

A Survey of Automated Visual Inspection

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In this paper, we survey the automated visual inspection systems and techniques that have been reported in the literature from 1988 to 1993. Several earlier systems are also discussed. In the survey, a taxonomy of inspection systems based on their sensory input is presented. The general benefits and feasibility of automated visual inspection are also discussed. We present common approaches to visual inspection and also consider the specification and analysis of dimensional tolerances and their influence on the inspection task(s). One of the recent developments in automated visual inspection, namely the expanded role of computer-aided design (CAD) data in many systems, is examined in detail. © 1995

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1. INTRODUCTION

The visual inspection of parts is one task within manufacturing that has been automated at a comparatively slow pace. Many inspection tasks also require a substantial amount of reasoning capability to make an accept/reject decision or to classify the type of defect. One reason for this is that many inspections require substantial visual abilities. Some inspection tasks also require flexibility. However, one hallmark of the automated inspection applications is their specialization. To our knowledge, nearly all of the existing automated inspection systems, with the exception of very few experimental systems (e.g., [136]), have been designed to inspect a single object or part whose position is highly constrained. Added flexibility to allow the inspection of parts whose poses are less constrained and/or to allow the porting of inspection protocols from one inspection domain to another would increase the number of automated inspection applications. Flexibility is thus one of the important research issues in the automated visual inspection arena, although great advances in the flexibility (i.e., the generic application) of commercial vision systems is probably more likely in the long—rather than short—term.

This paper first discusses the stages of inspection and motivates the need for and feasibility of automated visual inspection. A survey of many of the automated visual inspection systems that have been reported in the literature since 1987 is then presented. Earlier surveys of the automated visual inspection (AVI) literature have been presented in 1982 by Chin and Harlow [47] and in 1988 by Chin [44]. In addition, we devote special attention to a popular recent development in automated inspection, that is, the use of computer-aided design (CAD) models in inspection.

Since the 1988 literature survey [44], there have been several developments in AVI in addition to the expanded role of CAD models. For example, there is now more emphasis in the literature on the use of multiple images and on the use of color or range data. Processors have also become less expensive and much faster. The cost of memory and scanners have also been reduced. It is now feasible for a desktop workstation or PC to serve as the central processor in many industrial inspection applications. As a result, new inspection applications are also becoming more cost-effective. Finally, due to increased international competition, the market for automated visual inspection applications has become global.

1.1. Definition of Inspection

Inspection is the process of determining if a *product* (also referred to as a *part*, *object*, or *item*, both in this paper and in the literature) deviates from a given set of *specifications* [93, 98, 114, 119]. Inspection usually involves measurement of specific part features such as assembly integrity, surface finish and geometric dimensions. It is a quality control task, but is distinguished from *testing* tasks (e.g., stress analysis) that involve active examination of specific operational functions of the product [119]. Part identification or *recognition*, by contrast, consists of the positive identification of an object.

Identification of the object usually is not necessary for the inspection task; identity is usually assumed to be known *a priori* in inspection. Thus, inspection, testing, and recognition are distinct but related tasks.¹

Some of the papers in the literature labeled as inspection methods actually perform either recognition or segmentation. Ker and Kengskool [115], for example, have described a Hough transform-based edge segmentation method that they claimed as an inspection technique. Inspection should also be distinguished from guidance and control (i.e., *localization*) tasks. Guidance and control consist of measuring the relative position of objects to provide feedback to a robot [146]. The Partracker system by Automation, Inc., which was reported as an inspection system in the literature [189], is actually an example of a guidance and control system. Partracker locates parts whose position is not known precisely. After part position has been determined, Partracker allows a welding or assembly operation (or, potentially, inspection) to be performed. An area closely related to inspection, that is, the recognition of objects that contain flaws, has also received some attention in the literature. Wen and Lozzi [255], for example, have presented a technique that recognized manufactured parts with artificially induced flaws using moments of 2D boundaries.

1.2. A Taxonomy of Inspection Problems

One method for classifying inspection applications is by the type of inspection decision which must be made. It is also possible to classify an inspection application by the area of production in which it is used. In this section, several dichotomies of the types of the inspection operations are presented. The advantages of automated inspection and an examination of AVI's feasibility are also presented.

1.2.1. Inspection Stages

There are three generally accepted application areas (or stages) for inspection. These are *input* (also called *receiving or incoming inspection*) [65, 70, 114, 235, 257], *process inspection* [32, 65, 83, 108, 114, 221, 235, 250, 257, 271], and *output* (or, *product*) *inspection* [65, 114, 221, 235, 257, 271]. Receiving inspection is the examination of raw materials to determine if their quality is acceptable for use. It also involves determining if there is a sufficient amount of material for use in assembly. Process inspection is the 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

¹ The reader should note that these definitions are not universally accepted.

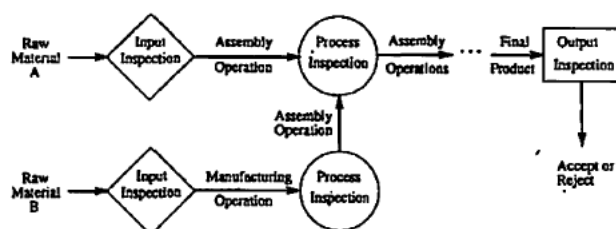


FIG. 1. Stages of inspection in a production sequence.

adjustments to be made for tool wear and helps prevent nonconforming parts or material from being used in a later production stage. The advantages of process inspection are discussed further in Section 1.2.4. Output inspection is the final exhaustive inspection of a product at the end of all assembly or manufacturing stages to determine the product's acceptability. Output inspection is also often used to collect statistical information to discover long-term trends in the assembly process, for instance, to find that tools need to be replaced or that general maintenance may be required [235]. Figure 1 shows several stages of production and inspection.

1.2.2. Inspection Dichotomies

Wetherill [257] presented several dichotomies of inspection. One dichotomy for batch inspection is *rectifying inspection* versus *acceptance inspection*. Rectifying inspection refers to sorting out bad products from the batch and adjusting (or replacing) those items. Acceptance inspection involves the labeling of batches of products into categories such as "accept," "reject," or, perhaps, "seconds" (e.g., products to be sold at a lower price).

Another dichotomy of inspection tasks is *inspection by attributes* versus *inspection by variables* [257]. Inspection by attributes classifies objects as either acceptable or defective. Mair prefers the term *qualitative inspection* for these visual inspections [133]. Typical attribute inspection tasks include qualitative and semiquantitative measurement, such as checking labels, examining cosmetic and surface finish properties (such as colors or blemishes), detecting cracks and flaws, and verifying part integrity and completeness (including spurious and missing features) [133, 201]. Inspection by variables produces a measurement of some feature, such as the product's length or weight. These dimensional inspections are termed *quantitative inspection* by Mair [133]. Some of the quantitative geometric features and the symbols commonly used to describe them on blueprints are provided in the chart in Fig. 2, taken from Kennedy *et al.* [114]. These symbols are used on blueprints to indicate manufacturing tolerances. Another inspection by variables

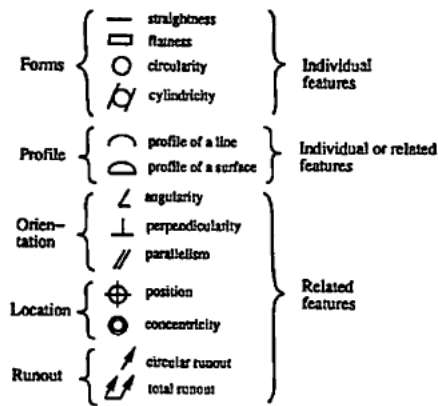


FIG. 2. Common blueprint symbols for geometric characteristics and features from Kennedy *et al.* [114].

task is measuring important part dimensions such as exterior wear, tool wear, and workpiece dimensions. *Grading inspection* is a hybrid classification that classifies products based on degree of acceptability of features, such as length or weight [257]. One example of this is grades of produce (for example, grade A versus grade AA eggs).

Lee [127] identifies an inspection task he terms *implicit inspection* which involves detecting that "novel but 'obviously' faulty items" are defective. Defects detected by implicit inspection include poor finishes, dents, scratches, incorrect color, wrong orientation, improper reflective properties, and other ill-defined faults. While these defects might appear to overlap with some of the inspection tasks defined above, implicit inspection involves recognizing an unanticipated defect. Human inspectors are quite flexible and can easily recognize novel defects. Many of these unanticipated defects are not described by explicit parameters, making automated detection difficult. Implicit inspection is an open research problem, calling for sophisticated representations of the object, task, and processing requirements [127].

1.2.3. Surface Geometry Inspection Scenarios

Figure 3 shows our dichotomy of the various surface geometry inspection problems [158]. In the diagram, the unlabeled subtree under "Arbitrary Surfaces" is identical to the subtree under "Quadric Surfaces." At the highest level, inspection tasks can be distinguished by the surface types that compose the object boundary. Many industrial objects can be modeled using only planar and a few quadric surface primitives (often only spheres and cylinders) [24, 136]; thus, most inspection systems do not have to deal with the complications arising from the use of arbitrary surfaces. However, with the increasing use

of plastics in industry, free-form surfaces are becoming more common [145], creating additional demand for inspection systems that can handle complex surface geometries. Modeling, representation, and inspection of objects consisting of free-form surfaces are difficult, although these issues have recently attracted some attention (e.g., [18, 179, 239]).

The next level of the tree indicates if inspection requires solution of the object recognition problem. Object recognition has received a great deal of attention in the literature. The survey articles by Arman and Aggarwal [4], Besl and Jain [19], Chin and Dyer [46], Flynn and Jain [76], Perrott and Hamey [188], and by Suetens *et al.* [231], the book edited by Jain and Flynn [104], and the workshop report on directions in computer vision research by Negahdaripour and Jain [156] provide excellent starting points for those unfamiliar with the status of object recognition research.

Finally, the lowest level of the tree indicates if the object's pose is known (perhaps through control of fixtures) or unknown. Most of the inspection systems in the literature focus on a problem domain in which object identity and position is known.

1.2.4. Why Automated Inspection?

100% Inspection vs Batch 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 [257] (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 [66].

However, in some critical applications, such as aerospace and medicine, even a single faulty product is unac-

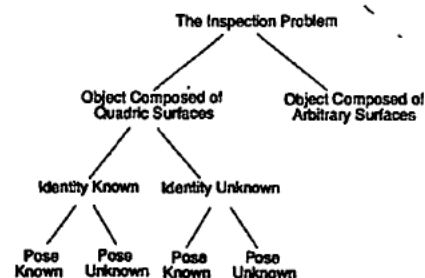


FIG. 3. Scenarios of visual inspection of surface geometry.

ceptable. In other markets (notably those for consumer products, especially foodstuffs) products having aesthetic appeal sell better [96, 253]. 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 [141]. The cost of poor quality components (in terms of lost sales) has been estimated to be between 5 and 10% of the total sales for most products, and approximately 20% of sales for manufactured goods [141]. In some industries, 100% visual inspection is also necessary to meet process yield goals [125]. Therefore, 100% inspection is desirable.

Sampling can be formally defined as the "process of selecting a representative set of data from a large number of measurements or observations (the population) in order to perform inferential reasoning about the population itself" [65]. Two types of risks are associated with sampling. These are known as *producer's risk* and *consumer's risk*. Producer's risk is the risk associated with a lot or batch of good quality that is mistakenly rejected due to the extraction of a random sample containing many defective parts. Consumer's risk is the chance of mistakenly accepting a lot of poor quality due to the extraction of a sample containing many good parts. Producer's and consumer's risk are analogous with Type I and Type II statistical inference errors, respectively, where the null hypothesis H_0 is that the product is acceptable. There are many consequences associated with high levels of consumer's risk, although the end result of all of them is that the manufacturer's reputation and market share are endangered. Consumer's risk can be reduced through 100% inspection.

General Benefits of Automated Inspection. Automatic inspection is desirable because human inspectors are not always consistent evaluators of products. In fact, it has been reported that human visual inspection is, at best, 80% effective, and, furthermore, this effectiveness can only be achieved if a rigidly structured set of inspection checks is implemented [222].² The consistency associated with automated inspection should allow the level of quality to be predicted [108], however. Many inspection tasks are also time-consuming and/or boring for humans to perform. For instance, human visual inspection has been estimated to account for 10% or more of the total labor costs for manufactured products [133]. Human inspectors may also reject products based on the satisfaction of quotas rather than the actual defect levels [66]. Furthermore, some manufactured part defects are too subtle for detection by an unaided human [155]. In contrast, machine vision results in lower labor costs and im-

proved quality. Finally, automated inspection allows objects to be inspected in environments unsafe for people.

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 [115]. Machine vision can alleviate the need for line stoppage and precise positioning. Since machine vision inspection operations are, in general, noncontact, there is also a lower level risk of product damage during inspection [96].

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 [88, 221]. Zeuch has estimated that a fault found on bare printed circuit boards immediately after fabrication costs only 25 cents to repair, but if the same fault is found only after the board is fully loaded with components, then the repair cost increases to approximately \$40 [271]. Assembly processes involving many parts pose a serious challenge to human inspectors. If the assembly process involves several operations per second, process inspection by humans is probably physically impossible [221]. One system that inspects the output of several assembly stages has been presented by Tsatsoulis and Fu [247].

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.* [250] 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 [45, 250]. For most assembly line inspections, the upper time limit for inspection is probably about 1 s. 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 [260]. Often, the rate of assembly for complex parts or for small batch production also allows for less rapid rates of inspection [13]. Automated inspection systems are also expensive and time-consuming to develop. Development costs can be as high as \$100,000 [250] or more.³ The development cost usually cannot be amortized over many systems, either, because special illumi-

² [125] claims that human inspection can be up to 90% effective.

³ Some inspection systems have cost several million dollars to develop.

nation, image analysis, and part orientation restrictions are usually necessary steps in achieving robust system performance [166]. 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. In some inspection systems, parts are placed on surfaces made of transparent glass or plastic to allow easy extraction of object silhouettes through backlighting [260]. Backlighting and other sensing environment constraints are appropriate for the inspection of simple objects. Constraints of these types have been successfully applied to the high-speed inspection of some products that are assembled quickly in large volumes. Unfortunately, using positioning aids and lighting constraints is not necessarily useful for more complex shapes; it is difficult and expensive to obtain well-jigged and uniformly lit parts on the factory floor [124]. 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 orientations.

The flexibility of human inspectors should not be underestimated. Wright and Bourne [262] have observed that machinists make many careful inspections and difficult acceptability judgments throughout the machining cycle. This is especially true when the part has a complex shape with tolerances on the order of several thousandths of an inch. For instance, aircraft parts have very complex profiles which require special tooling, fixturing, and numerical control programming. These parts are usually made of alloys that are difficult to machine. These alloys impose great stress on the machining tools, forcing the machinist to carefully monitor tool wear throughout the process. Many of the parts also contain internal cavities that reduce weight but also result in thin exterior walls, compounding the machining difficulty. Wright and Bourne claim that the machining process for these aircraft parts is "nondeterministic and unstable" and that the machinist's judgments and abilities are "irreplaceable secret ingredients of expert machining [262]." Automation of the expert inspective and adaptive capabilities of a human machinist would be quite a challenging task for a vision researcher.

Logging Defect Rates and Types. 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 [96, 235]. Consumer complaints and field service records could also be integrated with the factory log of defects to monitor the complete lifespan of the product. An integrated record of product defects should enable better part design and production in the future.

In the remainder of this paper, we present a review of the automated visual inspection literature, classifying systems by their sensing modality. We first review systems that use binary images, then systems that use intensity images, color images, and range images, and then systems that use other sensing modes. Next, we discuss common approaches to the inspection problem, and finally we investigate CAD-based inspection methods.

2. REVIEW OF THE INSPECTION LITERATURE

Many automated inspection systems have been presented in the literature. Chin and Harlow have surveyed some of the early work in automated visual inspection in [47]. Chin presented a second survey of papers published from 1981 to 1987 in [44]. The complete inspection literature is quite vast, appearing not only in the computer vision conferences and journals, but also in the robotics, manufacturing, CAD, and other engineering disciplines' literature. Many of the inspection systems have not even been reported in the literature, probably due to proprietary considerations. There appear to be two general schools of thought about inspection. In the machine vision community, the emphasis seems to be on specialized techniques that allow the inspection of one part, while in the computer vision literature, the emphasis seems to be on more general inspection applications. In addition, many of the systems and techniques presented in the computer vision literature appear to use contrived defects and "widget" objects that may not be an accurate portrayal of actual likely manufacturing defects and objects. There needs to be greater interaction between the machine vision and computer vision communities if more usable general-purpose inspection systems are to be developed.

Most of the papers surveyed below discuss inspection systems. We focus on actual inspection systems rather than on theoretical algorithms that have not (yet) been applied to inspection. It is beyond the scope of this paper to explore theoretical techniques (e.g., texture-based approaches potentially applicable to surface inspection) in detail.

Commercial inspection systems are available for a wide variety of inspection tasks, including checking engine blocks, tool wear, automobile wheel hub structural integrity, spark plug dimensions, dimensions of ceramic supports for CRTs, and automatic transmission valve

body dimensions [146]. Automated inspection systems have also been used to search for impurities and fractures in casting processes, to inspect letters and numbers on labels, to check packaging and content of pharmaceutical and edible products, and to inspect glass objects for cracks and bubbles [30, 98, 170, 189] or for presence of loose slivers [12]. A robot that can detect some of the defects in nuclear reactor vessel shells and nozzles has also been developed [27]. The majority of the automated inspection systems have been developed by machine vision companies while others have been developed by manufacturers for in-house applications. In this section, many of the inspection systems that have been recently presented in the literature, including noncommercial inspection prototypes developed by the research community, are reviewed. However, most existing automated inspection systems probably have never been reported in the literature or have received only fleeting reference.

2.1. Typical Commercial Visual Inspection Systems

A few of the typical commercial visual inspection systems are presented in this section. Our attention is directed on some of the major machine vision companies that supply AVI systems. Several of these companies have focused on specific market niches and thus provide one or a series of products designed for a particular industry. For example, GEI, a machine vision company, has developed the Gemini system for inspecting semiconductor packages for proper closure and correct placement of labels [189]. Global Holonetics has developed the Lightware inspection system based on Fourier features that has been applied in manufacturing and packaging inspection applications [82]. IRT and Four Pi have recently developed systems for inspection of solder joints on printed circuit boards using X rays [110]. These systems are discussed briefly in Section 2.3.5. In the past, KLA Instruments has specialized in PCB inspection and provided a number of systems for this purpose ranging in price up to \$200,000. KLA now offers AVI machines for reticle and wafer inspections, at prices ranging from 1 to 3 million dollars per system. KLA is probably the largest company supplying AVI equipment for the semiconductor industry, with annual sales of over \$200 million. KLA and Japan Energy (formerly Nippon Mining) have also formed a joint venture, KLA Acrotec, that develops systems for inspection of flat panel displays [132].

A few of the other machine vision companies which have delivered AVI systems recently include Machine Vision International, which has delivered systems for inspection of painted surfaces [12], and Sira, which has built automated inspection systems for monitoring photographic film [12] and for checking gloss level and other car body paint defects [32, 250]. European Electronic Systems has built high-speed metal surface inspection

systems for use in applications such as a rolling mill [12]. Geodetic Services has developed a system useful for dimensional inspection tasks [77]. Computer Recognition Systems has built a system that was applied to orange grading and inspected at a rate of 64 oranges per second using eight processing elements' and intensity images [53]. Cognex and Matrox Electronics Systems have recently offered machine vision systems on cards that can be plugged into a bus on a PC [110, 199]. Some of these systems have been used in inspection applications (e.g., a Matrox Image 1280 board was used in [74] to inspect continuous aluminum strips). Other companies include ADEPT, AISI, Allen-Bradley, and Itran. Innovision is another example of a machine vision company that has delivered several custom-designed AVI systems, for applications such as inspection of continuous webbing, measurement of dimensional tolerances and gaging, and inspection of surface characteristics [2]. Most of these companies do not offer universal inspection machines but rather deliver custom integrations and solutions for each application. The cost of the systems can vary greatly, from as low as \$30,000 up to \$200,000 or more. The solutions presented are typically VME-based with embedded CPUs. None of the commercial systems have been truly general purpose, however, which may be one cause for the lack of business success for some machine vision companies. The successful companies have either developed expertise in a single inspection domain (e.g., the semiconductor industry) or have been able to understand customer needs and deliver custom integrations for varied applications.

2.2. Typical Industrial In-house Inspection Systems

Some large industrial companies have developed their own inspection systems. Saab, for example, built a system for automated inspection of flywheel castings [250]. Westinghouse has developed an automated visual inspection system for turbine blade inspection and Delco has developed an automated system for inspecting chip structure [146]. General Motors has developed a system for dimensional inspection of automobile body openings [204]. Volkswagen has developed a system for inspection of dimensional measurements of automobile bodies [122]. IBM developed a system to inspect key-return springs on PS/2 keyboards [151]. Texas Instruments has developed the Modular Advanced Vision System (MAVS) that was incorporated in a number of their in-house inspection systems, including the AT4600, a system that used two MAVS and multiple cameras to perform full DIP inspection for marking, lead, and package defects [153]. The Tokyo Electric Power Company has developed and installed an inspection robot that visually inspects for steam or water leakage in a high-radiation area in a nuclear power plant [266]. Mitsubishi has developed a sys-

tem to measure several dimensional tolerances of color picture tube shadowmasks (at a resolution of $100\text{ }\mu\text{m}$) and the screens' black matrices (at a resolution of better than $5\text{ }\mu\text{m}$) with a triangulating structured light arrangement [120]. Mitsubishi has also implemented a system that can inspect submicron gate patterns in GaAs field effect transistors [205]. A few additional systems are discussed in more detail within Section 2.3.

2.3. A Taxonomy of Inspection Systems

This section presents a taxonomy of inspection systems based upon the sensory data used by the system. We describe many of the systems presented in the literature that use binary images, gray level images, color images, and range images. Other possible sensing modalities are also discussed.

Imaging constraints and special lighting arrangements can often be used to simplify an inspection task. Specifically, through exploitation of such methods, many of the AVI systems have been able to use "simpler" forms of sensory input (e.g., binary data). Systems which rely on simpler input tend to have reduced computational processing demands, increased inspection speeds, and often lower system development costs.

A summary of some of the specific applications are exhibited in Table 1. A block diagram of one typical inspection system is shown later in the chapter in Fig. 4. (The diagram, from [136], is of an automated inspection system that uses range data.)

2.3.1. Inspection Using Binary Images

Historically, most commercial vision systems for automated inspection have used binary images. Many of these systems use images of limited resolution and perform only simple coarse verifications, such as testing for the presence of a part [108]. Binary data are sufficient to inspect many industrial objects which can be represented using only their silhouettes. Flat objects with no surface characteristics are also inspected using binary data [250]. It is economical to use binary images since these can usually be acquired using inexpensive sensors in conjunction with simple lighting arrangements, such as back-lighting [260]. High-contrast backgrounds and controlled lighting eliminate unwanted shadows, highlights, and noisy backgrounds but also make it difficult or impossible to use orientation, texture, and reflectance information in the inspection procedure [45]. The use of binary images also reduces the amount of data that need to be processed, aiding the system's designers in meeting speed and cost requirements [45]. Typically, the binary vision systems use only simple verification schemes [98] such as pixel counting or boundary examination [12, 45] that can be executed very rapidly.

TABLE 1
A Taxonomy of Selected Visual Inspection Systems

Input image	Application	Date	Reference
Binary	Bolts	1992	[12]
	Brake shoes	1990	[9]
	Color picture tube photomasks	1988	[101]
	IC chip patterns	1989	[163] ^a
	Packaging	1988	[71]
	Printed Wiring Boards (PWBs)	1988	[270]
		1991	[172]
		1992	[164]
	Shrimp grading	1991	[112]
	Surgical staples and ligating clips	1990	[240]
Intensity	Aircraft jack seals	1990	[171]
	Casing labels	1993	[245]
	Ceramic tiles	1993	[61]
	Drill bit wear	1990	[130]
	Glass CRT faceplates	1988	[259]
	Lumber	1990	[48]
	Nuclear reactors	1992	[266]
	PWBs	1985	[98]
		1989	[219]
		1990	[182] ^b
Color		1991	[227]
		1993	[200]
	Sandpaper	1989	[79] ^b
	Semiconductor packages	1989	[189]
	Solder joints	1992	[38]
	Videocassette labels	1991	[208] ^b
	Web textiles	1992	[169]
	Batteries	1989	[189]
	Citrus fruit grading	1989	[189]
	Color CRT displays	1992	[5]
Range	Denim dye streaks	1990	[55]
	Integrated circuit chips	1991	[265]
	Microelectric gate thickness	1987	[184]
	Plywood	1992	[1]
	Poultry grading	1991	[56]
	Automobile bumpers	1988	[178]
	Beverage cans	1990	[170]
	Castings	1993	[158]
	Extruded aluminum profiles	1990	[54]
	Open-die forgings	1988	[262]
	PWBs	1988	[6]
	PWB solder joints	1988	[101]
	Ship propellers	1990	[126]
	Solder joints	1988	[155]
	Tubes	1993	[85]

^a Used multiple binary images.

^b Used multiple intensity images.

A number of binary vision systems have been presented in the literature. Hitachi, for example, developed an inspection system that used binary images to find 10 different types of defects on the photomask for a color picture tube [101]. Olympieff *et al.* inspected screws using polygonal approximations of object contours [175]. Their system operated at a speed of approximately 5 s per inspection and reduced consumer's risk from 0.5% for

manual inspection to 0.05%. Diffracto built a system that can inspect bolt threads, head profiles, and overall dimensions at a rate of three per second [12]. JAI of Denmark built systems that can be used to inspect items such as rivets at high speeds [12]. Escher [71] developed several systems that verified presence or placement of items within packages. His systems used techniques such as perimeter measurement, centroid position, and height to make the determination in low-resolution (e.g., 32×32) images. Shabestari and Miller [212] inspected dimensions of molded rubber parts using binary images collected from two cameras. Smyth [223] inspected print quality using a process that first used correlation to find areas of discrepancy of printed characters from stored template characters and then utilized morphology to determine if these discrepancies were within the design rules. Lapidus has presented a brief description of the Itran 8000, an automated visual inspection system which avoided the use of special lighting and jigs by matching edge templates for object localization [124]. The Itran 8000 inspection system used a number of pixels along an edge as the feature for comparison to a defect-free part.

Ishizaka and Shimomura [100] presented techniques for binary image inspection using template matching, although they did not present any specific applications of their methods. Their techniques were able to determine position and orientation prior to template matching and operated in real time. They determined pose by matching principal component axes, boundary arcs, and straight lines on boundaries. The pose determination and template matching together executed in less than 67 ms on a 256×200 image.

Edward Weck, Inc., a subsidiary of Bristol-Meyers Squibb, is developing a machine vision inspection system for dimensional verification of surgical staples and ligating clips [240]. In this critical inspection task, 100% inspection is required. Few details of the inspection system were presented, although it appears to use boundary features extracted from backlit objects. The objects have some freedom of position and orientation, although each object was required to be in approximately the same pose.

Baldur and Horth [9] developed a system that sorted up to 4000 brake shoes an hour. Their system also rejected damaged parts that varied excessively from a stored set of user-supplied training patterns. The width and span of the brake shoe along with several user-specified features (such as position or size of certain holes) were used to perform the sorting.

Kassler *et al.* [112] developed a machine vision system for grading inspection and packaging of shrimp for the Australian prawn industry. Their system operated at a rate of approximately 20 shrimp per second. It used silhouette area to grade the shrimp and used other statistics

to determine the shrimp's orientation and to find if the shrimp was deheaded or not.

PWB and IC Inspection. Due to increasing miniaturization and growing complexity, human inspection of printed wiring board (PWB) and integrated circuit (IC) patterns has become quite difficult and time consuming. In fact, the cost of inspection may equal the cost to fabricate a PWB [218]. Automated PWB inspection is already cost-effective because the inspection systems are faster and more accurate than human inspectors [189]. Soon, the complexity and miniaturization of PWBs and ICs may make inspection possible only through automated systems [6, 269]. Currently, many steps in semiconductor production can be reliably performed only through the use of machine vision [272]. PWB inspection is considered one of the most important applications of machine vision. Zuech has estimated that 20% of the U.S. market for machine vision is semiconductor inspection [272].

Many algorithms and techniques for inspecting PWBs have been presented. Typical defects which must be detected include over-etchings (opens), under-etchings (shorts), flaws, cracks, holes, etc. Geometric features, such as conductor length and width, hole and pad diameters, and distances between conductors, can be examined to find these defects [260]. Two well-known techniques that have been used to find the defects are image subtraction and feature-based approaches [260]. Approaches based on mathematical morphology have also been presented (e.g., [59, 172]).

Inspection of IC patterns is a task somewhat similar to PWB inspection, although it is generally a more difficult task due to the complexity of IC patterns. Many techniques for the inspection of patterns in ICs have been presented. Brecher and Dom [31] examined some of the recent developments in pattern defect inspection in IC chips. They discussed several inspection systems in detail, including [58, 63, 68, 89, 107, 106, 254]. Yoda *et al.* [269] used CAD data to inspect multilayer wafer patterns for submicron defects. Their system acquired gray-level images but performed its image processing on binarized images created by thresholding. The system is discussed in more detail in Section 4. Khotanzad *et al.* [117] presented a system that inspected wire bonds that connect to IC bond pads. Their system acquired gray-level images but performed most of its image processing and inspection on binary images created by thresholding after an early edge enhancement stage. Bond quality was determined by examining the parameters of ellipses fitted to the image data.

Hunt has presented an overview of several of the earlier (i.e., pre-1985) PWB/IC inspection systems in [98]. Baird at General Motors, for example, developed an IC chip inspection system that detected cracked or fractured

chips by thresholding images and then matching against templates of IC corners. Hsieh and Fu developed a top-down and model-driven "tree-like syntactic approach" for inspecting IC chips. Chin *et al.* developed a PWB inspection system that checked assembly correctness using graph matching of extracted edges against prestored ideal edges. Krakauer and Pavlidis developed a PWB inspection system that used binary template matching with a quick lookup table technique. Jarvis also inspected PWBs using 5×5 binary templates. Jarvis's system performed additional inspection in regions that appeared to contain a defect.

Darwish and Jain [59] also developed an inspection method that they applied to PWB inspection. Their system conducted inspection by verifying design rules through graph matching. A semantic graph representing the circuit was constructed using morphological thinning followed by steps that merged some segments and deleted others. The semantic graph's nodes represented objects or primitives. Several attributes representing properties of the object or primitive were also associated with each node. The links of the graph represented relationships between nodes. The graph of the inspection object was matched to a graph representing an ideal board. The ideal board's graph was created during an interactive off-line training phase. Darwish and Jain used their technique to inspect 95 PWBs for shorts, wire cuts, and violations of minimum wire widths. All of the defects were detected and no false alarms were signalled for the test data.

Hara *et al.* [87] used a technique primarily based on image subtraction of a registered input image from an image of a "golden" PWB. The input image was aligned with the reference image using alignment marks. Their system illuminated the PWBs with ultraviolet light and detected fluorescence emitted by the boards' base material. The emitted light was filtered optically with a band-pass filter to produce an essentially two-color image. They performed several image processing operations using a pipelined architecture on certain regions of the image to allow line features to be reliably inspected. They reported that their system required 18 min to inspect a 50 by 60-cm surface. This task would have required 10 or more hours for a human to inspect. Hara *et al.* tested their method on images of boards containing artificial defects.

Yu *et al.* [270] implemented (in hardware) a PWB inspection algorithm that allowed line width, spacing, pin hole, and short and open circuit defects to be detected. Their technique was based on design rule checking, although some template matching was used to detect common defect conditions during design rule verification. Their method could inspect at rates up to 4 million pixels per second using a 1024-element line scan camera and an

xy translation stage. The method was made robust to illumination changes, oxidation, and sensor distortions through the use of optical fiber lighting and adaptive binary thresholding.

In general, binary inspection systems are advantageous because their hardware and software requirements are usually modest. Binary inspection is inadequate for many inspections of surface characteristics and 3D shapes, however.

2.3.2. Inspection Using Gray-Level Images

Several systems have been presented in the literature that use gray-level intensity data for inspection. There are few systems, however, that are capable of performing visual inspection on intensity images in complex industrial environments with dirt and unfavorable lighting conditions [45]. Most of the industrial inspection systems that use intensity imagery have limited capability and use image subtraction or localized histogramming methods for defect detection [12].

Sokolov and Treskunov [226] developed a real-time system for inspection of liquid crystal display (LCD) appearance and function. It executed the inspection in approximately 5 s. Most of the system's image processing operations were performed on a special video processor. The system used a microcomputer as the central CPU; e.g., the microcomputer regulated the video processor, calculated histogram thresholds, and made decisions about defects.

Beyer [20] presented an experimental system for inspecting the dimensions of vehicles after crash testing. His system utilized two exterior cameras and one interior camera at known viewpoints as well as a turntable for revolving the vehicle. During a training phase, a model was built using images of an "uncrashed" vehicle. Regions of interest (or, "target areas") in the model that comprised several pixels in the image(s) were used as estimates of the expected position of target points on the crashed vehicle. A least-squares template matching procedure was used to determine the probable dimensional measurements of the crashed car. Beyer's system executed in 15 min on a Sun 3 workstation and measured the target points with an average error of approximately 1 mm, which was acceptable for the application. Fraser and Legac [77] have developed a commercial product, V-STARS, offered by Geodetic Services, that uses a CCD camera for dimensional inspection tasks, such as measuring points on automobile body panels (in that application, 400 target points were measured in about 1 h), jigs used in nuclear reprocessing plants (the system was able to measure 50 points with 0.1 mm accuracy in approximately 30 min), and rocket engines. The tasks that V-STARS performs are those that conventionally would have been performed using touch sensors, such as CMM probes.

Ratcliff *et al.* [193] developed a system for defect detection on ground metal components. They detected defects first at a coarse resolution and then "zoomed in" on any potential defective regions to find the size and location of the defect. Their system performed the inspection using images collected from several known viewpoints. The position of the part was also known *a priori*.

Siemens developed a robot vision system called Gray-Scale Sensor (GSS) which has been used to detect flaws in the hub of cast aluminum car wheels [203]. The system matched edge features against geometric models to recognize different types of wheels and detect defects.

Xian *et al.* [264] described an experimental system for inspection of bearing rollers. Their system could detect cracks, nicks, scratches, and rust of width as small as 20–30 μm on 14 mm diameter by 15 mm length rollers. They used a line-scanning technique to collect the data. Image processing was performed on a Vax 11/750 and consisted of "unrolling" an image that was composed of several line scans. The system was able to detect defects in the presence of "noise" such as surface grease or oil smears.

Intensity images have also been used in the inspection of tool wear. Currently, tool wear is usually monitored manually by a machine operator. Wright and Bourne have noted that machinists occasionally examine tool points during machining to make certain that the tool edge is still acceptable and to estimate the time duration in which the tool will remain usable [262]. Liu [130] developed a tool wear inspection system that examines flank wear of a multifaceted drill bit to determine if the bit is still usable. A typical test for drill wear would use the width of the drill flank wear, but because the drill in Liu's application was multifaceted, he used drill wear area instead. Liu found that worn areas of the drill had a higher reflectivity than unworn surfaces; thus he located regions of high wear using an intensity histogram. Liu compared his system's performance to manual measurement of areas under a microscope and found that his system exhibited a 3.5–4.5% deviation from the performance of a human expert.

Wilder has developed an operational inspection system for detection of small defects in glass panels (CRT faceplates) [259]. The inspection was performed using two stages of image acquisition. A coarse-resolution image was acquired first and used to identify image regions that might contain defects. Then, a series of high-resolution images was acquired for each of the potential defect regions. Defects were detected using components of the gradients of a Sobel edge operation computed in real time. Several gradient components were used to select the "best" image from the series and the other components were used in the computation of an adaptive threshold that allowed defect detection. Wilder's system was tested on several thousand faceplates on the factory

floor and was found to deliver acceptable results. The system could inspect one faceplate every 15 s. An inspection system has also been reported that inspects position, width, height, distortion, brightness, and focus of PC CRTs [253]. The inspection system was built using off-the-shelf equipment such as a Panasonic CCD camera, a framegrabber, and an Apple Macintosh computer.

Applied Intelligence Systems and AECL Advanced Systems developed a fluorescent lamp inspection system for General Electric [8]. This system used six cameras, controlled lighting, and three SIMD array computers to inspect for nine defects in lamp bases. It performed 100% inspection at a rate of 8000 lamps per hour. The system was somewhat flexible for lamp pose, although the assembly line imposed some constraints on the general position of the lamp. Pose was determined by locating two salient features on the ends of the lamp. All dimensional inspections on the lamp were made with respect to these data.

Shih and Mitchell [214] presented techniques that use recursive adaptive thresholding and mathematical morphology to inspect the positions, orientations, and size of corners and holes in industrial parts. Laligant *et al.* [123] developed a prototype system that could detect defects as small as 2 mm in size in the threads of plastic cosmetic bottle caps. Their system inspected at a rate of 3 s per cap by examination of wavelet coefficients. All processing was performed on a 386 PC using 50 images of the cap threads captured with a linear CCD array. Giet and Kleinemeier [80] used a pyramidal approach to match templates of flaws that have known length and width parameters. The Jet Propulsion Laboratory is developing image subtraction techniques to detect small defects (surface pits approximately 0.2 to 6.0 mm in size caused by collisions with small meteors) in large structures in space (e.g., a space station) [92, 190]. Olsson and Gruber [176] have presented a method for defect detection in coated sheet steel. Their method involved first extracting features that measured the intensities of scattered coherent light within image regions. They then located defects using a neural net that performed a *k*-means clustering followed by Kohonen Learning Vector Quantization. Fernandez *et al.* [74] have developed a system that can detect approximately 15 types of defects on continuous aluminum strips. Their system first segmented the defect regions using local smoothing followed by detection of local intensity variations and then classified the defect type using syntactic methods. They implemented their methods on Matrox's Image 1280 image processing board but also performed some processing using five digital signal processing boards each of which had two CCD cameras attached.

Hattori *et al.* [91] developed a pipelined image processing architecture designed to meet automated inspection's

real-time requirements. Their system has been applied for the automated visual inspection of 40 different objects using intensity images. Simon and Rogala [220] developed a technique for real-time inspection of correct insertion of components on computer boards. Their technique, which exploited model information about expected component location and the types of neighboring components, was somewhat flexible under different lighting conditions and was able to conduct its inspections in approximately 10 s. Hanahara *et al.* [86] detected cracks in the thin film head of a magnetic disk using Hough line detection in edge maps.

Agricultural Applications of Inspection. Several studies of the visual inspection of foods using intensity images have been conducted. Pau and Olafsson [186], for example, have discussed applications of computer vision for fish quality control. One application was presented by Bengoetxea [16] who used average spectral reflectivity features to detect black skin and blood spots in cod fillets. Bardin [10] used histograms of rectangular regions within intensity images to detect blood spot defects in fish. Wu and Rodd [263] presented a rule-based boundary extraction technique that they have applied in the inspection of crackers. They were able to determine the boundary of overlapping crackers in intensity images at a rate of approximately 80–90 ms per object using a single INMOS T800 transputer. An experimental chicken grading system was developed by Daley *et al.* [57]. They simulated discoloration and exposed flesh defects on rubber models of chickens and were able to detect these defects using a thresholding technique. Aneshansley *et al.* [3] determined watercore damage to apples using histogram analysis.

Label and Packaging Inspection. Several systems have been developed to inspect packaging of products. White *et al.* [258], for example, have developed an inspection that R. J. Reynolds uses to detect defects in cigarette container labels. The system can distinguish from among 88 different cigarette brands and can inspect over 500 packages per minute. Novini [170] has reported the FastTrack inspection system for detection of defects in the bottoms of glass bottles. FastTrack was able to inspect at a rate of 1000 containers per minute. Novini also reported an industrial inspection system that inspected metal beverage containers for scratches, dents, lid placement, and other features at rates between 200 and 1000 parts per minute.

Truchetet *et al.* [245] have developed a system that inspects printing quality on plastic casings. Their system was designed with a goal of low-cost implementation and thus consists of a CCD camera, fluorescent lamp illumination, and a 386 PC. The system could inspect one casing every 3 s, which is the assembly line speed for their

end application. The processing consisted of a number of steps including, first, an alignment (with subpixel accuracy) of several windows of the casing image with windows of a reference image and, later, an adaptive thresholding of the difference image formed by subtracting the aligned image from the reference image.

Sato *et al.* [208] are developing a system for inspecting Sony videocassette labels. Their system currently uses five cameras, five special-purpose image processing boards, and a MC68020 master CPU to inspect the characters on the videocassette label. Each camera is used to inspect a small portion of each character for missing ink, incorrect centering, and ink spots. The method first performs a coarse localization step using horizontal and vertical histogram profiles. The estimate of position is then refined using normalized correlation of each character with an image of a master character. If the correlation value is below a threshold in any of the five regions, the character (and thus the label) is considered defective. The present version of the system requires 1.2 s per label for all processing.

PWB and IC Inspection. Several systems have been presented in the literature for defect detection in PWBs and ICs using gray-level images. Ninomiya *et al.* [164], for example, presented techniques for inspection of PWBs and of the screen-printed circuit patterns in an unbaked ceramic layer (known as the green sheet). They used connectivity-preserving shrinking to reduce the amount of data their system must process, allowing the green sheet to be inspected in approximately 16 s. Their system exhibited a false alarm rate of about 0.2 per 100 cm². Ninomiya *et al.* [163] presented a shape inspection system that detected defects in via hole fillings on green sheets. The system could detect concave and convex defects as small as 30 μ m and lack-of-fitting defects as small as 10 μ m. To find defects in the fillings, two silhouette, or "shadow," images were acquired from different viewpoints and compared against predetermined criteria. Their method was fast but it was unable to recover 2½D shape perfectly. Nevertheless, the technique was very suitable for inspection of simple objects. They reported perfect defect detection for 161 sample defects with a false alarm rate of less than one occurrence per green sheet. Kim *et al.* [118] also developed a system for the inspection of via hole fillings on green sheets. Their system is similar to the Ninomiya system, although they claimed much faster and more accurate operation due to use of a laser scanning technique. Kim *et al.*'s system could inspect up to 100,000 via holes on a 16 by 16-cm sheet in less than 4 s.

Sprague *et al.* [227] inspected wire width and separation and the presence of the desired circuit pattern in PWBs. Their method consisted of building a segment

graph that represented a skeleton of the circuit wires. This graph was compared with a reference (ideal) board's segment graph. Sprague *et al.*'s method was designed to combine reference comparison with design rule checking in a more efficient manner than systems that used morphological-based reference comparison techniques alone. They implemented their method on a 386-based PC that allowed the inspection of a 3-in. PWB in 13 s. Park and Tou [183] developed a system that inspects for common PWB component defects. This system collected images from three viewpoints. Each of the images was then split into specular and Lambertian components using highlight separation. A dual channel processing paradigm was followed to process these components. Board pose was restricted through the use of fixtures. The system correctly classified over 77% of the components inspected. Bose and Amir [28] investigated the optimal size and shape of alignment markers for fixture-free PWB inspection. Chehdi and Corazza [38] inspected distances between circuit links and the quality of solder joints in two small circuit boards. Their system first determined the area of interest within the image and then used histogramming to subsequently binarize the image region and inspect it. Kuczborski and Attikouzel [121] proposed that a pipeline of gray-scale morphological processors be used for PWB inspection. Silvén *et al.* [217–219] and Takagi *et al.* [232] have also investigated PWB inspection using intensity images. Their systems are discussed in more detail in Section 4.

Sreenivasan *et al.* [229] presented a method for inspection of the ball and wedge bonds that connect bond pads to the lead fingers of microelectronic circuit chips. Their method used histogramming with varying thresholds that were dependent upon the region (e.g., bond region, background, and pad region) of the intensity image. Following the histogram-based segmentation, bond size and shape were inspected.

Bartlett *et al.* [11] inspected solder joints on PWBs using two techniques to determine acceptability of solder joints and to classify the defective joints. The first inspection technique was a statistical pattern recognition approach based on minimization of a quadratic distance metric. The metric was based on 27 features which were decorrelated and weighted using a method based on in-class and out-of-class covariance. A number of training samples of each class of defect were used in the feature weight calculation. The statistical method correctly classified between 75 and 94% of the defects. Its acceptance decision was correct in approximately 98% of the cases. The other method Bartlett *et al.* investigated was an expert system that used 40 features. Defect class was assigned through a voting technique on the features; whichever class had the most evidence was hypothesized as the most likely defect class. The expert system correctly

classified 78% of the defects. Its acceptance decision was correct in 96% of the test cases. Teoh *et al.* [241] also developed and tested algorithms for inspecting solder joints, component alignment and orientation, and for detecting missing components on surface mount printed circuit boards. Most of their techniques detected defects by examining pixel frequency (that is, histograms) within windows in the image. The user specified the windows during a training phase on defect-free images of the boards. Kashitani *et al.* [111] developed a prototype system for inspection of solder joints between PWBs and surface-mounted pin grid arrays. Their system illuminated the solder joints using an optical fiber light guide and acquired its images using a CCD sensor that was connected to an optical fiber image guide. Their system extracted possible defect locations in these images using fuzzy clustering. They tested their method on images of 7100 good solder joints and four bad solder joints and were able to detect all the bad solder joints and nearly all of the good solder joints; the system had a false alarm rate of less than 1%.

Inspection of IC chips has also been conducted using intensity images. Berard *et al.* [17], for example, detected excessively high solder points in IC mounts. Chi *et al.* [43] developed an expert system that used 64 classification rules to detect six different types of defects on IC chips. Nishihara and Crossley [165] inspected the dimensions of the smallest features in an IC and also the registration accuracy between circuit layers using correlation of signs of Laplacian of Gaussian filter output. Bose and Kim [29] developed a system that inspected defects in the bonding of the IC chip to its carrier. Their system used low resolution data to inspect for presence of the chip and for wedge finger scratches and then used high-resolution data to determine chip pose (using alignment marks on the chip) and to inspect for cracks and location of edges. Bose and Kim's system exhibited less than a 1% rate of false rejections and was 12–40% better than human inspectors at the defect detection tasks. Chemaly [39] used controlled lighting and mathematical morphology to detect surface defects (holes, blisters, and grease marks) on integrated circuit packages. Khalaj *et al.* [116] presented a method to find defects in repeated pattern wafers. Their method first estimated the period of the pattern in the horizontal and vertical directions using spectral estimation techniques. This information was then used to construct a reference, or building block, pattern that was shifted throughout the image and then subtracted from image windows to find defects. This approach allowed template matching to be used without explicitly registering the image to a prestored reference image. Texas Instruments developed the MAVS system, an image processing system that has a Motorola 68030 CPU and special-purpose hardware for template match-

ing applications [153]. This system has been used in Texas Instruments' AT4600 inspection system. The AT4600 used multiple cameras and two MAVS to inspect dual in-line packages from all sides for marking, package, and lead defects. Okabe *et al.* [174] of Hitachi developed a system that inspects for lead pitch and coplanarity, surface marks, for foreign objects between LSI package leads, and for defects on mold and lead surfaces. Their system used three 2048-pixel line scanners, six digital signal processing boards, and a single CPU to extract several features which are compared to similar features extracted during a training phase. The system had a resolution of 25 μm , had less than a 3% false alarm rate, and performed all processing in less than 3 s. Sakamoto *et al.* [205] of Mitsubishi Electric developed a system that can inspect a 2- or 3-in. gallium arsenide field effect transistor wafer for submicron line width defects, electrode pattern defects, and for correct interelectrode distance in 15 s, which was fast enough to allow its use in a production line. The system conducted the inspection in images collected with a laser scanning microscope.

Texture Inspection. Many techniques have been presented for the inspection of textured surfaces in intensity images. In this subsection, the recent papers on textural inspection are surveyed. For a review of the general texture analysis literature, the reader may wish to consult the recent survey paper by Tuceryan and Jain [248].

Marutani [139] investigated the use of controlled lighting, Sobel edge detection, and morphology to detect defects in silk crepes. Norton-Wayne *et al.* [169] are developing a low-cost system for real-time inspection of rolls of web textile fabric. Their system used a CCD linescan camera to detect defects as small as 2 mm² on a 2-m wide piece of fabric moving at 5 cm/s (1/20 of factory line speed). They used a thresholding and filtering step to reduce the effects of noise and then located any clusters of pixels that represented defects. Cohen *et al.* [49] have inspected textile fabrics for defects through the use of stochastic texture models, specifically the Gaussian Markov random fields. Defects were detected using likelihood ratio tests in nonoverlapping windows within the image. For faster execution, Cohen *et al.* performed the test using easily computable sufficient statistics of the model parameters. Neubauer [157] presented a segmentation algorithm for use in the rapid detection of defects in textile fabric. Neubauer's method involved first filtering the image and then evaluating the filtered images using a histogram calculated in windows within the image. Finally, the textures were classified using a perceptron net trained by backpropagation. Neubauer trained his net on images containing defects. Dewaele *et al.* [62] detected point, band, and line defects in fabric textures. Their technique used convolution filters whose spatial

form adapted to the textures for inspection. Specifically, the filter size was based on an estimate of the repetitiveness of the pattern. Filter coefficients were computed using the eigenvectors of a covariance matrix for several image points. Chen and Jain [41] also presented a technique to inspect for defects in fabrics.

Tobin and the Advanced Computing and Machine Vision Group at Oak Ridge National Laboratory are developing an automated fabric inspection system [242]. They will initially concentrate on inspection of unbleached fabric but hope to eventually inspect solid colors and then patterns. Inspection in a textile mill is challenging because the line rate is typically 8 to 12 in. per minute, with the forward motion accompanied by a great deal of vibration [243]. Tobin is also developing a ceramics inspection system that is based on a commercial image analysis workstation, Data Translation's PC-based GLIDE system. GLIDE is used to investigate the suitability of various image processing operations for defect detection and then generate inspection scripts of the image processing commands that were found to be suitable for inspection.

In addition, Tobin and colleagues have investigated currency inspection with the Bureau of Engraving and Printing [242, 243]. They developed techniques allowing inspection of a continuous currency web that have been transferred to commercial industry for implementation. Their system used a 1024 \times 1024 8-bit intensity camera to inspect at a rate of approximately 1 s per note. The actual inspection system will have to operate at a rate of about 80 ms per note (600 ft per minute), however. Their technique performed a grading inspection using a template matching technique that first "warped" an image to allow for deviations in printing and then matched the warped image to a "golden" (i.e., defect-free) image.

Conners *et al.* [50] presented a rule-based production system that detects defects in hardwood lumber. Their system can be easily modified to handle changing defect specifications. Cho *et al.* [48] also developed a system to detect four types of defects in rough lumber from four different species of hardwoods. Their technique used a blackboard framework to store all available knowledge about properties of the defects. Fuzzy logic was used to compute the confidence of different defect types based on spectral and shape features. Paul *et al.* [187] presented a multiprocessor architecture for visual inspection which they applied to the inspection of hardwood to detect and classify three groups of defects. They used adaptive and fixed thresholding techniques and the rate of intensity extrema to perform the classification in a hierarchical tree classifier. They anticipated that their system could inspect 5 boards per second, which is seven times the rate of the current production line. Ojala *et al.* [173] also investigated the detection of defects in images of wood surfaces. They were able to detect over 90% of the de-

fects in their samples using texture measures based on first-order statistics derived from edges in the image.

Schmitt [211] used a technique based on gray-scale morphology (which he implemented on a massively parallel computer) to remove surface texture patterns on machined metal surfaces. He was then able to inspect for defects such as pits and holes on the machined surfaces. Schmitt tested his system on machined exhaust manifolds and found almost no false acceptances and less than 1% false rejections. Jain *et al.* [103] presented a technique for inspection of painted surfaces on automotive body panels. Brzakovic *et al.* [33] developed an approach for defect detection in complex textures. Their system used statistical pattern recognition to detect simple defects in the textures. The textures were segmented using a pyramidal linking scheme and then classified using a modified tree classifier. Limas-Serafim [128] used a multiresolution pyramid scheme for segmenting edges that was applied to the segmentation of certain defects in leather. Desoli *et al.* [61] developed several techniques suitable for defect detection in textured ceramic tiles. Glaze clots, spots, and other defects with distinct edges were detected using rank order filtering. Defects, such as water droplets, that covered large areas were found using rank functions that estimated the "distance" of an image histogram from the histogram of ideal tile textures. Desoli *et al.* also were able to find scratch and surface defects. Siew *et al.* [216] graded carpet using carpet wear estimates based on first- and second-order statistics of gray-level differences. Chetverikov [42] detected texture defects by median filtering and thresholding the image subtraction of sample images from the image of a golden standard. Gerhardt *et al.* [79] inspected sandpapers using 4 CCD cameras. They inspected the size of the coating of the sandpaper's bonding agent using a technique based on morphology and found wrinkle defects using a Hough-based method.

Gray-level images continue to be a popular image modality for inspection. Gray-level images provide an adequate level of information for many industrial applications, although gray-level inspection, like binary inspection, is not appropriate for some inspections of surface characteristics and 3D shapes.

2.3.3. Inspection Using Color Images

As Daley and Rao [55] have observed, color is an especially important factor in apparel and food inspection where changes in shade or variations in color indicate a defect. Humans are not reliable color inspectors, primarily because humans do not have a very good memory for color. Therefore, color inspection tasks are very appropriate for automated systems. A few experimental automated inspection systems using color images are cur-

rently under development. Barriers to more widespread application of color inspection systems include the necessity for more computing power, intricate optics, and for careful or controlled lighting. Factors such as light source intensity, color temperature, angle of illumination, and magnification and lens aperture are crucial for accurate color monitoring [184] due to the inspection system's increased sensitivity to the energy distribution from the light source [55].

Some of the current commercial agricultural applications of automated color vision inspection include systems that check the color of bell peppers, examine apples for bruises, or find defects in tomatoes [189]. Sunkist Corporation developed a citrus grading machine that uses machine vision to grade oranges and lemons according to size, color, blemishes, and frost injury. This machine grades eight pieces of fruit per second [189]. Van Renesse [251] developed a system called Apple Quality and Ripeness Inspection System (AQUARIUS) that has been used to grade three varieties of apples for ripeness and quality. AQUARIUS actually used three CCD cameras, each of which captured information from a different spectral band. Ripeness was judged using the ratio between two of the bands and quality was primarily determined by examining the reflectance of small regions in the other band. The performance of the system was not stated, however.

Daley and Rao [55] are exploring automated inspection to find dye streaks on denim. They were able to find the dye streaks by transforming color data into HSI (hue, saturation, and intensity) space and then segmenting the image using a histogram-based thresholding on the hue values. Daley and Carey [56] have also used thresholding and morphological operations to segment HSI color images of poultry. They aim to detect discoloration defects (e.g., overscalds) on poultry skin. Their current system achieved near real-time performance using 4 T800 transputers. Their goal is to achieve real-time processing (human inspectors currently examine one bird every 2 s) using an array of 16 T9000 transputers.

Alapuranen and Westman [1] developed a prototype system for detection of defects on plywood boards. Their technique utilized an iterative split-and-merge region segmentation using RGB information to locate potential defects. The defect candidates were then classified using a *k*-nearest neighbor classifier on 10 geometric, color, and structural features. They tested their method on 200 boards containing 600 defects and were able to classify approximately 88% of the defects correctly.

Richards and Casasent [196] inspected cigarette packages using edges detected in the blue channel of RGB data. Their system was designed to detect if the label printing was skewed or if blemishes were present. The system operated in real time and was relatively low cost;

the component cost was less than \$6000. They detected structures within the edges using an optical Hough binning technique with a computer-generated hologram.

Poole [189] reported an automated inspection system for batteries. Color registration of the label, battery length and width, and correct formation of the positive and negative tips were checked by this system. Since 80% of the defects were color registration errors, the system first checked for that defect, and, if no registration errors were encountered, proceeded to search for other defects. The battery was removed from the assembly line as soon as the first defect was detected.

Asano *et al.* [5] of Hitachi have presented a system for inspection of whiteness uniformity on color CRT displays. Their system detects defects using a two-step process. In the first step, a fixed threshold on hue and saturation was used to signal potential defects. In the second step, each of the potential defects was graded through the use of adaptive thresholds. The grade was assigned based on the color contrast, hue, defect area, and edge strength. The system was able to inspect color CRTs in 10 s, similar to the time for human inspection, and exhibited error rates similar to human rates, although the repeatability rate was three times better than that for human inspection. The system is now in use on production lines. Bien *et al.* [21] have developed a prototype system for measuring color purity and convergence on color picture tubes. Their system is used not to make accept/reject decisions but rather to determine the nature of any adjustments to make the tube image quality acceptable. Their system uses six Motorola 68030 CPUs for vision processing and collects images from nine cameras to make this determination. They use thresholding to prepare the images for purity measurement and use a fuzzy algorithm to measure convergence.

Parthasarathy *et al.* [184] developed an experimental inspection system using color vision for rapid inspection of microelectric gate oxide thickness. Microelectric structures are usually fabricated using a thin film that is optically transparent. Optical interference effects produce colors that are characteristic of film thickness. Parthasarathy *et al.* presented two schemes to determine the film thickness. One method determined thickness with a resolution of 20 Å in less than 100 ms using a nearest-neighbor matching in the RGB color space. It achieved an accuracy of approximately 90%, but this percentage was optimistic because every test sample had a thickness identical to one of the training samples.

Capson and Eng [34] inspected solder joints on PCBs using a tiered lighting arrangement. Their lighting scheme used a red-and-blue-colored ring light to create color contours on the solder joints. Different defect types produced particular contour patterns, allowing the identification of defect class using simple shape and intensity

features. They identified defects using a classification tree constructed with training samples. They tested their method on 1400 solder joints on two boards and were able to detect 97% of the defective joints. The rate of correct defect classification was 76% for one board and 93% for the other board.

Xie and Beni [265] used fuzzy clustering to detect defects in the thin film layer of IC chips. Particles on IC wafers cause the film thickness to vary nonuniformly in the region around the particle, which produces light interference patterns that appear as several concentric rings of different colors around the defect. They were able to estimate the size of the defect by counting the number of color rings in the interference pattern.

2.3.4. Inspection Using Range Images

For many applications, inspection using binary, gray-level, or color images is impractical. Pryor noted that surface inspection of turbine blades is usually not possible using intensity (binary, gray-scale, or color) imagery because silhouette information provides negligible information about the blade surface and intensity data can contain variations in reflected light as large as 100,000:1 over the surface of the blade [191]. Pryor listed gears, female thread forms, and bore inner diameters as other surfaces for which 3D information (depth or range images) is necessary for inspection. Dimensional inspection of parts that have etched height variances, warp, or reliefs also requires accurate 3D measurement of depth [221]. The greatest advantage in using range data, though, is that it explicitly represents surface information [105, 136]. As Marshall has observed, when explicit surface information is available, the shape information can be used for efficient matching [135]. In contrast, matching on edges, which is the practice of many of the gray-level inspection systems, discards much of the surface information [136]. Unfortunately, there do not appear to be any complete 3D industrial inspection systems for complex objects that have been placed online [45].

Robotic Vision Systems developed a structured light sensor and MC 68000-based image processing system in 1984 which were claimed to acquire 3D data in real time [209, 210]. Their claim of real-time operation is somewhat dubious, however, because the sensor was reported to take 40 min to scan all six sides of a cubic object (although over 800,000 points were scanned). The sensor has been used for inspecting large propeller surfaces (i.e., the propellers are up to 24 ft in diameter) for the U.S. Navy [126, 209], engine castings for Cummins Engine (in this application, over 1250 dimensional inspections were required), sheet metal hole and edge features [126], and weld seams (with inexact workpiece positioning) on production lines at General Motors, Westinghouse, and Caterpillar.

Pryor developed several inspection systems using structured light, some of which are discussed in [191]. These systems were developed in the early 1980s but were able to achieve high accuracy. We briefly review the systems here to provide additional historical context of inspection using range images.⁴

1. One system inspected pitch line runout⁵ and tooth spacing errors in gears at a rate of one pair of mating gears every 10 s.

2. Another system qualified and sorted bolts on 10 different dimensions at rates of 10,000 bolts per hour.

3. A third system inspected the internal bores of a power steering housing, performing a complete inspection for surface defects such as pits, scratches, voids, tool marks, and cracks in less than 6 s.

4. Twelve cameras were used to inspect the dimensions of engine valves at a rate of 4200 valve inspections per hour on a production line.

5. Power steering worm assemblies were inspected at a rate of 1500 parts per hour using two cameras and two microcomputers.

6. Threaded and machined holes in cylinder heads were inspected using 80 image sensors to check for the presence of each thread in every hole and to detect hole blockage. A part throughput rate of 600 parts per hour was achieved.

Many recent inspection systems have also used structured light arrangements for the collection of range data. Ye *et al.* [267], for example, inspected edge locations of an automotive subassembly in range data collected using structured light. Ozeki *et al.* [178] inspected several dimensions of a plastic automotive bumper using a triangulating structured light arrangement. Their system measured bumper flushness at 12 positions and width and depth of a hole used to mount the bumper at 4 other positions. They were able to perform this inspection in 3 min, which is approximately one-fifth of the time it would take a human inspector. A system for inspecting the dimensions of car bodies has also been installed [185]. The system used 90 triangulating structured light sensors to determine the exact position of the car body and to examine its dimensions before insertion of doors, fenders, and hood. Approximately 1 car per minute was inspected. The system included LEDs to light hold and slot locations that were not visible to the triangulating sensors. Mistretta and Gerhardt [147] inspected simple 3D objects (spheres and cylinders, for instance) using preconditioned structured light. They distorted a grid before projection such that a uniform grid pattern would be pro-

duced on the image plane by the object to be inspected. Belilove and Hekker [15] extracted Fourier features from moiré interference patterns to detect dented cans and bottles. Blumenkrans and Viano [22] used Fourier techniques to determine depth in images illuminated with light passing through a grating. After determining depth, they detected deformations and discontinuities in aluminum bars by comparison to a reference (ideal) surface's characteristics.

Newman *et al.* [160] developed several matching statistics to use in template matching to inspect for gross defects in range images of objects for which there is a CAD model. She *et al.* [213] used a stereo camera technique to monitor motion in structures in order to assess structural damage. Grimson *et al.* [85] inspected long tubes (of length up to 13 ft) in range data. Their system first coarsely located the tube in sparse range data. The coarse estimate of pose was used to plan a scanning strategy for acquiring dense range data. The components of the tubes were then verified. Their system typically required 2 min to inspect a 6-ft long tube.

Many systems have also been created for automatic inspection of solder joints. Range images are well suited for solder joint inspection because the joints and their key process indicators are complex geometric shapes [198]. Nayar *et al.* [155] developed the SHINY system that used structured highlighting⁶ which consists of illuminating the object by a large number of point light sources, to compute local surface orientations. These orientations were utilized to build an Extended Gaussian Image (EGI) representation [97] of the joints. The solder joints were then classified using features extracted from the EGI. The system required 12 s to inspect each joint. This inspection time included image capture and all computation steps. A misclassification rate of 3% of the joints was observed, a rate which is within the variance of human experts in solder inspection. This system was later used by Westinghouse Electric to inspect solder joints on circuit boards [154]. The system at Westinghouse used special-purpose hardware to allow inspection at a rate of 2 joints per second, or approximately 18 min to inspect a typical board.

An automated 3D inspection system has also been developed for the inspection of open-die forgings [262]. The 3D image was constructed by backlighting the object and using a rotary turntable to collect silhouette data from 360 viewpoints. Three cross-sectional measurements and two vertical measurements were extracted from the image and verified by the system. The system replaced a person who had manually measured some of the critical locations on the forging using calipers.

⁴ These systems also appear to have been omitted from the earlier AVI literature surveys.

⁵ Pitch line runout refers to the eccentricity in the line of contact between gear teeth.

⁶ The structured highlight technique Nayar *et al.* used is described by Sanderson *et al.* in [207].

Several PWB or IC inspection systems that utilize range data have been reported in the literature. Hitachi, for example, developed a system that examined solder joints on printed circuit boards [101]. Their system detected four types of defects and inspected 10 points per second using a 3D structured light arrangement. Davis *et al.* [60] also used structured lighting for PWB inspection. Their system detected missing or misplaced components. Kelley *et al.* [113] developed a camera head and prototype inspection system based on triangulation techniques for inspecting component position on surface mount technology printed circuit boards. Harrison and Weir [90] developed a triangulating structured light range sensing technique that they applied to inspection of PWBs before soldering. Badami *et al.* [6, 7] presented a system that used dense range data to inspect leads on a PWB. The system checked for the presence or absence of leads and verified lead height and angle when necessary. They used a triangulation arrangement for data acquisition with a depth resolution of 0.0006 in. that measured 120,000 points per second (i.e., about 0.5 in.² of the board per second). Few other details were presented about how accurately the system conducted the actual inspections. McIntosh [142] developed a system that used multiple intensity images to inspect dimensional tolerances of lead tips of surface mount devices prior to their soldering to the PWB. Rao *et al.* [192] have developed techniques for inspection of height tolerances and presence or absence of material in semiconductor layers using confocal imaging followed by deconvolution with a Wiener filter and cluster-based smoothing.

General-Purpose Inspection. All of the range image-based inspection systems discussed previously are highly optimized and constrained for use in a single application. Several experimental systems are under development at research laboratories and universities that are somewhat more general, however. Freeman [78], for example, is designing LESTRADE, a system that will learn an inspection task by tracking the human inspector's eye movements to determine regions of interest on the product. The system would then extract features from the areas of interest and correlate them with the inspector's acceptance or rejection decision to create automated inspection rules. Tarbox *et al.* [236–238] also developed a system (called Integrated Volumetric Inspection System (IVIS)) for inspecting objects in range images. IVIS used a volumetric representation to model the object and a golden (i.e., perfect reference) object. Tolerances were incorporated in the reference object by defining a minimum and maximum allowable volume, offset by the allowable tolerance distance from the nominal reference surfaces of the object. Their system is useful for finding gross deformities in objects, but is not appropriate for inspections requiring high accuracies. Newman and Jain

[158, 162] also developed a system for the inspection of a class of objects, specifically, the class of casting objects that contain planar or quadric surfaces. Their system is discussed in Section 4.3. Marshall *et al.* [135–138] has developed a system for gross geometric feature inspection, including verification of hole presence, part dimensions, and feature relationships (e.g., distances and angles) using dense range data collected from multiple views. His system inspected objects composed of planar, cylindrical, or spherical faces, although only planar surfaces (which were extracted more reliably) were used to match the model to the sensed object.

Marshall matched the surfaces in one of the sensed views to the model surfaces using a depth-first search of an interpretation tree. Thus, the search strategy used a single view to estimate the position and orientation of the object. The interpretation tree was pruned to a manageable size using rigidity constraints; i.e., the model-to-view transformation generated after several (usually, three or four) surfaces had been matched. Specifically, a "current transformation" between model and scene was computed after several surfaces had been matched. Searches deeper than the first few levels were pursued only at nodes that satisfied the current transformation, which was then refined using this new relation. Several of the approaches to 3D object recognition in the literature, including those of Faugeras and Hebert [73] and Chen and Huang [40],⁷ have also used rigidity constraints.

Marshall's system used all of the views in the inspection tasks. Specifically, the system inspected geometric tolerances, such as errors in position, size, and shape of model primitives. No details about system execution times were presented, although real-time performance did not seem to have been a goal. Marshall's work is significant because of its generality (any object's geometry can be inspected if a model of the object exists, provided that the object contains several planar surfaces that are visible to the sensor) and its use of multiple range images. Marshall apparently inspected only two fairly simple objects, however. Also, many of the defects the system detected were artificially induced on the objects; thus the general application of the method may be limited. A diagram of Marshall's inspection method is shown in Fig. 4.⁸

⁷ The local-feature-focus method of Bolles and Cain [25] and the 3DPO object recognition scheme of Bolles and Horaud [26] also employ rigidity constraints, although Bolles, Cain, and Horaud employed different terminology.

⁸ Marshall's system follows a paradigm that might be termed match-and-compare. This approach is not uncommon for the AVI systems, although in many of the highly special-purpose industrial systems, part position (and identity) is known, due to the use of fixturing. In some systems, especially those that compare scene object features with rules of an ideal part's characteristics, an explicit correspondence between the ideal part (or model) and the scene object is also not necessary.

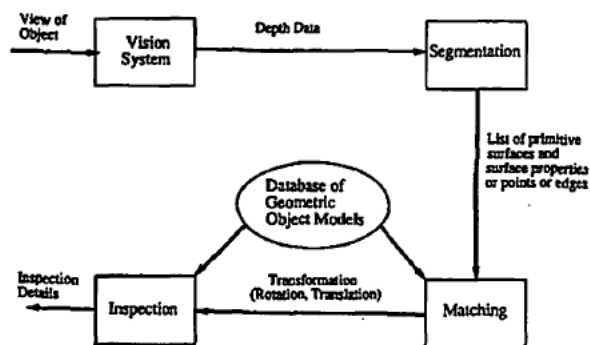


FIG. 4. Schematic diagram of Marshall's 3D Inspection System. Reproduced by permission of the publisher, from A. D. Marshall, Automatically inspecting gross features of machined objects using three-dimensional depth data, in *Proceedings of the SPIE Conference on Machine Systems Integration in Industry*, Boston, 1990, Vol. 1386, pp. 243-254.

2.3.5. Inspection Using Other Sensing Modalities

Other sensing modalities are also possible for inspection. For example, X ray inspection is often used to inspect complex industrial parts [94]. Noble *et al.* [152, 166, 167] proposed a technique based on deformable templates to inspect drill holes in X ray images. Hedengren [94] has developed real-time algorithms to verify the presence, size, and location of drill holes in metal using X ray images. Boerner and Strecker [23] developed a pilot system for detection of pit defects in cast aluminum wheels using X rays. They segmented defect regions from defect-free areas using two techniques, one based on edge detection using DOG filters and the other based on rotationally invariant features derived from Zernicke circular polynomials. Jain and Dubuisson [102] located defects in X ray and ultrasonic C-scan images of composite materials using adaptive thresholding and Canny edge detection.

A number of PWB, IC, and semiconductor inspection systems have also been presented recently. Four Pi [99, 110], a subsidiary of Hewlett-Packard, has developed a PWB inspection system that uses X ray scanned beam laminography. The scanned beam laminography technique collects X ray images from several parallel planes, allowing inspection of some 3D features. One of Four Pi's newer systems, the 5DX series, whose price is approximately \$370,000, uses a RISC processor to inspect solder joints with a repeatability of within 2.5 μm at rates up to four images per second [110]. IRT Corporation has developed a system that does X ray inspection of PWB solder joints using parallel multitasking with several Motorola 68040 CPUs [110]. Shu *et al.* [215] have used a modified Hough technique to detect and inspect submicron resist lines in VLSI wafers imaged with scanning electron microscopy (SEM). SEM is a method that col-

lects images using a focused electron beam. SEM generally has 10 to 100 times better resolution than optical methods and has 100 or more times greater depth of field [215]. A commercial wafer (and X ray mask) inspection system that uses SEM is available at a cost of approximately \$4 million from KLA Instruments [132].

Onda *et al.* [177] identified welding defects in ultrasound images using a neural network based on back propagation. Casasent and Carender [36] inspected cigarette warning labels using 1D acousto-optic transducers. Batten [14] proposed that inspection for cracks in railcar wheels be conducted using infrared sensing while the wheels are heated with AC electricity. Durrani *et al.* [67] inspected for surface and interior flaws in composite materials by heating the object with a thermal pulse followed by Laplacian of Gaussian filtering to detect edges surrounding defect regions in infrared images.

Alternate Modalities for Food Inspection. Chan *et al.* [37] examined the suitability of other sensing modalities for use in automated visual inspection of foodstuffs. X rays could be used to detect foreign bodies in food, for instance, although only foreign bodies whose density is higher or lower than the food sample's density can be detected. X rays are also useful for texture analysis of foods. Other advantages in using X ray images for inspection include the high contrast nature of the images and the potential for real-time imaging. There are cost and safety considerations, however, in the use of X rays.

Gamma rays are similar to X rays but can be used to inspect denser materials. Chan *et al.* [37] noted that while gamma ray images can be acquired in real time, they also present several disadvantages. One disadvantage is that gamma ray images typically are of lower contrast than X ray images. There are also several safety considerations. Like X rays, there are dangers from gamma radiation, but unlike X ray machines, gamma ray machines cannot be switched on and off. This makes transportation and storage difficult and also presents constant safety concerns.

Chan *et al.* [37] also discussed the potential application of nuclear magnetic resonance (NMR) imaging for inspection of the texture and composition of food. NMR equipment is very expensive, however.

Ultrasound images may also be useful for foodstuff inspection, particularly for packaged foods with no air content and high water content [37]. There are no safety concerns about ultrasound although it is not well suited to many industrial environments because it requires special transducers for imaging. Aneshansley *et al.* [3] graded beef by enhancing ultrasound images of the area near the 12th rib and then detecting edges.

Another potential sensory source for automated visual inspection of foodstuffs is thermal (infrared) imaging [37]. Infrared (IR) sensors are flexible and easily recalibrated. As many as 5 images per second can be collected with current IR sensors. There are also no safety consider-

ations about IR sensors. A disadvantage of IR imagery is that the sensors have limited sensitivity and produce images which usually require preprocessing.

Ultraviolet (UV) light can be used for fluorescent analysis of certain foods.⁹ While ultraviolet light does not penetrate materials, some foods, such as eggs, milk, and fish, exhibit changes in fluorescence with freshness [37]. Fresh milk, for example, exhibits a yellow fluorescence while sour milk has a fluorescence which is white to gray violet in color. Fluorescent images can be acquired in real time, although high-intensity UV light can cause eye damage or skin cancer. UV light may also affect some foodstuffs. Furthermore, automated vision systems using ultraviolet light sources usually require color processing, which adds complexity to the system software and hardware.

Defect Enhancement—Magnetic Particle and Liquid Penetrant Testing. Nondestructive visual inspection has also been conducted using magnetic particle and liquid penetrant testing. These two testing techniques are especially applicable to inspection of cast or forged parts [81, 114]. Both techniques increase the contrast between defective and defect-free regions of a part. Liquid penetrant testing (LPT) consists of applying a visible dye to make cracks, pores, and other surface defects more visible. Usually, a penetrant is sprayed on a surface, and after the penetrant dries, the surface is treated with a developer that colors the area of inspection white while also removing the penetrant from defects. As a result, defects usually appear as dark or red lines or spots [114]. Often a fluorescent penetrant dye is used which, when viewed under ultraviolet light, allows defects to appear bright and sharp [114].

Magnetic particle testing (MPT) is one of the most widely used contrast enhancement techniques [81, 114]. Magnetic particle testing consists of applying fine ferromagnetic particles to the object surface by dipping the object in a water- or oil-based suspension [114]. The part is then magnetized using either a longitudinal or circular magnetic field. Magnetic particles are attracted to regions where the magnetic field crosses a crack or pore, indicating defect location to a human operator. In a similar fashion, near-surface nonmetallic inclusions in castings can also be detected [81]. The object is often inspected under ultraviolet light to further enhance the contrast of the defects. Magnetic particle testing is preferable to many other inspection techniques because it is affected less by surface geometry, roughness, and material structure [81].

LPT and MPT testing are particularly important due to their ability to greatly enhance detection of surface defects. As Goebbels and Ferrano [81] have noted, mechan-

ical and thermal loads as well as corrosion are directed at surfaces. Surface defects greatly reduce the ability of objects to withstand such loads.

Gages and machines to aid human inspectors in LPT or MPT have been developed by many companies. Magnaflux, for example, dominates the market for MPT machines. Automated inspection using LPT or MPT techniques has also been conducted. Goebbels and Ferrano [81], for instance, have developed automated inspection systems for many applications. Their systems use from one to four cameras under both visual and ultraviolet light sources to detect flaws in many small parts, including casting rods, coil springs, axle housings, turbine blades, and wheel hubs.

3. INSPECTION SCHEMES

Automated visual inspection techniques can be separated into two general approaches. The first approach involves matching a template of a defect-free model (often this is a synthetic image) to the sensed image of the object to be inspected. Objects which are defect-free match the model well. The second approach involves extracting features from the sensed object and comparing those features to a description or list of rules that describes an ideal model. If all of the rules are satisfied, the object is considered to be defect-free. The two approaches are described in detail in the following two subsections.

3.1. Template Matching

Automated inspection has been performed on object silhouettes and also on gray-scale images using template matching schemes. These pixel-by-pixel matching schemes compare the value of pixels in an image of the sensed object against pixels in stored images of a defect-free model. The image of the defect-free model may be a sensed image or, alternately, a synthetically generated image, perhaps from a CAD model.

One area in which template matching techniques have been successful is the automated visual inspection of printed circuit boards [166, 219]. One example of a pixel-by-pixel matching system for printed wiring board inspection was proposed by Silvén *et al.* [219]. (Their system is discussed in more detail in Section 4.) Template matching has also been used for inspection of integrated circuit photomasks [219]. The template matching was performed in that system by comparing images of fabricated photomasks with images of perfect photomasks. The system experienced difficulty with frequently occurring variations of patterns, however. This is a common complication in template matching approaches; there are natural (nondefective) variations between parts that arise in most manufacturing processes [166]. We have used a

⁹ Hara *et al.* [87] have noted that UV lighting has also been used in at least one commercial product (by the Lincoln Laser Company) for PCB inspection.

CAD-based bidirectional template matching technique for finding gross defects in castings [161]. Rioux *et al.* [197] have inspected bumper subassembly dimensions and ceramic tile "flatness" using template matching in dense range images. Template matching techniques have also been used for seam detection in industrial seam tracking applications [250], for propeller dimensional inspection [126], and for inspection of drill holes [166].

Pixel-level comparison schemes are flexible and are probably the only reliable way to detect many faults [217]. However, comparing low-level pixel values utilizes only a small portion of the potential information which could be used in inspection [217]. Exhaustive template matching is also quite time consuming; no matching strategy can efficiently match the hundreds of thousands of pixels commonly encountered in an image [136, 250]. Schemes for reducing the size of the template have been proposed, though, such as the learning algorithm based on statistical pattern recognition presented by Lin *et al.* [129]. Template matching becomes painstakingly slow if the pose (orientation and position) of the object is unknown, or if the scale of the pattern to be matched is unknown [250]. (In practice, many template matching schemes are not very flexible because they assume that the approximate pose of the object is known.) Some methods have been proposed, however, to resolve the pose determination problem in template matching, such as Rodriguez and Mandeville's [200] least-squares fitting of points in edges extracted from an image of a PWB to points in edges extracted from a CAD reference model. Furthermore, "good" and "bad" parts can often take a variety of shapes, making it difficult to detect which objects deviate from the ideal [198]. This is one of the key problems in inspection of solder joints [198] and wire bonds on ICs [117], for example. Noble and Mundy [168], however, have suggested that acceptable part deviations (e.g., deviations of a dimension less than the allowable tolerance) can be incorporated in a template built from the model through a subsequent refinement process that uses data sampled from real parts that deviate from the ideal. On the other hand, most inspection techniques that rely on high-level features suffer from the difficulty and time-consuming nature of extracting features from the imagery.

3.2. Rule-Based Methods

Most of the industrial inspection systems that have been reported in the literature utilize rule-based comparison schemes. Rule-based schemes make decisions about object quality according to classification rules [250]. The sensed object is checked against a list of design rules or against features that can be extracted from the design rules. Most industrial inspection systems use attributes such as surface area, perimeter, ratio of perimeter to

area, number of holes, area of holes, minimum enclosing bounding box area, maximum radius, and minimum radius [250]. One advantage of the rule-based schemes over template matching is that it is unnecessary to maintain an extensive database of templates [198]. The rule-based methods suffer from the disadvantage that they are less adaptable to design changes than pixel-level comparison schemes, however. Extraction of design rules from an object design model (e.g., a CAD model) is also not always trivial. Some rule-based schemes also require complicated schemes to eliminate false alarms [217].

3.3. Hybrid Methods

Hybrid techniques that combine template matching and rule-based reasoning are also possible. Noble *et al.* [166], for example, presented a variation on the usual template-based and rule-based techniques. Their technique used deformable "templates" in X ray images to examine drill holes. Their technique did not use strict pixel-based matching, but instead determined a coarse match between edges extracted from the image and a template consisting of curve primitives. After a coarse fit was made, the curves in the model template were locally deformed to more closely match the edges extracted from the image. In addition, the model template was augmented with higher level geometric constraint rules which were evaluated to determine acceptability. The part was accepted only if the deformations necessary to align the model template to the edges extracted from the image fell within the ranges specified by the constraint rules. Noble *et al.* established their constraint rules by collecting statistics on a large sample of defect-free parts.

4. CAD-BASED INSPECTION

Several CAD-based inspection schemes have been presented in the literature. In this section, we motivate the need for CAD models in inspection and discuss several of the CAD-based inspection systems.

4.1. Use of CAD Models

It is desirable to use CAD models in inspection because the models contain an exact specification of an object. Also, the models are preexisting; they provide a ready, well-defined model for inspection [98]. A mathematical description of the shape of an object, including an explicit parameterization of surface shape and an explicit encoding of intersurface relationships, is provided by most CAD models. CAD databases can also be augmented with manufacturing information, including material type, geometric tolerances, desired quality of surface finish, and finish color, thus providing a unified description applicable for inspection and other downstream manufacturing applications. Another advantage of using CAD

representations for inspection is their flexibility. It is possible to add new object models to the inspection system, for example.

CAD models are also useful because they offer the potential of modeling common defects. It is likely that some of the possible part defects are known *a priori* and therefore can be modeled geometrically [93]. If a part is defective, an automated inspection scheme can attempt to determine the nature of the defect by comparing the observed defect to the models of common defects. The generality of the CAD representation also allows new defects to be quickly introduced into the existing structure. It should be noted, however, that there do not appear to be any current CAD packages that allow descriptions of potential defects to be included in the model of a part; defects must be modeled separately from the part.

4.1.1. Tolerances

When an object is designed using a CAD system, the collection of part dimensions forms the specification of an ideal part. But variances in the production process make it impossible to build a part in exact accordance with the specification. Thus, the design is usually augmented with information defining acceptable limits (or, tolerances) on size and shape variations. Historically, most mechanical design tolerances have been expressed informally and are mathematically nonrigorous [249]. This makes it very difficult to compute tolerances [249], especially for automated inspection applications [109]. The study of formal tolerance specification and analysis has received some attention, especially in the CAD and manufacturing literature [75, 109, 194, 195, 246, 249]. Most of the current tolerance analysis techniques rely on the designer to formulate the problem and explicitly resolve any ambiguities resulting from groups of related features or tolerances [64].

One of the problems with tolerancing information is that there is no robust definition of tolerance [136]. Specifically, tolerances usually involve no precise definition of the features and do not formally define the allowable "size." Requicha has presented several papers addressing this problem and has proposed that tolerances be specified using a volume that defines the maximum and minimum allowable offsets from faces of the object [194, 195]. Tarbox *et al.* [237, 238] have used Requicha's formulation in the volumetric inspection of objects modeled with octrees. Turner and Wozny [249] have proposed that tolerances be interpreted as variables that define a real-valued normal vector space of model variations.

Deciding what actually needs to be inspected to determine tolerance fulfillment is difficult. Merat *et al.* [144] have formalized the problem of determining the optimal number of inspection points to determine adherence to tolerance as:

Given a surface S , let $P = \{P_i; 1 \leq i \leq m\}$ and $Q = \{Q_j; 1 \leq j \leq n\}$ be sets of variables representing points on S . Let C be a set of constraints on the points in P and let D be a set of constraints on the points in Q . We want to find values for all P_i and Q_j such that (1) all constraints in C and D are satisfied, and (2) the set $P \cup Q$ is as small as possible—i.e., as many points of Q are identified with points of P , and vice versa.

Although this formulation is aimed at determining points for a coordinate measuring machine (CMM) to sense, it is also applicable to the related problem in vision-based inspection. Apparently, there are only some heuristics available that attempt to achieve this [144]. Etesami [72], however, has presented a formulation of the steps necessary to inspect certain circular dimensional tolerances in 2D. Menq *et al.* [143] have also presented techniques for determining suitable representative points for measurement by a CMM. Their method first determines an accurate transformation between the CAD model and the acquired image and then determines if the part falls within acceptable tolerance limits.

Spyridi and Requicha [228] presented techniques for determining accessibility of points in dimensional inspection. Their techniques were designed for CMM measurement, but are also applicable to AVI's concern with determining feature visibility. They computed "accessibility cones" for this purpose and then clustered these cones to determine a minimal collection of viewpoints necessary for part inspection. Cowan and Kovesi [52] presented a method for planning camera or range sensor location based on resolution, focus, field of view, and visibility constraints. Their technique was applied to the inspection of slot dimensions on sheet metal and other vision applications. In [51], Cowan and Bergman extend Cowan and Kovesi's method to allow planning of acceptable camera apertures and location of a light source. Sakane and Sato [206] have investigated placement of light sources for photometric stereo systems using visibility constraints calculated on a geodesic dome constructed about an object model. Tarabanis *et al.* [233] developed an optimization procedure that determines acceptable camera poses and optical settings that allow the viewing of polyhedral object features subject to visibility, field of view, focus, and resolution constraints. Tarabanis *et al.* demonstrated their technique using a vision system whose sensors were mounted on robotic arms. Yi *et al.* [268] presented an optimization approach to light and camera positioning based on edge visibility. Mason and Gruen [140] developed an expert system that determined camera placement for dimensional inspection using the CAD model of the product. Trucco *et al.* [244] are also developing techniques that automatically determine optimal sensor position for feature inspection. Additional details on the recent literature in sensing planning are available in the survey paper by Tarabanis and Tsai [234].

Several researchers have evaluated the dimensional

tolerance inspection capabilities of vision systems. Griffin and Villalobos [84] determined if the tolerance requirements of a part design could be met by a visual inspection system that used binary images of flat (2D) objects. They evaluated the effects of the three principal sources of error, which are quantization error, illumination error, and positional error, to make the decision. El-Hakim and Westmore [69], Lu and Ahlers [131], and Wong *et al.* [261] conducted performance evaluations of the dimensional measurement capability of stereoscopic vision systems. Modayur and Shapiro [148–150] examined the role of measurement uncertainty in determining acceptability of part dimensions. They propagated uncertainties in detection of edges into a measurement task and determined that this resulted in decreased inspection error rates. They modeled their objects using a CAD representation that included tolerance information about part dimensions. In [149], they used adaptive Kalman filtering to fuse uncertainty in a fixtured part's position with an estimate of image noise to determine the size and position of a region of interest for inspection.

With the exception of a few recent releases, CAD modeling packages generally lack capabilities for representing and manipulating variational information such as dimensional tolerances [136, 180]. One problem with current dimensional tolerancing is that there are often ambiguities in interpretation depending on which area or point on the object is treated as a datum (i.e., reference landmark) [136].

Tolerance Analysis and Inspection Plan Generation. Several methods related to tolerance analysis and generation of tolerance inspection plans have been presented in the literature. Merat *et al.* [144] presented a system that allowed automatic generation of inspection plans from certain feature-based CAD models. Their system presented the feature-based computer-aided designer with a menu of choices that allowed the designer to describe feature dimensions and tolerances. The selected dimensioning technique was translated into a representation that conformed to the ANSI Standard for Geometric Dimensioning and Tolerancing. The selection of a technique also triggered the generation of an appropriate prefabricated inspection plan for use by a coordinate measuring machine.

Dong and Soom [64] proposed a technique for resolution of tolerance stackup through a tree search method. Their technique extracted tolerance information from Initial Graphics Exchange Standard (IGES) entities that contained a CAD drawing's text annotations. A tree structure was constructed from this extracted data which implicitly contained the relationships between all tolerances. Search of the tree allowed recovery of related tolerances.

Hermann [95] presented an expert system for planning dimensional tolerance inspection. His system built the inspection plan using information about tool and measuring instrument capabilities, including their capabilities and their cost in time and money. The inspection plan was designed for use by a human inspector, although it may be possible to extend Hermann's method to automated visual inspection. Ruhl and Death [202] developed a decision support system that aided a user in adjusting a dimensional inspection system's lighting and other parameters to reduce levels of false acceptance and false rejection. Their system also assisted the user in determining if the inspection arrangement can reliably measure the dimensions within the required tolerance.

Marefat and Kashyap [134] used the CAD model of a part to generate a list of the camera viewing directions and the feature entities (edges) which must be measured to verify dimensional tolerances. Their method used a breadth-first search of a tree that enumerated camera positions and directions to determine an acceptable geometry that would permit the necessary verification.

4.1.2. Features

Form features such as holes and slots usually are not explicitly represented in current solid models. (The notion of a "feature" is defined only vaguely in the manufacturing and CAD literature, usually as a region of interest on a part [145].) As a result, features for inspection usually have to be extracted from the CAD database.¹⁰ A few of the commercial CAD packages are beginning to support feature-based representations, however. Feature-based representations allow a higher level of abstraction than the geometric primitives of traditional CAD systems and form a connection across design, analysis, and manufacturing aspects of CAD [145]. Although there are advantages to design by features, there are some disadvantages if strictly *manufacturing* features are used; functional features may be more appropriate for design [252]. Merat *et al.* [144] have identified a dichotomy of features that includes "form features" and "geometry-modifying features." One class of features includes slots, through-holes, ribs, pockets, etc. The other class includes chamfers, fillets, and other features that modify the geometry that the form features define. Park and Mitchell [180, 181] have inspected a simple flat 3D object in a single 2D image using a feature-based CAD modeler.

4.2. Disadvantages of CAD Models

There are a few barriers to the widespread use of CAD models for automated visual inspection, however. One problem is that the process of image formation is very

¹⁰ The extraction of machinable features from a solid model has recently been addressed by Vandenbrande and Requicha [252].

complex and is usually not modeled completely by the CAD model or by a supplemental image formation model [166, 167]. For example, images often contain specular reflections, complicating the inspection and/or recognition tasks. Another problem is that computing offset surfaces that are a tolerance offset from curved surfaces is very difficult, requiring the solution of high-degree polynomial equations [166]. For some surfaces, there are no known methods to compute exact offsets. Although tolerance information can be included in the CAD models produced by some CAD packages, it has been difficult to build general-purpose models that combine mathematical models of the semantics of dimensions and tolerances with a solid model [109]. The greatest barrier to using CAD models for inspection or recognition, however, is that many times the actual manufactured part is different from the original model [166]. This difference arises due to adjustments made in the actual manufacturing process during development. The CAD model should be updated to reflect these adjustments, but often there is no feedback loop from manufacturing back to the design stage.

4.3. Applications of CAD-Based Inspection

Silvén *et al.* [217–219] developed an experimental CAD-based visual inspection system for verifying printed circuit boards using edge information. Their system was somewhat robust with respect to board alignment. Minor misorientations were resolved by choosing several line segments and then rotating the board to align the line segmented in the sensed image with those in an image generated from the model [217]. The system used both a statistical and a structural approach for defect recognition. The statistical analysis performed well for simple, tightly controlled wiring patterns, while the structural analysis worked better in complex wiring patterns. In the structural approach, defects were recognized by a depth-first matching of a structural graph derived from a sensed image with stored structural graphs of commonly occurring defects. Heuristic rules, such as commencing the search from those nodes which exhibited high matching scores, were used to simplify the matching [218].

Park and Tou [182] presented a CAD-based inspection method for examining printed circuit board solder joints. Fifteen features were extracted from four frames of 512×512 intensity images. Each frame was collected using a different light source. Features were extracted using CAD models that contained the sizes and locations of ideal solder joints and pads. Park and Tou used a fuzzy set-based classification algorithm to categorize defects into one of seven classes. The classifier was designed using training data of defective joints. They reported an average correct classification rate of 93.9% and a false alarm rate of 5.6%. In 3.8% of the cases, the defect could

not be identified. Their system used a simple lighting arrangement and was able to process up to 250 solder joints per frame. Because four images were used, however, the inspection process was not very fast.

Takagi *et al.* [232] used a CAD model of a component-less PCB to recognize the position of the board. Their system then inspected the board for solder defects within certain regions of interest. The method used the change in reflectance of the joints under illumination with two different light sources to determine if the joints were acceptable or not. The method was able to determine board position, create an inspection plan, and conduct the inspection in approximately 6 min. They observed a 99% rate of defect detection on nine PCBs that were evaluated 10 times each.

Yoda *et al.* [269] used CAD data to inspect multilayer wafer patterns of ICs. The system collected gray-level images using a linear array sensor but performed most of its image analysis operations using binary images. The first processing step involved subtracting the input image from an image of an "ideal" chip pattern to find candidate defect areas. Thresholding and binary morphology were then used to "filter" the candidate defect areas. CAD data were used to guide the thresholding and morphology. The "filtered" defect candidates were also compared to the CAD data to make an acceptability decision. The system's image processing and defect detection algorithms were implemented in hardware using a pipelined architecture. The system did not perform 100% inspection of the wafer pattern; to save time, a statistical decision of acceptability was made based on intensive inspection of three areas on the wafer. Their system has been used for inspection of 1 Mbit DRAMs and 256 Kbit SRAMS at Hitachi's Musashi Works. The system required less than an hour to inspect one wafer, which is 30 times faster than human inspectors, and was able to detect more than 95% of the defects on the chips.

Dahle *et al.* [54] are developing a system that inspects extruded aluminum profiles using a structured light arrangement. Their system uses information extracted from CAD-generated models for inspecting surface planarity, gap dimensions, and angular deviations. Their goal is an inspection rate of 1–2 objects per second, although the current inspection rate is not yet that fast.

Sobh *et al.* [224, 225] proposed that inspection can be conducted by first building a CAD model from CMM and intensity image inputs. The object could then be inspected by comparing the CAD model of the object with the original CAD model.

West *et al.* [256] developed an experimental CAD-based system for flat object inspection in intensity images. Their system inspected positional tolerances of planar and cylindrical surfaces. They determined approximate object pose using Stockman's pose clustering tech-

nique [230] and then inspected distances between edges, positions of circle centers, and circularity.

Newman and Jain developed a CAD-based system for inspection of unmachined iron castings in range images [158, 162]. The system inspected for common casting defects and verified manufacturing features and dimensional tolerances. Information extracted from a model built with a commercial CAD package was used in several stages of processing, including surface classification, localization, and inspection. Following image acquisition, "homogeneous" regions in the range images were identified and labeled using a range image segmentation scheme, based on a split-and-merge region growing method, and a suite of model-based quadric surface classification techniques [159]. The system correctly classified 45 of 47 defective castings and 9 of 11 defect-free castings. A limitation of the system was that the range sensor's configuration could result in object self-occlusions. There was also no method to acquire data from the underside of the object.

Park and Mitchell [180, 181] developed an experimental system for feature-based inspection of objects in intensity images. Their system was designed to inspect dimensional tolerances and for the presence or absence of features such as holes, slots, edges, and vertices. Their research was aimed at automatically generating an inspection plan based on a CAD model of a part. They used a polygonal B-rep as their CAD model. This model was extracted from a feature-based CAD model whose features were subtractive (machining) operations that removed material from a workpiece. In [180], they estimated part position using a variant on Bolles and Horaud's [26] local feature focus method. Specifically, they used holes/circles, line fitting, and morphological image operations as well as the pairwise relations between these features in a hypothesize-and-verify scheme to recognize the part and determine its position. Park and Mitchell restricted object position and orientation, however; i.e., they did not allow six degrees of freedom in pose. After the part was identified, the dimensional tolerances extracted from the CAD model by the inspection planning algorithm were examined. Park and Mitchell did not quantify the performance of their technique. In [181], they used depth-first search to match intensity images to 60 stored views of a model (i.e., intensity images taken from 60 "evenly-spaced" viewpoints). This allowed for six degrees of freedom in pose and allowed the estimation of approximate pose. Pose was refined by matching edge features of the 10 highest ranking coarse matches.

5. CONCLUDING REMARKS

In this paper, a taxonomy of the stages of inspection was presented. An overview of the automated visual in-

spection systems reported in the literature was also presented. The methodologies of the various inspection systems were discussed when they were known. In addition, we have highlighted the commonly used techniques in the literature. Special attention was placed on the use of CAD data in inspection.

Since the last survey on AVI, a number of trends have developed, including more systems utilizing CAD data, an increasing number of PC-based solutions, an increased usage of multiple processors and multiple sensors, and a larger number of systems using 3D, X ray, ultrasound, and other sensing modalities. We believe that these trends will continue in the next few years. PC-based solutions will probably become more feasible for many applications as processing capability increases and price decreases, although it is unlikely for PC-based systems to become fast enough within the next 5 years for the most intricate inspections, e.g., IC pattern inspections. It is difficult to predict which CPUs will be the most popular for inspection applications in the next few years, however, there will likely be a large number of projects that make use of the next generation CPUs such as the MC 68060, Pentium, and Power PC CPUs, as well as the popular workstation RISC CPUs.

Future research efforts in automated visual inspection will likely focus on making the systems more flexible and on adding inspection capability for the free-form surfaces. In industrial inspection applications, there will also likely be increased exploitation of CAD models as manufacturing enterprises become more integrated. The immediate efforts of applied AVI systems will probably center on improving the speed of inspection through the use of better inspection algorithms, faster processing units, and multiple processing units. Additional work will also be concerned with improving ease of operation and programming of the AVI systems. The cost of many AVI systems is also fairly high and must be reduced for further automation of inspection to be profitable. Finally, tolerance specification and analysis will receive attention, perhaps leading to the adoption of accepted methods of tolerance and datum specification common to both design and inspection. It is necessary for the computer vision and machine vision communities to work closer together in problem resolution, too. This would allow real (not contrived) problems to be tackled by the computer vision community as well as avoid duplication of effort and promote dispersal of successful methodologies into both communities.

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