended and also tested for inspection of leadframes in the presence of translational and rotational misalignment. Experimental results showed that the proposed algorithms can be employed not only for inspecting individual cut leadframes but also for continuous inspection in the manufacturing line. It has been possible to detect and display defects in a fast and efficient way with minimal errors.

SISTEM PENGESANAN KECACATAN SECARA AUTOMATIK

UNTUK PEMERIKSAAN LEADFRAME

ABSTRAK

Pengesanan dan mengklasifikasikan kecacatan adalah penting untuk memastikan kualiti produk dan meningkatkan kebolehan sesuatu proses dalam industri pembuatan. Sistem penglihatan mesin menawarkan beberapa kelebihan dalam perkara seperti konsisten, kejitian dan pemeriksaan berterusan. Disertasi ini mempersembahkan keputusan dalam membangun dan implementasi sistem penglihatan mesin untuk pemeriksaan secara automatik bagi 'leadframe'. Dalam penyelidikan ini, tumpuan diberikan kepada pemeriksaan kecacatan hentakan dan 'slug mark'. Punca kecacatan hentakan adalah kerana ketidakbetulan proses hentakan di mana spesifikasi geometri dan pembuangan bahan tidak ditepati. Kecacatan 'slug mark' berpunca daripada alat hentakan yang meninggalkan kesan lekuk pada 'leadframe' selepas proses hentakan. Dalam hal ini beberapa aturcara dihasilkan untuk memeriksa ketidakbetulan bagi 'lead' dalaman yang kritikal dan juga untuk memeriksa keseluruhan 'leadframe' yang merangkumi sempadan luar yang mempunyai lubang 'pilot'. Kaedah yang dicadangkan mengikut tiga langkah untuk menguji kualiti produk. Langkah pertama ialah perolehan imej 'leadframe' yang diperiksa. Langkah kedua menggunakan morfologi pemprosesan secara matematik di mana imej ditolak daripada template imej yang tiada kecacatan. Langkah terakhir adalah untuk menandakan dan mempamirkan kecacatan yang dikesan. Aturcara yang dicadangkan telah diuji bagi beberapa jenis 'leadframe' dan keputusan eksperimen ditunjukkan. Aturcara dilanjutkan dan diuji untuk pemeriksaan 'leadframe' bagi kesalahjajaran translasi dan putaran misalignment. Keputusan eksperimen membuktikan aturcara yang dicadangkan boleh digunakan untuk pemeriksaan 'leadframe' individu dan

...naga untuk 'leadframe' secara berterusan dalam situasi industri. Sistem pemeriksaan ini telah menunjukkan kebolehan untuk mengesan dan mempamerkan kecacatan secara cepat dan berkesan dengan ralat yang minimum.

CHAPTER 1

INTRODUCTION

1.1 Background of Research

A leadframe is a miniature sheet of metal, generally made up of copper or nickel alloy, on which patterns consisting of a centre pad (mostly for Integrated Circuits) and Input / Output leads have been cut (Pin, 2000). IC leadframes are typically plated with precious metal on the centre pad and the lead tips around the centre. Leadframe forms the core part of a semiconductor as the primary package metallurgical bond pad interface, or interconnection structure for plastics (Tunmala, 2001). It functions as a substrate in ICs, a base level on which the silicon chip is mounted for support, serving as an electrical connection between the silicon chip and the printed circuit board (Lim et al., 2001). Leadframe also functions as a skeleton to save the chip from shock and moisture, thus it is a very important component and it plays a very important role in the semiconductor industry.

Leadframe is manufactured by two processes either by stamping or by etching. Etched leadframe is made by using photochemical machining (PCM) techniques i.e. photolithography and etching (Lim et al., 2001). Photolithography is a technique by which a pattern is generated on the plate after printing photosensitive fluid on the plate, using blue light from mercury vapour lamps. After photolithography, the plate is etched by using chemicals. Stamped leadframe manufacturing consists of stamping the thin sheet of metal in high precision presses with tolerances as tight as 0.127 mm (Pin, 2000).

Although leadframe manufacturing is not as complicated as the production of the chip, the specification requirement is very strict to ensure the functionality of the desired circuit. Leadframes are manufactured to precise specification with tight control on dimensions, tolerance level and contamination levels, to meet the stringent conditions required in the packaging of semiconductors. Due to defects in the stamping process, caused by worn stamping tool or misalignment between the feed metal and the stamping tool, stamping may not be done properly (Pin, 2000). If these defects are not detected and rectified immediately, there will be wastage of material and the product rejection rate will be high.

Currently, leadframes are inspected by highly trained personnel. Samples of leadframe are taken immediately after stamping and are checked for geometric tolerances (Pin, 2000). With the increasing demand for higher production rate and new varieties of leadframes with even more complex designs, the task of visual inspection has become very tedious and difficult for human inspectors.

2 Problem Statement

Visual defect inspection and classification are important parts of most manufacturing processes in the semiconductor and electronics industries. An important objective of defect inspection is the early detection and identification of manufacturing process problems. Defect classification is the task of sorting the defects into a set of predefined, meaningful categories, often related to the cause or the consequences of the defects. The classification data are used in yield prediction, process improvement and rework / scrap decisions. Therefore, defect detection is essential for product quality assurance, while defect classification leads to process improvement and cost reduction with decrease of defects (Newman and Jain, 1995).

According to Chou et al. (1997), the current trend towards miniaturization of components, line widths, feature sizes and denser packaging of boards makes human visual inspection a very tedious task. The visual sense of a human worker features a number of operational deficiencies which can make industrial machine vision more attractive. Following are a few advantages that machine vision systems offer over inspection by humans:

- (a) Humans are subjective whereas machine vision systems can make measurements with greater objectivity and repeatability than humans.
- (b) Humans are fragile, but machine vision systems can be used in situations where humans would be uncomfortable or in danger.
- (c) Humans are fallible, but machine vision systems never make a mistake through boredom or inattention.

- (d) Humans can be too slow whereas machine vision systems can often operate in real-time relative to the manufacturing process, where humans cannot.
- (e) Humans can be insensitive to subtle changes but machine vision systems can observe such changes and react to them objectively.
- (f) In humans, the ability to concentrate continuously for long hours gets reduced due to fatigue and hence the inspection becomes error prone.

Machine vision system, as an integration of optical technology, computer technology, image processing technique as well as our basic understanding of human visual capability and analysis, shows remarkable advantages of accuracy, consistency and round-a-clock repeatability, in contrast to the subjectivity, fatigue, boredom, slowness and cost associated with human inspection (Chou et al., 1997). Machine vision technology has over the years become more powerful and accessible providing cost effective solutions to a number of inspection tasks demanding accuracy and reliability on a consistent basis (Zamani et al., 2003). As a result, extensive research is being carried out worldwide on developing new algorithms and improving existing machine vision systems to solve various inspection and gauging problems.

According to Zamani et al. (2003), the driving force in the field of automated vision inspection for leadframe is to improve quality. They developed an Automatic Visual Inspection (AVI) System detecting stamping defects in leadframes. The system developed requires images captured while the leadframe is precisely aligned and synchronized with the camera. The method developed gives a warning signal upon detection of defects, after which defects are located by operator review. Hence, there is a chance of error while locating the defects. Therefore, there is a need to develop algorithms

to completely automate the inspection which not only indicate the presence of defects but also locate and display them, thereby minimizing operator involvement.

Lim et al. (2001) developed a novel computer vision system for inspecting leadframes. Their approach comprised of mathematical morphology, a thinning algorithm to generate a master pattern and heuristic rule of decision. Their method employs the use of a few points within the image and not the entire image to check for the presence of defects. The proposed method is computationally very intensive and requires images captured without any misalignment. Since the process is very computationally intensive and employed for continuous inspection, the system for image capture and processing makes use of special high end processors. Therefore, there is a need to develop fast, efficient and computationally simple algorithms which can be customized to suite the inspection task as required.

The importance of computer vision systems for inspection tasks in the semiconductor industry is increasing, especially for leadframes which is such a vital component. Though several algorithms have been developed for defect detection in leadframes, with newer complex designs and increasing variety of leadframes, there is a need for better and customizable defect detection algorithms. The algorithms should also be computationally simple and be able to process images captured in the presence of translational and rotational misalignment overcoming the limitation of requiring camera synchronization required for inspecting in real time both continuous strip and individual cut leadframes.

3 Objective of Research

The objective of this research is to develop a machine vision system to automate the inspection process in leadframe manufacturing. To achieve this objective, several sub-objectives were identified, which are as follows:

- ❖ Development of several algorithms to detect stamping defects in
 - the internal critical area of a leadframe.
 - the entire area including the railing part of a leadframe.
 - the entire area of a leadframe in the presence of translational misalignment.
 - the entire area of a leadframe in the presence of translational and rotational misalignment for a variety types of leadframes.

- ❖ Development of an algorithm to detect slug mark defects in the entire area of a leadframe for different types of leadframe.

1.4 Scope of Research

This scope of this research is focused on the development of a machine vision system to automate the inspection process in leadframe manufacturing. The research consists of development and testing of several algorithms for detecting stamping defects in leadframes. For complete 100 % inspection of leadframes, inspection of both stamping and plating defects should be automated. However, considering the variety and number of plating defects, it requires a completely different perspective. Hence, the scope of the work is limited to inspection of stamping defects.

The first part of this research is focused on development of algorithms for detecting stamping defects caused due to improper stamping, which creates geometrical discrepancies in leadframes like unstamped or uncut internal leads, pilot holes on the tailing etc. In the next part of this research, an effort has been made to extend the algorithms to detect stamping defects in leadframes without requiring camera synchronization during image capture. Hence overcoming the limitation of aligning the leadframe during image capture. This will enable the system to inspect continuously moving leadframes as well as individual cut leadframes. The algorithms were tested with images of three types of Small Outline Integrated Circuit (SOIC) leadframes containing simulated stamping defects, since the number of actual defective samples was limited. The third part of this research, compared to existing literature (Lim et al., 2001 and Zamani et al., 2003) consists of development of an algorithm to detect another type of stamping defect which is a surface defect known as slug mark or tool mark.

1.5 Research Approach

An algorithm was developed based on referential method of image comparison (Moganti et al., 1996) for detecting stamping defects only in the internal critical area of a leadframe which used images that were grabbed offline from static leadframes perfectly aligned under the camera. The basic setup of the system consisted of a personal computer (PC), a frame grabber card, a charge coupled device camera (CCD) for grabbing images and the lighting system. In order to detect stamping defects caused due to improper stamping, a back lighting system was used since it was easier to study geometrical discrepancies in the complete leadframe. The algorithm consisted of several image

processing operations which were part of four major steps. The first step was to binarize the test image and remove noise using morphological closing operation. After this, required features were extracted from the test image in the form of regions of interest using blob analysis. Next, the regions of interest were subtracted from the template image to obtain defects if any. Finally using blob analysis results from these subtracted results, defects if any were marked with their location and displayed on the screen by the graphical user interface. The algorithm was further extended to inspect the entire area of a leadframe including the railing part which is stamped for creating the pilot holes. The research was taken further with focus on detecting stamping defects while the leadframe was moving, with special attention to eliminate the requirement of camera synchronization during image capture. The algorithms were tested for defect detection on three different types of leadframes. To test the performance of the algorithm, simulated defects were created on defect free images, since the number of actual defective leadframe samples was less.

After this, research was further carried on with special focus on detecting slug mark defects in leadframes. To facilitate this, directional front lighting technique was used since slug mark defect is a surface defect. The leadframe to be inspected is kept in a perfectly aligned position, inclined at an angle under the field of view of the camera for capturing the image. The test image was binarized at a high threshold to eliminate noise caused due to the high intensity focus of lighting. In this case, only one region of interest is extracted from the test image for analysis and is subtracted from the template image. Blob analysis is performed on the subtracted result to mark, locate and display the detected defects. The algorithm was tested with limited actual samples from the industry.

6 Thesis Organisation

This thesis is organised in such a way that it systematically leads to the research objectives as follows:

Chapter 1 presents a general introduction on the research work. The problem and the motivation of this research are discussed and the research objectives are identified.

Chapter 2 presents the literature review on machine vision systems developed for inspection of leadframes and PCBs. This chapter covers the current and past research that has been carried out worldwide.

Chapter 3 deals with the development of algorithms for detection of stamping defects in leadframes. Development of algorithms progresses through one step at a time starting with detection of stamping defects in the internal critical area, to detection of defects in the entire area of the leadframe.

Chapter 4 deals with the development of algorithms for detection of stamping defects in the entire area of the leadframe in the presence of translational misalignment, rotational and translational misalignment and for real time inspection.

Chapter 5 deals with the development of algorithms for detection of slug mark defects in leadframes.

Chapter 6 concludes this thesis with a summary of the dissertation, an outline of the contribution and direction for future research which are mostly unsolved problems that remain open in this thesis.

CHAPTER 2

LITERATURE SURVEY

2.1 Introduction

The main aim in this literature study is to review the work carried out worldwide by researchers on developing machine vision systems, especially those developing machine vision systems for detecting defects in leadframes. In order to provide a broader perspective, this study also covers related research carried out in developing machine vision systems for other related inspection tasks like PCB inspection, solder inspection etc., in the semiconductor industry.

2.2 Inspection

Inspection is a process of determining if a product (also referred to as a part, object, or item) deviates from a given set of specifications. Inspection usually involves measurement of specific part features such as assembly integrity, surface finish and geometric dimensions (Newman and Jain, 1995).

There are three generally accepted inspection areas for inspection. These are as follows:

1. Input inspection (receiving / incoming inspection): examination of raw materials to determine if their quality is acceptable for use and also if there is sufficient amount of material for use in assembly.

Process inspection: examination of the output of an intermediate work stage. It is useful for determining if the operations at a stage were performed within specified tolerances and whether the assembly process is in control or if tools are worn or broken. Process inspection allows fine adjustments to be made for tool wear and helps prevent non-conforming parts or material from being used in a later production stage.

Output inspection: it is the final exhaustive inspection of a product at the end of all assembly or manufacturing stages to determine the product's acceptability. It is also used to collect statistical data to discover long term trends in the manufacturing process, for instance, to find that tools need to be replaced or that general maintenance maybe required.

2.2.1 Automated Inspection

In industrial environments, inspection has usually been performed by human inspectors on a small sample from the lot or batch. In this modality (called *batch inspection*) the quality characteristics of the sample are generalized to the batch from which the sample was drawn. Some experiments have indicated that batch inspection by human inspectors tends to be more accurate than an inspection modality of 100% inspection of parts (Wetherill, 1969) (where every product in the lot is inspected), probably because of inspector fatigue and inconsistency. As a result, achieving 100% inspection using human inspectors typically requires high levels of redundancy, thus increasing the cost and time for inspection (Dreyfus, 1989).

However, in some critical applications, such as aerospace and medicine, even a single faulty product is unacceptable. Many manufacturers also desire 100% inspection to enhance a product's competitiveness in the marketplace. Part suppliers to factories using just-in-time inventory practices are especially conscious of product quality since the recipient factories are generally unwilling to store and pay for inventory that requires testing before use (McGarry, 1984).

Currently, many automated inspection tasks are performed using contact inspection devices that require the part to be stopped, carefully positioned, and then repositioned several times. Machine vision can alleviate the need for line stoppage and precise positioning. Since machine vision inspection operations are, in general, non-contact, there is also a lower level risk of product damage during inspection (Hill, 1985).

Traditionally, most industrial inspection has focused on product inspection. Usually, only the final assembly of the product is inspected. However, process inspection offers certain advantages. Without inprocess inspection, for example, parts that fit poorly can cause machines to jam or break, interrupting assembly. If defects are not detected as they occur, material, time, energy, and labor are also wasted (Skaggs, 1983).

One of the great advantages of automated inspection is that defect rates can be automatically logged for each defect. This allows defect detection to be more closely connected with production. A high frequency of a certain type of defect might indicate that a tool or machine in the production process is malfunctioning, for example, or that the product design needs to be improved (Tarbox and Gerhardt, 1990).

2.2 Feasibility of Automated Inspection

Although automated inspection might seem to be a panacea for improving quality and reducing costs, it may not always be feasible. For automated inspection to be feasible, it must run in real time and be consistent, reliable, robust, and cost-effective. It is difficult to formally define what is meant by real-time inspection, although Van Gool et al. (1991) have suggested a working definition "that the visual inspection system should not be the major bottleneck for reducing cycle time or robot operation speed". On many production lines, this would require the inspection of several parts per second. For most assembly line inspections, the upper time limit for inspection is probably about 1 second. A few inspection tasks, such as printed wiring board or semiconductor inspection, are not as time-critical, however, and can take as long as several minutes (Winkler, 1983). Automated inspection systems are also expensive and time-consuming to develop. The development cost usually cannot be amortized over many systems, either, because special illumination, image analysis, and part orientation restrictions are usually necessary steps in achieving robust system performance (Newman et al., 1992). This makes it necessary for the development process to begin afresh for each application. Therefore, automated inspection is feasible when the application has large part volumes, demands very precise measurement, requires very consistent inspection, or is in a hazardous environment.

The complexity of automated inspection procedures can be reduced by requiring precise placement of the objects to be inspected. Positioning aids such as special fixtures, conveyor belts, and rotating tables have been used for this purpose. Unfortunately, using positioning aids and lighting constraints is not necessarily useful for more complex shapes. Furthermore, for automated inspection to compete with the flexibility of human inspectors,

The inspection procedure must be able to handle objects that are in unexpected positions and orientation.

2.3 Artificial and Human Vision

Improved communication and delivery abilities have opened many industries to worldwide markets, forcing manufacturing companies to compete on a global basis. The high level of competition amongst manufacturers has led to rapid developments in the areas of computer integrated manufacturing, flexible manufacturing, agile manufacturing and intelligent manufacturing. These developments have generated a need for intelligent sensing and decision making systems capable of automatically performing tasks traditionally performed by human operators (Newman and Jain, 1995). The advantage of such "smart systems" is that they continue to make use of the ever increasing reliability and speed of computers, while offering the flexibility and cognitive abilities of humans. Visual inspection is one such area in particular that can benefit directly from a smart engineering system that can display adaptable intelligence (Enke and Dagli et al. 1997).

Manufacturing applications of artificial vision technology include everything from printed circuit board inspection to robot place (map) learning for navigation (Newman and Jain, 1995). Nonetheless, even with new industrial applications and advances in technology, difficulties still exist with traditional artificial vision systems. Ironically it is often the hierarchical and serial nature of the algorithms and not necessarily the functions they perform, that becomes a limiting factor because it reduces the performance and flexibility of the algorithms.

Traditional vision approach rested upon three basic tenets (Churchland et al.,1994):

The goal of a vision system is to create a detailed model and full representation of the visual world.

The visual system is hierarchical, with each stage being responsible for performing a specific task until finally only features are left that can be acted upon by the later stages of processing.

3. There is a dependency of the higher levels of visual processing on the lower levels, but in general the reverse is not true.

2.3 Machine Vision Systems

Industrial design and manufacturing offers a breadth of opportunities to address many key issues in computer vision (Alison, 1995). These include defect classification, signal processing, feature enhancement, part dimensioning, measurement error analysis, multi-modality image analysis and fusion, rapid response software system prototyping and performance assessment of image analysis algorithms. There are many untapped opportunities in materials science, including volumetric defect analysis (active imaging), 3D or higher dimension material characterization (multi dimensional visualization and analysis), and surface imaging. Also another application of computer vision and image analysis is in the field of biomedical studies, e.g. CAT scan, X- ray etc...

Industrial vision research has traditionally focused on inspecting products rather than improving the manufacturing processes. One of the most popular approaches to part inspection is based on CAD models which place strong emphasis on part design. However,

ns has limitations from the manufacturing perspective. Industrial vision technology tends to be fairly inflexible and rapidly becomes obsolete as manufacturing processes change since the solutions developed are not customizable. Future successful industrial vision systems will be those that are designed to readily adapt to the changing demands of manufacturing process technology (Newman and Jain, 1995).

Vernon (1991) reviewed the current exploitation of machine vision in the electronics industry from two perspectives: from the existing and emerging markets perspective and from a scientific and technological perspective. In addition to the introduction of new robust vision techniques to solve emerging inspection and control problems, there is a strong trend in the industry for the deployment of vision to effect in-line process monitoring and control in the manufacture of PCBs. As a consequence, machine vision systems increasingly have to be able to achieve accuracy, repeatability, and reproducibility performances with strict industry-standard statistical process control parameters. In turn, this creates an urgent need for the adoption of acceptable benchmarking, characterization, and testing strategies for industrial machine vision.

Existing standard vision techniques, such as segmentation, blob analysis, feature extraction and classification will remain key to the success of PCB applications. Paradoxically, the key to success here has been the adoption of "low-tech" rather than "high-tech" approaches to solve vision problems. Significantly, this strategy is based on the crucial need for highly-robust, highly-accurate, highly-repeatable, and highly-reproducible functionality. Hence, it is fundamentally important to have strong expertise and deep experience of these "low-tech" techniques. Improving the likelihood of successful application of machine vision, inherently limits the scope to the simpler

problems. The consequence is that, more complex vision techniques are going to be deployed to solve more difficult problems, hence making it a necessary condition that they exhibit the requisite robustness (Vernon, 1991).

2.4 Machine Vision Systems for the semiconductor industry

Many defect detection tools are available from commercial vendors such as Keyence, KLA Instruments, Tencor, Orbot etc. Each is tailored for inspecting certain products with the objective of locating the defects accurately, while maximizing throughput (Chou et al., 1997). However, the output of these tools reveals little information about the defects themselves, and hence it is usually reviewed by human operators. In the defect review process, the operator first locates (redetects) the defect in the microscope's field of view, and then classifies the defect based on its appearance and context. This process is usually more time consuming than the initial detection itself. Hence it is customary to review and classify only a small fraction of the defects detected previously by the detection tool. Moreover operators tend to be inconsistent and hence defect classification is error prone.

Chou et al. (1997) developed an Automatic Defect Classifier (ADC), which classifies defects on 16 MB (megabit) DRAM at various manufacturing stages in the manufacturing line. Their system uses a golden template method for defect re-detection and measures several features of the defect such as size, shape, location and color. A rule-based system then classifies each defect into pre-defined categories that are learnt from training samples.

Their method comprises of the following steps:

1. Defect detection: this step consists of the use of a commercial KLA 2130 detection system which performs the task of defect detection with the help of a defect free template image (golden image).
2. Defect grouping: in this stage, defects detected in the previous stage are adaptively labeled according to pre-classified types of defect and grouped together based on their region and location.
3. Defect measures: in this stage entire defect clusters are characterised and their attributes computed based on their features for e.g. shape, size, location, contrast, composition etc.
4. Defect classifier: in this stage the defects are classified based on the conditions they meet. In their system they have used both Probabilistic Neural Networks and classifiers that offer explicit classification rules.

The system makes use of a KLA 2130 commercial detection tool before ADC, and also requires operator review hence the cost of the system becomes a factor. The images were not of good quality because the system operates on RGB color images of lower bits per channel respectively. The system needs to be updated frequently to keep up with newer and different types of defect classes.

Zoroofi et al. (2001) conducted research for visual inspection of contamination on the surface of integrated circuits (IC) wafers arising from the dicing process. By using a set of multi-spectral optical filters and a charged coupled device (CCD) video camera, they acquired several images from each IC wafer under different illumination conditions of straight and oblique lighting from which feature space data (calculated means and

iances) were generated. After this, they evaluated and compared the performance of three conventional classification methods – an artificial neural network (ANN) using a back propagation technique with a minimum distance algorithm, and a maximum likelihood classifier.

Contamination of IC wafers is often associated with color / shade variations, human inspectors are not always very reliable color inspectors, primarily because people often do not have very good memories for color. Hence training contamination inspection experts is both very difficult and very expensive. For these reasons, contamination inspection is a task that ideally suits an automated system. Zoroofi et al. (2001) concluded that, acquiring several IC wafer images by optical filtering, as well as using different degrees of straight and oblique illumination was effective in providing robust feature data for the classification.

Enke and Dagli et al. (1997) developed a machine vision system to make use of and demonstrate the advantages of using artificial neural networks in visual inspection. According to them, neural network modeling offers a direct link to natural visual processing. By modeling neural regions speculated to be involved in visual attention it is possible for a vision system to focus on a particular area / region of interest rather than processing the entire image. According to them, the true potential of neural network architecture can be realized when placed into existing vision systems. The flexibility provided by interactive approaches to vision will allow these systems to operate in environments that are continuously changing, resulting in enhanced performance and added intelligence to existing manufacturing systems.

Zhou et al. (1998) developed a machine vision system for detecting die extrusion defects caused due to incorrect mounting of the die on the leadframe. The defect feature is represented by two faint linear features, one horizontal and the other vertical. The system uses an optimal filter which responds to linear features in the image of the IC package, while effectively filtering noise. The minimum response of defect features is used as a threshold to generate the binary image. Then finally a decision regarding whether the die extrusion defect exists is made by analyzing the resulting binary image. The algorithm developed uses the defect characteristics which are projections in the horizontal and vertical directions. It then enhances these linear features of the defect after analyzing the distribution about the global peak obtained from projection profile analysis of the image. If the peak exceeds the set threshold, it indicates the presence of a defect.

Since the algorithm is pixel based, it is computationally very intensive. Also, in this algorithm the horizontal and vertical linear characteristics of the defect are utilized to reduce the computation and to isolate defect features, but when the package image is such obtained that the defect feature is not horizontal or vertical, then the orientation of the IC package has to be checked and accordingly the region of interest has to be rotated to the desired direction before application of the algorithm.

Kim et al., (2001) developed an advanced PCB inspection system based on the referential method of comparison to detect defects in PCBs moving on a conveyor. Their method uses an image processing Full Scale Block Matching (FSBM) algorithm to reduce the translational and rotational displacement. After which the aligned test image is subtracted from a stored reference image and the resulting difference image is binarized at a threshold determined from a shading correction algorithm which compensates for the

on-constant intensity of the light source. Finally, morphological operations are applied to the binary image to enlarge the results of image subtraction. Defects are detected by a decision algorithm which counts the number of cross points in the binary reference image as tracking the boundary of the dilated candidates.

The system makes use of four Pairs of 1008×1018 area scan cameras and Pentium 1.4 Ghz processors with SSE2 technology. Information regarding type, position and shape of defect is gathered from each pair of camera and pc by a "host PC". The system makes use of mechanical guiding system to reduce the rotational displacement to ± 0.2 degrees for the PCBs moving on the conveyor.

Tatibana and Lotufo (1997) developed a novel automatic PCB inspection technique based on the comparison of Connected Table of a Reference and a Test image. The connectivity table is a list of connected holes. The method extracts the connectivity information of the conductors of a PCB via the concept of connected components of binary images. The hole correspondence between the reference and test images is solved by the zones of influence technique. In the method, a labeling operator identifies each connected component in the binary image and assigns a unique number to its pixels. A Holes Connected Table is built using the centroid co-ordinates of the hole pads from the labeled images. Each hole center is identified to its zone influence, which is the region where all the points are nearer to that point than any other point in the image. After this, each connected table is converted to the Zone of Influence Connected Table by the Region Table operator, solving the misalignment problem. The maximum misalignment allowed between the images is half of the distance between two closest holes of the PCB image. In the final step, the Comparison operator accepts the two Connected Tables of the Reference

Test images based on zone of influence and outputs a table with a colour code for each conductor label of the Test image, indicating possible defects if found. The inspection technique was implemented using MMach – A Mathematical Morphology Toolbox for the Boros system (Barrera et al., 1994). The algorithm can be further improved by avoiding reading and writing files and including more than one operator for raster image scanning.

2.5 Machine Vision Systems for Leadframe Inspection

In this section, the review focuses on machine vision systems developed so far in the field of leadframe inspection.

2.5.1 Vision System for inspecting stamping defects on leadframes

Zamani et al. (2003) developed a machine vision system primarily for inspecting stamping defects on leadframes manufactured by Dynacraft Industries. The techniques they have used in their system for defect detection are blob analysis and gauging of the edge information from the leadframe images. By gauging the edge information from the leadframe images, any deviation of measurements that are out of tolerance are traced and determined as defects.

The AVI system developed consists of a Charged Coupled Device (CCD) camera in conjunction with a frame grabber card. Diffused front lighting was used to create a contrast of the leadframe with the background. All the computing and image processing was done on a personal computer (PC). Their method is a two step process. In the first

after image is grabbed it is binarized at threshold value determined from the program of the image. Then blob analysis is performed on the binary image to segment required parts of the image from the background. In the second step, gauging operation performed to measure the geometrical specifications and tolerances by using an edge detection algorithm. Any deviation from the set tolerances indicates the presence of a defect.

The method proposed by Zamani et al. (2003), uses images which are grabbed at regular intervals with camera synchronization. Also the algorithm developed is restricted to an image grabbed in a defined visible frame perfectly aligned both laterally and longitudinally. Hence, the images grabbed do not consist of translational or rotational misalignment. Once the defect is detected, there is only a signal indication at that workstation to warn that defects are being generated, but the location of the defect detected is not marked on the image of the stamped leadframe.

2.5.2 Optical Inspection Method of Leadframe Using Mathematical Morphology

Lim et al. (2001), developed an inspection system which uses three linear CCD cameras and an algorithm based on mathematical morphology method for inspection of etched leadframes (ELF) which are manufactured by etching instead of stamping. Their method is a three step process. In the first step, the master pattern of the lead frame which is a binary image is generated by using a modified thinning algorithm. The master pattern is then precisely placed on the target image (which is also binary). Next, the resulting mismatched points, those which have abnormal gray values in the object are identified and

ected as defective candidates. In the last step, these defective candidates are evaluated according to a heuristic rule of decision. At first it looks like a proper way to use Computer Aided Design (CAD) data to reconstruct a good image, but then the pattern is improper to overcome actual limitations like misalignment. Also, inherent optical characteristics cause distortion and hence it needs a long time to adjust the component for proper working of machine. To overcome some of the difficulties such as rough surface, electrical noise, object rotation and translation, their system focuses and investigates a smaller region leaving a boundary of the object. Local matching work is implemented for the small region to decide whether it is defective or defect free.

One drawback of the method proposed by Lim et al. (2001) is that the entire image is not inspected, but instead only a few critical parts of the image are inspected. In their method, the defect has been defined as a region that has minimum dimension of abnormal gray values. Hence if there would be smaller defective pixels in the vicinity of another defective pixel, they were merged into one defect. There are many types of defects which cause a variation of dimension and gray value for a type of defect. Thus their method faces difficulty to classify the various type of defect. Also since the method is very computationally intensive, their system makes use of special high end processors for capturing and processing the images.