CHAPTER

# Automated Visual Inspection

20

Humans are good at searching for the unusual and locating faults in manufactured products, but rapidly tire when large number of items have to be scrutinized. The aim of automated visual inspection is to achieve 100% untiring inspection and control of quality. This chapter describes the processes and principles needed to achieve this end, the main limitation being the impossibility of covering the full variety of products in a single chapter.

*Look out for*:

- the variety of products to be inspected.
- the main categories of inspection.
- how deviations relative to a standard template can be measured.
- the methodology for scrutinizing circular objects.
- the problems of inspecting products exhibiting high levels of variability.
- the principles of X-ray inspection.
- the importance of color in inspection.

Note that this chapter aims to give a broad view of inspection, and is counterbalanced by the following chapter that covers a particular application area in more depth: this approach is appropriate as case studies provide one of the best ways for extending the work to the wide variety of products.

## 20.1 INTRODUCTION

Thirty years ago, it was already apparent that machine vision would have an important role in the design of automated manufacturing systems. Indeed, it was

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clear that it would be applied on two main fronts. First, it would be important for helping to control quality during manufacture. Second, it would be vital for providing precise information to assembly robots on the placement of the components and the products being constructed. Note also that it is important for an assembly cell to be flexible, and in this respect, vision is key to adapting from one set of components to another.

In the early days of automated manufacturing, there was a feeling that the vision tasks needed for inspection and assembly would be quite different. Although there was an element of truth in this, it was soon realized that the majority of vision algorithms, such as edge detection and object location, are common to both. Indeed, machine vision is highly generic, and its methods are readily adapted from one application to another.

There are three main aims for automated visual inspection:

1. To check components and products for quality, with a view to rejecting those that are dimensionally inaccurate or otherwise defective.
2. To assess the general quality of production in order to provide feedback to earlier stages of the plant and thereby to correct erroneous trends. For example, in the case of food products, if coatings of jam or chocolate are found to be spreading too rapidly, feedback will need to be provided to reduce the temperature at an earlier stage in the production line.
3. To gather logistics on the operation of the plant, including such parameters as temperatures, variations in product dimensions, and reject rates, in order to help with advance planning.

A further aspect that is important when setting up an inspection system is what can be learned via modalities such as X-rays and thermal imaging, for which the acquired images often resemble visible light images. Similarly, it is relevant to ask what additional information color can provide that is useful or even vital for inspection. Sections 20.10 and 20.11 aim to give answers to some of these questions.

In automated assembly—the other application of vision mentioned above—vision is valuable for monitoring both the positions and rotation parameters of the robot arm and wrist and those of the various components it is working on. Interestingly, an assembly robot should be able to examine the components it is about to assemble, so as to prevent it from attempting impossible tasks such as fitting a screw into a nonexistent hole.

The above discussion broadly confirms that inspection and assembly require basically the same vision algorithms, although there is a potential difference in that a line-scan camera will be more suitable for inspecting components on a conveyer, while an area (whole picture) camera will be better suited for monitoring assembly operations within a workcell. However, once acquired, the images will be much the same in the two cases, so algorithms that are suitable for the one type of task will broadly be suited for the other. Thus, little will be lost by concentrating on automated visual inspection in the remainder of this chapter.

## 20.2 THE PROCESS OF INSPECTION

Inspection is the process of comparing individual manufactured items against some preestablished standard with a view to maintenance of quality. Before proceeding to study inspection tasks in detail, it is useful to note that the process of inspection commonly takes place in three definable stages:

1. Image acquisition
2. Object location
3. Object scrutiny and measurement

We defer detailed discussion of image acquisition until Chapter 25 and comment here on the relevance of separating the processes of location and scrutiny. This is important because (either on a worktable or on a conveyor) large number of pixels usually have to be examined before a particular product is found, whereas once it has been located, its image frequently contains relatively few pixels and so rather little computational effort need be expended in scrutinizing and measuring it. For example, on a biscuit line, products may be separated by several times the product diameter in two dimensions, so some 100,000 pixels may need to be examined to locate products occupying, say, 5000 pixels. This means that product location is likely to be a much more computation-intensive problem than product scrutiny. Although this is generally true, sampling techniques may permit object location to be performed with much increased efficiency (Chapter 12). Under these circumstances, it is possible that location may be faster than scrutiny, since the latter process, although straightforward, tends to permit no shortcuts and requires all pixels to be examined.

## 20.3 THE TYPES OF OBJECT TO BE INSPECTED

It is evident from the huge variety of products that are made in factories that there is a correspondingly large variety of inspection tasks to be carried out. However, products fall rather neatly into two main categories. The first is typified by precision metal parts: these have demanding specifications because they are required to fit exactly together, and will usually have standard hole or thread sizes. The second is typified by food products, which vary in appearance between nominally identical samples; for instance, no two apples will look identical. Textiles also fall into the second class, as samples will vary in 3-D shape, closeness of weave, and degree of stretch in any direction. Interestingly, while soldered joints can vary in size and shape, today's electronic components fit more closely into the first category. Broadly, the difference between the two categories is that, for the first, exact dimensional measurement is the prime concern, whereas for the second, appearance to the consumer is more important. We shall look at these two categories more closely in the following sections.

### 20.3.1 Food Products

At one end of the scale, this category covers raw vegetables, grain, fruit, meat, and fish, and at the other, bread, cakes, chocolate biscuits, pizzas, frozen food packs, and complete set meals. Over time, the food industry has developed toward high added value and quality packaging. Although it is both logical and desirable to inspect food products at every stage of manufacture, starting with the raw materials, in practice it would be too expensive to entertain this aim. This is because the cost of each inspection station, including camera, computer hardware + software, and mechanical rejection hardware, will be sizeable. This usually means that only a single inspection station can be afforded. The main question is then whether it should be placed at the beginning, middle, or end of the line. If at the beginning, expensive processing of low-quality material will be minimized; if at the end, inspection of final appearance in the form that the product will reach the consumer will be monitored and its overall acceptability checked. In fact, there is some gain from inspecting just prior to final packaging, as undersize and, *a fortiori,* oversize products can jam packaging machines—a major problem on food lines. Interestingly, inspecting at the end of the line does not prevent pizzas or other food products from being scrutinized fairly thoroughly, as parts of most of the additives will normally be detectable. Finally, note that chocolate is expensive, so inspection needs to check that minimizing the amount of chocolate cover on biscuits or cakes does not result in incomplete coverage, with consequent consumer dissatisfaction.

It is well known that the human eye can detect many features of objects at a glance. However, vision tasks that seem simple to the eye can take a substantial effort to program on a computer. For example, chocolates often have a jagged "footing" around the base, making it difficult to determine their overall shape or orientation (this may be important if a robot is to place each chocolate in its proper place in a box). As a result, algorithms employing silhouette analysis may be less successful than those examining the full grayscale profile of the object, or in certain cases its 3-D shape.

Returning to packaged meals, these present both an inspection and an assembly problem. A robot or other mechanism will have to place individual items on a plastic tray, and it is clearly preferable that every item should be checked to ensure, for example, that each salad contains an olive or that each cake has a blob of cream.

### 20.3.2 Precision Components

Many other parts of industry have also progressed to the automatic manufacture and assembly of complex products. It is clearly necessary for items such as washers and O-rings to be tested for size and roundness, and for mains plugs to be examined for the appropriate pins, fuses, and screws. Engines and brake assemblies also have to be checked for numerous possible faults. Perhaps the worst

**Table 20.1** Features to be Checked on Precision Components

| |
|---|
| Dimensions within specified tolerances |
| Correct positioning, orientation, and alignment |
| Correct shape, especially roundness, of objects and holes |
| Whether corners are misshapen, blunted, or chipped |
| Presence of holes, slots, screws, rivets, etc. |
| Presence of a thread in screws |
| Presence of burr and swarf |
| Pits, scratches, cracks, wear, and other surface marks |
| Quality of surface finish and texture |
| Continuity of seams, folds, laps, and other joins |

problems arise when items such as flanges, slots, holes, or threads are missing so that further components cannot be fitted properly. In addition, although it might seem certain that a thread, if present, would necessarily have the correct pitch, the author has seen at least one application where this assumption was not justified.

Table 20.1 summarizes some of the common features that need to be checked when dealing with individual precision components. Note that measurement of the extent of any defect, together with knowledge of its inherent seriousness, should permit components to be graded according to quality, thereby saving money for the manufacturer (rejecting all defective items is often too crude an option).

### 20.3.3 Differing Requirements for Size Measurement

Size measurement is important both in the food industry and in the automotive and small-parts industry. However, the problems in the two cases are often rather different. For example, the diameter of a biscuit can vary within quite wide limits (~5%) without giving rise to undue problems, but when it gets outside this range, there is a serious risk of jamming the packing machine, and the situation must be monitored carefully. In contrast, for mechanical parts, the required precision can vary from 1% for objects such as O-rings to 0.01% for piston heads. This variation clearly makes it difficult to design a truly general-purpose inspection system. However, the manufacturing process often permits little variation in size from one item to the next. Hence, it may be adequate to have a system that is capable of measuring to an accuracy of rather better than 1%, so long as it is capable of checking all the characteristics mentioned in Table 20.1.

For cases where high precision is vital, it is important that accuracy of measurement is proportional to the resolution of the input image. Currently, images of up to $512 \times 512$ pixels are common, so accuracy of measurement is basically of the order of 0.2%. Fortunately, grayscale images provide a means of obtaining significantly greater accuracy than indicated by the above arguments, since the exact transition from dark to light at the boundary of an object can be estimated more closely. In addition, averaging techniques (e.g., along the side of a rectangular block of metal) permit accuracies to be increased even further—by a factor $\sqrt{N}$ if $N$ pixel measurements are made. These factors permit measurements to be made to subpixel resolution, sometimes even down to 0.1 pixels, the limit often being set by variations in illumination rather than by the vision algorithms themselves.

### 20.3.4 Three-Dimensional Objects

Next, note that all real objects are 3-D, although the cost of setting up an inspection station frequently demands that they are examined from one viewpoint in a single 2-D image. This is clearly highly restrictive, and in many cases overrestrictive. Nevertheless, it is generally possible to do an enormous amount of useful checking and measurement from one such image. The clue that this is possible lies in the prodigious capability of the human eye—e.g., to detect at a glance from the play of light on a surface whether or not it is flat. Furthermore, in many cases, products are essentially flat and the information that we are trying to find out about them is simply expressible via their shape or via the presence of some other feature that is detectable in a 2-D image. In cases where 3-D information is required, methods exist for obtaining it from one or more images, for example, via binocular vision or structured lighting, as has already been seen in Chapter 15. More is said about this in Sections 20.4, 20.7 and 20.14.1.

### 20.3.5 Other Products and Materials for Inspection

This section briefly mentions a few types of product and material that are not fully covered in the foregoing discussion. First, electronic components are increasingly having to be inspected during manufacture, and of these, printed circuit boards (PCBs) and integrated circuits are subject to their own special problems that are currently receiving considerable attention. Second, steel strip and wood inspection are also of great importance. Third, bottle and glass inspection has its own particular intricacies because of the nature of the material, glints being a relevant factor—as also in the case of inspection of cellophane-covered foodpacks. In this chapter, space permits only a short discussion of some of these topics (see Sections 20.7 and 20.8).

## 20.4 SUMMARY: THE MAIN CATEGORIES OF INSPECTION

Sections 20.1–20.3 have given a general review of the problems of inspection but have not shown how they might be solved. This section takes the analysis a stage further. First, note that the items in Table 20.1 may be classified as *geometrical* (measurement of size and shape—in 2-D or 3-D as necessary), *structural* (whether there are any missing items or foreign objects), and *superficial* (whether the surface has adequate quality). It is evident from Table 20.1 that these three categories are not completely distinct but they are useful for the following discussion.

We start by noting that the methods of object location are also inherently capable of providing geometrical measurements. Distances between relevant edges, holes, and corners can be measured; shapes of boundaries can be checked both absolutely and via their salient features; and alignments can usually be checked quite simply, for example, by finding how closely various straight line segments fit to the sides of a suitably placed rectangle. In addition, shapes of 3-D surfaces can be mapped out by binocular vision, photometric stereo, structured lighting, or other means (see Chapter 15), and subsequently checked for accuracy.

Structural tests can also be made once objects have been located, assuming a database of the features they are supposed to possess is available. In the latter case, it is necessary merely to check whether the features are present in predicted positions. As for foreign objects, these can be looked for via unconstrained search as objects in their own right. Alternatively, they may be found as differences between objects and their idealized forms, as predicted from templates or other data in the database. In either case, the problem is very data dependent and an optimal solution needs to be found for each situation. For example, scratches may be searched for directly as straight line segments.

Tests of surface quality are perhaps more complex. In Chapter 25, methods of lighting are described, which illuminate flat surfaces uniformly, so that variations in brightness may be attributed to surface blemishes. For curved surfaces, it might be hoped that the illumination on the surface would be predictable, and then differences would again indicate surface blemishes. However, in complex cases, there is probably no alternative but to resort to the use of switched lights coupled with rigorous photometric stereo techniques (see Chapter 15). Finally, the problem of checking quality of surface finish is akin to that of ensuring an attractive physical appearance, and this can be highly subjective; this means that inspection algorithms need to be trained to make the right judgments (note that "judgments" are decisions or classifications and so the methods described in Chapter 24 are appropriate).

Overall, accurate object location is a prerequisite to reliable object scrutiny and measurement, for all three main categories of inspection. If a CAD system is available, then providing location information permits an image to be generated that should closely match the observed image, and template matching (or correlation) techniques should in many cases permit the remaining inspection functions to be fulfilled. However, this will not always work without trouble—as in the case where object surfaces have a random or textured component. This means that preliminary analysis of the texture may have to be carried out before relevant templates can be applied—or at least checks made of the maximum and minimum pixel intensities within the product area. More generally, in order to solve this and other problems, some latitude in the degree of fit should be permitted.

It is interesting that the same general technique—that of template matching—arises in the measurement and scrutiny phase as in the object location phase.

However (as remarked earlier), this need not consume as much computational effort as in object location. This is because template matching is difficult when there are many degrees of freedom inherent in the situation, since comparisons with an enormous number of templates may be required. However, when the template is in a standard position relative to the product and when it has been orientated correctly, template matching is much more likely to constitute a practical solution to the inspection task, although the problem is very data dependent.

Despite these considerations, there is a need to find computationally efficient means of performing the necessary checks of parts. The first possibility is to use suitable algorithms to model the image intensity and then to employ the model to check relevant surfaces for flaws and blemishes. Another useful approach is to convert 2-D to 1-D intensity profiles. This approach leads to the radial histogram technique; the latter can conveniently be applied for inspecting the very many objects possessing circular symmetry, as will be seen below. However, we first consider a simple but useful means of checking shapes.

## 20.5 SHAPE DEVIATIONS RELATIVE TO A STANDARD TEMPLATE

For food and certain other products, an important factor in 2-D shape measurement is the deviation relative to a standard template. Maximum deviations are important because of the need (already referred to) to fit the product into a standard pack. Another useful measure is the area of overflow or underfill relative to the template (Fig. 20.1). For simple shapes that are bounded by circular arcs or straight lines (a category that includes many types of biscuit or bracket), it is straightforward to test whether a particular pixel on or near the boundary is inside the template or outside it. For straight line segments, this is achieved in the following way. Taking the pixel as $(x_1, y_1)$ and the line as having equation:

$$lx + my + n = 0 \tag{20.1}$$

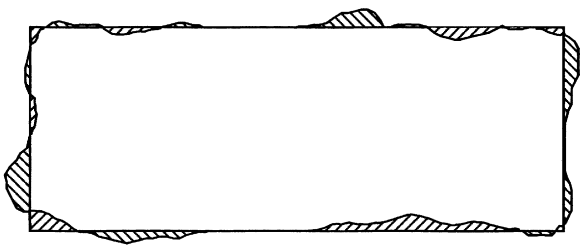

**FIGURE 20.1**

Measurement of product area relative to a template: in this example, two measurements are taken, indicating, respectively, the areas of overflow and underfill relative to a prespecified rectangular template.

the coordinates of the pixel are substituted in the expression:

$$f(x, y) = lx + my + n \tag{20.2}$$

The sign will be positive if the pixel lies on one side of the line, negative on the other, and zero if it is on the idealized boundary. Furthermore, the distance on either side of the line is given by the formula:

$$d = \frac{lx_1 + my_1 + n}{(l^2 + m^2)^{1/2}} \tag{20.3}$$

The same observation about the signs applies to any conic curve if appropriate equations are used, for example, for an ellipse:

$$f(x, y) = \frac{(x - x_c)^2}{a^2} + \frac{(y - y_c)^2}{b^2} - 1 \tag{20.4}$$

where $f(x, y)$ changes sign on the ellipse boundary. For a circle, the situation is particularly simple, since the distance to the circle center need only be calculated and compared with the idealized radius value. For more complex shapes, deviations need to be measured using centroidal profiles or the other methods described in Chapter 10. However, the method outlined above is useful as it is simple, quick, and reasonably robust, and does not need to employ sequential boundary tracking algorithms. A raster scan over the region of the product is sufficient for the purpose.

## 20.6 INSPECTION OF CIRCULAR PRODUCTS

Circular objects and holes are so common that it is important to have well-designed techniques for inspecting them. We have already seen (Chapter 12) that they can be located relatively straightforwardly using the Hough transform. For surface scrutiny, it is useful to make use of their rotational symmetry to obtain a 1-D measure of intensity as a function of distance $r$ from the center. However, the resulting "radial histograms" are complicated by the varying number of pixels at different distances $r$ from the center and have to be normalized to eliminate this effect (Davies, 1984c, 1985). Typical results are shown in Figs. 20.2 and 20.3. Note that radial histograms can be used to make accurate measurements of all relevant radii within the product—e.g., both radii of a washer. Because of the averaging of all intensity values for each value of $r$, accuracy of measurement can be as high as 0.3% for values of $r$ as low as 40 pixels.

As indicated above, the varying numbers of pixels at different radial distances $r$ complicate the problem and prevent the histograms from accurately representing the radial intensity distribution. The obvious way of tackling this problem is to make the independent variable $r^2$ rather than $r$. However, it is also necessary to normalize the distribution so that regions of uniform intensity give rise to a uniform radial intensity distribution—a fact made clear by the statistics shown in

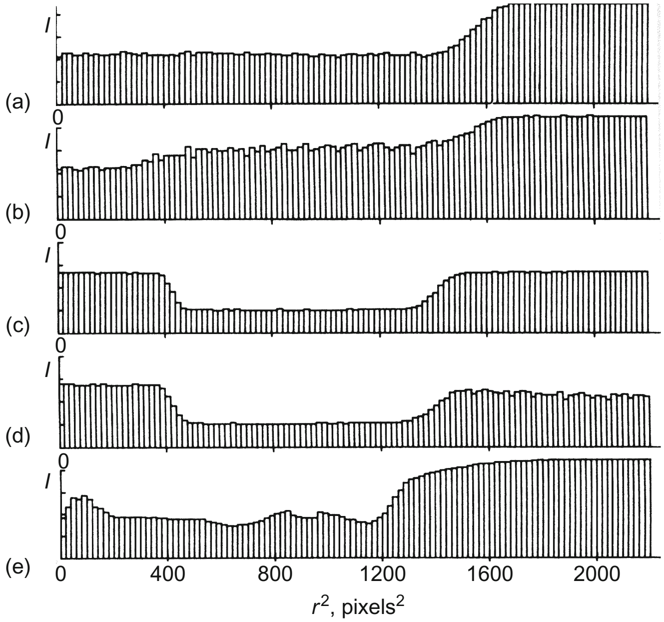


**FIGURE 20.2**

Practical applications of the radial histogram approach. In all cases, an $r^2$ base variable is used and histogram columns are individually normalized. These histograms were generated from the original images of Fig. 20.3.

*Source:* © *IEE 1985*

Fig. 20.4. This means dividing the value for each column of the histogram by the number of pixels contributing to it.

Figure 20.2 shows practical applications of the above theory to various situations, depicted in Fig. 20.3: (see also Fig. 20.5, which relates to the biscuits shown in Fig. 10.1). In particular, note that the radial histogram approach is able to give vital information on various types of defect: the presence or absence of holes in a product such as a washer or a button; whether circular objects are in contact or overlapping; broken objects; "show-through" of biscuit where there are gaps in a chocolate or other coating; and so on. In addition, it is straightforward to derive dimensional measurements from radial histograms. In particular, radii of discs or washers can be obtained to significantly better than 1 pixel accuracy because of the averaging effect of the histogram approach. However, the method is limited here by the accuracy with which the center of the circular region is first located. This underlines the value of the high-accuracy center-finding technique described in Chapter 12. To a certain extent, accuracy is limited by the degree of roundness of the product feature being examined: radius can be measured only to the extent that it is meaningful. In this context, it is emphasized that the

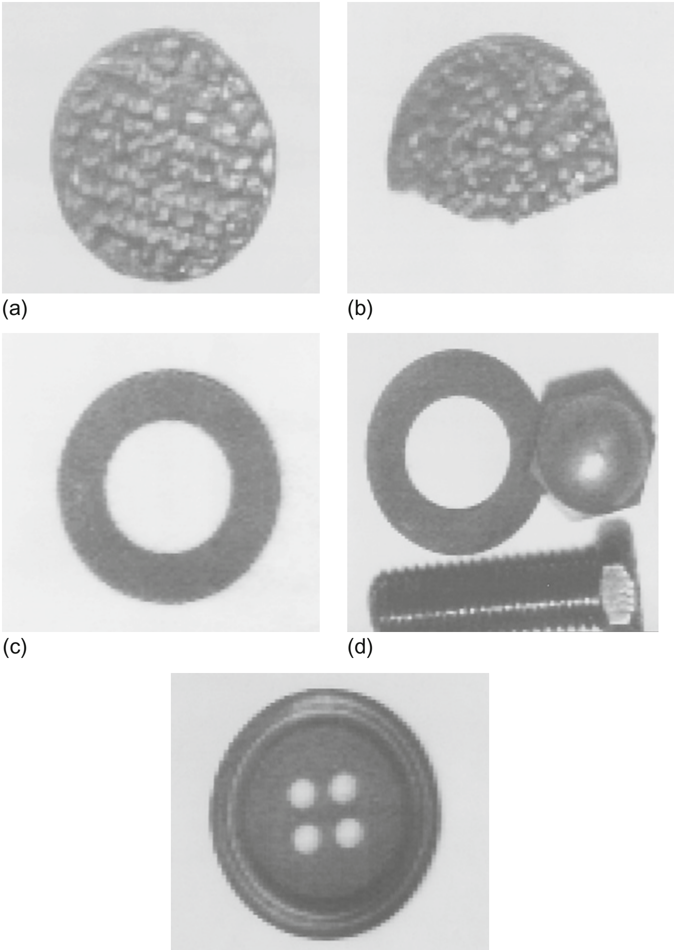
(a) (b) (c) (d) (e)

**FIGURE 20.3**

Original images used in generating the radial histograms of Fig. 20.2.

*Source:* © *IEE 1985*

combination of techniques described above is not only accurate but also computationally efficient.

Radial histograms are particularly well suited to the scrutiny of symmetrical products that do not exhibit a texture, or for which texture is not prominent and may validly be averaged out. In addition, the radial histogram approach ignores correlations between pixels in the dimension being averaged (i.e., angle); where such correlations are significant, it is not possible to use the approach. An obvious example is the inspection of components such as buttons, where angular

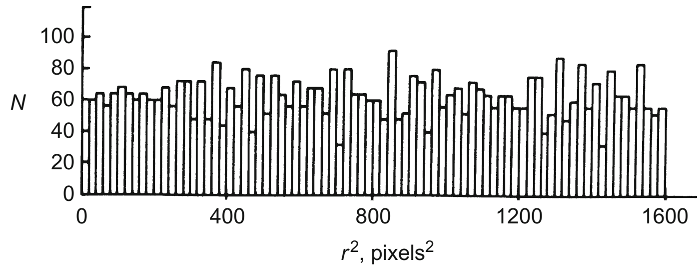


**FIGURE 20.4**

Pixel statistics for an $r^2$ histogram base parameter: the pixel statistics are not exactly uniform even when the radial histogram is plotted with an $r^2$ base parameter.

*Source:* © *IEE 1985*

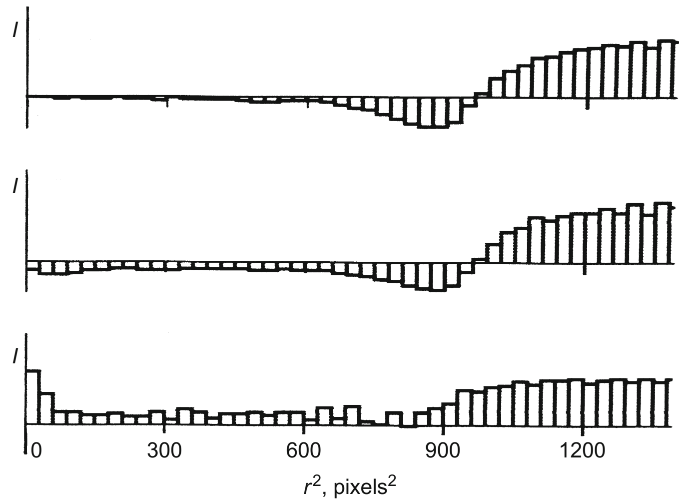


**FIGURE 20.5**

Radial intensity histograms for the three biscuits of Fig. 12.1: the order is from top to bottom in both figures. Intensity is here measured relative to that at the center of an ideal product.

*Source:* © *IFS Publications Ltd 1984*

displacement of one of four button holes will not be detectable unless the hole encroaches on the space of a neighboring hole. Similarly, the method is not able to check the detailed shape of each of the small holes. Clearly, the averaging involved in finding the radial histogram mitigates against such detailed inspection, which is then best carried out by separate direct scrutiny of each of the holes.

It might be imagined that the radial histogram technique is applicable only for symmetrical objects. However, it is also possible to use radial histograms as signatures of intensity patterns in the region of specific salient features. Small holes are suitable salient features but corners are less suitable unless the background is saturated out at a constant value; otherwise, too much variation arises from the background and the technique does not prove viable.

Finally, the radial histogram approach has the useful characteristic of being trainable, since the relevant 1-D templates may be accumulated, averaged over a number of ideal products, and stored in memory, ready for comparisons with less ideal products. This characteristic is valuable, not only for convenience in setting up but also because it permits inspection to be adaptable to cover a range of products.

## 20.7 INSPECTION OF PRINTED CIRCUITS

Over the past two or three decades, machine vision has been used increasingly in the electronics industry, notably for inspecting PCBs. First, PCBs may be inspected before components are inserted; second, they may be inspected to check that the correct components have been inserted the correct way round; and third, all the soldered joints may be scrutinized. The faults that have to be checked for include touching tracks, whisker bridges, broken tracks (including hairline cracks), and mismatch between pad positions and holes drilled for component insertion. Controlled illumination is required to eliminate glints from the bare metal and to ensure adequate contrast between the metal and its substrate. With adequate control over the lighting, most of the checks (e.g., apart from reading any print on the substrate) may be carried out on a binarized image, and the problem devolves into the checking of shape. This may be tackled by gross template matching—using a logical exclusive-or operation—but this approach requires large data storage and precise registration has to be achieved.

Difficulties with registration errors can largely be avoided if shape analysis is performed by connectedness measurement (using thinning) and morphological processing. For example, if a track disappears or becomes broken after too few erosion operations, then it is too narrow; a similar procedure will check whether tracks are too close together. Likewise, hairline cracks may be detected by dilations followed by tests to check for changes in connectedness.

Alignment of solder pads with component holes is customarily checked by employing a combination of back and front lighting. Powerful back lighting (i.e., from behind the PCB) gives bright spots at the hole positions, whereas front lighting gives sufficient contrast to show the pad positions; it is then necessary to confirm that each hole is, within a suitable tolerance, at the center of its pad. Counting the bright spots from the holes, plus suitable measurements around hole positions (e.g., via radial histogram signatures), permits this process to be performed satisfactorily.

Overall, the main problem with PCB inspection is the resolution required. Typically, images have to be digitized to at least $4000 \times 4000$ pixels—as when a

$20 \times 20$ cm board is being checked to an accuracy of 50 μm. In addition, suitable inspection systems will typically check each board fully in less than 1 min; they also have to be trainable, to allow for upgrades in the design of the circuit or improvements in the layout; and they should cost no more than approximately £40,000. However, considerable success has been attained with these aims.

To date, the bulk of the work in PCB inspection has concerned the checking of tracks. Nevertheless, useful work has also been carried out on the checking of soldered joints. Here, each joint has to be modeled in 3-D by structured light or other techniques. In one such case, light stripes were used (Nakagawa, 1982), and in another surface reflectance was measured with a fixed lighting scheme (Besl et al., 1985). Note that surface brightness says something about the quality of the soldered joint. This type of problem is probably completely solvable (at least up to the subjective level of a human inspector) but detailed scrutiny of each joint at a resolution of, say, $64 \times 64$ pixels may well be required to guarantee that the process is successful, and this implies an enormous amount of computation to cope with the several hundreds (or in some cases thousands) of joints on most PCBs. Hence, Besl et al. needed special hardware to handle the information in the time available.

Similar work is under way on the inspection of integrated circuit masks and die bonds, but space does not permit discussion of this rapidly developing area. For a useful review, see Newman and Jain (1995).

## 20.8 STEEL STRIP AND WOOD INSPECTION

The problem of inspecting steel strip is one that is very exacting for human operators. First, it is virtually impossible for the human eye to focus on surface faults when the strip is moving past the observer at rates more than 20 m/s; second, several years of experience are required for this sort of work; and third, the conditions in a steel mill are far from congenial, with considerable heat and noise constantly being present. Hence, much work has been done to automate the inspection process (Browne and Norton-Wayne, 1986). At its simplest, this requires straightforward optics and intensity thresholding, although special laser scanning devices have also been developed to facilitate the process (Barker and Brook, 1978).

The problem of wood inspection is more complex, since this natural material is very variable in its characteristics. For example, the grain varies markedly from sample to sample. As a result of this variation, the task of wood inspection is still in its infancy and many problems remain. However, the purpose of wood inspection is reasonably clear: first, to look for cracks, knots, holes, bark inclusions, embedded pine needles, miscoloration, and so on; and ultimately to make full use of this material by identifying regions where strength or appearance is substandard. In addition, the timber may have to be classified as appropriate for different categories of use—furniture, building, outdoor, etc. Overall, wood inspection is something of an art—i.e., it is a highly subjective process—although valiant attempts have been made to solve the problems (e.g., Sobey, 1989). It is notable that in at least one country (Australia), there is a national standard for the inspection of wooden planks.

## 20.9 INSPECTION OF PRODUCTS WITH HIGH LEVELS OF VARIABILITY

In Sections 20.4–20.8, we have concentrated on certain aspects of inspection—particularly dimensional checking of components ranging from precision parts to food products, and the checking of complex assemblies to confirm the presence of holes, nuts, springs, and so on. These could be regarded as the geometrical aspects of inspection. For the more imprecisely made products such as foodstuffs and textiles, there are greater difficulties as the template against which any product has to be compared is not fixed. Broadly, there are two ways of tackling this problem: one is the use of a range of templates, each of which is acceptable to some degree; the other is the specification of a variety of descriptive parameters. In either case, there will be a number of numerical measurements whose values have to be within prescribed tolerances. Overall, variable products demand greater amounts of checking and computation, and inspection is significantly more demanding. Nowhere is this clearer than for food and textiles, for which the relevant parameters are largely textural. However, "fuzzy" inspection situations can also occur for certain products that might initially be considered as precision components, for example, for electric lamps the contour of the element and the solder pads on the base have significant variability. Thus, this whole area of inspection involves checking that a range of parameters do not fall outside certain prespecified limits on some relevant distribution that *may* be reasonably approximated by a Gaussian parameter.

We have seen above that the inspection task is made significantly more complicated by natural variability in the product, although in the end it seemed best to regard inspection as a process of making measurements that have to be checked statistically. Defects could be detected relative to the templates, either as gross mismatches or else as numerical deviations. And missing parts could likewise be detected since they do not appear at the appropriate positions relative to the templates. Foreign objects would also appear to fit into this pattern, being essentially defects under another name. However, this view is rather too simple for several reasons:

1. Foreign objects are frequently unknown in size, shape, material, or nature.
2. They may appear in the product in a variety of unpredictable positions and orientations.

3. They may have to be detected in a background of texture that is so variable in intensity that they will not stand out.

Overall, it is the unpredictability of foreign objects that can make them difficult to see, especially in textured backgrounds (Fig. 20.6). If one knew their nature in advance, then a special detector could perhaps be designed to locate them. But in many practical situations, the only means of detecting them is to look for the unusual. In fact, the human eye is well tuned to search for the unusual. On the other hand, there are few obvious techniques that can be used to seek it out automatically in digital images. Simple thresholding would work in a variety of

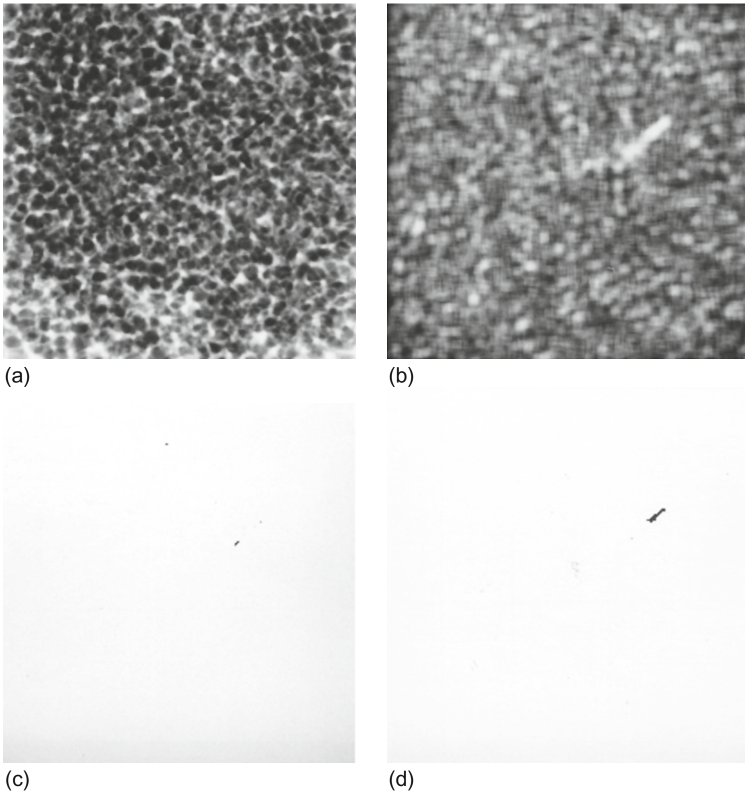


**FIGURE 20.6**

Foreign object detection in a packet of frozen vegetables (in this case sweetcorn). (a) The original X-ray image, (b) an image in which texture analysis procedures have been applied to enhance any foreign objects, and (c) and (d) the respective thresholded images. Note the false alarms that are starting to arise in (c), and the increased confidence of detection of the foreign object in (d). For further details, see Patel et al. (1995).

*Source: © MCB Univ. Press 1995*

practical cases, especially where plain surfaces have to be inspected for scratches, holes, swarf, or dirt. However, looking for extraneous vegetable matter (such as leaves, twigs, or pods) among a sea of peas on a conveyor may be less easy, as the contrast levels may be similar, and the textural cues may not be able to distinguish the shapes sufficiently accurately. Of course, in the latter example, it could be imagined that every pea could be identified by its intrinsic circularity. However, the incidence of occlusion, and the very computation-intensive nature of this approach to inspection, inhibits such an approach. In any case, a method that would detect pods among peas might not detect round stones or small pieces of wood—especially in a grayscale image.

Ultimately, the problem is difficult because the paradigm means of designing sensitive detectors—the matched filter—cannot be used, simply due to the high degree of variability in what has to be detected. With so many degrees of freedom—shape dimensions, size, intensity, texture, and so on—foreign objects can be difficult to detect successfully in complex images. Naturally, a lot depends on the nature of the substrate, and while a plain background might render the task trivial, a textured product substrate may render it impossible, or at least practically impossible in a real-time factory inspection milieu. In general, the solution devolves into not trying to detect the foreign object directly by means of carefully designed matched filters, but in trying to model the intensity pattern of the substrate sufficiently accurately, so that any deviation due to the presence of a foreign object is detected and rendered visible. As hinted above, the approach is to search for the unusual. To achieve this, the basic technique is to identify the $3\sigma$ or other appropriate points on all available measures, and initiate rejection when they are exceeded.

There is a fundamental objection to this procedure. If some limit (e.g., $3\sigma$) is assumed, this cannot easily be optimized, since the proper method for achieving this is to find both the distributions—for the background substrate and for the foreign objects—and to obtain a minimum error decision boundary between them. However, in this case, we do not have the distribution corresponding to the foreign objects, so we have to fall back on "reasonable" acceptance limits based on the substrate distribution.

It might appear that this argument is flawed in that the proportion of foreign objects coming along the conveyor is well known. Although this might occasionally be so, the levels of detectability of the foreign objects in the received images will be unknown and will certainly be less than the actual occurrence levels. Hence, arriving at an optimal decision level will be difficult.

However, a far worse problem often exists in practice. The occurrence rates for foreign objects might be almost totally unknown because of (a) their intrinsic variability and (b) their rarity. We might well ask "How often will an elastic band fall onto a conveyor of peas?", but this is a question that is virtually impossible to answer. Maybe it is possible to answer somewhat more accurately the more general question of how often a foreign object of some sort will fall onto the conveyer, but even then the response may well be that somewhere between 1 in

100,000 and 1 in 10 million of bags of peas contain a foreign object. With low levels of risk, the probabilities are extremely difficult to estimate, and indeed there is little available data or other basis on which to calculate them. Consumer complaints can indicate the possible levels of risk, but these arise as individual items, and in any case many customers will not make any fuss and by no means all instances come to light.

With food products, the penalties for not detecting individual foreign objects are not usually especially great. Glass in baby food may be more apocryphal than real, and may be unlikely to cause more than alarm. Similarly, small stones among the vegetables are more of a nuisance than a harm, although cracked teeth could perhaps result in compensation in the £1000 bracket. Far more serious are problems with electric lamps, where a wire emerging from the solder pads is potentially lethal and is a substantive worry for the manufacturer. Litigation for deaths arising from this source could run to a million pounds or so (corresponding to an individual's potential lifetime earnings).

This discussion reveals very clearly that it is the cost rate[1] rather than the error rate that is the important parameter when there is even a remote risk to life and limb. Indeed, it concerned Rodd and his coworkers so much in relation to the inspection of electric lamps than they decided to develop special techniques for ensuring that their algorithms were tested sufficiently (Thomas and Rodd, 1994; Thomas et al., 1995). Computer graphics techniques were used to produce a large number of images with automatically generated variations on the basic defects, and it was checked that the inspection algorithms would always locate them.

## 20.10 X-RAY INSPECTION

In inspection applications, there is a tension between inspecting products early on, before significant value has been added to a potentially defective product, and at the end of the line, so that the quality of the final products is guaranteed. This consideration applies particularly with food products, where additives such as chocolate can be expensive and constitute substantial waste if the basic product is broken or misshapen. In addition, inspection at the end of the line is especially valuable as oversized products (which may arise if two normal products become stuck together) can jam packing machines. Ideally, it would be beneficial if two inspection stations could be placed on the line in appropriate positions, but if only one can be afforded (the usual situation), it will generally have to be placed at the end of the line.

With many products, it is useful to be absolutely sure about the final quality as the customer will receive it. Thus, there is especial value in inspecting the packaged products. Since the packets will usually be opaque, it will be necessary

[1]In fact, the *perceived* cost rate may be even more important, and this can change markedly with reports appearing in the daily press.

to inspect them under X-radiation. This results in substantial expense, since the complete system will include not only the X-ray source and sensing system but also various safety features including heavy shielding. As a result, commercial X-ray food inspection systems rarely cost less than £40,000, and £100,000 is a more typical figure. Such figures do not take account of maintenance costs, and it is also important that the X-ray source and the sensors deteriorate with time so that sensitivity falls, and special calibration procedures have to be invoked.

Fortunately, the X-ray sensors can nowadays take the form of linear photodiode packages constructed using integrated circuit technology.[2] These are placed end to end to span the width of a food conveyor that may be 30−40 cm wide. They act as a line-scan camera that grabs images as the product moves along the conveyor. The main adjustments to be made in such a system are the voltage across the X-ray tube and the electric current passing through it. In food inspection applications, the voltage will be in the range 30−100 kV, and the current will be in the range 3−10 mA. A *basic* commercial system will include thresholding and pixel counting, permitting the detection of small pieces of metal or other hard contaminants, but not soft contaminants. In general, the latter can only be detected if more sophisticated algorithms are used that examine the contrast levels over various regions of the image and arrive at a consensus that foreign objects are present—typically with the help of texture analysis procedures.

The sensitivity of an X-ray detection system depends on a number of factors. Basically, it is highly dependent on the number of photons arriving at the sensors, and this number is proportional to the current passing through the X-ray tube. There are stringent rules on the intensities of X-radiation to which food products may be exposed, but in general, these limits are not approached because of good sensitivity at moderate current levels.

Sensitivity also depends critically on the voltages that are applied to X-ray tubes. In fact, the higher the voltage, the higher the electron energies, the higher the energies of the resulting photons, and the greater the penetrating power of the X-ray beam. However, greater penetrating power is not necessarily an advantage, as the beam will tend to pass through the food without attenuation, and therefore without detecting any foreign objects. While a poorly set up system may well be able to detect quite small pieces of metal without much trouble, detection of small stones and other hard contaminants will be less easy, and detection of soft contaminants will be virtually impossible. Thus, it is necessary to optimize the contrast in the input images.

Unfortunately, X-ray sources provide a wide range of wavelengths, all of which are scattered or absorbed to varying degrees by the intervening substances. In a thick sample, scattering can cause X-radiation to arrive at the detector after passing through material not in a direct line between the X-ray tube and the sensors. This makes a complete analysis of sensitivity rather complicated. In what

[2]The X-ray photons are first converted to visible light by passage through a layer of scintillating material.

follows, we will ignore this effect and assume that the bulk of the radiation reaching the sensors follows the direct path from the X-ray source. We will also assume that the radiation is gradually absorbed by the intervening substances, in proportion to its current strength. Thus, we obtain the standard exponential formula for the decay of radiation through the material, which we shall temporarily take to be homogeneous and of thickness $z$:

$$I = I_0 \exp\left(-\int \mu \,\mathrm{d}z\right) = I_0 \exp\left(-\mu \int \mathrm{d}z\right) = I_0 e^{-\mu z} \tag{20.5}$$

where $\mu$ depends on the type of material and the penetrating power of the X-radiation. For monochromatic radiation of energy $E$, we have:

$$\mu = \left(\frac{\rho N}{A}\right)\left[\frac{k_{\mathrm{P}} Z^a}{E^b} + \frac{k_{\mathrm{C}} Z}{E}\right] \tag{20.6}$$

where $\rho$ is the density of the material, $A$ is its atomic weight, $N$ is Avogadro's number, $a$ and $b$ are numbers depending on the type of material, and $k_{\mathrm{P}}$ and $k_{\mathrm{C}}$ are decay constants resulting from photoelectric and Compton scattering, respectively (see, for example, Eisberg, 1961). It will not be appropriate to examine all the implications of this formula. Instead, we proceed with a rather simplified model that nevertheless shows how to optimize sensitivity:

$$\mu = \frac{\alpha}{E} \tag{20.7}$$

By substituting into Eq. (20.5), we find:

$$I = I_0 \exp\left(\frac{-\alpha z}{E}\right) \tag{20.8}$$

If a minute variation in thickness, or a small foreign object, is to be detected sensitively, we need to consider the change in intensity resulting from a change in $z$ or in $\alpha z$ (ultimately, it is the integral of $\mu$ d$z$ that is important—see Eq. (20.5)). It will be convenient to relabel the latter quantity as a generalized distance $X$, and the inverse energy factor as $f$:

$$I = I_0 \exp(-Xf) \tag{20.9}$$

$$\therefore \quad \frac{\mathrm{d}I}{\mathrm{d}X} = -I_0 f \exp(-Xf) \tag{20.10}$$

so that:

$$\Delta I = -\Delta X\, I_0 f \exp(-Xf) \tag{20.11}$$

The contrast due to the variation in generalized distance can now be expressed as:

$$\frac{\Delta I}{I} = \frac{-\Delta X\, I_0 f \exp(-Xf)}{I_0 \exp(-Xf)} = -\Delta X f = \frac{-\Delta X}{E} \tag{20.12}$$

This calculation shows that contrast should improve as the energy of the X-ray photons decreases. However, this result appears wrong, as reducing the photon energy will reduce the penetrating power, and in the end, no radiation will pass through the sample. First, the sensors will not be sufficiently sensitive to detect the radiation. Specifically, noise (including quantization noise) will become the dominating factor. Second, we have ignored the fact that the X-radiation is not monochromatic. We shall content ourselves here with modeling the situation to take account of the latter factor. Assume that the beam has two energies, one fairly low (as above), and one rather high and penetrating. This high-energy component will add a substantially constant value to the overall beam intensity, and will result in a modified expression for the contrast:

$$\frac{\Delta I}{I} = \frac{-\Delta X\, I_0 f \exp(-Xf)}{[I_1 + I_0 \exp(-Xf)]} = \frac{-\Delta X\, I_0 f}{[I_1 \exp(Xf) + I_0]} \tag{20.13}$$

To optimize sensitivity, we differentiate with respect to $f$:

$$\frac{\mathrm{d}(\Delta I/I)}{\mathrm{d}f} = \frac{-\Delta X\, I_0\{[I_1 \exp(Xf) + I_0] - XfI_1 \exp(Xf)\}}{[I_1 \exp(Xf) + I_0]^2} \tag{20.14}$$

This is zero when:

$$XfI_1 = I_1 + I_0 \exp(-Xf) \tag{20.15}$$

$$\text{i.e., } E = \frac{X}{[1 + (I_0/I_1)\exp(-X/E)]} \tag{20.16}$$

When $I_1 \ll I_0$, we have the previous result that optimum sensitivity occurs for low $E$. However, when $I_1 \gg I_0$, we have the result that optimum sensitivity occurs when $E = X$. In general, this formula gives an optimum X-ray energy that is above zero, in accordance with intuition. In passing, we note that graphical or iterative solutions of Eq. (20.16) are easily obtained.

Finally, we consider the exponential form of the signal given by Eqs. (20.5), (20.8), and (20.9). These are nonlinear in $X$ (i.e., $\alpha z$), and meaningful image analysis algorithms would tend to require signals that are linear in the relevant physical quantity, namely, $X$. Thus, it is appropriate to take the logarithm of the signal from the input sensor before proceeding with texture analysis or other procedures:

$$I' = \log I = \log[I_0 \exp(-Xf)] = A - Xf \tag{20.17}$$

where

$$A = \log I_0 \tag{20.18}$$

In this way, doubling the width of the sample doubles the change in intensity, and subsequent (e.g., texture analysis) algorithms can once more be designed on an intuitive basis. (In fact, there is a more fundamental reason for performing this transformation—that it performs an element of noise whitening, which should ultimately help to optimize sensitivity.)

### 20.10.1 The Dual-Energy Approach to X-Ray Inspection

When inspecting solid objects by means of X-rays, there is often the problem that defects will be masked by variations in the thickness of the objects under scrutiny. This applies both with bags of frozen vegetables and with slabs of meat (and *a fortiori* with human bodies undergoing radiology), to take two relevant examples. What is needed is a means of canceling out the effect of varying thickness. Fortunately, over the past 10 years or so, a dual-energy approach called dual-emission X-ray absorptiometry (DEXA) has been developed for achieving this. The method involves moving the object on a conveyor past two rows of solid-state sensors placed within a millimeter or so of each other so that they generate line-scan images of the same section of the object (due allowance has to be made for the time difference between corresponding sets of signals). Each sensor is made sensitive to different X-ray energies by using different phosphors to convert the X-rays into visible light. To understand how the method works, we use the notation of Eq. (20.5) and define:

$$\eta(t) = \frac{\log\big(I_1(0)/I_1(t)\exp(-\mu_1 z)\big)}{\log\big(I_2(0)/I_2(t)\exp(-\mu_2 z)\big)} \tag{20.19}$$

where $I_1(t)$ and $I_2(t)$ are the time developments of the two sets of received X-ray signals in the absence of any objects. Assuming these are normalized to time $t = 0$ by periodic checking, they cancel from the above equation. Then the log functions cancel the exponential variations, leaving the simple result:

$$\eta(t) = \frac{\mu_1}{\mu_2} = \text{constant} \tag{20.20}$$

Note that this result is completely independent of the sample thickness $z$, although its "constant" nature depends on the nature of the materials involved, and their homogeneity.

The method is so successful that it is routinely used for scanning humans to measure bone mineral density. A recent application of its use for inspecting meat samples is given by Kröger et al. (2006).

## 20.11 THE IMPORTANCE OF COLOR IN INSPECTION

In many applications of machine vision, it is not necessary to consider color because almost all that is required can be achieved using grayscale images. For example, many processes devolve into shape analysis and subsequently into statistical pattern recognition. This situation is exemplified by fingerprint analysis and by handwriting and optical character recognition. However, there is one area where color has a big part to play: this is in the picking, inspection, and sorting of fruit. For example, color is very important in the determination of apple quality. Not only is it a prime indicator of ripeness, but also it contributes greatly to physical attractiveness, and thus encourages purchase and consumption.

Although color cameras digitize color into the usual RGB (red, green, blue) channels, humans perceive color differently. As a result, it is better to convert the RGB representation to the HSI (hue, saturation, intensity) domain before assessing the colors of apples and other products.[3] Space prevents a detailed study of the question of color. The reader is referred to more specialized texts for detailed information (e.g., Gonzalez and Woods, 1992; Sangwine and Horne, 1998). However, some brief comments will be useful. Intensity $I$ refers to the total light intensity and is defined by:

$$I = \frac{(R+G+B)}{3} \tag{20.21}$$

Hue $H$ is a measure of the underlying color, and saturation $S$ is a measure of the degree to which it is *not* diluted by white light ($S$ is zero for white light). $S$ is given by the simple formula:

$$S = 1 - \frac{\min(R,G,B)}{I} = 1 - \frac{3\min(R,G,B)}{R+G+B} \tag{20.22}$$

which makes it unity along the sides of the color triangle, and zero for white light ($R = G = B = I$). Note how the equation for $S$ favors none of the $R$, $G$, $B$ components. It does not express color but a measure of the proportion of color and differentiation from white.

Hue is defined as an angle of rotation about the central white point **W** in the color triangle. It is the angle between the pure red direction (defined by the vector **R**−**W**) and the direction of the color **C** in question (defined by the vector **C**−**W**). The derivation of a formula for $H$ is fairly complex and will not be attempted here. Suffice it to say that it may be determined by calculating cos $H$, which depends on the dot product (**C**−**W**).(**R**−**W**). The final result is:

$$H = \cos^{-1}\left(\frac{\frac{1}{2}[(R-G)+(R-B)]}{\left[(R-G)^2+(R-B)(G-B)\right]^{1/2}}\right) \tag{20.23}$$

or $2\pi$ minus this value if $B > G$ (Gonzalez and Woods, 1992).

When checking the color of apples, the hue is the important parameter. A rigorous check on the color can be achieved by constructing the hue distribution and comparing it with that for a suitable training set. The most straightforward way to carry out the comparison is to compute the mean and standard deviation of the two distributions to be compared and to perform discriminant analysis assuming

[3]Usually, a more important reason for use of HSI is to employ the hue parameter that is independent of the intensity parameter, as the latter is bound to be particularly sensitive to lighting variations.

Gaussian distribution functions. Standard theory (Section 4.5.3, Eqs. (4.19)–(4.22)) then leads to an optimum hue decision threshold.

In the work of Heinemann et al. (1995), discriminant analysis of color based on this approach gave complete agreement between human inspectors and the computer following training on 80 samples and testing on another 66 samples. However, a warning was given about maintaining lighting intensity levels identical to those used for training. In any such pattern recognition system, it is crucial that the training set be representative in every way of the eventual test set.

Finally, note that full color discrimination would require an optimal decision surface to be ascertained in the overall 3-D color space. In general, such decision surfaces are hyperellipses and have to be determined using the Mahalanobis distance measure (see, for example, Webb, 2002). However, in the special case of Gaussian distributions with equal covariance matrices, or more simply with equal isotropic variances, the decision surfaces become hyperplanes.

## 20.12 BRINGING INSPECTION TO THE FACTORY

The relationship between the producer of vision systems and the industrial user is more complex than might appear at first sight. The user has a need for an inspection system and states his need in a particular way. However, subsequent tests in the factory may show that the initial statement was inaccurate or imprecise, for example, the line manager's requirements[4] may not exactly match those envisaged by the factory management board. Part of the problem lies in the relative importance given to the three disparate functions of inspection mentioned earlier. Another lies in the change of perspective once it is seen exactly what defects the vision system is able to detect. It may be found immediately that one or more of the major defects that a product is subject to may be eliminated by modifications to the manufacturing process; in that case, the need for vision is greatly reduced, and indeed the very process of trying out a vision system may end in its value being undermined and its not being taken up after a trial period. Clearly, this does not detract from the inherent capability of vision systems to perform 100% untiring inspection and to help maintain strict control of quality. However, it must not be forgotten that vision systems are not cheap and that they can in some cases be justified only if they replace a number of human operators. Frequently, a payback period of 2–3 years is specified for installing a vision system.

Textural measurements on products are an attractive proposition for applications in the food and textile industries. Often, textural analysis is written into the prior justification for, and initial specification of, an inspection system. However,

[4]In many factories, line managers have the brief of maintaining production at a high level on an hour-by-hour basis, while at the same time keeping track of quality. The tension between these two aims, and particularly the underlying economic constraints, means that on occasion quality is bound to suffer.

what a vision researcher understands by texture and what a line inspector in either of these industries means by it tend to be different. Indeed, what is required of textural measurements varies markedly with the application. The vision researcher may have in mind higher order[5] statistical measures of texture, such as would be useful with a rough irregular surface of no definite periodicity[6]—as in the case of sand or pebbles on a beach, or grass or leaves on a bush. However, the textile manufacturer would be very sensitive to the periodicity of his fabric, and to the presence of faults or overly large gaps in the weave. In such cases, a major problem is likely to be that of minimizing computation so that considerable expanses of fabric, or large numbers of products, can be checked economically at production rates. Similarly, the food manufacturer might be interested in the number and spatial distribution of pieces of pepper on a pizza, while for fish coatings (e.g., batter or breadcrumbs) uniformity will be important and "texture measurement" may end by being interpreted as determining the number of holes per unit area of the coating. Thus, it may sometimes be beneficial to characterize a texture by rather simple counting or uniformity checks instead of higher order statistics. More generally, it is important to keep the inspection system flexible by training on samples so that maximum utility of the production line can be maintained.

With this backcloth to factory requirements, it is clearly vital for the vision researcher to be sensitive to actual rather than idealized needs or the problem as initially specified. There is no substitute for detailed consultation with the line manager and close observation in the factory before setting up a trial system. Then the results from trials need to be considered very carefully to confirm that the system is producing the information that is really required.

## 20.13 CONCLUDING REMARKS

This chapter has been concerned with the application of computer vision to industrial tasks, and notably to automated visual inspection. The number of relevant applications is exceptionally high, and for that reason, it has been necessary to concentrate on principles and methods rather than on individual cases. The repeated mention of hardware implementation has been a necessary one, since the economics of real-time implementation is often the factor that ultimately decides whether a given system will be installed on a production line. However, speeds of processing are also heavily dependent on the specific algorithms employed, and

[5]The zero-order statistic is the mean intensity level; first-order statistics such as variance and skewness are derived from the histogram of intensities; second- and higher order statistics take the form of gray-level co-occurrence matrices, showing the number of times particular gray values appear at two or more pixels in various relative positions. For more discussion on textures and texture analysis, see Chapter 8.

[6]More rigorously, the fabric is intended to have a long-range periodic order that does not occur with sand or grass: in fact, there is a close analogy here with the long- and short-range periodic order for atoms in a crystal and in a liquid, respectively.

these in turn depend on the nature of the image acquisition system—including both the lighting and the camera setup (indeed, the decision of whether to inspect products on a moving conveyor or to bring them to a standstill for more careful scrutiny is perhaps the most fundamental one for implementation). Hence, image acquisition and real-time electronic hardware systems are the main topics of two later chapters (Chapters 25 and 26).

More fundamentally, the reader will have noticed that a major purpose of inspection systems is to make instant decisions on the adequacy of products. Related to this purpose are the often fluid criteria for making such decisions and the need to train the system so that the decisions that are made are at least as good as those that would have arisen with human inspectors. In addition, training schemes are valuable in making inspection systems more general and adaptive, particularly with regard to change of product. Hence, the pattern recognition techniques discussed in Chapter 24 are highly relevant to the process of inspection.

On a different tack, note that much of automated visual inspection falls under the heading of computer-aided manufacture (CAM), of which computer-aided design (CAD) is another part. Nowadays, many manufactured parts can in principle be designed on a computer, visualized on a computer screen, made by computer-controlled (e.g., milling) machines, and inspected by computer—all without human intervention in handling the parts themselves. There is much sense in this computer-integrated manufacture (CIM) concept, since the original design data set is stored in the computer, and therefore it might as well be used (a) to aid the image analysis process that is needed for inspection and (b) as the actual template by which to judge the quality of the goods. After all, why key in a separate set of templates to act as inspection criteria when the specification already exists on a computer? However, some augmentation of the original design information to include valid tolerances is necessary before the dataset is sufficient for implementing a complete CIM system. Also, the purely dimensional input to a numerically controlled milling machine is not generally sufficient—as the frequent references to surface quality in the present chapter indicate.

> Automated industrial inspection is a well-worn application area for vision that severely exercises the reliability, robustness, accuracy, and speed of vision software and hardware. This chapter has discussed the practicalities of this topic, showing how color and other modalities such as X-rays impinge on the basic vision techniques.

## 20.14 BIBLIOGRAPHICAL AND HISTORICAL NOTES

It is very difficult to provide a bibliography of the enormous number of papers on applications of vision in industry or even in the more restricted area of automated visual inspection. In any case, it can be argued that a book such as this ought to concentrate on principles and to a lesser extent on detailed applications and "mere" history. However, the review article by Newman and Jain (1995) gives a representative overview covering an earlier period.

The overall history of industrial applications of vision has been one of relatively slow beginnings as the potential for visual control became clear, followed only in recent years by explosive growth as methods and techniques evolved and as cost-effective implementations became possible as a result of cheaper computational equipment. In this respect, 1980 marked a turning point, with the instigation of important conferences and symposia, notably that on "Computer Vision and Sensor-Based Robots" held at General Motors Research Laboratories during 1978 (see Dodd and Rossol, 1979), and the Robot Vision and Sensory Controls (ROVISEC) series of conferences organized annually by IFS (Conferences) Ltd, UK, from 1981. In addition, useful compendia of papers were published (e.g., Pugh, 1983), and books outlining relevant principles and practical details (e.g., Batchelor et al., 1985).

Noble (1995) presented an interesting and highly relevant view of the use of machine vision in manufacturing. Davies (1995) developed the same topic by presenting several case studies together with a discussion of some major problems that remained to be tackled in this area.

The 1990s saw considerable interest in X-ray inspection techniques, particularly in the food industry (Boerner and Strecker, 1988; Wagner, 1988; Chan et al., 1990; Penman et al., 1992; Graves et al., 1994; Noble et al., 1994). In the case of X-ray inspection of food, the interest was almost solely in the detection of foreign objects, which could in some cases be injurious to the consumer. Indeed, this was a prime motivation for much work in the author's laboratory (Patel et al., 1994, 1995).

Another topic of growing interest was the automatic visual control of materials such as lace during manufacture, together with high-speed scalloping of lace using lasers (King and Tao, 1995; Yazdi and King, 1998).

A cursory examination of inspection publications reveals growth in emphasis on surface defect inspection, including color assessment, and X-ray inspection of bulk materials and baggage, e.g., at airports. Two journal special issues (Davies and Ip, 1998; Nesi and Trucco, 1999) cover defect inspection, while Tsai and Huang (2003) and Fish et al. (2003) further emphasize the point regarding surface defects.

Work on color inspection includes both food (Heinemann et al., 1995) and pharmaceutical products (Derganc et al., 2003). Work on X-rays includes the location of foreign bodies in food (Patel et al., 1996; Batchelor et al., 2004), the internal inspection of solder joints (Roh et al., 2003), and the examination of baggage (Wang and Evans, 2003). Finally, a recent volume on inspection of natural products (Graves and Batchelor, 2003) has articles on inspection of ceramics, wood, textiles, food, live fish and pigs, and sheep pelts, and embodies work on color and X-ray modalities. In a sense, such work is neither adventurous nor glamorous. Indeed, it involves significant effort to develop the technology and software sufficiently to make it useful for industry—which means this is an exacting type of task, not tied merely to the production of academic ideas.

### 20.14.1 More Recent Developments

More recently, Chao and Tsai (2008) describe an inspection system for detecting surface defects in glass substrates for liquid crystal displays. It is based on an anisotropic diffusion-based smoothing technique. This type of technique is designed to smooth the image in directions parallel to edges, and *not* normal to edges, that is, it is designed to perform edge-preserving smoothing. Thus, it tends to enhance features such as cracks or indentations or breaks in a substance, and to eliminate noise or the effects of minor lighting or lightness variations. By the time this has been achieved, it is much more likely that defects will be locatable by thresholding. In this case, a special new anisotropic diffusion algorithm was designed to improve the situation further. Tsai et al. (2010) had a similar problem—that of looking for micro-cracks in textured solar wafers. Although they used anisotropic diffusion to initiate the process, and followed this with binary thresholding, they completed the task of removing noise and identifying the micro-cracks by use of morphological operations. Mak et al. (2009) had the problem of locating defects in textured materials. Here, texture forms a complex background pattern and this imposes difficulties. In this case, these were solved by applying a special type of neural network—a Gabor wavelet network. Following this, a sequence of morphological operators was applied to locate the defects. In a typical case, this involved $1 \times 7$ linear opening, $1 \times 7$ linear closing, $3 \times 3$ median, $3 \times 3$ closing, and finally thresholding. Sun et al. (2010) describe a more general type of system for inspecting electric contacts for a variety of types of surface defect including cracks, breaks, and scratches, using multiple 3-D views. There was some concentration on dimensional measurement, although morphological analysis was also required, including the top-hat transform for locating cracks; edge breaks were located by deviations from circularity. For further details, the reader is referred to the original paper.

Alexandropoulos et al. (2008) worked on template-guided inspection, primarily of under-vehicle views of the exhaust and other vehicle components and structures. Here, the inspection fell into a template registration phase followed by a template differencing phase. In fact, the latter had to contend with noise, illumination variations, shadows, and so on. Problems with change detection were addressed by using a block-based segmentation technique, which contrasted noise and structural variations. Variations were judged relative to statistical significance for the particular block sizes. In general, in block-based change detection, it proved necessary to take into consideration the anticipated scene complexity and adjust the operation parameters accordingly. For example, too small a block size was undesirable as it accentuated edge effects.

Work on X-ray inspection has continued, in particular, using the by now important and well-established dual-energy (DEXA) approach outlined in Section 20.10.1. For a recent application of its use for inspecting meat samples, see Kröger et al. (2006).