A SURVEY ON INDUSTRIAL VISION SYSTEMS, APPLICATIONS AND TOOLS[1]

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ABSTRACT

The state of the art in machine vision inspection and a critical overview of real-world applications are presented in this paper. Two independent ways to classify applications are proposed, one according to the inspected features of the industrial product or process and the other according to the inspection independent characteristics of the inspected product or process. The most contemporary software and hardware tools for developing industrial vision systems are reviewed. Finally, under the light of recent advances in image sensors, software and hardware technology, important issues and directions for designing and developing industrial vision systems are identified and discussed.

Keywords: Machine vision, automated visual inspection, image processing, image analysis.

1 INTRODUCTION

Machine vision provides innovative solutions in the direction of industrial automation [1]. A plethora of industrial activities have benefited from the application of machine vision technology on manufacturing processes. These activities include, among others, delicate electronics component manufacturing [2], quality textile production [3], metal product finishing [4], glass manufacturing [5], machine parts [6], printing products [7] and granite quality inspection [8], integrated circuits manufacturing [9] and many others. Machine vision technology improves

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productivity and quality management and provides a competitive advantage to industries that employ this technology.

1.1 OVERVIEW ON INDUSTRIAL VISION SYSTEMS

Traditionally, visual inspection and quality control are performed by human experts [10]. Although humans can do the job better than machines in many cases, they are slower than the machines and get tired quickly. Moreover, human experts are difficult to find or maintain in an industry, require training and their skills may take time to develop. There are also cases were inspection tends to be tedious or difficult, even for the best-trained experts. In certain applications, precise information must be quickly or repetitively extracted and used (e.g., target tracking and robot guidance). In some environments (e.g., underwater inspection, nuclear industry, chemical industry etc.) inspection may be difficult or dangerous. Computer vision may effectively replace human inspection in such demanding cases [11].

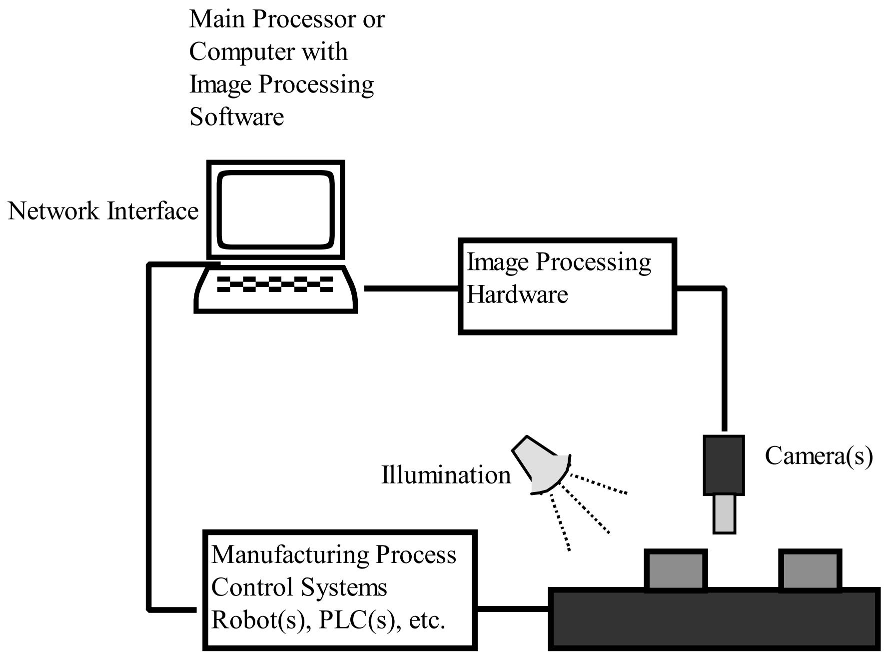

Figure 1: *A typical industrial vision system.*

Figure 1 illustrates the structure of a typical industrial vision system. First, a computer is employed for processing the acquired images. This is achieved by applying special purpose image processing analysis and classification software. Images are usually acquired by one or more cameras placed at the scene under inspection. The positions of the cameras are usually fixed. In most cases, industrial automation systems are designed to inspect only known objects at fixed positions. The scene is appropriately illuminated and arranged in order to facilitate the reception of the image features necessary for processing and classification. These features are also known in advance. When the process is highly time-constrained or computationally intensive and exceeds the processing capabilities of the main processor, application specific hardware (e.g., DSPs, ASICs, or FPGAs) is employed to alleviate the problem of processing speed. The results of this processing can be used to:

- Control a manufacturing process (e.g., for guiding robot arms placing components on printed circuits, painting surfaces etc.).

- Propagated to other external devices (e.g., through a network or other type of interface like FireWire) for further processing (e.g., classification).

- Characterize defects of faulty items and take actions for reporting and correcting these faults and replacing or removing defective parts from the production line.

The requirements for the design and development of a successful machine vision system vary depending on the application domain and are related to the tasks to be accomplished, environment, speed etc. For example, in machine vision inspection applications, the system must be able to differentiate between acceptable and unacceptable variations or defects in products, while in other applications, the system must enable users to solve guidance and alignment tasks or, measurement and assembly verification tasks.

There exists no industrial vision system capable of handling all tasks in every application field. Only once the requirements of a particular application domain are specified, then appropriate decisions for the design and development of the application can be taken. The first problem to solve in automating a machine vision task is to understand what kind of information the machine vision system is to retrieve and how this is translated into measurements or features extracted from images. For example, it is important to specify in advance what "*defective*" means in terms of measurements and rules and implement these tasks in software or hardware. Then, a decision has to be made on the kind of measurements to be acquired (e.g., position or intensity measurements) and on the exact location for obtaining the measurements.

For the system to be reliable, it must reduce "*escape rates*" (i.e., non-accepted cases reported as accepted) and "*false alarms*" (i.e., accepted cases reported as non-accepted) as much as possible. It is a responsibility of the processing and classification units to maintain system reliability, but the effectiveness of classification depends also on the quality of the acquired images. An industrial vision system must also be robust. Thus, it should adapt itself automatically and achieve consistently high performance despite irregularities in illumination, marking or background conditions and, accommodate uncertainties in angles, positions etc. Robust performance is difficult to achieve. High recognition and classification rates are obtained only under certain conditions of good lighting and low noise. Finally, an industrial vision system must be fast and cost efficient.

In this survey, we emphasize the important attributes of an industrial machine vision inspection system such as, flexibility, efficiency in performance, speed and cost, reliability and robustness. In order to design a system that maintains these attributes it is important to clearly define its required outputs and the available inputs. Typically, an industrial inspection system computes information from raw images according to the following sequence of steps:

1. ***Image acquisition:*** Images containing the required information are acquired in digital form through cameras, digitisers etc.

2. ***Image processing:*** Once images have been acquired, they are filtered to remove background noise or unwanted reflections from the illumination system. Image restoration may also be applied to improve image quality by correcting geometric distortions introduced by the acquisition system (e.g., the camera).
3. ***Feature extraction:*** A set of known features, characteristic for the application domain, is computed, probably with some consideration for non-overlapping or uncorrelated features [12], so that better classification can be achieved. Examples of such features include size, position, contour measurement via edge detection and linking, as well as and texture measurements on regions. Such features can be computed and analyzed by statistical or other computing techniques (e.g. neural networks or fuzzy systems). The set of computed features forms the description of the input image.
4. ***Decision-making:*** Combining the feature variables into a smaller set of new feature variables reduces the number of features. While the number of initial features may be large, the underlying dimensionality of the data, or the intrinsic dimensionality, may be quite small. The first step in decision making attempts to reduce the dimensionality of the feature space to the intrinsic dimensionality of the problem. The reduced feature set is processed further as to reach a decision. This decision, as well as the types of features and measurements (the image descriptions) computed, depends on the application. For example, in the case of visual inspection during production the system decides if the produced parts meet some quality standards by matching a computed description with

some known model of the image (region or object) to be recognized. The decision (e.g., model matching) may involve processing with thresholds, statistical or soft classification.

At the last level of decision-making and model matching mentioned above, there are two types of image (region or object) models that can be used namely, declarative and procedural. Declarative models consist of constraints on the properties of pixels, objects or regions and on their relationships. Procedural models are implicitly defined in terms of processes that recognize the images. Both types of models can be fuzzy or probabilistic, involving probabilistic constraints and probabilistic control of syntactic rules respectively. A special category of models is based on neural networks.

Model-based approaches often require that descriptions (e.g., features) of the image at different levels of specificity or detail be matched with one of possible many models of different classes of images. This task can become very difficult and computationally intensive if the models are complex and a large number of models must be considered. In a top-down approach to model matching, a model might guide the generation of appropriate image descriptions rather than first generating the description and then attempting to match it with a model. Another alternative would be to combine top-down and bottom-up processes. The above control strategies are simplified when one is dealing with two-dimensional images taken under controlled conditions of good lighting and low noise, as it is usually the case in industrial vision applications. Image descriptions and class models are easier to construct in this case and complex model matching can be avoided. Model-based approaches to visual inspection tasks [13] have been applied in a variety of application fields and many of them are reviewed in the following sections.

1.2 Development Approaches and Environments

The development of a machine vision system begins with understanding the application's requirements and constraints and proceeds with selecting appropriate machine vision software and hardware (if necessary) to solve the task at hand. Older machine vision systems were built around low-level software, requiring full programming control. They were based on simple frame grabbers providing low-level interface capabilities with other system components. They were also characterized by low-level user interfaces, low-level image analysis capabilities and difficulties in system integration and maintenance. Eventually, machine vision inspection systems became more modular, providing more abstract capabilities for system development and maintenance and reaching higher level of robustness.

Today's applications need environments that are developed in short time and are adjusted to modifications of the manufacturing process. In addition, the system must be simple to operate and maintain. The key here is to select an appropriate development environment providing Graphical User Interfaces (GUIs) or other programming tools (see Section 3 of this survey). Through GUIs and visual programming tools, even non-vision experts but authorized users like e.g., manufacturing engineers, are allowed to interact with the application and specify sequences of operations from pull-down menus offering access to large pools of tested algorithms. Programming is easier in this case, since the algorithms are selected based on knowledge of what they do and not on how they do it. The use of GUIs shifts the effort of application development to the manufacturing engineer from the programmer expert, as in the earlier days of machine vision systems. This feature not only results in faster and cheaper application developments, but also allows addressing several applications with a single piece of re-configurable software (i.e., the application development tool).

Industrial vision systems must be fast enough to meet the speed requirements of their application environment. Speed depends on the task to be accomplished and may range from milliseconds to seconds or minutes. As the demands of processing increase, special purpose hardware is required to meet high-speed requirements. A cost saving feature of industrial vision systems is their ability to meet the speed requirements of an application without the need of special purpose hardware. PCs and workstations are nowadays fast enough so that this can be achieved in many application domains, especially in those with less demanding run time requirements [14, 15].

Advances in hardware technology in conjunction with the development of standard processing platforms have made the production and maintenance of industrial automation systems feasible at relatively low cost. Pentium PCs with Windows NT (Windows 2000, XP) or UNIX based systems like Linux are considered the main alternatives with Windows being preferred to achieve labor saving application development with maximum portability based on ready-to-use software (e.g., commercially available software). Linux is becoming eventually a standard especially in cases where customized or cost saving solutions are preferred. Linux is sometimes offered as open-source freeware and appears to be the ideal solution in the case of dedicated applications where independency on vendor specific software has to be achieved. However the limited availability of application development tools (e.g., interfacing software) is a serious drawback of Linux.

1.3 APPLICATIONS OF INDUSTRIAL VISION SYSTEMS

Interesting surveys specializing in a single application field include among others Ref. [16] for automatic PCB inspection, Ref. [17] for wood quality inspection, and Ref. [18] for automatic fruit harvesting. Other important general reviews that cover all the fields of visual inspection have been published in Ref. [13], whereas model-based approaches to visual inspection are considered in [19] and [20] and more recently in [21, 22] and [23]. In Ref. [21], a classification of automated visual inspection applications is presented based on the type of images to be processed. Binary, gray-scale, color, and range image systems are considered, each one showing certain characteristics in the context of the particular application field being used. In Ref. [22] and [23] on the other hand, machine vision systems are classified according to the qualitative characteristics of the objects or processes under inspection. Three classes are presented, namely dimensional verification, surface detection, and inspection of completeness.

1.4 CONTRIBUTIONS AND STRUCTURE OF THE SURVEY

In this survey, we present an overview of machine vision applications in the industrial environment. Two independent ways of classifying industrial vision applications are proposed. First, industrial vision applications are classified according to the inspected features of the industrial product of process in four categories, namely: (a) *Dimensional quality*, (b) *Structural quality*, (c) *Surface quality* and (d) *Operational quality*. Industrial vision applications are also classified in terms of flexibility according to the so-called "*Degrees of Freedom*" (DoFs) that form inspection independent features. This classification enables the evaluation of tools intended towards similar industrial vision applications. A variety of software and hardware solutions available for the development of applications are presented. Finally, the future trends of machine vision technology are also discussed.

The rest of this survey is organized as follows: In Section 2, a review of the recent literature in industrial vision along with our proposed classifications of industrial vision applications is presented. Issues related to the development of industrial vision systems are discussed in Section 3. A variety of software and hardware tools that can be used to assist the development of machine vision inspection systems in the industry are also presented in this section. Future trends in the field are presented and discussed in Section 4, followed by concluding remarks in Section 5.

2 Classification of Industrial Vision Applications

In modern industrial-vision-system research and development, most applications are related to at least one of the following four types of inspection:

1. Inspection of *dimensional quality*,
2. Inspection of *surface quality*,
3. Inspection of *correct assembling (structural quality)* and
4. Inspection of *accurate or correct operation (operational quality)*.

A formalization of the above categorization is attempted in the following, by probing further onto the characteristics of products being inspected. Table 1 gathers some of the most ordinary inspected features of products [1].

Dimensional	Dimensions, shape, positioning, orientation, alignment, roundness, corners	
Structural	Assembly	Holes, slots, rivets, screws, clamps
	Foreign objects	Dust, bur, swarm
Surface	Pits, scratches, cracks, wear, finish, roughness, texture, seams-folds-laps, continuity	
Operational	Incompatibility of operation to standards and specifications	

Table 1: *Potential features of inspected products.*

Notice that, despite the inherent differences in the nature of the four categories of inspection, they are all reduced to the action of confirmation of quality standards satisfaction, which is, in most cases, a binary ("yes/no") decision. Figure 2 illustrates this relationship.

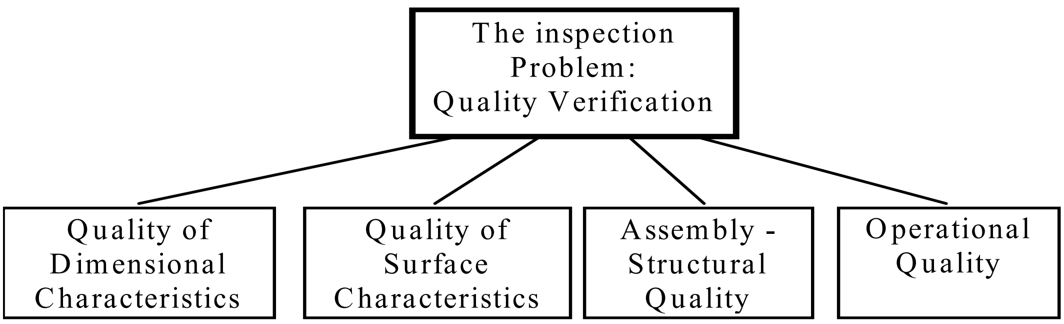

Figure 2: *Major categories of industrial vision applications.*

Industrial vision applications may also be classified based on features whose measurements do not affect the inspection process (may take any value) allowing the system to be independent on these types of features. The set of such features defines the so-called *"Degrees of Freedom"* (DoFs) of the inspection process. Some of the most common DoFs met in the industrial world are shown in Figure 3 and concern shape, geometrical dimensions, intensity, texture, pose, etc. The DoFs of objects are strongly related to the variances of their characteristics and are considered to be a measure of the flexibility of the vision system.

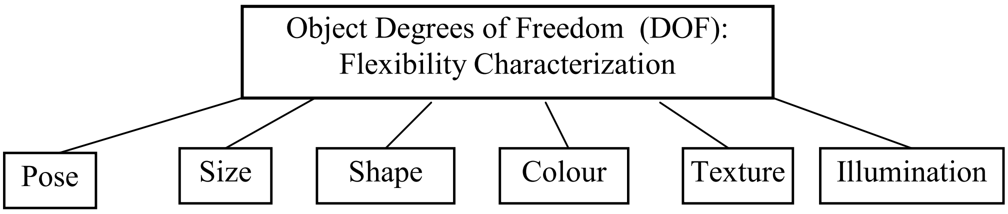

Figure 3: *Major DoFs of industrial vision systems.*

The less the DoFs the stronger the dependency of the inspection system on the application for which it is originally designed. Therefore, systems with low DoFs are less likely to be expandable. High levels of variability, on the other hand, are characteristic of more general or expandable systems. To allow many DOFs, the system must employ sophisticated image classification approaches based on carefully selected models and algorithms, as to minimize its dependency on the inspected item and its potential deformations. Moreover, the more the DoFs of a system the greater its potential for expandability. For example, the system can be enhanced to detect new types of defects if additional image processing and analysis functions are introduced to the system and applied independently from the old ones to capture more image features (e.g., capture surface in addition to dimensional characteristics). The above considerations concerning the proposed classification based on DoFs reveals a known trade-off in the design of inspection systems between flexibility, complexity and cost which is not obvious in other classifications.

Table 2 illustrates the relationship between DOFs and quality inspection systems developed for applications discussed in the survey. Most applications focus on the inspection of a single characteristic (e.g., size). The remaining characteristics (e.g., finish, texture, etc.) can be considered as DOFs for these applications indicating the flexibility of the vision system. However, not all of them are equally important. In the rest of this survey, only the important characteristics that relate to an application are discussed.

QUALITY INSPECTION	REFE-RENCE	APPLICATION FIELD	DEGREES OF FREEDOM (DOFS)
SURFACE	[24]	Mini resistor painting	Resistor orientation
	[25]	Aluminium sheet casting	Sheet width
	[26]	Railroad line inspection	Illumination/Rail-foot –head position,
	[27]	Oil seals	Illumination
	[28]	Chicken meat defects	Illumination/Skin
	[9]	Wafer surface inspection	Distortion/Scale/Orientation/Position
	[29]	Surface approximation	Illumination
	[8]	Granite surface inspectopn	Texture
	[30]	Directional texture	Illumination/Rotation of direction
	[31]	Surface roughness	Orientation
	[32]	Surface defects	Pose
	[3]	Textile seam defects	Translation/Rotation
	[17]	Internal wood defects	Wood density
	[33, 34]	Wood veneer surface	Scale/Intensity
	[35]	Surface corrosion	Shape
DIMENSIONAL	[36]	Machined parts inspection	Scale/Translation/Orientation
	[37]	Solder joints inspection	Orientation
	[38]	Solder joints inspection	Orientation/Position
	[12]	Solder joints inspection	Position/Orientation/Size
	[39]	External screw threads	Thread position
	[7]	Banknotes inspection	Position
	[40]	Image segmentation	Shape/Texture
	[15]	Object classification	Scale/Orientation
	[41]	Object classification	Shape
	[42, 43]	Circular parts	Peripheral occlusion
	[44]	Packaging	Position/Orientation
	[45]	Line segment measurement	Orientation/Scale
	[18, 46]	Fruit harvesting	Maturity/Illumination/Occlusion
	[47]	Packaging	Shape/Size
	[48]	Packaging	Illumination/Shape
	[49]	Automotive industry	Size/Shape/Pose
STRU-CTU-RAL	[50]	Object assembly	Orientation (limited)
	[51]	Railroad parts inspection	Illumination/Shape
	[52]	Railroad parts inspection	Illumination/Shape/Texture
	[53]	Automotive industry	Illumination/Position
	[54]	Automotive industry	Illumination/Position/Shape/Size
	[55]	PCB inspection	Illumination
OPERATIONAL	[56]	Laser butt joint welding	Welding path Shape/Gap size/Beam position
	[57]	Wrist watch quality	Hands Shape/Size/Orientation/Distortion

Table 2: *Classification of industrial vision systems.*

2.1 DIMENSIONAL QUALITY

Checking whether the dimensions of an object are within specified tolerances or the objects have the correct shape, are ordinary tasks for industrial vision systems. Such tasks involve inspection of geometrical characteristics of objects in two or three dimensions and are related to the first of the four types of inspection defined in the previous section, namely the inspection of dimensional quality.

Various industries are involved in the development of vision systems for automated measurement of dimensional quality. In packaging industry, the tasks vary from measurements of the fill level in bottles, to sell by date inspection and to airbag canister inspection (e.g., online gauging systems that measure height, concentricity and diameter of airbag canisters). In Ref. [48], a vision-guided system for the automated supply of packaging machines with paper and foil material is presented. The system enables the manipulator to locate the proper bobbin, depalletize it and transfer it to the requesting machine. A similar application is addressed in [44] were, a vision system is used to determine the correct position of pallets and recognize the arrangement pattern of sacks on the pallets. The system enables a robot mechanism to grasp the sacks and pass them along a rotating cutting disk.

A popular and demanding real-time application is the inspection and classification of solder joints on Printed Circuit Boards (PCBs). A typical inspection system for this application consists of a camera with appropriate illumination placed on top of the PCB conveyor system [37]. Processing PCB images consists of two major stages: First a pre-processing is performed in order to remove noise and make the tracking of solder joints on the image of the PCB easy. Then, the solder joints are classified according to the types of defects. The usual classification is concerned with the quantity of the solder paste placed on a joint. Four classes are defined, namely good, excess solder, insufficient and no solder. Simulation results on geometric models of joints have shown that efficient classification can be achieved only by an optimal feature selection, so that the classes do not overlap [12]. Current research has shown that histogram-based techniques [38] perform better than two and three-dimensional feature-based techniques [37], both in terms of system and computational complexity. The major problem is that two-dimensional features alone are insufficient for correct classification and an extra classifier is required to separate overlapping classes. In Ref. [58], it is shown that a combination of histogram and 2D, 3D feature-based techniques can overcome the performance of other techniques relying only on topological features. Many PCB inspection systems rely on neural networks for the design of classifiers that can deal with both distribution (histogram) and topological features of defects.

An approach to the problem of cutting two-dimensional stock sheets is reported in [47]. A machine vision system is employed to acquire images of irregularly shaped sheets. Then, a genetic algorithm is applied to generate part layouts that satisfy the manufacturing constraints (e.g., minimization of trim loses). This method is particularly useful for the leather and apparel industries, were irregular parts are commonly used.

An automatic visual system for the location of spherical fruits on trees, under natural conditions, is presented in [18]. The system utilizes a laser range finder that provides range and attenuation data of the inspected fruit surface and shape analysis algorithms are employed to process the acquired reflectance and range images to locate the fruit and, finally, to determine the position of the fruit on the tree. Experimental results report 74% detection over green (low degree of ripeness) fruits and 100% detection of visible fruits. In [46] the above system is embedded in the AGRIBOT integrated robotic system, aimed at the automatic harvesting of fruits.

The problem of measuring line segments, a primary machine vision problem, is addressed in [45]. A heuristic algorithm for line segment measurement is proposed and used to assess the efficiency of a machine vision system in accurately measuring properties of line segments, such as length, angle and straightness. A similar application concerns the detection of circular parts with peripheral defects or irregularities [43]. A two-stage Hough transform is applied for the detection of circular machine parts.

A model-based computer vision system for the estimation of poses of objects in industrial environments, at near real-time rates, is presented in [15]. A demanding real time application is the detection of high quality printed products [7]. This application deals with products with high degree of resemblance, where minor differences among them makes the application very difficult to cope with, considering its real-time nature. An original algorithm based on morphological operations facilitates the detection of flaws at near-pixel resolution. The system is applied for the inspection of banknotes, which is clearly a very delicate application, considering the requirements in the validity of the produced printings.

An interesting application in this category deals with the inspection of screw threads for compliance with manufacturing standards [39]. Edge detection algorithms (based on linear interpolation to the sub-pixel resolution) are applied to detect regions of interest. Each such region is matched with multiple models of threads, since the dimensions and positions of the inspected threads are allowed to vary. The system has been tested on the production line and has been shown to perform better than other competitive methods, such as manual measurement. Active Shape Models as the basis of a generic object search technique are employed in [49]. The approach is based on the identification of characteristic or “landmark’’ points (i.e., points that exist in all aspects of the object) in images and on the recording of statistics concerning the relationships between the positions of the landmark points in a set of training examples. The effectiveness of the approach is demonstrated on inspection of automotive brake assemblies.

2.2 Surface Quality

Inspecting objects for scratches, cracks, wear, or checking surfaces for proper finish, roughness and texture, are typical tasks of surface quality inspection. Significant labour savings are achieved in textile, wood and metal industries employing vision systems for fault detection and quality verification.

In [3], the quality of textile seams is assessed using feature classification (based on self-organizing neural networks). The system also enables the expedition of seam quality judgement, compared to human inspection, by locating seams on images of low contrast and then inspecting the waviness of the seam specimens (this information is in fact three-dimensional).

CATALOG [17] is a system for internal wood log defects detection, based on Computer Axial Tomography (CAT or CT). Sequences of CT image slices are acquired and each one is segmented into two-dimensional regions. Each segmented image slice is analyzed and is characterized as defect-free or defect-like. The correlation of defect-like regions across a CT sequence enables the three-dimensional reconstruction of the log defects. In [33], the use of a decision tree in combination with a modular neural network topology is shown to be more efficient than a single large neural network alone for the classification of wood veneer. The design of this topology is based on normalized inter-class variation of features for separating between classes. An improved version of this topology [34], based on intra-class variation of features, allows for the reduction of the complexity of the neural network topology and results in improved classification accuracy. A review of research activities for locating defects on wood surfaces is presented in [17].

Machine vision can also be used for the inspection and visualization of defects on ground or machined components (e.g., cracks, pitting and changes in material quality). Segmentation techniques for the detection of characteristic surface faults (e.g., indentations, protrusions) are proposed in [32]. Similar techniques are applied for the detection of scratches during machine polishing of natural stone. The assessment of surface roughness of machined parts is addressed in [31]. Fourier transform is applied first for the extraction of roughness measures. Then, neural networks are employed for the classification of surfaces based on roughness. The inspection of defects on objects with directionally textured surfaces (e.g., natural wood, machined surfaces and textile fabrics) is addressed in [30]. A global image restoration scheme based on Fourier transform is applied. High frequency Fourier components corresponding to line patterns are discriminated from low-frequency ones corresponding to defective regions. An alternative approach for the inspection of randomly textured color images is presented in [8]. This method considers both color and texture image properties and introduces a color similarity measure that allows the application of the watershed transform. The problem of recovering depth information for surface approximation of objects is examined in [29]. This is achieved using stereo image pairs, a Scanning Electron Microscope (SEM) and involves computation of disparity estimates utilizing a feature-based stereo algorithm.

The use of a finite-window robust sequential estimator for the detection and analysis of corrosion in range images of gas pipelines is presented in [35]. Deviations from the robust surface fit (which correspond to statistical outliers) represent potential areas of corrosion. The algorithm estimates surface parameters over a finite sliding window. The technique is shown to be robust in that it estimates the pipeline surface range function in the presence of noise, surface deviations and changes in the underlying model. Despite the fact that the method exhibits real-time execution capability, it fails to interpret correctly the combinations of high magnitude and high frequency ripples with large patches of corrosion.

Surface inspection is also applied to the aluminium strip casting process. Infrared (IR) temperature measurements (providing a measure of the distribution of surface temperature) are used to evaluate the quality of aluminium sheets. A two level process for the inspection of aluminium sheets is addressed in [25]. First, the system inspects both sides of an aluminium sheet and captures images of potential defective areas. These images are then classified according to defect type and stored for review by experts. In [9], machine vision is applied for the inspection of wafer surfaces in Integrated Circuits (IC) production. A fuzzy membership function is used to cope with the wide range of shape variations of the dimple defects.

Potential applications of surface quality inspection also include detection of damages on railroad tracks [26], where on-board detection and classification of defects is performed in real time. Exhaustive (100%) quality inspection of painting of metal film mini resistors is addressed in [24], were detection of low quality products is achieved by the acquisition of a line pattern image of a correctly painted resistor, which is compared with each acquired line pattern image. Inspection of machined parts (e.g., circular oil seals) is reported in [8], where both surface and dimensional qualities are verified. The centre of each circular seal is computed and the intensities of its circumferential pixels are inspected.

In food industry, the inspection of the quality of goods is of primary interest. In [28], an intelligent system for the detection of defects on chicken meat before packaging is presented. The system relies on the analysis of chromatic content of chicken images, the extraction of potential defective areas by morphological processing and their classification according to a predefined list of defects.

2.3 Structural Quality

Checking for missing components (e.g., screws, rivets, etc.) on assembled parts or checking for the presence of foreign or extra objects (e.g., leaves, little sticks) are typical tasks of this class of quality inspection.

In semiconductor and electronic industries, the tasks vary from connector presence, capacitor polarity checking, Integrated Circuit (IC) pin gauging, IC identification, IC alignment and positioning, to information gathering tasks such as automatic defect classification on electronic circuit boards etc. For example, a connector inspection system is designed in [16], which is fast and capable of detecting bent pins on connectors with 20-1000 pins.

The work in [55] deals with inspection of structural quality of PCB components. The inspected objects (electronic components) are assumed to have little variations in size or shape but significant variation in grey-level appearance. Statistical models of the intensity across the objects structure in a set of training examples are built. Subsequently, a multi-resolution search technique is used to locate the model that matches a region of an input image. A fit measure with predictable statistical properties is also used to determine that this region is a valid instance of the model. The method demonstrates failure rates that are acceptable for use in a real environment (i.e., 1 in 1000 samples).

Template matching methods for the detection of anomalies in a car assembly line in real time is proposed in [53]. Templates corresponding to four image regions of a car are selected by a human supervisor and are analysed by the system. This work is part of an integrated system for automatic inspection of a complete car assembly line. A second part of the same system aimed at the inspection of the condition of vehicle doors is presented in [54]. In order to detect whether a vehicle door is open or closed, a line-fitting algorithm is applied.

The detection of components of railroad lines is addressed in [26] and [52]. Filtering techniques for detecting rail clamps and neural networks for detecting screws are employed in [51]. The detection of wooden ties of rail lines in real time is presented is addressed in [52]. The system enables the detection of tie boundaries on rail line images. An adaptive edge detector based on a modified Marr-Hildreth operator is employed to cope with the steep transitions in the image resulting from wood grain. A stochastic model-based inspection algorithm (based on Bayesian estimation) for the detection of assembly errors on rigid objects in presented in [50]. The image models describe the appearance of a complex three-dimensional object in a two-dimensional monochrome image. This method is applied for verifying correct assembly in a gear assembly line and a VHS cassette production line.

2.4 OPERATIONAL QUALITY

Inspection of operational quality is related to the verification of correct or accurate operation of the inspected products according to the manufacturing standards.

The inspection of laser butt joint welding is addressed in [56]. A camera captures the welding seam track and determines the proper welding path and gap size. A noise-eliminating step is applied first. Then, the welding path and gap are calculated on segmented welding images. Segmentation is based on Laplacian filters. The information computed above enables the control of the laser for the automatic welding of butt joints. Quality inspection of wristwatches is addressed in [57]. All inspected watches are first synchronized with a reference clock. Images of watch hands are acquired by a camera and are classified as hour, minute, second, and 24-hour hands. The difficulty of this task stems from the overlapping of hands, as well as from the existence of a curved magnifying glass over the date window of the watch, which corrupts the clarity of captured images of hands. To compensate for such problems, the time that a watch shows is detected and compared with the time of the reference clock using neural network classifiers.

3 DEVELOPMENT OF INDUSTRIAL VISION SYSTEMS

Today's machine vision systems can be regarded as consisting from standard platform components. The migration to standard PC-based platforms also standardized networking, backup and storage technologies. Powerful Graphical User Interface (GUI) environments running on PCs coupled (if necessary) with image processing accelerators provide the core technologies necessary for building powerful, user-friendly machine vision environments at moderate cost. System development involves integration of software and hardware tools into a complete application. Today's machine vision systems are offering far easier integration of various components originating from various software and hardware vendors. Even conventional programming environments such as C and C++ allow for software components to be embedded into a single system.

With the advent of new hardware for sensors, grabbers and computers, machine vision for industrial inspection tackles even more sophisticated problems. High complexity algorithms can nowadays be implemented for real time vision and new sensors (e.g., CMOS sensors) offering high dynamic range allow for more reliable, flexible and faster image acquisition than traditional CCD sensors, even under poor lighting conditions. At the same time, image-processing software has become user friendly and powerful utilizing software libraries implementing some of the most popular image processing and analysis algorithms. Most of these environments support both, visual programming in combination with flexible GUI interfaces and traditional programming. Both programming practices can be combined to facilitate application development. Visual programming can be employed to accelerate application's prototyping whereas the final application can be implemented and optimized using standard programming methods and languages.

The current trend in industrial vision is to use commercial products instead of customized. This reduces the effort and risk in developing new products and allows for immediate exploitation of new hardware. When higher performance is needed, specialized DSP processors can be used. The selection of the appropriate software tools is of crucial importance. A software tool must have the following desirable features:

- **Multi-processing level support:** The type of processing in an industrial vision system varies from *low level* (e.g., filtering, thresholding), to *medium level* (e.g., segmentation, feature computation) and *high level* (e.g., object recognition, image classification etc.). An image software package must support all levels of functionality. Otherwise, different software tools must be adopted and integrated into the same system.

- **Ease of manipulation:** Graphical user interfaces, visual programming and code generation are typical features facilitating application development. Image functions must be categorized by type and scope so that even a non-expert may choose the appropriate function based mostly on what it does rather than on how it is done.

- **Dynamic range and frame-rate support:** New types of sensors (e.g., CMOS sensors) offer high dynamic range and faster image acquisition (e.g., 16 bits per pixel instead of 8 bits per pixel). Image software must support the processing of such high dynamic range images at variable frame rates.

- **Expandability:** The software package must be able to accommodate new or better algorithms substituting old ones. In addition, the software package must easily adjustable to new requirements of the running application without major programming effort.
- **Dedicated hardware support:** The software package must be able to work in collaboration with hardware (e.g., DSPs, ASICs, or FPGAs) to alleviate the problem of processing speed in the case of computationally intensive applications.

In the following, a survey of popular software and hardware products for image processing and industrial inspection is presented. The tools of each category are discussed separately for ease of presentation. This list is by no means complete. However, it presents either the most commonly used or best-suited tools for industrial vision applications.

3.1 SOFTWARE TOOLS

This review includes image processing and analysis tools, as well as, tools based on neural networks, fuzzy logic and genetic algorithms.

3.1.1 IMAGE PROCESSING AND ANALYSIS TOOLS

Image processing is usually performed within rectangles, circles or along lines and arcs. Image processing operators include filtering (e.g., smoothing, sharpening), edge detection, thresholding, morphological operations etc. Such operations can be used to improve image quality (e.g., remove noise, improve contrast) and to enhance or separate certain image features (e.g., regions, edges) from the background. Image processing operations transform an input image to another image having the desired characteristics.

Image analysis transforms images to measurements. In particular, image analysis is related to the extraction and measurement of certain image features (e.g., lines, and corners) and transforms these image features to numbers, vectors, character strings etc. For example, lines, regions, characters, holes, rips, tears can be gauged or counted. Image analysis involves feature extraction operations (e.g., Hough transform for line and curve detection) in conjunction with operations that measure average light intensity, texture, and shape characteristics such as Fourier descriptors, moments, edge thinning, edge connectivity and linking etc. The ultimate goal of image analysis is geared towards pattern recognition i.e., the extraction of features that can be used by classifiers to recognize or classify objects.

An image processing environment to be suitable for industrial inspection, must (at least) contain algorithms for edge and line detection, image enhancement, illumination correction, geometry transforms, Region of Interest (RoI) selection, object recognition, feature selection and classification. Table 3 provides a review of some of the most popular image processing tools offering the desired functionality. These tools offer adequate features and performance for several applications involved in the industrial sector. In terms of combined software and hardware, there are four alternatives: (I) IM-PCI with IPL of Sherloc32/MVTools, (II) MaxPCI with PC Image Flow or WiT and (III) Matrox Genesis with Matrox Imaging Library and (IV) Philips Trimedia VLIW processor board with Rhapsody.

Software Package	Library	Visual Programming	Command Line	Dedicated H/W Available	Source Code
Khoros	Yes	Yes	No	No	Yes
SCIL-Image	Yes	Yes	No	No	Yes
LeadTools	Yes	Yes	No		
IPL Lib	Yes	Yes	No	Yes	No
Sherlock32 / MVTools	Yes	Yes	No	Yes	Yes
Image-Pro plus	Yes	Yes	No	No	No
OPTIMAS	Yes	Yes	No	No	No
WiT	Yes	Yes	Optional	Yes	No
PC Image Flow	Yes	Yes	Datacube	Yes	No
Intel Image Processing Lib.	Yes	No	MMX		No
HALCON	Yes	Yes	No	No	No
VISION97	Yes		Yes (frame grabber)	No	No
AdOculos	Yes	Yes	No		No
MIL	Yes	Yes	Matrox	Yes	No
Rhapsody	Yes	No	No	Yes	No

Table 3: *Image processing and analysis software tools.*

3.1.2 NEURAL NETWORKS (NNS)

Neural Networks (NNs) are being successfully applied across a wide range of application domains in business, medicine, geology and physics to solve problems of prediction, classification and control. Neural networks are composed of a number of similar elementary processing units (neurons) connected together into a network [59]. Neurons are arranged in layers with the input data initializing the processing at the input layer. The processed data of each layer passes through the network towards the output layer. Neural networks adapt the weights of their neurons during a training period based on examples, often with a known desired solution (supervised training). After sufficient training, the neural network is able to relate the problem data to the appropriate solution spaces, i.e. generate input/output relations, thus offering a viable solution to a new problem through examples [60]. They are capable of handling a variety of image classification tasks in industrial vision environments, ranging from simple gauging to advanced classification problems, such as fault detection, optical character recognition, operation prediction, engine monitoring and control etc. They can be used either as standalone techniques (e.g., wood [33], seam [3], surface roughness [31] inspection) or in conjunction with other methods (e.g., solder joint inspection) [37]. Neural networks have been applied in all classes of quality inspection introduced in Section 2, namely dimensional quality [36-38], surface quality [3, 31, 34], structural quality [51] and operational quality [57]. They are applicable in almost every situation where a relationship between input and output parameters exists, even in cases where this relationship is very complex and cannot be expressed or handled by mathematical or other modelling means.

Table 4 summarizes the features of the most commonly used neural network tools. Beyond general purpose and stand-alone tools, there exist library tools, such as the SPRLIB and the ANNLIB (developed by the Delft University Technology at Netherlands) emphasizing on image classification and pattern recognition applications. Almost all tools provide a plethora of neural architectures, covering the most popular, as well as some less known. Some of them provide the ability for user defined topologies as well.

Package Name	New Algorithms	Types of NN	Industrial Applications	Package or Library	User Interface	Code Generation or DLL
Braimaker		Back-propagation		Software package	Graphical	C
Neuro Solutions	Offers user defined neural topologies and components	Recurrent back propagation, back propagation through time	Summaries of applications included	Software package	Graphical	C++ /DLL
G2 NeurOnLine		Back propagation, RBF, Rho, auto associative	Detailed petrochemical application included	Software package	Graphical object oriented	
SPRLIB ANNLIB	Can build exotic network architectures using the same data types	Back-propagation, pseudo-Newton, Levenberg-Marquadt, conjugate gradient descent, BFGS, Kohonen maps		C/C++ Libraries		
ILIB				C/C++ Libraries		
Neural Connection		Multilayer Perceptron, RBF, Kohonen, Bayesian		Software Package	Graphical	
DataEngine, v.i,ADL		Multilayer Perceptron, Kohonen, Feature map, Fuzzy, Kohonen network		Software Package	Graphical	C++ / DLL
Trajan 3.0	Allows building of hybrid networks	Offers all of the above architectures and training algorithms		Software Package	Graphical	DLL

Table 4: *Neural network tools.*

3.1.3 Fuzzy Systems (FSs) and Neuro-Fuzzy Systems (NFSs)

A variety of industrial vision applications of diverse nature have been benefited by the use of Fuzzy Systems (FSs) and Neuro-Fuzzy Systems (NFSs). Examples of such applications are cork quality inspection [61], identification of mechanical component dimensional tolerances [62], IC product quality control [63] etc. Fuzzy sets are based on decisions on linguistic variables, which get linguistic values described by fuzzy sets, called "*membership functions*" [64]. Their basic processing elements are fuzzy sets instead of numerical values. A *fuzzy* set can be considered as an extension of a classical (crisp) set in the form that a crisp set permits only full membership or no membership, whereas a fuzzy set permits partial membership with a certain degree. Thus, a fuzzy set, say *A*, in a domain *U* is characterized by its membership function μ_A that takes values in the real interval 0…1. For each $x \in U$, $\mu_A(x)$ expresses the degree of membership of this value to the set *A*, where 1 denotes full membership and 0 denotes no membership at all. For example a dimensional tolerance in length can define fuzzy sets "small", "medium" and "large" with respect to its values, as illustrated in Figure 4:

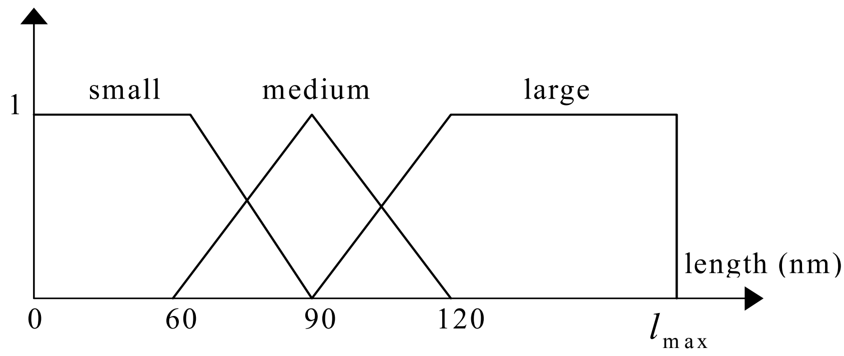

Figure 4: *Example of membership function definition for dimensional tolerance*.

Classical decision making systems usually try to avoid vague, imprecise or uncertain information. Fuzzy systems on the other hand, deliberately make use of this information through the membership functions that describe the degree to which a measurement belongs to certain sets or classes. The membership function is the essential component of a fuzzy set. Thus, the operations 'intersection', 'union' and 'complement' of fuzzy sets are defined via the membership functions of the sets involved. Input values are matched with the preconditions of "if-then" rules on fuzzy sets, describing the system's behavior. This kind of structured knowledge provides the system with a rule based processing (or rule based reasoning) mechanism. This mechanism supports independent rules (i.e., changes in one rule do not effect the result of other rules). FSs and NNs differ mainly on the way they map inputs to outputs, the way they store information or make inference steps. Table 5 lists the most popular software and hardware tools based on FSs as well as on merged FSs and NNs methodologies.

Neuro-Fuzzy Systems (NFS) form a special category of systems that emerged from the integration of Fuzzy Systems and Neural Networks [65]. There are two major subcategories characterizing this integration namely: "*Neural Network Fuzzy Systems (NNFSs)*" incorporating FSs represented on a Neural Network topology and "*Fuzzy Neural Networks (FNNs)*" which include Neural structures with a number of fuzzyfied parts [62]. NNFSs aim at providing fuzzy systems with automatic tuning methods typical to neural networks but, without altering their functionality. Neural Network's learning ability can be used to build membership functions and rules to encode system's behavior. The learning techniques employed are mainly based on multilayer feed forward networks with the back-propagation algorithm. Fuzzy systems offer their users better in-sight of neural black box structures, by encoding structured information in the form of rules and by offering tools for exploring this knowledge.

FNNs retain the basic properties and architectures of NNs and simply fuzzify some of their elements. The system obtains increased flexibility in storing, recalling and associating information. Not only binary but also continues values can be given as inputs, which highly increases system robustness. Usually, fuzzified components result in higher training speed of NNs. Fuzzy Logic also makes neural models understandable and this increases user's flexibility. There exist a large variety of Neuro-Fuzzy topologies in the literature, such as the Fuzzy ARTMAP in [66], the MCFC for speech recognition in [67], the ASAFES2 network in [68] etc. The most popular topology though is the ANFIS [69], which follows the general structure of Neural-Fuzzy systems [70] and moreover has an extra layer to perform normalization of rule's firing strengths.

Recently, Genetic Algorithms (GAs) [71] have also been employed to deal with certain tasks ns certain application domains. For example, an application of genetic algorithms in industrial vision is pattern detection, which defers from pattern matching in the sense that the item sought is not known in advance. The use of genetic algorithms has also been reported for the classification of objects [41], the detection of circular objects [42], image segmentation [40] as well as for the minimization of trim loses in cutting two-dimensional stock sheets [47] etc. Sugal 2.1 (TRAJAN Software Ltd.) and the Generator (NEW LIGHT INDUSTRIES Ltd.) are the two packages that can simulate genetic algorithms for various purposes and provide complete control over these algorithms. The main difference between them is that, Generator is designed to interact with Excel while, Sugal is autonomous.

Software Package	Requirements	Code Generation	Features*	Hardware Support
Mathematica	Windows/Unix, Mathematica S/W	No	FS only, Variety of built-in functions	No
FIDE	DOS/Windows, 4MB RAM, 4MB HD, >386	ANSI C/ Java/ MatLab/ Assembly	FS only, High and low level debugging, waveform generator, composer	MC6805, MC68HC05, MC68HC11, MC68HC16, MC68HC33x
TILShell/ FuzzyCLIPS	Windows, CLIPS (for Fuzzy CLIPS)	C code	FS only, Programming language, simulation	VY86C570 dedicated fuzzy processor
FCM	Windows	C Code, Assembly	FS only, Neurally optimized description, high complexity of fuzzy systems	NEC 17K/75X/ 78K0/78K3 and V Panasonic MN1500, 68HC11, 8051, Inmos Transputer T805
MatLab	Windows, Unix, Linux, HP, Solaris, Matlab S/W	C code	FS and NFS, ANFIS, Graphical Editors	No
DataEngine, V.i lib	Windows, Labview(for the V.i library), Pentium, 64MB RAM, 50MB HD	DLL	FS and NFS, Graphical programming language, Signal and Image processing algorithms	No
FuzzyTECH+NeuroFuzzy Module	Windows	C code, Assembly, DLL	FS and NFS, Fuzzy Design Wizard, Interface to other S/W	Motorola 68HC12 MCU
NeuFrame v.4	Windows	C, C++, Java, MatLab	FS and NFS, Variety of Neural Topologies	No

*: FS=Fuzzy System, NFS=Neuro-Fuzzy System

Table 5: *Fuzzy and neuro-fuzzy software systems.*

3.2 Hardware Tools

Software implementations are often insufficient to meet the real time requirements of many industrial vision applications. The ever-increasing computational demands of such applications call for hardware tools implementing image processing algorithms. In the following ASICs, DSPs, FPGAs and general-purpose processors are considered as possible alternatives in dealing with the problem of processing speed. The choice among them has to be made taking into account issues such as, size of chip, power dissipation and performance. However, issues such as flexibility of usage, programming environment are now becoming of great importance for the application developers. Table 6 summarizes the characteristics of some commonly used image processing boards.

Board	Processing chip	Clock Speed	Image Acquisition	Video Display	Image Processing Library
TriMedia (Philips)	DSP TM-1300	166 MHz	Yes	Yes	Yes
IM-PCI (Imaging Technology)	ASIC	40 MHz	Optional	Optional	Yes
MaxPCI (Datacube)	ASIC	40 MHz	Yes	Optional	Yes
PCI/C6600 (Texas Instruments)	DSP C6201	200 MHz	Optional	Optional	Yes
Genesis (Matrox)	DSP C80	60 MHz	Yes	Yes	Yes
Mpact 2 (Chromatic)	ASIC	125 MHz	Yes	Yes	Yes
Mamba (Coreco)	Pentium II	466 MHz	No	Optional	Yes
TPE3 (AG Electronics)	PowerPC 7400	400 MHz	Optional	Optional	Yes
VigraVision (Visicom)	FPGA Xilinx Virtex	Up to 300 MHz	Yes	Yes	Yes

Table 6: *Image processing boards.*

3.2.1 APPLICATION SPECIFIC INTEGRATED CIRCUITS (ASICS)

There are several ways to perform hardware image processing. The first one is to build a circuit dedicated to the application using an ASIC. As algorithms become more complex, the future of ASIC design will use more and more Intellectual Property (IP) blocks available on the market either as a hardware black box units (i.e., layout cells) or software packages (in a hardware description language such as VHDL or Verilog). Development time decreases this way because these cells have already been validated on various technologies. Then, the design of ASICs consists of assembling IP blocks and putting some glue logic between them for their interface.

The main disadvantage of the ASIC approach is that the circuit is usually limited to work for one application (e.g., the system developed in [29] for stereo vision). To overcome this limitation, programmability can be achieved using processor cores that are included in the ASIC. A few companies (e.g., ARM, I.C.COM, Clarkspur, DSP Group, Argonaut) propose RISC or DSP cores, mainly dedicated to portable applications (i.e., with low power consumption, but also with performances below what is achieved with packaged chips). One of the most attractive products comes from Argonaut with the ARC processor core. This is a 32-bit general purpose RISC processor offering a lot of flexibility. The core size is very small (i.e., lower than 16 kgates, about 2 mm^2 area in a 0.35-µm technology) and the processor has high clock speed (i.e., greater than 100 Mhz). A software tool allows for building a configuration adapted to the specifications of the application. For example, the synthesis can be targeted for area or for speed, the instruction cache size and the register file size can be adapted accordingly etc. VHDL code is then produced and can be synthesized in any technology.

Reconfigurability is another way of dealing with the limited applicability of ASICs. Reconfigurable multiprocessor networks compromise the trade-off between the need for low network diameter and the limited number of interconnection links among processors. In [72], an ASIC architecture of this kind is presented. It enables the implementation of a variety of image processing algorithms for low and intermediate level computer vision, such as FFT, edge detection, template matching, Hough transform etc. The use of general purpose processing elements implementing several image processing tasks on the same architecture, is another way of dealing with the limitations of ASICs. Several approaches have been reported in the literature, including [73], with on-chip photo detectors for early visual processing [74], and [75] for high-level image processing.

3.2.2 Digital Signal Processors (DSPs)

An alternative is to use a chip instead of a processor core. Many different processor architectures have being proposed. Each has its own advantages and disadvantages. The use of DSP boards for the fast execution of image processing algorithms has been extensively used in industrial vision applications with hard real-time constraints. Some popular DSP architectures are the TriMedia Mediaprocessor by Philips Semiconductors [76], IM-PCI by Imaging Technology, MaxPCI by Datacube, Texas Instruments (TI) TMS320Cxx Family, the Genesis Vision processor by Matrox based on the TI's TMS320C80 DSP and on the PCI platform, the Mpact media processor by Chromatic Research Inc. [77] etc.

3.2.3 General Purpose Processors

General-purpose processors develop faster than DSPs. They run at much higher frequencies than their predecessors, approaching this way the performance of DSPs. Intel with the MMX and the SIMD Instruction on the Pentium, AMD with the Athlon architecture and Motorola with the Altivec on the PowerPC, propose new coprocessor architectures dedicated to intensive computations on large sets of data, fitting well for image processing applications. The main advantage of the general-purpose processors is of course the programming environment, allowing the user to develop applications without having any knowledge of the inside architecture. On the other hand, the power consumption and the size of these chips are often prohibitive, especially for embedded applications. A review of the RISC architectures available today capable of performing image processing tasks can be found in [14].

3.2.4 Field Programmable Gate Arrays (FPGAs)

FPGAs are now competitive to ASICs both, in terms of capacity (i.e., number of equivalent gates contained in one chip) and performance. This allows to quickly having prototype of the circuit that has to be designed and able to operate in real conditions. The main advantage compared to ASICs is that FPGAs can be reprogrammed. Complex FPGAs allow to design reconfigurable systems that can efficiently implement real-time image processing algorithms. FPGA-based PCI boards are an attractive alternative to DSP systems. Recent FPGAs include processor core such as the ARM or PowerPC cores with RAM and peripherals. This feature allows the designer to develop a 1-chip reconfigurable hardware-software solution and highly facilitates redesign and testability of large circuitry with the same components. Thus, the FPGA chip can be reused in case of changes in the specifications or simply when errors have been introduced in the design process.

3.2.5 Neural, Fuzzy, and Neuro-Fuzzy Hardware Systems

There exist also platforms that are capable of implementing fuzzy, neural, or hybrid systems. Most of them are based on general-purpose micro-controllers, which are fast enough to execute assembly programs that describe fuzzy or neural systems. On the other hand, there are dedicated processors, such as the SGS-Thomson WARP family of fuzzy controllers, for the acceleration of fuzzy-oriented applications. In between the two methodologies, there exist processors, such as the Motorola 68HC12, which offers a 4 instruction set of fuzzy operations, in addition to its general-purpose architecture. All of the presented systems are supported by software packages, which enable either the high-level or the low-level description of fuzzy or neural systems and the generation of speed-optimized code for each platform. Table 7 summarizes the characteristics of fuzzy-oriented hardware products.

Board	Processing Chip	Clock Speed	Description	Software Support
CNAPS server	CNAPS	20MHz	NN, Kohonen, BP, other	BrainMaker, CNAPS-C, BuildNet, CodeNet
NeuroChip PCI	SAND	50MHz	NN, feedforward, RBF, Kohonen, other	NeuroLution
Siemens SYNAPSE	MA-16	50MHz	NN, MLP, RBF, Kohonen, other	SYNAPSE S/W
IBM ZISC	ZISC036	16MHz	NN, on-chip learning, RBF, Kohonen, other	S/W Development Tools
RC Module NeuroMatrix	8-bit NM6403	50MHz	NN, forward propagation, Sobel transform, other	C++ compiler, assembler, debugger
Nestor Ni1000	Ni1000	-	NN, on-chip learning, variety of topologies	NestorACCESS
AAC NNP	NNP	-	NN, on-chip learning, variety of topologies	NNP S/W
Intel 8XC196Kx	8, 16bit MCS 96	0-20MHz	FS, General Purpose, Fast on-chip peripherals	Any C code generating S/W (FuzzyTECH, TilShell, FCM)
Motorola 68HC12 MCU	16 bit 68HC12	8MHz	FS, General Purpose, 4 fuzzy instructions implemented	FuzzyTECH, FCM (HC-11ver.)
SGS-Thomson WARP	8 bit WARP 1.1, 2.0	40MHz	FS,Fuzzy dedicated Processor	FuzzyStudio v3.0
FDG EZ-LAB	16bit ADSP 21xx	33MHz	FS,General Purpose	FID
Rigel R-535J	8 bit 80C5x5	12 MHz	FS,General Purpose	FLASH
National NeuFuz/COP8	8-bit COP8	10 MHz	NFS,General Purpose	NeuFuz 4
Philips L-Neuro	16-bit L-Neuro 1.0, 2.0, 2.3	60 MHz	NFS, Neuro-Fuzzy Processor	Several

Table 7: *Fuzzy-oriented hardware systems.*

4. FUTURE DIRECTIONS

The major trade-off in industrial vision is that, for a vision system to be viable, it should satisfy increasingly demanding performance criteria against budget constraints on behalf of the end user [78]. There are three technological trends that enable the alleviation of this gap: (a) Rapid development in semiconductor technology along with development of multipurpose mainstream Operating Systems, (b) Improvements in Human-Computer Interfaces, and (c) Advances in solid state imaging sensors.

4.1 SOFTWARE AND HARDWARE TECHNOLOGY

The trend to fast and cheap multipurpose solutions (software or hardware) in image processing [79] is especially important to the industrial environment, because there is an increasing demand for cost-effective and high quality products that can only be fulfilled only by very sensitive, automated quality monitoring. Moreover, the industry is a volatile and competitive environment, thus industrial applications must be flexible enough to adjust to new production methods. These requirements call for multipurpose hardware and mainstream Operating Systems (OS), so that fast image processing can be achieved with moderate cost. The industrial OS standard in contemporary vision systems is UNIX, since it is the most popular platform for image processing. However, Windows NT seems to be a challenge, while a wide range of inexpensive statistical-analysis and standard image manipulation applications is available for this platform. A problem that arises in heavy-duty real-time applications is that a single system can't handle the data streams of several hundred Mbytes per second. Systems integrators have addressed the challenges of constantly accelerating process speeds, increasing optical solutions, and more complex classification criteria in the industrial area with specialized hardware, frame grabbers, DSPs, or even arrays of RISC systems working in parallel.

Referring to semiconductor technology, the advances in the field have allowed for the integration of image processing and feature extraction algorithms onto silicon. More specifically, they enable hardware implementation of algorithms that are essential to industrial vision (e.g. contour extraction, color inspection, morphology, etc.), but are time consuming if implemented on software run from a host computer. The trends of this integration are in the form of either an ASIC system running as a specialized processor and supervised by the host, or a co-processor embedded in the architecture of the host (e.g. the MMX technology imported in PC-compatible systems). It is clear that the latter is the optimum solution in terms of cost for most applications, except some demanding real-time cases where a network of ASIC-boards is used to cope with processing demands [7, 25].

4.2 HUMAN-COMPUTER INTERFACES

Another major demand of state-of-the-art systems in industrial inspection is fast prototyping, which requires adjusting an established inspection system to variations in the manufacturing process with the lowest cost and the minimum time possible. This calls for flexible and comprehensive image processing libraries that include special modules for all aspects of industrial inspection, along with multipurpose hardware. This is the reason that model-based solutions have not been adopted widely by the industry, since they require the development of a model for the images to be processed, which is either very complex or very tedious, especially for applications concerning the inspection of highly irregularly-shaped objects (e.g., plastic parts industry). A solution to this problem to a certain extend, has been given by the use of CAD-based vision systems [21].

Interfacing the industrial vision system with the human operator is very important for the end user. This interface should enable any operator to efficiently adjust the parameters of the system and handle some low-level problems occurring during inspection, without having to call the software supplier. Windows-style tools (such as the ones described in Section 3) for PC-based applications are the common case for contemporary systems. Along with the simplification of software interfaces, the use of hardware interfaces especially for on-line intervention, such as the mouse or the light pen, have also contributed to the acceptance of machine vision in the industrial field [80].

4.3 IMAGE SENSORS

The third technological trend that boosts the performance of industrial vision systems is the advances in imaging sensors. Solid-state technology has allowed the elimination of thermionic technology from the capturing of images, which was inappropriate for such applications due to slow frame rates, increased device volume, increased noise [81] etc. The introduction of solid-state technology in image capturing has led to some breakthroughs in industrial vision, since they offer a number of advantages as opposed to the predecessor technology. Some of these advantages are smaller device sizes, robustness against EM noise, higher resolutions, asynchronous triggering (capturing the image the time it is needed), stop-motion techniques (capturing fast-moving objects) [81], on-chip signal processing [82-84], robustness against changes of lighting conditions [85, 86] etc. The most important technologies used in integrated imaging sensors are the Charge-Coupled Device (CCD), Charge-Injection Device (CID) and Complementary MOS (CMOS) [87].

Table 8 summarizes the most important characteristics of the three families of sensors. We have chosen typical devices at the 300K pixel resolution level, since in practice the majority of industrial vision systems perform image capturing at this level of resolution [27, 37, 47]. Notice at this point that there is a trade-off between speed and resolution, since higher resolution supplies the image processing system with larger image-data streams, thus image processing algorithms are slowed down. A popular solution to this trade-off is the use of high resolution when detailed analysis is required and objects under inspection remain stationary [28] or a network of processing boards is available [7], as opposed to the use of low resolution or consideration of only small Regions of Interest (ROIs) when detail is not important [9, 44, 47] or the inspection controls high speed actions [26].

Technology@ Model	CCD@ DALSA CA-D8-0512W[1]	CID@ CIDTEC RACID810/811[2]	CMOS@ VLSI Vision VV5500[3]
Resolution (Array Size)	512x512	512x512	648x484
ROI* Processing Capability	No	Yes	Yes
On-Chip Processing	No	Yes	Yes
Consumption	6.750W	11/22mW	< 125mW
Pixel Size	10μm	20μm	7.5μm
Dynamic Range&	54dB	57.5dB	57dB
Data Bits	8	8	10
Data Rate	25MHz	10-20MHz	20-30MHz
Full Frame Rate	77fps+ (max)	30-70fps+	30fps+

Table 8: *Typical characteristics of the three solid-state imaging sensor families. (*ROI: Region of Interest, &Dynamic Range=20log(ratio), +fps: frames per second, 1: reference [88], 2: reference [89], 3: reference [90])*

The future trends of imaging sensor technology are very prosperous. Image resolution can reach 16Mpixels (4096x4096) for area scan devices and can serve the most demanding applications [81]. Frame rates can be as high as desired and can reach up to 60Kfps with the capabilities of region-of-interest (ROI) processing on behalf of CID and CMOS cameras. Such high speeds are of course possible only for the acquisition of ROI windows of very small extent, or for quite low resolution frames. Data bit resolution is increasing and the technology moves from the 8-bit era to the 16-bit era. Color cameras are also advancing their capabilities mostly using CCD sensor technology. Commercially available cameras use single CCD sensor of size ¼'', 1/3'', or even ½'' chip for standard PAL/NTSC video quality. Digital cameras are also becoming available at affordable prices, using 3 CCD chips for 24 bit true color acquisition separating the image into Red, Green and Blue channels. Using advanced CCD imager with 680K pixel capacity, they achieve high DV picture quality. Digital color cameras capture still images in standard JPEG format, whereas interconnection, communication and video transmission is often performed through the IEEE 1394 interface, also known as FireWire, which tends to become a standard. The integration of IEEE 1394 interface into the computer's operating system is achieved via available device drivers. Camera systems achieving 640x480 frame acquisition with 24bit true color are becoming of widespread use, while megapixel cameras are gaining their share in today's market.

Several criteria are used to evaluate image sensors, the most important being the following [91-93]: a) *Responsivity*, which is a measure of signal level per unit of optical energy. CMOS sensors are slightly better than CCD in this category, due to the fact that gain elements are easier to place on their chip. b) *Dynamic Range* defined as the ratio of a pixel's saturation level to its signal threshold. CCD sensors are better because they have less on-chip circuitry, which reduces the noise and increases the sensitivity of the sensor. c) *Uniformity*, indicating the consistency of response for different pixels under identical illumination conditions. Circuitry variations affect the uniformity of pixels on an image sensor. CMOS sensors are more sensitive to these variations because of the more additional circuitry on sensor. Newer CMOS devices have added feedback to the amplifiers to compensate these variations, but this only works well under illuminated conditions. CCD has better uniformity because the lack of any amplification in the sensor itself. d) *Speed* of operation, with CMOS sensors operating faster because most of the circuitry is on board. Thus, the signals communicate less distance and don't have to be piped to other chips on the printed circuit board. CCD imagers still operate adequately fast for most applications, but anticipated demanding applications will consider CMOS sensors instead. e) *Reliability*, in which respect CMOS sensors are superior to CCDs because of the high level of integration contained on the chip. More integration means less external connections that are susceptible to corrosion and other problems associated with solder joints in harsh environments. Overall, CCDs offer superior image performance and flexibility at the expense of system size. CMOS imagers offer more integration, lower power dissipation, and smaller system size at the expense of image quality and flexibility. For next-generation applications, CMOS evolves in order to get around the low–quality problem. Improvements are incorporated by the use of microlenses, which are small lenses manufactured directly above the pixel to focus the light towards the active portion, and the minimization of the space circuitry in the CMOS pixel.

On-chip A/D conversion and signal processing have been enabled from the advances in semiconductor technology, thus eliminating the need for separated chips. The trend is to move from the imaging sensor to the image processing sensor, with on-chip capabilities for image processing algorithms such as low-pass filtering [94], velocity measuring [83], edge detection, smoothing [73] etc. Although CCD is a mature technology that is commonly used in industrial vision applications, the potential of the alternative technologies (CID and CMOS) is very high, considering their on-chip intelligent and autonomous post-processing.

Many applications in industrial vision require stand-alone operation, which means that there is a need for intelligent cameras providing fast processing capabilities inside the camera. The major challenge in this direction is to maintain an easy-to-program feature by providing the end-user with commercial image processing libraries. The integration of a general-purpose processor or a DSP inside the camera offers such features, since compiling tools are widely available for these kinds of architectures. Unfortunately, even when using instruction-level parallelism like in VLIW processors, the performance achieved is often not sufficient to handle the amount of data generated by high resolution and dynamic-range cameras. One complementary approach is to add a coprocessor exploiting data-level parallelism, i.e. capable of performing the same operation on several different data. The combination of the two approaches (i.e. intelligent camera and coprocessor) should result in very powerful systems able to offer flexible programming facilities together with increased performance for most of the algorithms included in image processing libraries.

5 CONCLUSIONS

The state of the art in machine vision inspection research and technology is presented. The cardinal factors affecting the development of automated inspection systems are discussed and related to the literature in the field. Contemporary applications of machine vision in the industry are also reviewed and classified according to (a) Their measured parameters (i.e., dimensions, surface, assembly and operation) and (b) The system's "Degrees of Freedom". Tools and techniques either dedicated to specific application requirements or targeted towards a wider variety of applications with similar requirements are presented. This review covers a wide range of software and hardware products including integrated image processing software packages, image processing libraries, neural network, fuzzy, neuro-fuzzy tools, genetic algorithms as well as hardware tools. The paper concludes with a critical perspective and a summary of future directions in the field, as they are determined by the increasing performance criteria imposed to the industrial vision technology and the restricted end-user budget. Trends on technological fields affecting industrial vision, including semiconductor technology, human-computer interfacing and imaging sensors, are also emphasized.

REFERENCES

[1] E. R. Davies, "Automated Visual Inspection," in *Machine Vision*, vol. Chapter 19, 2nd Edition ed: Academic Press, 1998, pp. 471-502.

[2] J. L. C. Sanz and D. Petkovic, "Machine Vision Algorithm for Automated Inspection of Thin-Film Disk Heads," *IEEE Trans. on PAMI*, vol. 10, pp. 830-848, 1988.

[3] C. Bahlmann, G. Heidemann, and H. Ritter, "Artificial Neural Networks for Automated Quality Control of Textile Seams," *Pattern Recognition*, vol. 32, pp. 1049-1060, 1999.

[4] J. W. Tucker, "Inside Beverage Can Inspection: An Application from Start to Finish," presented at *Proc. of the Vision '89 Conference*, 1989.

[5] A. R. Novini, "Fundamentals of Machine Vision Inspection in Metal Container Glass Manufacturing," presented at *Vision '90 Conference*, 1990.

[6] J. Ker and K. Kengskool, "An Efficient Method for Inspecting Machine Parts by a Fixtureless Machine Vision System," presented at *Vision '90 Conference*, 1990.

[7] T. Torres, J. M. Sebastian, R. Aracil, L. M. Jimenez, and O. Reinoso, “Automated Real-Time Visual Inspection System for High-Resolution Superimposed Printings,” *Image and Vision Computing*, vol. 16, pp. 947-958, 1998.
[8] L. Shafarenko, M. Petrou, and J. Kittler, “Automatic Watershed Segmentation of Randomly Textured Color Images,” *IEEE Trans. on Image Processing*, vol. 6, pp. 1530-1543, 1997.
[9] H. Li and J. C. Lin, “Using Fuzzy Logic to Detect Dimple Defects of Polisted Wafer Surfaces,” *IEEE Transactions on Industry Applications*, vol. 30, pp. 1530-1543, 1994.
[10] A. Mital, M. Govindaraju, and B. Subramani, “A Comparison between Manual and Hybrid Methods in Parts Inspection,” *Integrated Manufacturing Systems*, vol. 9, pp. 344-349, 1998.
[11] P. Kopardekar, A. Mital, and S. Anand, “Manual, Hybrid and Automated Inspection Literature and Current Research,” *Integrated Manufacturing Systems*, vol. 4, pp. 18-29, 1993.
[12] O. Oyeleye and E. A. Lehtihet, “A Classification Algorithm and Optimal Feature Selection Methodology for Automated Solder Joint Inspection,” *Journal of Manufacturing Systems*, vol. 17, pp. 251-262, 1998.
[13] C. Taylor, J. Graham, and D. Cooper, “System Architectures for nteractive Knowledge-Based Image Interpretation,” *Philosophical Transactions of the Royal Society of London (A) Mathematical and Physical Sciences*, vol. 324, pp. 457-465, 1988.
[14] P. Baglietto, M. Maresca, M. Migliardi, and N. Zingirian, “Image Processing on High-Performance RISC Systems,” *Proceedings of the IEEE*, vol. 84, pp. 917-930, 1996.
[15] M. Magee and S. Seida, “An Industrial Model-Based Computer Vision System,” *Journal of Manufacturing Systems*, vol. 14, pp. 169-186, 1995.
[16] M. Moganti, F. Ercal, C. H. Dagli, and S. Tsunekawa, “Automatic PCB Inspection Algorithms: A Survey,” *Computer Vision and Image Understanding*, vol. 63, pp. 287-313, 1996.
[17] S. M. Bhandarkar, T. D. Faust, and M. Tang, “CATALOG: A System for Detection and Rendering of Internal Log Defects Using Computer Tomography,” *Machine Vision and Applications*, vol. 11, pp. 171-190, 1999.
[18] A. R. Jimenez, A. K. Jain, R. Ceres, and J. L. Pons, “Automatic Fruit Recognition: A Survey and New Results Using Range/Attenuation Images,” *Pattern Recognition*, vol. 32, pp. 1719-1736, 1999.
[19] R. T. Chin and C. A. Harlow, “Automated Visual Inspection: A Survey,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 6, pp. 557-573, 1982.
[20] R. T. Chin, “Automated Visual Inspection: 1981 to 1987,” *Computer Vision Graphics Image Processing*, vol. 41, pp. 346-381, 1988.
[21] T. S. Newman and A. K. Jain, “A Survey of Automated Visual Inspection,” *Computer Vision and Image Understanding*, vol. 61, pp. 231-262, 1995.
[22] B. C. Eduardo, “Review of Automated Visual Inspection 1983 to 1993-Part I: Conventional Approaches,” *SPIE-Intelligent Robots and Computer Vision XII*, vol. 2055, pp. 128-158, 1993.
[23] B. C. Eduardo, “Review of Automated Visual Inspection 1983-1993-Part II: Approaches to Intelligent Systems,” *SPIE-Intelligent Robots and Computer Vision XII*, vol. 2055, pp. 159-172, 1993.
[24] J. M. R. Sanches and M. S. Piedade, “An Automatic Visual Inspection System of the Quality of Painting of Metal Film Mini Resistors,” presented at *International Conference on Signal Processing Applications and Technology (ICSPAT'97)*, 1997.
[25] W. Miller, J. Jaskot, B. McCoy, and E. Schiller, “A Distributed System for 100% Inspection of Aluminum Sheet Products,” presented at *International Conference on Signal Processing Applications and Technology (ICSPAT'96)*, 1996.

[26] I. Khandogin, A. Kummert, and D. Maiwald, “Automatic Damage Detection for Railroad Tracks by the Analysis of Video Images,” presented at *International Conference on Signal Processing Applications and Technology (ICSPAT'97)*, 1997.
[27] B. C. Jiang and S. J. Jiang, “Machine Vision Based Inspection of Oil Seals,” *Journal of Manufacturing Systems*, vol. 17, pp. 159-166, 1998.
[28] M. Barni, V. Cappellini, and A. Mecocci, “Colour-Based Detection of Defects on Chicken Meat,” *Image and Vision Computing*, vol. 15, pp. 549-556, 1997.
[29] A. J. Lacey, N. A. Thacker, S. Crossley, and R. B. Yates, “A Multi-Stage Approach to the Dense Estimation of Disparity from Stereo SEM Images,” *Image and Vision Computing*, vol. 16, pp. 373-383, 1998.
[30] D. M. Tsai and C. Y. Hsieh, “Automated Surface Inspection for Directional Textures,” *Image and Vision Computing*, vol. 18, pp. 49-62, 1999.
[31] D. M. Tsai, J. J. Chen, and J. F. Chen, “A Vision System for Surface Roughness Assessment Using Neural Networks,” *Int. J. Adv. Manuf. Technology*, vol. 14, pp. 412-422, 1998.
[32] M. L. Smith, G. Smith, and T. Hill, “Gradient Space Analysis of Surface Defects Using a Photometric Stereo Derived Bump Map,” *Image and Vision Computing*, vol. 17, pp. 321-332, 1999.
[33] P. R. Park and M. S. Packianather, “A Decision Tree of Neural Networks for Classifying Images of Wood Veneer,” *International Journal of Advanced Manufacturing Technology*, vol. 14, pp. 280285, 1998.
[34] M. S. Packianathe and P. R. Park, “Neural Networks for Classifying Images of Wood Veneer, Part II,,” *International Journal of Advanced Manufacturing Technology*, vol. 16, pp. 424-433, 2000.
[35] K. L. Boyer and T. Ozguner, “Robust Online Detection of Pipeline Corrosion from Range Data,” *Machine Vision and Applications*, vol. 12, pp. 291-304, 2001.
[36] T. H. Hou and M. D. Pern, “A Computer Vision-Based Shape-Classification System Using Image Projection and a Neural Network,” *International Journal of Advanced Manufacturing Technology*, vol. 15, pp. 843-850, 1999.
[37] T. H. Kim, T. H. Cho, Y. S. Moon, and S. H. Park, “Visual Inspection System for the Classification of Solder Joints,” *Pattern Recognition*, vol. 32, pp. 565-575, 1999.
[38] S. Janannathan, “Automatic Inspection of Wave Soldered Joints Using Neural Networks,” *Journal of Manufacturing Systems*, vol. 16, pp. 389-398, 1997.
[39] R. J. Hunsicker, J. Patten, A. Ledford, C. Ferman, and M. Allen, “Automatic Vision Inspection and Measurement System for External Screw Threads,” *Journal of Manufacturing Systems*, vol. 13, pp. 370-383, 1994.
[40] P. Andrey, “Selexionist Relaxation: Genetic Algorithms Applied to Image Segmentation,” *Image and Vision Computing*, vol. 17, pp. 175-187, 1999.
[41] R. Cucchiara, “Genetic Algorithms for Clustering in Machine Vision,” *Machine Vision and Applications*, vol. 11, pp. 1-6, 1998.
[42] J. Y. Goulermas and P. Liatsis, “Genetically Fine-Tuning the Hough Transform Feature Space, for the Detection of Circular Objects,” *Image and Vision Computing*, vol. 16, pp. 615-625, 1998.
[43] D. M. Tsai, “A Machine Vision Approach for Detecting and Inspecting Circular Parts,” *Int. J. Adv. Manuf. Technology*, vol. 15, pp. 217-221, 1999.
[44] M. Kavoussanos and A. Pouliezzos, “An Intelligent Robotic System for Depalletizing and Emptying Polyethylene Sacks,” *International Journal of Advanced Manufacturing Technology*, vol. 14, pp. 358-362, 1998.
[45] Y. R. Shiau and B. C. Jiang, “Study of a Measurement Algorithm and the Measurement Loss in Machine Metrology,” *Journal of Manufacturing Systems*, vol. 8, pp. 22-34, 1999.

[46] A. R. Jimenez, R. Ceres, and J. L. Pons, “A Vision System Based on a Laser Range-Finder Applied to Robotic Fruit Harvesting,” *Machine Vision and Applications*, vol. 11, pp. 321-329, 2000.
[47] S. Anard, C. McCord, and R. Sharma, “An Integrated Machine Vision Based System for Solving the Nonconvex Cutting Stock Problem Using Genetic Algorithms,” *Journal of Manufacturing Systems*, vol. 18, pp. 396-414, 1999.
[48] H. K. Tonshoff, C. Soehner, and G. Isensee, “Vision-Guided Tripod Material Transport System for the Packaging Industry,” *Robotics and Computer-Integrated Manufacturing*, vol. 13, pp. 1-7, 1997.
[49] J. J. Hunter, J. Graham, and C. J. Taylor, “User Programmable Visual Inspection,” *Image and Vision Computing*, vol. 13, pp. 623-628, 1995.
[50] D. Tretter, C. A. Bouman, K. W. Khawaja, and A. A. Maciejewski, “A Multiscale Stochastic Image Model for Automated Inspection,” *IEEE Trans. on Image Processing*, vol. 4, pp. 1641-1654, 1995.
[51] I. Khandogin, A. Kummert, and D. Maiwald, “DSP Algorithms for the Automatic Inspection of Fixing Devices of Railroad Lines,” presented at *International Conference on Signal Processing Applications and Technology (ICSPAT'98)*, 1998.
[52] J. Velten, A. Kummert, and D. Maiwald, “Real Time Railroad Tie Inspection Implemented On DSP And FPGA Boards,” presented at *International Conference on Signal Processing Applications and Technology (ICSPAT '99)*, 1999.
[53] K. H. Kim, Y. W. Kim, and S. W. Suh, “Automatic Visual Inspection System to Detect Wrongly Attached Components,” presented at *International Conferernce on Signal Processing Applications and Technology (ICSPAT'98)*, 1998.
[54] Y. K. Chung, K. H. Kim, and H. B. Kim, “Extracting of Line Features for Automatic Inspection of Vehicle Doors,” presented at *International Conference on Signal Processing Applications and Technology (ICSPAT)*, 1997.
[55] T. F. Cootes, G. J. Page, C. B. Jackson, and C. J. Taylor, “Statistical Grey-Level Models for Object Location and Identification,” *Image and Video Computing*, vol. 14, pp. 553-540, 1996.
[56] J. Y. Jeng, T. F. Mau, and S. M. Leu, “Gap Inspection and Alignment Using a Vision Technique for Laser Butt Joint Welding,” *International Journal of Advanced Manufacturing Technology*, vol. 16, pp. 212-216, 2000.
[57] M. Moreira, E. Fiesler, and G. Pante, “Image Classification for the Quality Control of Watches,” *Journal of Intelligent and Fuzzy Systems*, vol. 7, pp. 151-158, 1999.
[58] S. Jagannathan, D. Seebaluck, and J. D. Jenness, “Intelligent Inspection of Wave Soldered Joints,” *Journal of Manufacturing Systems*, vol. 11, pp. 137-143, 1992.
[59] S. Haykin, *Neural Networks*: Prentice-Hall, 1999.
[60] N. K. Bose and P. Liang, *Neural Network Fundamentals with Graphs, Algorithms, and Applications*: McGraw-Hill, 1996.
[61] J. Chang, G. Han, J. M. Valverde, N. C. Griswold, J. F. Duque-Carrillo, and S. E., “Cork Quality Classification System using a Unified Image Processing and Fuzzy-Neural Network Methodology,” *IEEE Transactions on Neural Networks*, vol. 8, pp. 964-973, 1997.
[62] T. Sarkodie-Gyan, C. W. Lam, D. Hong, and A. W. Campbell, “An Efficient Object Recognition Scheme for a Prototype Component Inspection,” *Mechatronics*, vol. 7, pp. 185-197, 1997.
[63] Y. H. Chen, “Computer Vision for General Purpose Visual Inspection: a Fuzzy Logic Approach,” *Optics and Lasers in Engineering*, vol. 22, pp. 181-192, 1995.
[64] J. C. Bezdek, J. Keller, R. Krisnapuram, and N. R. Pal, *Fuzzy Models and Algorithms for Pattern Recognition and Image Processing*: Kluwer, 1999.

[65] S. K. Pal and S. Mitra, *Neuro-Fuzzy Pattern Recognition: Methods in Soft Computing*: Willey, 1999.
[66] G. A. Carpenter, S. Crossberg, N. Markuzon, J. H. Reynolds, and D. B. Rosen, "Fuzzy ARTMAP: A Neural Network Architecture for Incremental Supervised Learning of Analog Multidimentional Maps," *IEEE Transactions on Neural Networks*, vol. 3, 1992.
[67] U. H. Kuo, J. P. Hsu, and C. I. Kao, "MCFC: A Fuzzy Neural Network Model for Speech Recognition," *Journal of Intelligent and Fuzzy Systems*, vol. 4, pp. 257-268, 1996.
[68] K. C. Zikidis and A. V. Vasilakos, "ASAFES2: A Novel Neuro-Fuzzy Architecture for Fuzzy Computing Based on Functional Reasoning," *Fuzzy Sets and Systems*, vol. 83, pp. 63-84, 1996.
[69] J. S. Jang, "ANFIS: Adaptive-Network-based Fuzzy Inference Systems," *IEEE Transactions on Systems, Man and Cybernetics*, vol. 23, pp. 63-84, 1993.
[70] C. T. Lin and C. S. G. Lee, *Neural Fuzzy Systems, A Neuro-Fuzzy Synergism to Intelligent Systems*. NJ: Prentice Hall, 1996.
[71] D. E. Golberg, *Genetic Algorithms in Search, Optimization and Machine Learning*: Addion-Wesley, 1999.
[72] S. M. Bhandarkar and H. R. Arabnia, "Parallel Computer Vision on a Reconfigurable Multiprocessor Network," *IEEE Transactions on Parallel and Distributed Systems*, vol. 8, pp. 292-309, 1997.
[73] T. Komuro, I. Ishii, and M. Ishikawa, "General-Purpose Vision Chip Architecture for Real-Time Machine Vision," *Advanced Robotics*, vol. 12, pp. 619-627, 1999.
[74] D. W. Hammerstrom and D. P. Lulich, "Image Processing Using One-Dimensional Processor Arrays," *Proceedings of IEEE*, vol. 84, pp. 1005-1018, 1996.
[75] C. L. Wang, P. B. Bhat, and K. Prasanna, "High-Performance Computing for Vision," *Proceedings of the IEEE*, vol. 84, pp. 931-946, 1996.
[76] S. Fathnam and G. Slavenburg, "Processing the New World of Interactive Media: The Trimedia VLIW CPU Architecture," *IEEE Signal Processing Magazine*, vol. 15, pp. 108-117, 1998.
[77] S. Purcell, "The Impact of Mpact 2: The Mpact 2 VLIW Media Processor Improves Multimedia Performance in PCs," *IEEE Signal Processing Magazine*, vol. 15, pp. 102-107, 1998.
[78] J. McKrory and M. Daniels, "The Impact of New Technology in Machine Vision," *Sensor Review*, vol. 15, pp. 8-11, 1995.
[79] E. J. Delp, "Image-Processing Software and Hardware," *IEEE Signal Processing Magazine*, vol. 15, pp. 8-11, 1997.
[80] D. L. Dechow, "Fundamentals of Machine Vision Systems Integration," presented at *The Vision Show*, 1997.
[81] D. Braggins, "Recent Developments in Image Capture for Machine Vision," *Sensor Review*, vol. 15, pp. 11-14, 1995.
[82] M. Loinaz and B. Ackland, "Video Cameras: CMOS Technology Provides On-Chip Processing," *Sensor Review*, vol. 19, pp. 19-26, 1999.
[83] M. Schanz, W. Brockherde, R. Hauschild, B. J. Hosticka, and A. Teuner, "CMOS Photosensor Arrays With On-Chip Signal Processing," presented at *Proc. Of European Solid State Circuits Conference (ESSCIRC'97)*, Southampton U.K., 1997.
[84] E. R. Fossum, "CMOS Image Sensors: Electronic Camera-On-A-Chip," *IEEE Transactions on Electron Devices*, vol. 44, pp. 1689-1698, 1997.
[85] K. Yamada, T. Nakano, and S. Yamamoto, "Robot Vision Robust to Changes of Lighting Conditions Using a Wide-Dynamic Range Visual Sensor," *Electrical Engineering in Japan*, vol. 120, pp. 34-40, 1997.

[86] K. Yamada, T. Nakano, and T. Yamamoto, "A Vision Sensor Having an Expanded Dynamic Range for Autonomous Vehicles," *IEEE Transactions on Vehicular Technology*, vol. 47, pp. 332-341, 1998.
[87] D. Braggins, "Creating the Right Image," *Sensor Review*, vol. 16, pp. 16-21, 1996.
[88] "MotionVision Cameras-CA-D8: 1O/P, 25MHz," : Dalsa Specification Datasheet, 2000.
[89] "RACIC810/811 Random Access Charge Injection Device Imaging Sensors," : CIDTEC Specification Datasheet, 2000.
[90] "VV5500/6500 Multi Format Digital Output Sensor," : VLSI Vision Inc. Specification Datasheet, 2000.
[91] D. Litwiller, *CCD vs. CMOS: Facts and Fiction*: Laurin Publishing, 2001.
[92] C. Seibold, "Comparison of CMOS and CCD Image Sensor Technologies," : ECE 442 Senior Design, 2002.
[93] "CMOS vs. CCD and the Future of Imaging," , 2001.
[94] R. Hauschild, M. Hillebrand, B. J. Hosticka, J. Huppertz, T. Kneip, and M. Schwarz, "ACMOS Image Sensor with Local Brightness Adaptation and High Intrascene Dynamic Range," presented at *European Solid State Circuits Conference (ESSCIRC'97)*, The Hague, The Netherlands, 1999.