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Towards increased intelligence and automatic improvement in industrial vision systems

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Abstract

Robots and in-process inspection systems equipped with machine vision solutions are used for increased flexibility and quality in automated manufacturing. Although vision systems have found wide industrial use, there are still problems regarding optimization of vision system robustness and capabilities. This paper presents a comprehensive case study of vision system functions, techniques and capabilities in an automotive 1-tiers supplier. Based on the study, the paper further describes a method for systematic improvement of industrial vision systems on a continuous basis. This is proposed to be done by establishing a data store and data analysis system, based on training machine learning models in an off-line mode using the historical data, as well as on on-line stream processing.

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Keywords: Machine vision; Optimization; Machine learning; Stream processing; Data flow

1. Introduction

The contemporary factories are constantly becoming more automated. Technologies like robotics and machine vision have already become an integral part of many production systems, but there is still room for a lot of improvements in their capabilities. New emerging technologies are being discussed in context of manufacturing automation under the umbrellas of cyber-physical production systems and several strategic initiatives, like Industrie 4.0 and Industrial Internet. Clearly, manufacturing is becoming a highly knowledge-intensive industry, where the required knowledge is diverse.

According to the outlook report on the future of European assembly automation [1], the potential of exploiting modern information technology is not fully realized, particularly in system development, which needs to adopt more holistic methodologies. Rapid deployability and effective adaptability are considered the main targets when developing new assembly systems. In addition, the importance of vision-based feeding and other flexible feeding approaches is stressed, together with links between feeding and joining.

Automatic assembly greatly benefits from application of sensor technology, mainly because of inherent uncertainty in products and production systems, which can be tackled by sensory feedback. Industrial sensory/measurement systems based on machine vision have gained popularity in the industrial context due to their inherent characteristics: the ability for contactless measurement, reconfigurability, and relatively low cost (comparing to tactile data acquisition methods).

Theres is a rich body of research within the fields of imaging, image processing, and computer vision. A particularly notable role of the above fields is within robotics. However, the complexity of some of the solutions, the lack of commercially available tools, and the lack of in-house competence result in slow adoption of the state-of-the-art research ideas. In addition, many challenges exist in the area of industrial vision, most notably high sensitivity of machine vision algorithms to exterior conditions and difficulty in accommodating industrial parts variability. Machine learning in this case appears as a promising alternative to hand-crafted programs with fixed thresholds, due to better accuracy of functions for recognition of complex patterns learned from data.

In most cases, solutions based on machine learning greatly benefit from *big* amounts of data used for training, testing, and validation. In the automated manufacturing context, it is often the case that data acquired on-line does not get stored for future processing. However, with a reduced cost of data storage hardware and easier access to elastic computational resources,

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it becomes more feasible to store and process intermediate on-line data. In the case of vision systems, it is of interest to keep a temporal database of images acquired during continuous system operation.

This paper is aimed at analyzing the current status of the production system and machine vision capabilities/requirements at a highly-automated plant in Norway, producing air brake couplings in high volume. Because of the high-speed and high-volume requirements, the considered production systems are limited in applicability of classical 6-axis robotic manipulators for assembly. Instead, the company employs dedicated transfer machines, optimized for performance.

A focus on a specific product family is made, with the associated quality requirements and currently operating assembly system configuration. Based on the study of the current state of production systems and the associated machine vision solutions at the plant, a number of solutions are proposed in a direction towards establishing a system for continuous improvement of the vision systems' capabilities. Despite the company-specific nature of this paper, the resulting analysis and proposed solutions can be generalized and used in similar cases.

This paper is organized as follows. Section 2 overviews the fields of automated assembly, machine vision, and machine learning. Section 3 presents the applied method. Section 4 describes the case company, the case product, and vision systems capabilities in the considered production facility. Section 4.3 proposes a technical solution for future development.

2. Preliminaries

2.1. Automated assembly

Assembly constitute a vital part of modern manufacturing systems, and is concerned with producing compound products from individual parts and sub-assemblies. Because many assembly processes require high level of dexterity, they are often performed manually. However, because of requirements in higher quality, speed and repeatability, automated assembly is being introduced in manufacturing companies.

The main operations in assembly processes are parts mating, parts joining, parts handling, parts recognition (position and orientation of randomly-fed parts), and inspection [2].

Material handling has a special role in automated assembly. Typical material handling processes are handling of pieceparts into the system, handling of palettes, fixtures and tools, removal of the completed products from the system, accommodation of operations external to the assembly cell, and transportation of partially finished products to and from rework [3,4].

Feeding has always been a challenging process within automatic assembly. Though a widely-accepted industrial practice is to apply dedicated feeding solutions with a built-in mechanism for correct part positioning, an important research direction is towards flexible feeding approaches, including vision-based feeding. In relation to this, an attention is placed on the link between feeding and joining, as well as interfaces for modular system architectures [1]. Another approach to designing feeding systems (and also applicable to sorting, assembly and inspection) is *algorithmic automation*, focusing on using formal models of part behavior and computational geometry algorithms for rigorous specification, analysis, and synthesis of automated systems [5].

Assembly planning constitutes a high-level set of activities intended for mapping formalized assembly instruction to robot operations. These activities include CAD modeling of parts, tolerance modeling, workcell planning, sequence planning, mating pose determination and others [6]. When the results of assembly planning are mapped onto robot operational level, uncertainty becomes an inevitable part of the process, and sensory feedback serves the primary role of tackling it. Typically used types of sensors in assembly are force, torque, and tactile sensors, sensorized compliant devices, vision systems, optical sensors, mechanical probes, positional sensors, as well as sensors for measuring temperature, pressure, acoustic emissions, and acceleration [2].

2.2. Machine vision

2.2.1. Principles of industrial vision systems

Machine vision constitute an engineering field applying image processing and computer vision solutions for the industrial needs, particularly for automatic inspection and robot guidance.

In a general vision system, a camera acquires an image, which is then enhanced to simplify the later processing steps. After that, certain parts of the image are segmented, and the obtained parts are further used to detect the desired features. Such process is also referred to as feature reduction: a vision algorithm reduces the original features, i.e. large array of image intensities (or several arrays for color and multi-spectral images) to a small vector of the application-specific features.

The common characteristic of industrial vision systems is the actuation function that impacts the controlled process. In addition, vision measurement in the industrial context is typically performed under controlled conditions with the appropriate lighting and low noise [7].

The application domains of machine vision include the following [7]:

- Defect detection: determining product defects, differentiating between different types of defects, including acceptable and unacceptable;
- Guidance and alignment: providing a robot control program with visual estimate of an object pose or geometric displacement;
- Measurement: deriving metric estimates of geometric features of a physical object;
- Assembly verification: determining the correctness of an assembly process.

On-line vision system, which constitute a part of the production process, provide the necessary information (e.g. pass/fail classification or robot movement coordinates) at the cycle time of the process. Conversely, off-line vision systems are used for recording information and further analysis [8].

Typically computer vision applications utilize images from sensors that capture visible light (some applications benefit from IR and UV imaging). Though many modern computer vision algorithms aim at analysis of arbitrary scenes (e.g. outdoors), in the industrial settings one typically establishes highly controlled lighting environment, and appropriately choses suitable light sources.

Physically, lighting solutions for machine vision can be realized with incandescent lamps, gas vapor discharge lamps, and LEDs. Irrespective from the physical principles of illumination, one distinguishes between the following illumination techniques [8,9]:

- Back lighting: leads to high-contrast images with dark silhouettes against bright background;
- Diffuse lighting (full bright field): ensures even multidirectional light, eliminating the effect specular reflection;
- Directional lighting (partial bright field): enhances topographic details on a surface;
- Dark field lighting: enhances small surface imperfections because of light incident at low angles.

There are generally two characteristics of imaged objects that put requirements on which illumination technique is more useful, namely surface shape and surface reflectivity [9]. Objects with highly reflective and curved surface, such as metallic automotive parts, are generally better to image with diffuse lighting.

2.2.2. Machine vision challenges

The use of vision systems is a non-trivial field, associated with a number of challenges. There exist numerous factors that influence the accuracy of vision algorithms, including the measured object characteristics (size, shape, color, texture), camera characteristics (camera resolution, quality of lenses), environment characteristics (pose, illumination) [2,7]. Vision algorithms for industrial applications are typically very sensitive to the environment and the appearance of the observed objects. The measured part characteristics, such as color and reflectivity, may vary from one part to another. Lighting conditions are also difficult to maintain consistent [10]. Therefore, vision systems need to be robust enough to tackle this variability.

When camera measurements need to be expressed in real-world coordinates (e.g. for robot guidance or high-accuracy measurement), the quality of system calibration is of a vital importance. In multi-sensor and multi-device environments (e.g. comprising cameras, lasers, and robots), it is a challenge to integrate data from multiple sources under the same coordinate system [10]. Camera calibration, stereo calibration, and pose estimation provide the necessary parameters and rigid transformations making possible to operate in real-world space.

An important factor, specifically in industrial applications of vision systems, is the processing time [7,10]. Because the visual data has typically high-resolution, it requires efficient algorithms, often in combination with specialized hardware, to be processed.

Flexibility in manufacturing should be supported by the flexibility of vision systems [7]. The abovementioned issues of part appearance variability and difficulty in establishing a consistent imaging environment naturally present a challenge to a greater flexibility.

2.3. Machine learning

Machine learning (ML) is a field that studies computer algorithms for automatic learning ("to do something better in the future") from observation data ("based on what was experienced in the past"). That is, an ML application is associated with a particular *task* that has to be improved by learning rather than by implementation of am imperative procedure [11,12].

ML is typically considered a sub-area of artificial intelligence (AI), though it is highly related to statistics, optimization, computer vision, and other disciplines. There exist distinct scientific approaches to ML such as statistical learning theory and computational learning theory.

A large group of ML techniques, dubbed supervised learning, is focused on learning an unknown function $f_\mathbf{p} : X \to Y$ from a set of training samples $\{\mathbf{x}_i, \mathbf{y}_i\}$, where $\mathbf{x}_i \in X, \mathbf{y}_i \in Y$, and $\mathbf{y}_i = f_\mathbf{p}(\mathbf{x}_i)$. Hence, the known data samples are used to estimate the unknown function, which can be used for regression ($Y \subseteq \mathbb{R}^d$) or classification ($Y = \{0, 1\}$ or $Y = \{0, 1, 2, \ldots, k-1\}$, where k is the number of classes).

Function $f_\mathbf{p}(\cdot)$ typically constitutes a complex model with a large number of parameters. For many problems the learned $f_\mathbf{p}(\cdot)$ would surpass possible imperative implementations, while for many, it would be not possible at all to hand-craft equivalent procedures.

Supervised ML algorithms include linear regression, logistic regression, artificial neural networks (ANN), support vector machines (SVM), decision trees, adaptive neuro-fuzzy inference system (ANFIS), and others.

Unsupervised learning algorithms are aimed at finding regularities in unlabeled data, i.e. in a set $\{\mathbf{x}_i, i = 1, ..., m\}$, without dependent variables $\{\mathbf{y}_i\}$. Thus, supervised learning algorithms are used for clustering, dimensionality reduction, anomaly detection, and often are applied for preprocessing the original data before training some of the supervised learning algorithms.

Depending on the application, one could aim at building ML models for prediction or for inference. In the former case, it is of interest to predict an unknown value $\mathbf{y}^* \in Y$ given an observation $\mathbf{x}^* \in X$. Conversely, in the latter case one aims at building an *interpretable* model that describes the nature of mapping $X \to Y$ [13].

ML is often used for analysis of image data, due to better accuracy of functions for recognition of complex patterns learned from data, as compared to hand-crafted procedures [12]. In the context of automated visual inspection, applications of ML include, but not limited to SVMs, principal component analysis, decision trees, random forests, adaptive boosting, ANNs, and neuro-fuzzy approach [14–19].

Many ML implementations greatly benefit from large data quantities and powerful computational infrastructure. Software frameworks as Apache Hadoop and Apache Spark provide capabilities of efficient machine learning from Big Data using *batch processing* with map-reduce technique. In some situations the data is not already stored, but arrives online. To apply machine learning in this case, *stream processing* engines, such as Apache Storm, are employed.

3. Method

The purpose of the case study described in this paper is to gain an insight into the production systems of the Kongsberg Automotive AS (further referred as KA) plant in Raufoss, with particular focus on the applied machine vision systems and the required vision capabilities.

The study was conducted during the Autumn period of 2015, as a part of the Norwegian innovation project *MultiMat*, focusing on development of technical solutions for manufacturing of novel multi-material products.

During a meeting with KA employees of various levels of involvement in the company, a discussion was made regarding the desired properties of vision systems at the KA facilities and the areas of interest where a more thorough research should be conducted. The meetings were combined with shop floor visits and analysis of the machines' functionality. Apart from general plant-wide considerations, an in-depth study of the KArtridge™ product family and the corresponding assembly machine was done. To get a deeper insight, the available internal documentation was studied.

Though the presented case study is company-specific, the resulting analysis and proposed solutions may be applicable to the companies with similar specifics, such as handling of small and/or highly reflective parts, part appearance irregularities, high-speed dedicated machines, and high quality requirements.

4. Case study

4.1. The company and the products

Kongsberg Automotive AS is a global manufacturing company producing components and subsystems for the automotive industry. The study described in this paper concerns the production facilities of the KA plant in Raufoss, Norway, that supplies products for vehicular fluid transfer, marketed as Raufoss ABC™. Raufoss ABC™ is a product system having a function of coupling air brake tubes and targeting the commercial vehicle market (buses and trucks). It includes couplings themselves, building blocks, release tools, and rotation stops.

KArtridge™ is a product family of composite couplings with a metallic star washer and clamp ring, and a series of rubber O-ring seals. A coupling from the KArtridge™ family is depicted on fig. 1. It consists of a housing, the inner parts (cone element, environment seal, clamp ring, seal tube, and support sleeve), and the outer parts (main port seal, locking ring, star washer, and environmental port seal).

A star washer plays a critical role in the KArtridge™ assembly by securing the grip function between a coupling and its housing. It is important that it is assembled in the correct orientation, so that the teeth will create resistance against the housing after assembly. In addition, the washer need to be of the required geometry. The geometric requirements include the

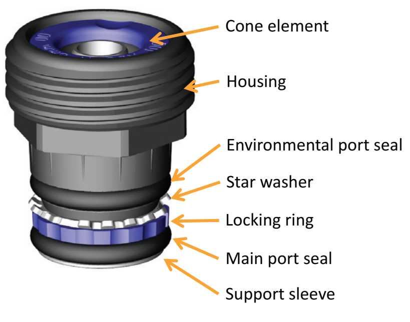

Fig. 1. A KArtridge™ coupling.

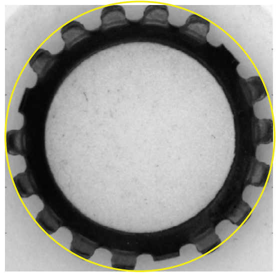

Fig. 2. View of a star washer from the top, highlighting the outer diameter.

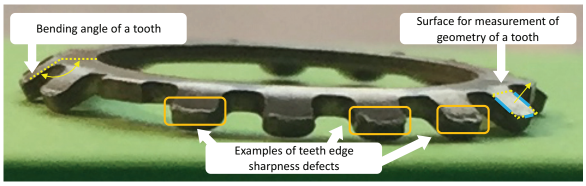

Fig. 3. View of a star washer from the side, highlighting examples of degraded edge sharpness and the area of interest for a tooth geometry measurement.

outer diameter, geometry of each tooth, bending angle of each tooth, and edge sharpness of each tooth. As shown in fig. 2, the outer diameter of a component is well-imaged from the top-down perspective. However, other characteristics require more intricate setup. Methods for analysis of top-down images of star washers were previously described in [17] and applied to the problem of ML-based classification of star washer orientation when lying on the surface of a feeder.

4.2. Current state of production systems

Most of the assembly operations at KA are performed by dedicated transfer machines, optimized for performance and requirement for high volume of production. Each machine is designed by one of the machine suppliers, and is typically comprised of standard modules of the respective suppliers.

KA utilizes a big number of vision systems installed at various production stages and serving the following functions:

- Individual components inspection: imaging of a component to verify whether no defects are present;
- Process inspection: imaging of a partly or fully assembled product to verify whether the assembly process did not introduce any structural defects;
- Object pose identification for picking: imaging of a feeding surface with randomly positioned components to estimate the pose of the next component to pick with a robotic arm or a Gantry mechanism.

Some of the assembly lines include robotic manipulators and flexible feeders. In the latter case, the parts to be picked are randomly distributed on the feeder surface, and vision systems in combination with robots are used to pick the parts.

Currently, the park of vision system at KA is heterogeneous, i.e. comprises solutions from different suppliers and with different software components. The heterogeneity of all the used vision systems shall be tackled by enterprise-wide standardization. A unified smart camera platform is seen by KA as a good solution to the current situation.

For illumination, LED lighting of various colors is used. The lighting units are turned on and off to coincide with camera exposure. Question regarding the role of illumination in vision systems is of a major importance for KA. A general consideration is on the question of what types of lighting are better for different materials. KA works with components made of brass, composite (differently-colored injection-molded parts), and rubber. Of a special difficulty is the problem of O-rings recognition because of process-caused color irregularity: O-rings' surface color can be from black to gray and the application of silicone oil induces reflections. Because there exists time-dependent variability in the appearance of the parts (specifically those obtained from the external suppliers), KA is interested in more effective automated inspection with application of vision systems.

The problem of pose estimation using a mono vision system is challenging for relatively big parts that have a large degree of freedom in terms of orientations. In the KArtridge$^{\mathrm{TM}}$ assembly, the housing and the cone element are characterized by such geometry.

Automatic vision-based inspection of star washers is an important task for KA, as manufacturing of the new generation of the KArtridge$^{\mathrm{TM}}$ family requires 100% inspection of the parts incoming from the supplier. Quality of the outer side of a star washer is of greatest importance. Therefore, a vision system shall be able to detect features that describe the quality requirements highlighted in section 4.1. he challenges include (1) the reflective surface of the parts, (2) batch-to-batch color variation, and (3) small dimension of the parts and the teeth respectively.

4.3. *Reflections upon the current state*

As shown above, assembly systems at the studied plant have a strong reliance on visual sensing. It is clear from the number of vision system installations throughout various stages of the production flow. The reviewed systems have different application contexts (e.g. inspection and robot guidance), and utilize various illumination principles.

The current configuration of vision systems does not completely unleash the potential from multi-sensor data analysis, as images taken by various vision systems are used solely for in-place real-time processing. To uncover the hidden historical information and create a room for improvement of the existing vision algorithms, it is beneficial to establish a data store, to which the vision systems would save the acquired images along with the associated processing results. When image data is acquired and stored for further off-line processing, it can be coupled with temporal metadata from the existing industrial IT systems. Then, various machine learning models could be trained in an off-line mode. Similarly, on-line stream processing pipelines could be coupled to the established image feed, thus making it possible to perform timely decisions reactively, as the the parameters of interest change.

Due to the safety-critical product function, i.e. ensuring the correct braking functionality, quality of the air brake couplings is a highly critical factor. The requirement for 100% inspection of the incoming parts, particularly star washers, can be realized by designing a dedicated inspection cell, where each part would be measured using a complex multi-sensor system. For instance, multi-pose imaging can be done to capture visual features from different sides of an inspected part. Multiple illumination modes can reveal features susceptible to each particular type of lighting. The first steps towards realization of such system were previously published in [17]. The latter constitutes a lab-based approach oriented at early-stage prototyping. However, when existing production systems are considered, it is important not to introduce disturbances in system operation when introducing new improvements.

5. Proposed solutions

The majority of vision algorithms can be configured with predefined parameter values, e.g. various thresholds. These parameters are fine-tuned for a particular setup, and, together with the dedicated lighting and lens configuration, create a particularly rigid and highly-controlled system. However, as the appearance of the imaged objects may change over time, fixed configuration may not suffice all the time. At first, the *change* itself needs to be detected, and based on that, a set of controllable parameter values could be adjusted. Clearly, this task can be highly application-specific, but a common approach can still be defined.

Vision algorithms are naturally modeled in a form of pipelines that gradually process "signals with almost no abstraction, to the highly abstract description needed for image understanding" [20]. Not only pipelines clarify the principle of a particular data processing algorithm, but also allow for systematic treatment of the associated parameters and their optimization. To illustrate the further discussion, a data processing pipeline P is defined as a tuple:

$$P = (G, \Theta, T) \quad (1)$$

where G is a directed acyclic graph (DAG) comprised of n data processing operators $\{O_i, i = 1, ..., n\}$ and their data dependency relations, Θ is a set of parameter vectors, each specifying the respective operator O_i: $\Theta = \{\mathbf{p_i}, i = 1, ...n\}$, and T is a set of data tokens, where each operator O_i, $(i = 2, ...n)$ accepts token t_{i-1} and produces token t_i.

In a general case, one can specify G as a DAG with arbitrary topology. In this paper, a simplified form of serial operator sequence is used, with O_1 being the operation processing the original image (or a set of images in case of multi-camera system), modeled as data token t_0, as shown in Figure 4.

Let $\mathbf{p}$ be a vector comprised of all parameter vectors $\mathbf{p_i} \in \Theta$ stacked together. It is of interest to be able to adjust $\mathbf{p}$ with respect to some objective function $C(\mathbf{p})$. The latter is computed by running the pipeline G with the starting token t_0 and operators initialized with the parameters in $\mathbf{p}$. Since t_0 corresponds

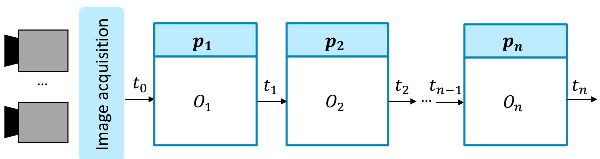

Fig. 4. A vision system, whose processing algorithm is modeled in a form of a pipeline.

to the original image data, the above procedure could be performed in an on-line/streaming mode, possibly with computation over a "temporal window" of several subsequently obtained starting tokens.

To allow such optimization, the DAG topology can be exploited to compute gradients of the objective function $\nabla C(\mathbf{p})$ in a manner similar to back-propagation and automatic differentiation [21,22].

In addition to the streaming approach, the stored data, as described in section 4.3, can be used in various off-line analysis scenarios. For example, alternative implementations of vision algorithms can be prototyped and tested on the stored image data. Also, various machine learning models can be trained using the available datasets. Similarly to on-line adjustments of pipeline parameters (as described above), one could be able to train models with similar purpose, but using a large dataset over a wide temporal window. The situation with variability in the appearance of parts can be better understood by analyzing the historical data.

Overall, numerous data-driven applications can be realized with operational data available on-line and off-line. The further step should be to establish such a data store and data analysis system at the production facility without major disturbances to the in-place systems. As more data is stored, one can proceed with ad-hoc experimentations with various off-line analysis techniques and getting a better understanding of the dynamics of the considered processes. A more proactive on-line approach can be implemented as a part of an upcoming reconfiguration project. Before that, the available historical data can be used in simulation mode for testing and commissioning of the new solution.

6. Conclusion

This paper presented a systemic overview of the machine vision capabilities at a Kongsberg Automotive AS plant in Norway that produces air brake couplings and the associated components. The current situation was analyzed with the challenges highlighted. The proposed solutions were formulated, which comprise a data store and data analysis system aimed at capturing operational data, including acquired images and the corresponding processing results, and using them for getting an increased understanding of the process dynamics, training ML models, and on-line optimization of controllable parameters of machine vision algorithms.

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