Robot Vision in Industrial Assembly and Quality Control Processes

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1. Introduction

In modern industrial assembly and quality control processes, that provide one of the crucial factors for the competitiveness of industry in general, there is a strong need for advanced robot-based object detection and recognition, object grasping and for the capability to perform assembling operations in non-structured environments with randomly positioned objects. Vision-based robotic assembly and quality control systems, that have been a topic of continued research interest for almost four decades, have now matured to a point where they can be effectively applied to advanced robot-based assembly and quality control tasks. This chapter will give an overview of research work related to the field of automated vision systems for assembly and quality control processes.

The nowadays' economy is more concentrated on producing customized products, however, and much less focused on mass manufacturing. In such an economy the need is far more dependent on ease of use, higher degrees of adaptation including assembling operations and control processes in non-structured environments with diversified and randomly positioned objects that enable small runs of made-to-order products. Automating a manual visual inspection process through a robot vision environment can create faster cycle times and level rates of throughput. Also robots will be ubiquitous in the industrial assembly of the future (table 1) and will support mass customization in smaller factories, where production runs are short, lot sizes small and products are modular in configuration and highly variable in features (Kellett, 2009).

Robots in Manufacturing	Today	Future
Production mode	Mass production	Mass Customization
Production runs	Long	Short
Lot sizes	Large	Small
Product configurations	Non-modular	Modular
Product features	Limited variety	Highly variable

Table 1. Robots in Manufacturing: Today Versus the Future (Kellett, 2009)

As advanced robotic systems are becoming more popular and widespread in many industrial assembly settings, the need for reliable operation with the least possible amount of downtime is a common, expected demand. Traditional assembly robots are programmed to pick up a part from the exact same location every time and if the part is even slightly out of the place, the robot will fail to pick that part. Significant advantages can be realized when these robots are coupled with vision systems. Modern robot vision configurations with advanced recognition systems are used more often in later time to adjust the coordinates from where the robot expected to find the object to where it actually is located. This can be achieved with using only a single camera, multiple cameras or different combination systems. Cameras, computer and software work together with the robot to adjust the robot's position, allowing retrieval of the part. One of the examples in this direction is the continued improvements to 3D robot vision. The advances in 3D vision have made robots adept at recognizing a changing environment and adapting to it. This flexibility has allowed robots to work on projects that lack precise consistency, something that was very difficult for a robot to do in the past. Nowadays, robotic vision research is expanding into many new areas. Robots can now pick variously shaped objects from an indexing conveyor, eliminating the need for part designated in-feed systems and machines (figure 1). Research in this area has even made it feasible to pick from a box for certain part configurations (Christe, 2009).

Fig. 1. Vision Guided Robotic Flexible Feeding (Christe, 2009)

Many current vision systems require extensive support from trained experts and are less reliable due to their complexity. This is the main reason why a fundamental step change to simplify the programming and mechanical complexity of robotic guidance applications is necessary. An innovative vision scheme is only half the battle. Mechanical reliability also plays an important role.

Implementation of robot vision in assembly and quality control processes is a multilayer problem and demands therefore expert knowledge, experiences, innovations and most often a problem specific solution. Usually, the procedure of the planning and development of a process of an assembly, inspection and measurement equipment using machine vision is split into precise determination of tasks and goals like detection, recognition, grasping, handling, measurement, fault detection, etc. and into machine vision component selection and working conditions determination like camera, computer, lenses and optics,

illumination, position determination, etc. With regard to the automatic assembly part handling, robotic handling and assembly systems offer good prospects for the rationalization and flexibilisation of assembly and quality control processes.

Fig. 2. Vision equipped robot in a bin picking application (Brumson, 2009)

Machine vision will certainly help take robot based assembly to the next level, and machine vision will probably be a part of the next generation safety solution. Off-the-shelf products already offer work cell protection based on 360-degree vision technology, and more robot controllers now come with built-in machine vision capability. Very frequently used operation in industrial assembly, a random part bin picking (figure 2), will probably benefit from such advancements, as will other complex tasks too (Brian, 2008).

2. Industrial assembly

Industrial assembly is a part of the production process (figure 3) and can be defined as an ordered sequence of physical handling tasks in which discrete parts and components are brought together and joined or mated to form a specified configuration. Assembly is a production process operation that provides a crucial factor for the competitiveness of industry in general. It is surprising, that such an important manufacturing process, that can take up to 30% of the manufacturing cost of an end product (Rowland & Lee, 1995), is still mainly performed by hand. Manual assembly becomes expensive, if high levels of quality are to be achieved, because it involves highly skilled human laborers. Also much verification and inspection is needed to compensate for potential human insufficiencies. Manual assembly is often difficult, tedious and time consuming.

Fig. 3. Assembly as part of the production process (Rampersad, 1994)

For this reason it is often difficult for companies to follow market demands, when their assembly is mainly based on manual assembly processes. This becomes even truer, as the market requires products which satisfy high expectations in the areas of quality, price and delivery time. The key word in achieving this goal is the continuous refinement of product and production. Assembly is often the weakest point in the whole production process, because this activity takes up a substantial part of the total production costs and the throughput time (figure 4). The main reasons for this fact are the increasing labour costs, product variety and the decreasing product quantity.

Taking into consideration all these facts, together with constant price cuts for robots and overall turnkey systems in assembly and especially with continually improving performance of robots and machine vision systems, it is possible to understand the reasons for considerable grow of the area of robot-based assembly in the world in the last few years Robotic assembly offers good perspectives also in small and medium sized batch production (Handelsman, 2006; Kellett, 2009; Christe, 2009; Rowland & Lee, 1995; Rampersad, 1994).

Assembly, as a part of production systems, involves handling of parts and subassemblies, which have mostly been manufactured at different times and possibly even in separate locations (Nof et al., 1997). Assembly tasks thus result from the requirement to join certain individual parts, subassemblies and substances such as lubricants and adhesives into final assemblies of higher complexity in a given quantity and within a given time period.
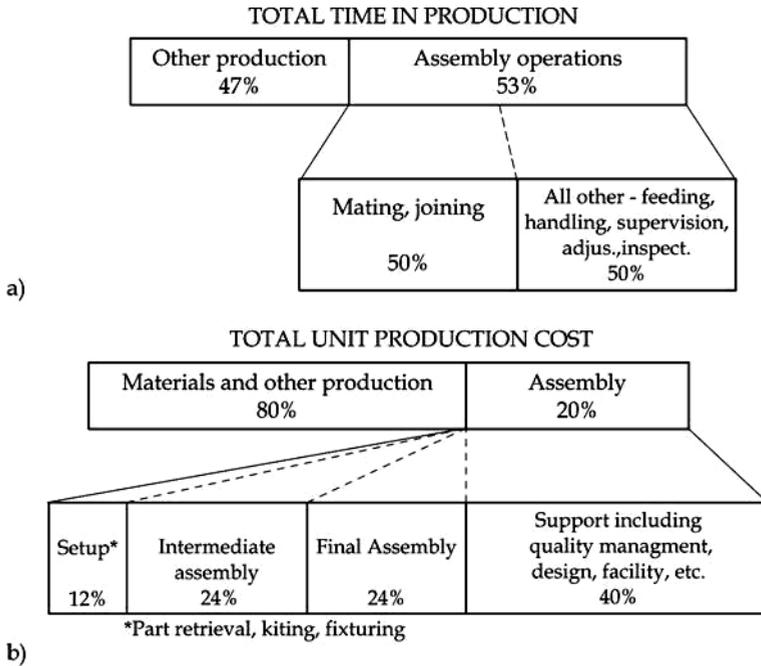
TOTAL TIME IN PRODUCTION

Other production 47%	Assembly operations 53%

Mating, joining 50%	All other - feeding, handling, supervision, adjus.,inspect. 50%

a)

TOTAL UNIT PRODUCTION COST

Materials and other production 80%	Assembly 20%

Setup* 12%	Intermediate assembly 24%	Final Assembly 24%	Support including quality managment, design, facility, etc. 40%

*Part retrieval, kiting, fixturing

b)

Fig. 4. Typical average breakdown of a) production time and b) production costs of industrial products (Nof et al. 1997)

A typical assembly cell, which exact configuration may vary, will comprise of computer-controlled devices (robots, grippers, etc.), components and fixtures that can functionally accomplish or support one or all of the following tasks (Cecil et al., 2007):

- grasping of an organized/randomly positioned target part from a belt or a bin,
- manipulation and placement/assembly of parts,
- part and object recognition before, during and after assembly,
- quality control and inspection,
- planning and control of the actuators and grippers to accomplish the physical assembly.

Industrial robots nowadays can perform assembly and material handling jobs with very high speed and impressively high precision. However, compared to human operators, robots are hampered by their lack of sensory perception and their need for advanced sensorial capabilities in order to achieve more sophisticated tasks in a non-structured environment (King et al., 1988; Peňa-Cabera et al., 2005). In assembly processes, computer vision is often required to provide data to the applied robot systems in order to allow reliable grasping of objects and performing assembly tasks. Using a vision system for assembly often involves several challenges especially in the areas of data aquisition, coordinate transformation, invariant object recognition with vision systems as well as for the configuration and integration of vision systems into the robot environment.

3. Computer and robot vision

Robot vision is concerned with the sensing of vision data and its interpretation by a computer and thus serves as a versatile robotic sensor. There is a growing demand requiring more complex and faster image processing capabilities in order to allow the implementation of vision systems into sophisticated industrial applications, like advanced assembly automation is.

Robot or machine vision is the application of computer vision to industry and manufacturing, mainly in robots. As computer vision is mainly focused on machine-based image processing, robot vision most often requires also digital input/output devices and computer networks to control other manufacturing equipment such as robotic arms (Davies, 2005). Specific advantages of robot vision systems include precision, consistency, cost effectiveness and flexibility.

Because of its primary mission, a computer vision is a part of a research discipline called artificial intelligence. Many methods, like neural networks and machine learning, developed in the field of artificial intelligence are used in computer vision. Computer vision is also linked with other research disciplines like neurophysiology, psychophysics, physics, computer graphics, digital signal processing etc. (Solina, 2006).
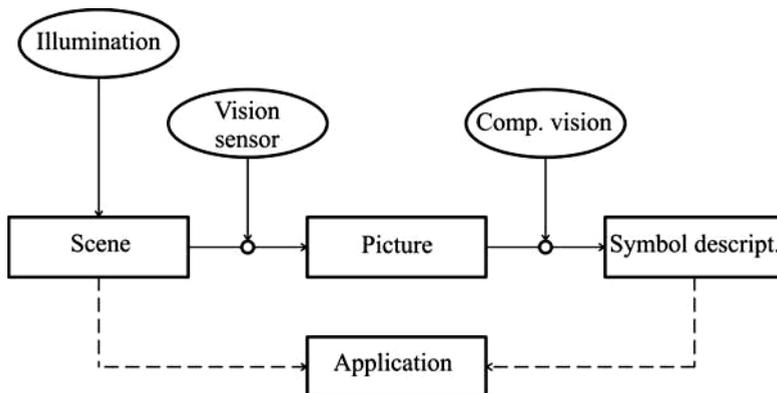
Fig. 5. Structure of a typical computer vision system (Solina, 2006)

Nevertheless, there are many research works being performed in this direction. In many cases in the area of assembly processes, especially in bin picking, a robot must perceive its 3-D environment to be effective. Jet recovering 3-D information and describing it still remains the subject of fundamental research. Some research works (Gupta & Knopf, 1993; Hou et al., 2007; Shapiro & Stockman, 2001) are dealing with artificial vision systems based on the neural morphology of the biological human vision system, aiming to design computational neural structures and artificial vision systems following neural paradigms, mathematical models and computational architectures (Neuro –Vision Systems). Basic components of the computer vision system are presented in figure 5. Appearance of a 3-D scene depends mostly on illumination, position and the direction of the vision sensor.

In a robot vision system, a variety of components are included. The systems layout mainly depends on factors like the environment, the application and the budget. Nevertheless, there are several common ingredients to all vision systems. A typical robot or machine vision system for assembly tasks consists of several of the following components (Davies, 2005; Griot, 2009; Batchelor, 2006; Batchelor & Whelan, 2002):

- one or more digital or analogue cameras (black-and-white or colour) with suitable optics for acquiring images,
- a camera interface for digitizing images (frame grabber) – depends on the application,
- a processor (often a PC or embedded processor, such as a DSP) – when processors and frame grabbers are integrated into the camera itself, such cameras are called »smart cameras«,
- input/Output hardware or communication links,
- optics - lenses to focus the desired field of view onto the image sensor,
- light source (LED, fluorescent or halogen lamps etc.),
- a program to process images and detect relevant features,
- a synchronizing sensor for part detection to trigger image acquisition and processing,
- actuators to sort or reject the processed parts.

Analog systems with classical frame grabbers have become well established in the marketplace and are built into many machines nowadays. The change from analog to digital technologies in the industrial image-processing sector causes that the classical frame grabber appears to be increasingly headed out to pasture. This is because digital communications interfaces such as Gigabit Ethernet, USB and FireWire allow for adequate camera-based solutions without image-capture cards (Leumann, 2009). The classical frame grabber is nowadays usually implemented in new projects primarily when a very short and calculable latency period plays a role in transmission of image data, such as for use with line scanning cameras or for implementation of high-speed cameras. They require data bandwidth from 25 to 70 megabytes per second, which exceeds the bit-serial standards such as USB 2.0, FireWire and Gigabit Ethernet. Additionally, the CameraLink Standard can achieve data-transfer rates up to 680 Mbps. So the classical frame grabber as plug-in card will have to support the CameraLink Standard for a long time to come.

Digital technology has some significant advantages in comparison to the analog one:
- digital image-processing systems allow significantly better image quality,
- up to 12-bit dynamic range,
- the camera's parameters can be set using software,
- the camera's availability, as well as its properties, can be maintained remotely,
- upgrading the camera in the field is easily achieved etc.

The most commonly used vision sensors in robot-based assembly are nowadays black-and-white (or colour for some applications) CCD (charge-coupled device) cameras. 2D-vision systems consist of standard industrial CCD cameras used to take images that are processed by the robot to make decisions on how parts should be handled. Such systems are appropriate for parts, which are laying flat on a belt or in a bin with separator sheets.

For parts that can stack upon each other or that may shift from side to side as the parts stack up or when parts are oriented randomly in a bin, depth estimation for a vision system is necessary. For depth estimation most commonly stereo vision systems are used. For such applications 3-D vision systems have to be applied to get a range image and the orientation of a part in 3D-space. Different laser sensors in conjunction with 2-D cameras, sensors with structured light and stereo cameras, together with different algorithms, can provide 3-D information (Baba et al., 2004; Thorsley et al., 2004; Schraft & Ledermann, 2003). Even though these systems work well, stereo vision systems can provide inaccurate depth estimations, especially in cases with texture-less regions of images or in situations with insufficient illumination of the scene. Most of all, stereo vision is fundamentally limited by the baseline distance between the two cameras, which tends to provide inaccurate depth estimations, as the distances considered are getting large.

Different research approaches are addressing the depth estimation problem by using monocular visual cues, such as texture variations and gradients, defocus, colour etc. With applying a Markov Random Field learning algorithm to capture some of these monocular cues and with incorporating them into a stereo vision system, a significantly better accuracy in depth estimation is obtained than it is possible using either monocular or stereo cues alone (Saxena et al., 2007 a; Saxena et al., 2007 b).

Some other papers treat monocular 3-D vision and object pose estimation in a robot assembly environment. The approach described by L. P. Ray (Ray, 1990) is based on the estimation of the three dimensional position and orientation of objects from one or more monocular images on the prerequisite that the identities of the objects are known and that the three dimensional geometrical models are available. The main weakness of these solutions is the fact, which they fail to achieve the real time performance, necessary in many assembly applications. A solution of this problem is proposed by (Winkler et al., 1997). In this research approach a feature map strategy for the real time 3-D object pose estimation from single 2-D perspective views is presented. Based on the neural network and the systematic training of the Kohonen's self-organizing feature map, the method satisfies the accuracy requirements of object pose estimation in more than 90% of all considered cases.

With the intention to achieve an economic and flexible automatic assembly system working with a SCARA-robot, operating in a random environment, some research activities present the use of simple 2-D CCD cameras in conjunction with additional force sensors and embedded fuzzy sliding mode controllers (Scharstein & Szelinski, 2002). The experimental results prove that the robotic motion control performance is good enough for executing the investigated assembly tasks.

The paper of Sharstein and Szelinski offers a very good overview of stereo vision systems and algorithms, developed by different researchers over the past few decades. In their work the authors present the taxonomy of dense, two-frame stereo methods, compare existing stereo methods and present experiments evaluating the performance of many different variants.

In robotic assembly, vision sensors have a different role than - for example - in mobile robots, where the tasks usually involve exploration of the environment. A robotic assembly

cell represents a relatively well ordered environment and is part of an integrated manufacturing process, rather than operating in isolation. This facilitates the fulfillment of some of the major requirements for effective robot assembly. This is especially helpful for applications where expensive and complex machine vision systems should be avoided. The application of vision systems in robot-based assembly systems can be simplified, when products and components are designed for a robot-based assembly and if parts are fed to the system with a relatively accurate position and orientation (Boothroyd, 2005).

The slightly asymmetrical screwed part (figure 6) would not present significant problems in manual handling and insertion, whereas for automatic handling, an expensive vision system would be needed to recognize its orientation. In fact, it can be said that one of the possible benefits of introducing automation in the assembly of a product is, that it forces a reconsideration of its design, which might not only facilitate the part recognition but might also be used to implement other cost-saving or quality-related improvements (e.g. Poka-Yoke design).
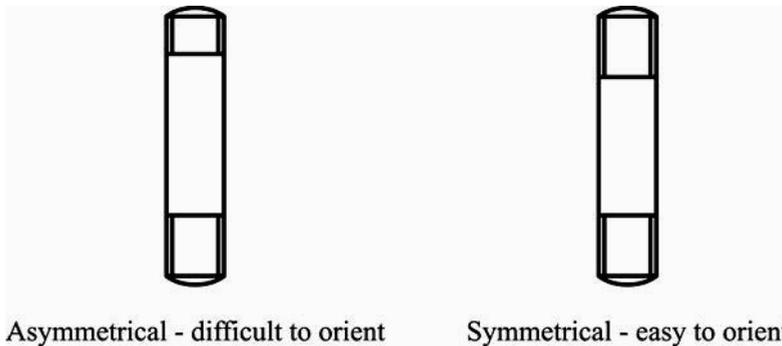

Fig. 6. Design change to simplify automatic feeding and orientation (Boothroyd, 2005)

The major role of vision sensors in a robot assembly cell is to compare reality with expectations and to evaluate discrepancies. Essentially this means detecting presence or absence of correct parts and measuring to allow for the detection of component tolerances and positioning errors during relevant stages of assembly.

On one hand, many industrial assembly applications are successfully being handled nowadays using computer vision and robots, especially in robot-based assembly cells. However, for these applications objects have a simple (2D) shape and/or are organized in a structured manner. On the other hand, a general so-called »Bin-picking«, where the objects have a 3-D shape and are randomly organized in a box, still remains a problem. Despite of many research works, that offer special solutions and improvements in the overcoming the bin-picking problem (Schraft & Ledermann, 2003; Kirkegaard, 2005; Kirkegaard & Moeslud, 2006; Hema et. al., 2007), the oldest challenge in robotics remains still unsolved.

4. Object recognition

In robot assembly, a vision recognition system aims to mimic the human sense of vision and must be capable of perceiving and detecting assembly parts as good as the humans can. Three-dimensional object recognition entails representation of a 3-D object, identification of

the object from its image, estimation of its position and orientation and registration of multiple views of the object for automatic model construction. Important stages in the design and development of a recognition system are presented in figure 7.
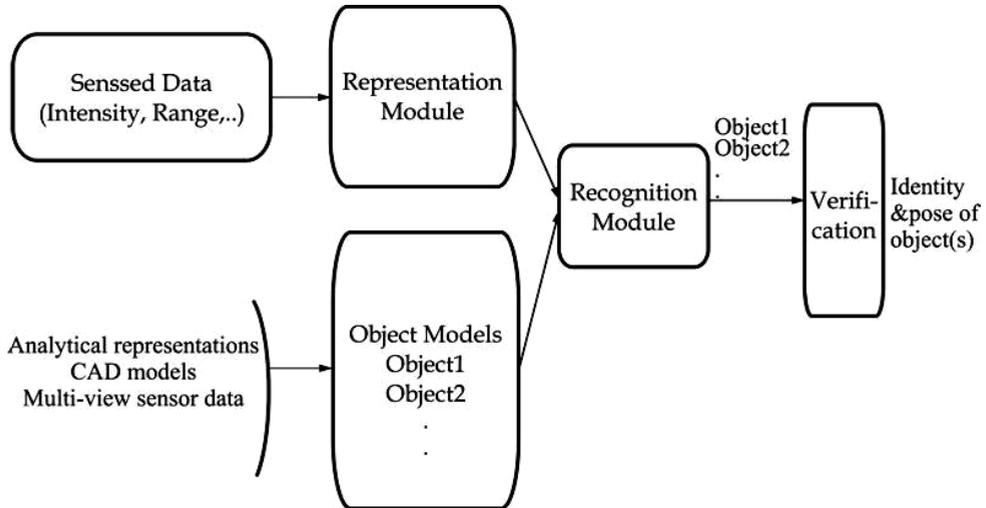

Fig. 7. Key components of a 3-D object recognition system (Jain & Dora, 2000)

A typical approach for handling the object recognition tasks using traditional image processing and computer vision methods usually consists of five steps (Kirkegaard, 2005; Jain & Dora, 2000; Pope, 1994; Faugeras, 1993; Yli-Yaasaki & Ade, 1996):

- Detection or pre-processing – is the low level signal processing which extracts information from the scene and represents it as some form of primitive symbols (Motai & Kosaka, 2004; Pope & Lowe, 2000; Pope & Lowe 1996; Roth et al., 2002; Vujovic et al., 2007).
- Grouping or segmentation – is based on the low level symbols, the primitive features are grouped into higher order features, which give more information for the selection and matching in the next steps (Lowe, 1987; Balslev & Eriksen, 2002).
- Indexing or feature extraction – selecting from the stable object features the most likely model from a library of models (model base) and finding a way of quickly comparing a set of features with a model, avoiding a search through all models. As a critical component, a stable, representative feature extraction system should be developed to extract key features for a specific problem domain in the feature extraction stage. The result of feature extraction is normally a feature vector (Kirkegaard, 2005). There is usually one of two methods of representation applied:
  - appearance-based approach – information about appearance of the object is used (Pope, 1994; Balslev & Eriksen, 2002),
  - model-based methods – information about geometrical features, type and spatial relations of the object is used (Motai & Kosaka, 2004; Lowe, 1987).
- Matching or classification – finding the best fitting between the scene features and the model features and solving the localization problem. In this stage, a classifier system uses extracted key features to distinguish the classes of the objects of interest. The algorithms

or methods for these stages are generally domain dependent, particularly when using traditional image processing and computer vision techniques. Learning paradigms such as neural networks or genetic programming approaches have usually been applied to the matching or classification stage Kirkegaard, 2005).

- Verification – verifying the estimated identity and location of an object (Kirkegaard, 2005, Pope & Lowe, 1996).

To facilitate the task of identification and localization, a description of each object to be recognized is available to the computer and can be used. These descriptions can either be model-based or appearance-based, or a combination of both.

Based on the dimensionality of their spatial description, various types of object recognition problems can be stated (Antrade-Ceto & Kak, 2000):
- recognition of a 2-D object from a single 2-D image,
- recognition of a 3-D object from a single 2-D image,
- recognition of a 3-D object from a single 3-D image (a range map),
- recognition of a 2-D or 3-D object from multiple 2-D images taken from different viewpoints, etc.

In the past decades, much progress has been made in the research of recognizing 2-D objects in single 2-D images and in recognizing 3-D objects in range maps. A considerable progress has also been made in the recognition of 2-D or 3-D objects using multiple 2-D images, as in binocular or stereo vision. However, today object recognition remains largely unsolved and is still a very active field of research.

The data of assembly parts is usually obtained by a CCD camera, giving intensity data or by laser line scanning which gives a range or depth map. From this data, features have to be extracted for object recognition, which involves the matching of image features from either range or intensity data, against a previous internal representation of the object (a model).

Certain features like curvatures are independent of the view point for the object. After inspection of respective signs of an object curvature using different approaches, it is possible to define the local surface area as being one of eight fundamental primitive types: peak, pit, ridge, valley, saddle ridge, saddle valley, minimal and flat. Different algorithms have been proposed to extract curvatures from an object (Fischler & Bolles, 1986; Rosin & West, 1995, Cox et al., 1993). The difficulty of these approaches is that extracted curvatures are highly dependent on the selected starting points and the order of the edge linking. Some other approaches (Alter & Basri, 1998) propose dynamic programming and relaxation to avoid such problems. In this case the edges are organized as nodes of a graph and linked to each other through graphs.

Other common features, which are extracted from objects are edges, planar regions etc. Edge detection is a very important step in low level image processing and can be used in measurement of a distance from the obstacle. In (Vujovic et al., 2007) a new approach is proposed, which promises much faster edge detection capabilities as previously known edge detectors can provide.

Many different approaches and methods have been developed or tackled in the field of object detection and recognition by different researchers in the past years. A quite detailed survey of previous work has been treated by (Jain & Dora, 2000) and (Antrade-Ceto & Kak, 2000). The authors discuss the recognition problems, methodologies and algorithms like object shape complexity, size of object model database, learning, individual and generic object categories, non-rigidity of objects, occlusion and viewpoint-dependency, object representations and recognition strategies (image sensors, models, matching strategies) and 3-D free form object recognition.

A very important field of research in object recognition is represented by the area of learning/adaptive algorithms. One of the major advantages of a learning system is the ability to learn/extract the useful features from the training data set and to apply these features to the test data. Some authors (Roth et al., 2002) use a PAC (Probably Approximately Correct) model for their learning strategies. In this research, authors quantify success relatively to the distribution of the observed objects, without making assumptions on the distribution. In (Pope & Lowe, 1996) authors model the appearance of an object using multiple views, including a training stage, in which the system learns to extract the models characteristics from training images and recognizes objects with it. The model uses probability distributions to characterize the significance, position, intrinsic measurements of various discrete features of appearance and also describes topological relations among features. A matching procedure, combining qualities of both iterative alignment and graph matching uses feature uncertainty information recorded by the model to guide the search for a match between model and image.

In recent years, since the late 1980s, neural and genetic learning paradigms (neural networks, genetic paradigms and genetic programming) have attracted attention as very promising methods of solving automatic target recognition and detection problems. In particular, neural and genetic systems offer potentially powerful learning and adaptive abilities and are very suitable for automatic object recognition in real time (Winkler et al., 1997, Klobucar et al., 2007).

In general, the currently available computer vision systems for object recognition are still not as adaptive and universal as biological systems are. Successful commercial systems of computer vision are usually designed to solve well defined and/or specific tasks. For solving tasks computer vision systems often combine multiple standard strategies or even apply strategies that have been developed individually for a specific application (Forsyth & Ponce, 2002).

In robot-based assembly production processes, there is very often a need for grasping and manipulating of complex objects. Most of the robot vision systems require the complete knowledge of both, the shape and the position of the assembly parts. Due to the fact that vision systems are often specifically adapted to the individual 2D-shapes and the individual way the parts are fed to the system, a change of the produced parts usually requires a time consuming adaptation of the overall system. This could represent a cost problem especially for small series. With respect to the before mentioned aspects, there is a need for efficient robots with advanced machine vision capabilities that allow the recognition of complex, and

randomly organized parts, lying on a conveyor belt or in a bin, with little or no prior knowledge about the pose and geometry of the parts. Especially the so called bin-picking problem - the picking of randomly organized 3-D parts in a bin - has not yet been solved in a general manner, primarily due to severe occlusion problems.

Many researchers are dealing with this basic problem, which represents one of the remaining obstacles to a widespread introduction of vision systems to robot-based assembly. In searching for appropriate solutions, the above mentioned methodologies and algorithms for object detection and recognition are applied. In (Boughorbel et al., 2003; Goldfeder et al., 2007) range maps have been applied for the reconstruction of objects using super quadric representations and decomposition trees. Based on laser scanners for 3-D object detection a model based approach in combination with CAD models (Schraft & Ledermann, 2003; Kristensen et al., 2001) or Harmonic Shape Context features (Kirkegaard, 2005; Kirkegaard & Moeslund, 2006), which are invariant to translation, scale and 3-D rotation, have been applied. Also some research has been done applying stereo vision together with a set of two neural networks (which are then compared with each other) namely the Radial Basis Function nets and Simple Feed forward nets (Hema et al., 2007). An algorithm for segmentation of partially occluded bin objects and the location of the topmost object is proposed. The experimental results have shown that the proposed algorithm might be appropriate for many bin picking applications if special attention is paid to the lighting situation. The results of the above mentioned research in bin-picking are very promising but the research is still more or less in research stage. Even though that grasping is not optimal and for some object not feasible, all contributions show an improved accuracy and efficiency in bin picking and sorting.

5. Applications of robot vision in control processes

Introduction of robot vision control to an assembly process initially demands a clarification of the purpose of the application, which is usually not just a problem of measuring one or more product parameters in a very short time, but also fault detection, usually detected in manual assembly by operators, based on an appropriate sample.

In many assembly processes, the control process is still undertaken by the operators. They are capable of making an estimation and judgment about the accuracy and shape faults of a product or part using their acquired skills for quick and accurate decisions based on the human vision system. These tasks are usually complex and the accuracy and speed depend on the operator's psychological and physical condition. The consequences are unreliable results and a very serious possibility of overlooking faults. The reliability of human decisions is also reduced by the monotony of the task and by tiredness (Herakovic, 2007a).

Today's robot vision and identification systems are more and more reliable and robust, and therefore convenient for industrial applications and are becoming indispensable to the assembly or disassembly process (Braggins, 2006; Ostojic et al., 2008). Control systems, based on robot vision, are capable of maintaining a control process even more efficiently than a human if the conditions for an appropriate use of the technical benefits of robot vision are ensured (West, 2006, West, 2009).

A robot vision system, which is used in an industrial environment for tasks such as inspection, measurement and fault detection, has to be a robust and very reliable system. For this reason, the development of measurement equipment using robot vision has to follow a fixed procedure (Trdic, 2000; Skvarc, 2000). Usually, the procedure is split into a precise determination of tasks (measuring, fault detection) and goals, into the robot vision selection and working conditions (illumination and position determination), component selection of the robot vision (camera, computer, lenses and optics), and finally, the development of an automatic robot handling system for the parts.

5.1 Fault detection and dimension control

When using a robot vision system for fault detection and dimension control, lighting is always a critical component and should be treated as one of the first steps of component selection. The effectiveness of an illuminating source in an inspection and fault detection process is determined by the direction at which light strikes an object and the direction of the reflected light into, or away from the camera. Suitable illumination covers the required field of view, creates a consistently measurable degree of contrast and does not cause reflected glare. Different light types are required to provide successful illumination for the broad range of products being inspected by automated systems (Merva, 2009).

Let us take an example of a robot vision application in quality control processes during the electromotor (EM) stator assembly. To get the optimal conditions for the effective robot vision quality control, some experimental research efforts of the robot vision tasks determination and especially of the influence of lighting on the fault detection and dimension control of electromotor (EM) stator are considered (Herakovic, 2007 b).

In control process, final product quality control is in fact an inspection of parts and of final product in technical and visual manner. The challenge is greater when the product is composed of parts, produced by an unstable process. The EM stator, assembled from thin metal plates, represents such an example (figure 8). The assembling process is performed by a well known special forming machine. High accuracy and no visible faults on the EM stator are demanded so the 100 percent control process should be guaranteed by the robot vision. Assembly process is followed by painting and drying, and in both processes inaccuracy and fault can occur. The control process involves:

- EM stator height measuring,
- slot width measuring,
- spherity or so called had-shape control
- position and rotation of claw,
- painting quality – uniformity,
- slot occurrence on the roll outside,
- plate derivation and
- randomly, the inside and outside diameters of EM stator have to be measured.

Fig. 8. EM stator assembled from thin metal plates

Mechanical defects on the inside and outside of EM stator, as a result of non-adequate assembly process, are shown in the figures 9a and b. Such defects are slot occurrences between plate (inside or outside) and broken EM stator.
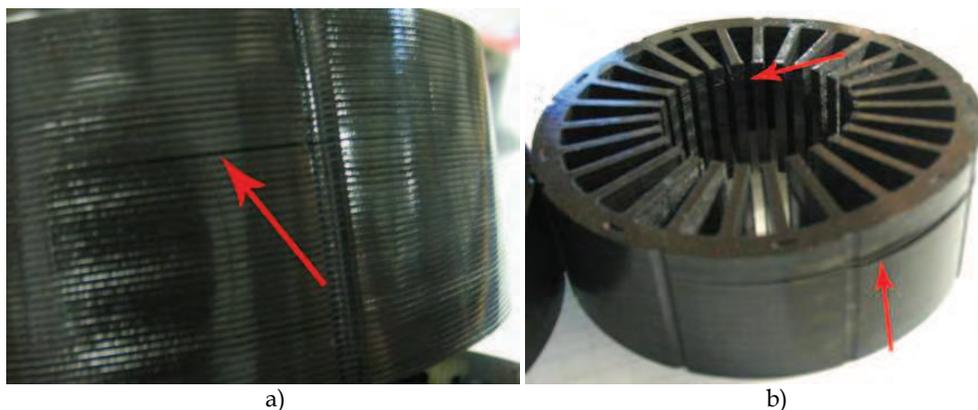

a)   b)

Fig. 9. Slots inside and outside (a, b) and broken EM stator (b)

Figure 10a shows mechanical damages, such as ruptured and derivate plats (can occur in performing the manual control by mechanical caliber). The derivations of plates inside of the EM stator are usually effected by assembly process (figure 10 b). The appearance of varnish or paint on the EM stator also means a false product (figure 10 b).

<center>a)   b)</center>
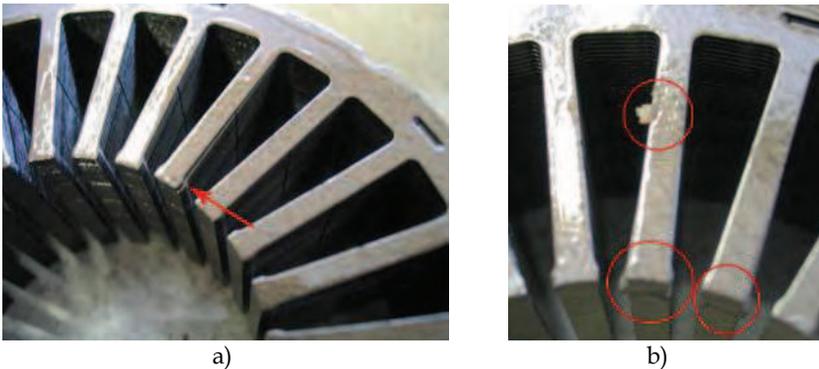
Fig. 10. Moved and derivate plates (a, b) and paint rest (b)

Manual control process of the above described critical places of the EM stator has been recognized as not reliable enough and is even a source of new damages of the finished product. The control process is also a bottleneck in the assembly process. In such a case the automation of the inspection and measuring of the EM stator can be the optimal solution for a reliable quality assurance.

The analysis of necessary conditions for the robot vision application in final quality control of the EM stator package can give very satisfying results through the experimental approach related to the technique and the type of illumination, which can guarantee a reliable robot vision quality control. For each critical area of the EM stator, the conditions which can influence the successful machine vision fault detection should be examined in grater detail. In the presented research this has been done by using the variation of influential parameters like the position of the camera and light source (Burns, 1999), type of the camera lenses (Jenny, 2000) and above all by the variation of the angle of the stator position regarding to the camera and the light source position. In the research the Sony XC-ST50-CE camera has been used.

Each critical area of the controlled stator demands a specific experimental setup, which must allow the analysis of all variations of different parameter influencees on the quality of the robot vision control of the stator. The aim of all presented experimental setups is to assure satisfactory quality of the detection of as many faults as possible, with a minimum number of handling operations of the stator and with the least possible changes of the type and sort of lighting and camera lenses.

Figure 11a represents an experimental setup for the analysis of the impact of a direct general-purpose different colour illumination (low angle ring illuminator) and the impact of different colour backgrounds on a depth control (for the reason of the light reflection), contrast and on a detection of visual defects of the EM stator. It is supposed that different background and illumination colours are more suitable for the visibility of some surface defects like remains of varnish and mechanical damages.
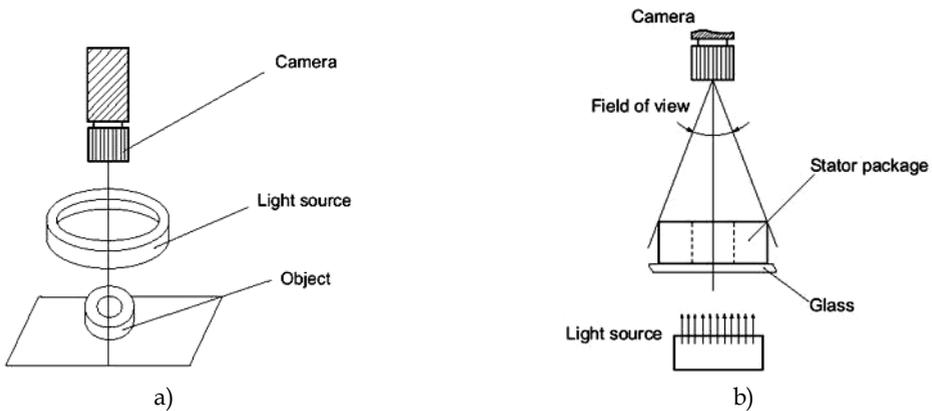
Fig. 11. Experimental setup: a) general-purpose different colour illumination and different colour background; b) backlight illumination

Experimental setup with the backlight illumination (figure 11b) enables the analysis of parameters like the rapture of the stator plates, dimensions of the stator slots, general stator dimensions etc. The presented experimental setup is suitable for the reliable detection of the many of before mentioned parameters only with the use of appropriate camera lenses (conventional, telecentric etc.). In this case the type of lighting is not so important for the quality of detection.

For the detection of some parameters like mechanical damages on the outer stator circumference and slot occurrence as well as plate derivation and shifting on the inner stator circumference, the experimental setups presented in figure 12 are convenient. Also in this case the reliability of the detection of before mentioned parameters depends on the use of appropriate camera lenses; however, the type of lighting is decisive for the quality of detection this time.
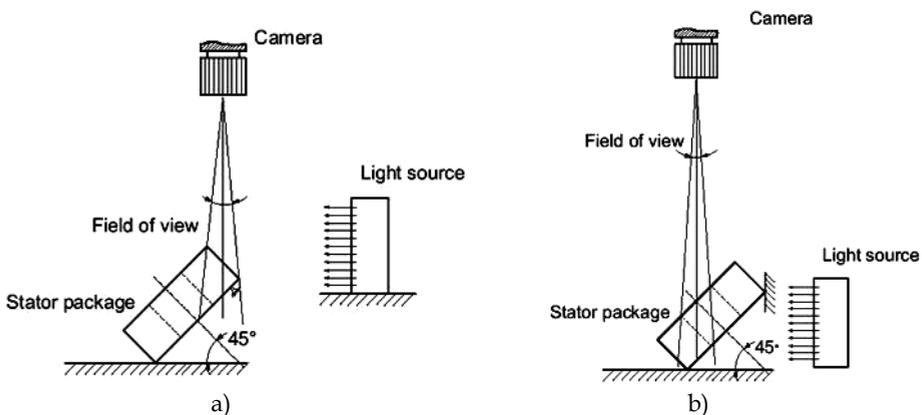

Fig. 12. Fault detection on a) outer stator circumference and b) inner stator circumference

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