

Preface

Imagine the consternation caused by the newspaper headline “*Glass found in Baby Food*”. Food safety is always an emotive issue, although most of us probably don’t give it much thought when we are actually eating. When you ate breakfast this morning, were you anxiously checking the food as you ate it? For example, did you consider the possibility that the cereal might contain broken glass, or metal swarf? Were you concerned that the bread might include body parts of a dead mouse? The fruit might have been contaminated by bird pecks. Did you check? A recent analysis of nominally “boneless” chicken meat, purchased at UK supermarkets, showed that bone fragments are roughly 30 times more common than the retailers claim. Although bone is a “natural contaminant”, it is nevertheless unwelcome and potentially dangerous; hard, sharp foreign bodies in food can damage teeth and soft tissue in the mouth and gut. They can cause choking, even death! Contaminants such as these are all too common, as even a casual glance at a local newspaper will show. Reports of legal action over contaminated food products appear regularly in local (not national) newspapers. The threat of litigation over real or imagined injury caused by negligence is a problem faced by all food manufacturing companies, and retailers. English law requires that companies take *all reasonable steps* to ensure that their products are both safe and wholesome. Of course, responsible companies exceed the legal minimum requirements in order to build/maintain a reputation for supplying high-quality produce and to minimise the risk of injury to their customers. However stringent the quality checks it imposes, a company is sometimes obliged to recall a large batch of a food product because some serious contamination has been discovered in samples from it. This is both expensive and damaging to the company’s public image. It is also detrimental to the reputation of other brands of the same type of product. There is and there always will be a need for improved instrumentation to detect foreign bodies in food. Non-critical defects in food products have a lesser impact, affecting financial, aesthetic or social parameters.

Detection of foreign bodies in food is just one example of many potential applications where the use of Machine Vision can help improve the quality, safety usefulness and aesthetic appearance of natural materials. This technology, called *Machine Vision*, has previously been refined to a high level of sophistication and

has been applied extensively in engineering manufacture. It combines optical, infrared, ultra-violet, or x-ray sensing, with digital video technology and image processing. A system combining these component technologies (and others) has to be designed very carefully, as there are many pitfalls that can all too easily spoil its performance. The essence of a good design is harmonious integration, so that all parts of the system are able to perform at or near their optimum level. No part of a Machine Vision system should ever be forced to work close to the limits of its range of reliable operation because the designer has neglected one part of a system, by concentrating too much on another. The cabinet is as important as the computer; the lens is as important as the software and the lights are as important as the mathematical procedures (algorithms) that it uses!

The following is a working definition of Machine Vision that will be used throughout this book:

Machine Vision (MV) is concerned with the engineering of integrated mechanical-optical-electronic-software systems for examining natural objects and materials, human artefacts and manufacturing processes, in order to detect defects and improve quality, operating efficiency and the safety of both products and processes.

In addition to inspection, Machine Vision can be used to control the machines used in manufacturing and materials processing. These may perform such operations as cutting, trimming, grasping, manipulating, packing, assembling, painting, decorating, coating, etc. In the following pages, we shall encounter non-food applications too. Plants, cut flowers, timber, decorative stone (e.g. marble), textiles, knit-wear and leather-ware are typical examples of highly variable objects that concern us here. Natural products and materials are processed and incorporated into a wide variety of industrial products, such as cigarettes, brushes, carpets, floor and wall tiles (both mineral-based and cork), bricks, abrasives (sheets and wheels), china and fine porcelain.

When browsing through the technical literature, the reader will soon encounter the term *Computer Vision* (CV) and will realise that it and *Machine Vision* (MV) are used synonymously by many authors. This is a point on which we strongly disagree; we are firmly convinced that these two subjects are fundamentally different. Some university researchers, working in what we regard as Machine Vision, oppose our view, since the computational techniques employed are similar. On the other hand, many industrial designers of vision systems simply ignore much of the academic research in CV, claiming that it is irrelevant to their immediate needs. In the ensuing pages, we shall see that *Machine Vision* is a practical and pragmatic subject that applies techniques borrowed from *Artificial Intelligence* (AI), *Pattern Recognition* (PR) and *Digital Image Processing* (DIP), as well as Computer Vision. While Machine Vision makes use of numerous algorithmic and heuristic techniques that were first devised through research in these other fields, it concentrates on making them operate in a useful and practical way. This means that we have to consider all aspects of a vision system, not just techniques for representing, storing and processing images inside a computer. This

is the essential difference between MV and CV, which naturally enough, is concerned almost exclusively with the information processing that takes place inside a computer. The problem of nomenclature arises because MV, CV, DIP (and sometimes AI and PR) are all concerned with the processing and analysis of pictures within electronic equipment. (We might refer to these collectively as *Artificial Vision*.) We did not mention computers explicitly in the definition of Machine Vision, because it does not necessarily involve a device that is recognisable as a computer. MV allows the image processing to take place in a conventional computer, specialised digital networks, arrays of field-programmable gate arrays (FPGAs), multi-processor systems, optical/opto-electronic computers, analogue electronics, and various hybrid systems. Although MV, CV and DIP share a great many terms, concepts and algorithmic techniques, they require a completely different set of priorities, attitudes and mental skills. The dichotomy between CV and MV may be summarised thus: Computer Vision is science, while Machine Vision is engineering.

Until very recently, Machine Vision was applied almost exclusively to the inspection of engineering components, manufactured by processes such as casting, stamping, pressing, moulding, rolling, turning, milling, extrusion, etc. These produce close tolerance artefacts, usually made in metal, plastic, ceramic, glass, rubber, wood or paper. On the other hand, some products, such as food, textiles, leather-ware and natural products (seeds, nuts, fruit, vegetables, etc.) exhibit wide variations in overall size and shape, internal structure, colour and surface texture. It is possible to define a number of metrics that reflect our intuitive concept of variability, or conformability. When we study the list of successful Machine Vision applications, it soon becomes apparent that almost all systems that have been installed to date are dedicated to inspecting products with a low variability score. On the other hand, there is an outstanding need for fast non-contact inspection systems that can ensure the quality and safety of a wide range of raw materials, semi-processed organic and mineral products and highly variable manufactured goods.

Even in industrial manufacturing, there are numerous inspection tasks where the scene/object to be examined is uncontrolled and, as a consequence, is highly variable. A notable example of this type of application is to be found in solder joints on printed circuit boards; solder flow and adhesion to a surface depends on microscopic features (surface texture and fine-detail shape) and contamination, neither of which can be controlled easily during machining. Manufacturing processes that rely on the flow of semi-fluid materials are nearly always prone to produce highly variable products. On the very day that I (BGB) wrote this Preface, I visited a factory where adhesive is applied by a needle injector, depositing an irregular “worm” of sticky black glue onto a smooth metal surface. The latter is produced to a close tolerance but the adhesive bead is not. The complete assembly is a high-precision home entertainment product. Many “high tech” products, like this, contain parts that have low-tolerance features embedded within them. The skill of an industrial design engineer is to hide them, to produce a close-tolerance assembly.

When an artefact is made in a mould, or cut to precise dimensional tolerances, there is one far-reaching principle that we can employ to design an inspection system:

If the product is not within its specified tolerance band, it is faulty and should be rejected.

Natural products do not have “design tolerances”; we do not, for example, have a specification for any dimension, or other feature, of a banana! (In some cases, rule-based criteria have been formulated to recognise natural products. This has been done, for example, so that the General Agreement on Tariffs and Trade (GATT) can be applied fairly. It is also necessary for the grading of fruit, vegetables, etc. In recent years, certain UK newspapers have poured scorn on EU regulations regarding the identification of fruit, such as bananas. This was mis-placed, because no account was taken of the need to control the price and protect poor farmers.) For this and other reasons, we are inevitably faced with some fundamental and severe difficulties in defining the tasks that a Machine Vision system is expected to perform. Here are some examples of ill-posed questions:

- How do we define a colour class, such as *yellow*?
- How do we formulate the rules for judging the aesthetic appearance of a slab of marble, or a wooden panel?
- How do we define an objective criterion for identifying the shapes of well-formed loaves, or cakes?
- How do we specify the texture of a piece of high-grade leather, suitable for making shoe uppers?
- What does a good “worm” of adhesive look like?
- How do we identify an unhealthy plant, such as an azelea, impatiens, etc.?

As so often happens, we must formulate questions appropriately before we can expect to obtain sensible answers. The questions just cited are not in this category, whereas the following are better:

- Does the shape of the loaf that you have given me resemble the shapes of the “good” samples you presented earlier?
- Does this apple satisfy the rules to be classed as Grade I?
- Does this object satisfy the GATT criteria to be classified as a banana?
- Does the texture of this piece of leather resemble one already seen on a piece of “good” leather?

Asking the right question is vital for Machine Vision, whether it is to be applied to engineering products or natural products.

Highly variable objects, such as natural products, are our chief concern in this book. However, they are notoriously difficult to characterise properly. A major problem is caused by the lack of consistency of opinion about what descriptive features are important. We can postulate various suggestions about meaningful measurements but, in the end, each one is supported by nothing more substantial than an opinion. The precise interpretation of qualitative terms varies from person

to person. For example, the word “tall” has different meanings for women over 1.85 m and men that are under 1.5 m. Even if we set this problem aside, there is an even more difficult one lurking: how do we combine all of the various pieces of evidence available to us, so that we can reach an appropriate decision about the acceptability of an item? How do we know what is acceptable and what is not? What authority do we consult, to know what is a “good” apple and what is not? When we are unable to formulate explicit rules for calculating an *accept/reject* decision, we must derive discriminatory criteria in some other way. Self-adaptive learning is one of the more effective techniques available to us and might be applied, for example, to design a classifier based on texture or colour. In more general terms, the computational procedures that we employ for inspecting highly variable products are likely to rely on Artificial Intelligence techniques and Pattern Recognition techniques. We shall see that heuristics, rather than algorithms, are our prime tools. The criteria by which we can judge them are ill-defined, so the concept of an algorithm is, in any case, a spurious one.

The growth of interest in Machine Vision is due, in large part, to the falling cost of computing power. The domestic video market is also exerting a major impact on the subject. LED light sources, plastic aspheric lenses, good-quality, low-cost cameras, with a variety of interface standards (CCIR, RS170, Ethernet, IEEE 1394 (“firewire”) and USB), are all available at low cost. They are all exerting a strong positive influence on our subject. (Notice the use of the present tense - the show is not over yet!) This has led to a proliferation of vision products and industrial installations in recent years. It has also enabled the development of cheaper and faster machines, with increased processing power. In many areas of manufacturing, serious consideration is being given now to applying Machine Vision to such tasks as inspecting, grading, sorting, counting, monitoring, controlling and guiding, etc. Automated Visual Inspection systems allow manufacturers to monitor and control product quality, thus maintaining/enhancing their competitive position. Machine Vision is also being used to ensure greater safety and reliability of manufacturing processes. The confidence being gained by applying Machine Vision to engineering manufacture is now spilling over into industries such as food processing, agriculture, horticulture, textile manufacturing, etc., where product variability is intrinsically higher. Thus, we are at the threshold of what we predict will be a period of rapid growth of interest in Machine Vision for applications involving natural products.

No Machine Vision system existing today, or among those planned for the foreseeable future, approaches the interpretative power of a human being. However, current Machine Vision systems are better than people at some quantitative tasks, such as making measurements under tightly controlled conditions. These properties enable Machine Vision systems to out-perform people, in certain limited circumstances. Vision systems can routinely inspect certain products at very high speeds, whereas people have considerable difficulty making consistent judgements in these circumstances. Machine Vision systems exist that can inspect peas individually at a rate of 16 tonnes per hour, which is well beyond human capability. On many tasks, a Machine Vision system can improve efficiency

substantially, compared to a human inspector. A machine can, theoretically, do this for 24 hours/day, 365 days/year. Machine Vision can be particularly useful in detecting gradual changes in continuous processes (e.g. tracking gradual colour or texture variations). Gradual changes in shade, texture or colour are unlikely to be detected by a person. On the other hand, people are better at making difficult decisions, based on novel and incomplete data. Machine Vision and human inspectors will both have a place in the food processing factory of the future but the balance will, we predict, shift slowly towards the machines in the next 10 years. The purpose of this book is to accelerate this movement, so that human beings can spend their lives doing more interesting things than watching fish, rice, peas or potatoes moving past on a conveyor belt, at high speed.

The stated aim of Machine Vision is to improve product quality and safety, enhance process efficiency, reduce waste and avoid human inspectors being placed in danger. Few will doubt the desirability of these aims but there is the ever-present spectre of unemployment resulting from work of this kind. We hope that by liberating the workforce from tedious inspection tasks, they can be re-employed in way that enhances human dignity. There can be no excuse for blaming Machine Vision for making people redundant; people make other people redundant.

We would like to thank our fellow authors who have provided us with so much excellent material to fill these pages. They have waited patiently while we have completed the editorial work on the manuscript. Our colleagues have all provided us with exciting material to read, new ideas to discover and have reminded us convincingly that this subject is growing rapidly. The cumulative experience of the contributors to this book is formidable, over 500 years of experience is to be found between these covers! We count ourselves privileged to be in such august company. We are proud and grateful for the links of friendship that we have established with our co-authors. The wide geographic spread of interest in this subject is also apparent from the list of authors' addresses. This is a technology that will eventually affect us all in the developed world and will one day have a significant impact on developing nations too. We hope that this book will make it happen a little sooner, with fewer false starts and greater confidence.

We are pleased to acknowledge the assistance of Mrs Terrie Hatley and Mrs Esther Graves, both of whom have worked hard in preparing the camera-ready document you are now reading. Our colleagues at Springer Verlag have helped us enormously by answering our many questions and helping us to turn a vague idea into a finished product.

Finally, we would like to thank our respective wives for their unending love, patient encouragement and support. During the final stages of the preparation of the manuscript, Mark's wife, Esther, gave birth to a baby boy. He has no excuse now for not changing nappies! On the other hand, Bruce is now free to enjoy his grandchildren and... write another book!

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