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Improved Automatic Quality Inspections through the Integration of State-of-the-Art Machine Vision and Collaborative Robots

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Abstract. In this paper, we discuss the concepts of a flexible and high-performing solution for automatic quality control that integrates state-of-the-art machine learning algorithms with collaborative robots. The overall aim of the paper is to take the first steps towards improved automatic quality inspections in the manufacturing industry, leading to reduced quality defects and reduced costs in the manufacturing process. For developing and evaluating a first version of a solution that integrates state-of-the-art machine vision and collaborative robots we use a real-world case study focusing on improved quality inspection. Results from the case study shows that it is possible to realize automatic quality inspections through the use of a collaborative robot as intended, but also that there are some challenges that need to be further addressed in order to achieve a top-performing system.

Keywords. Industrial Quality Control, Machine Vision, Collaborative Robot.

1. Introduction

To assure quality and prevent defect products, inspection is usually required throughout the whole manufacturing process. In many cases, especially when it comes to manual assembly lines, the quality inspections are performed manually by the shop-floor operators. Manual quality inspections are, however, unreliable since human factors impact the outcome of the inspections and inferior outcomes are not uncommon due to for example lack of training, fatigue, laziness, stress or unclear specifications [1]. Manual quality inspections are also time consuming and costly. To overcome the drawbacks of manual inspections, machine vision can be used. Machine vision is a camera-based quality inspection method being used not only in the manufacturing industry, but in a diversity of different domains such as medical diagnostics, food industry and safety applications [2]. A machine vision system can provide rapid and accurate quality inspection, and for critical inspections the use of machine vision is often recommended if the right image acquisition system can be implemented [3]. The idea is that the machine vision system should control if the product has been processed according to the specification and reject products that hasn't. The machine vision system could also be used to assess the general quality of the production and provide feedback to earlier stages in the manufacturing process if needed [4]. An example could

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be to feedback that certain nuts mounted in an upstream station should be tighten with another momentum in order to avoid problems detected at a later station.

Machine vision is a commonly used in the manufacturing industry today – however mainly in automated manufacturing processes and more rarely in manual assembly lines. A current problem of most of today's machine vision systems that limit their usage in manual assembly lines are that the system use fixed mounted cameras, making them inflexible and linear in their way of working. These cameras have a problem to reach inaccessible areas of the product such as underneath, inside and in some cases around. In manual assembly, the statives that the cameras are mounted on might also be in the way for the operator – and vice versa the operators might be in the way of the cameras.

In this paper we investigate if the flexibility of automatic quality inspections through machine vision can be improved by utilizing a collaborative robot, by mounting the inspection camera on the robot and connecting the quality control system to the robot's control system. Collaborative robots are becoming increasingly popular in manufacturing assembly, as a way of handling the ever increasing demands on flexibility and efficiency [5]. The overall objective of a collaborative robot is to combine the repetitive performance and strength of robots with the ability and skills of the human. There are several ways a collaborative robot can be used in an assembly line; delivering parts to be assembled, lifting heavy objects, performing nut running and many other things.

By mounting the inspection camera on the collaborative robot and integrating the quality control software with the software used to control the robot we believe that the current problem of inflexible machine vision system can be significantly reduced. Furthermore, if utilizing the latest state-of-the-art machine learning algorithms in the vision system we also believe that the accuracy of the inspections can be further improved. The vision systems used in the industry today are based on older algorithms and the ongoing and fast-progressing AI revolution has presented several very powerful algorithms for image processing that certainly are very promising also for industrial quality control. The overall aim of the paper is to integrate a state-of-the-art machine learning algorithm with collaborative robots to achieve a flexible and high-performing solution for automatic quality control.

The next chapter continues by discussing suitable machine learning algorithm for industrial quality inspection and identifies a possible implementation library to use for realizing the vision system. Chapter 3 presents an initial prototype implementation of the intended solution in a real-world industrial scenario, while Chapter 4 discusses the challenges identified from this implementation. Chapter 5 finally summarizes the paper and outlines the next steps of the work.

2. State-of-the-art machine learning algorithms for image processing

Image processing is a hot research topic and a literature review reveals that the current most successful image classifiers use deep learning with a convolutional artificial neural network (ANN) architecture. Therefore, this seems to be the most promising approach to implement also in an industrial vision system. Convolutional neural networks (CNN) works much like an ANN but have much more hidden layers and instead of using fully connected layers where one neuron takes one dimensional data as input, CNN uses convolutions that take two dimensional data. This preserves the spatial information in an image, which is crucial in order to make accurate predictions. Deep learning is basically achieved through the concept of Multilayer Perceptron. A multilayer perceptron is a mathematical function mapping set of input values to output values. Each layer provides a new representation of the input [6]. The concepts of a deep learning through CNN are shown in Figure 1 below.

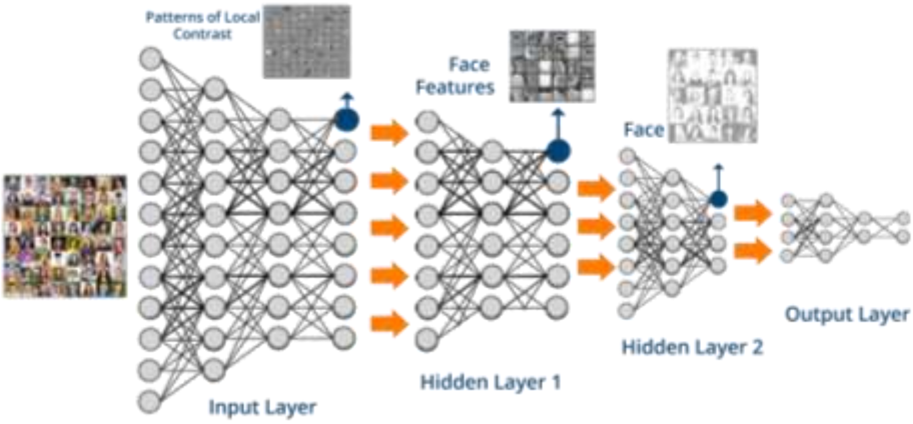

Figure 1: Concepts of deep learning using convolutional neural networks for image processing. Image from https://cdn.edureka.co/blog/wp-content/uploads/2017/05/Deep-Neural-Network-What-is-Deep-Learning-Edureka.png

When studying the literature, it becomes clear that most CNN architectures consist of convolutions, ReLU and pooling layers for feature detection, followed by fully connected layers and SoftMax for classification. This is therefore the recommended architectural set-up that we will continue with in this study. To implement the CNN, we have evaluated various software libraries and come to the conclusion that TensorFlow, the state-of-the-art machine learning library from Google, is the best choice. TensorFlow is open source and free for anyone to use without cost, and the software has proven very powerful in numerous of applications and competitions. Basically, the library works by generalizing every mathematical function as a graph where the nodes takes a tensor as an input and produce a tensor as an output. A tensor is a very general mathematical object to which the vector and matrix are special cases. At the lowest abstraction level of TensorFlow it is possible to build custom-made execution graphs and at the highest level predefined components can be used. Overall, TensorFlow seem to be very flexible, powerful and not at least useful for industrial quality inspection applications.

3. Industrial prototype implementation

For developing and evaluating a first version of a solution that integrates state-of-the-art machine vision and collaborative robots we use a real-world case study focusing on improved quality inspection. The case study is undertaken at the truck manufacturer Volvo Group Truck Operations in Sweden, in one of the company’s factories producing engines. The case study is focused at an assembly station where one of the tasks to perform is to apply two strings of glue on a frame to mount the engine cover. When applying the glue strings it is of critical importance that there is a space between the strings, otherwise there is a risk of major problems with the product later on. Today, the quality inspection is performed manually by the operator working at the station and the instruction provided to the operator for determine if the glue strings are correct or not is provided in Figure 1 below. As previously discussed in the introduction, manual quality inspections are exposed to failures due to human factors and so is also this inspection which have motived the company to evaluate a machine vision system that can replace the manual procedure.

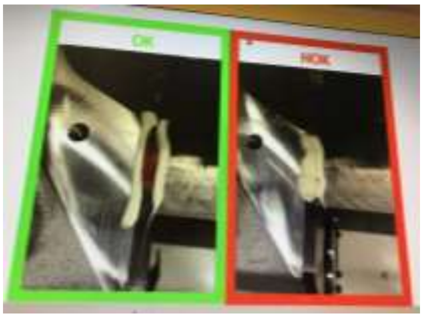

Figure 1: Instruction to operator for what to check for when performing the quality inspection. Correct glue strings shown to the left (OK, green box), incorrect glue strings shown to the right (NOK, red box).

When it comes to the collaborative robot, we use a UR3 from Universal Robots as such robot was available for lend from the company's lab and was considered having an appropriate size. It should, however, be pinpointed that virtually any collaborative robot of appropriate size regardless of brand would fit for the purpose. The UR3 that we have used can carry three kilos and reach 0.5 meters, see Figure 2 below. A clear advantage of the UR robot is that it comes with a wrist camera that can be easily mounted on the robot and is already integrated in the robot's control software.

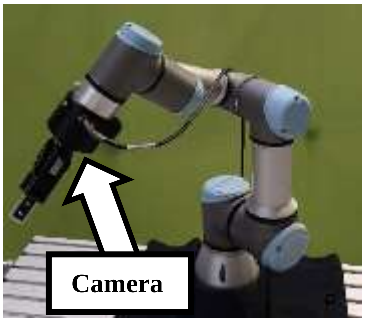

Figure 2: Collaborative robot used in the study.

The results from implementing TensorFlow and the UR3 robot for performing the inspection of the glue strings in the case study show that it is possible to use the state-of-the-art machine learning library TensorFlow for industrial quality controls. They also show that it is possible to integrate the control system of a collaborative robot with TensorFlow and achieve a seamless two-way communication between the two software. Furthermore, the results show that it is possible to use a collaborative robot to control the camera for a machine vision system. We have not yet been able to fully evaluate the precision of the automatic quality control system developed and compare its performance with the manual inspection process, but the initial evaluations show promising results. Right now the precision of the system is 97% and considering that this is just the first version of the system and that finetuning has not yet been undertaken, we feel optimistic about reaching a precision near 100% in the end. We have, however identified a number of challenges that needs to be further investigated in future studies in order to achieve a top-performing solution. These challenges are discussed in the next chapter.

4. Challenges

It is generally acknowledged that machine vision is hard to perfect, not at least since human vision is very complex and hard to replicate [4]. Industrial quality control is no exception and we have identified a number of critical issues for the successful implementation of an automatic vision system based on machine learning algorithms that are discussed in the following sub-chapters.

4.1. Training data

The performance of a machine learning algorithm is completely dependent on a rigorous training and that appropriate training data (images) can be provided. In the case of quality inspection, the training data consists of two categories of images: correct quality (in the industrial case study of this paper corresponding to correct glue strings) and inferior quality (incorrect glue strings). The harder to problem to solve (that is, the quality inspection to undertake), the more training data being needed. From the prototype implementation it is clear that an industrial real-world problem needs a large amount of training data, emanating both from the fact that the identification of quality defects as such is hard and from the fact that the image recognition is taking place in an ever changing work environment (with respect to light, shadows, angles, etc.). In an industrial scenario it is fairly easy to generate training data belonging to the category of correct quality, but it really hard to generate enough training data for inferior quality as quality defects happens rarely.

4.2. Object location

The basis for the vision system is to be able to locate objects of interest. For a human, it is usually very simple to identify the object of interest, but it is considerable harder for an algorithm to do the same. Locating an object involve demanding mathematics which is subject to a combinatorial explosion, a rapid growth of complexity in the problem affected by pixel inputs. To put this into perspective an image of 256 x 256 pixels (low quality) will result in over 1,5 million operations for one single image. This indicates that even on low quality images object detection becomes complex. There exist various methods to handle this problem which are based on features, for example to search for features of sets objects or to detect a few distinct features in the image. During the real-world case study we noticed that object location is hard in an industrial setting since the contents of the image might vary a lot depending on for example product variant or angle from which the image is taken. When there are randomness and disturbances in the images, it becomes hard to accomplish an accurate feature recognition for the object location. How to handle this challenge in in efficient way is an open question that needs to be further investigated.

4.3. Recognition problem

During the prototype implementation, we discovered that a big issue for the machine vision system was to recognize objects, that is, to know what object it is looking at. The algorithm needs to have stable reference points to know what it is supposed to recognize and what it sees, which might be hard to accomplish in an industrial setting. The usual way to improve the recognition is to standardize the position of the image so that the spot where the images are taken is fixed, as this creates an illusion for the algorithm that makes it think it is working in two dimensions instead of three, which is much easier. However, in our case we want to move away from fixed image positions and increase the flexibility. One way to tackle this problem might be to implement a two-stage recognition scheme as suggested by Davies [4] and this is something that we will investigate more in the future.

5. Summary

In this paper, we discuss the concepts of a flexible and high-performing solution for automatic quality control that integrates state-of-the-art machine learning algorithms with collaborative robots. Collaborative robots are becoming increasingly popular in manufacturing assembly, as a way of handling the ever increasing demands on flexibility and efficiency [5]. By mounting the inspection camera on the collaborative robot and integrating the quality control software with the software used to control the robot we believe that the current problem of inflexible machine vision system can be significantly reduced. The overall aim of the paper is to take the first steps towards improved automatic quality inspections in the manufacturing industry, leading to reduced quality defects and reduced costs in the manufacturing process.

For developing and evaluating a first version of a solution that integrates state-of-the-art machine vision and collaborative robots we use a real-world case study focusing on improved quality inspection. The case study considers an assembly station at the truck manufacturer Volvo Group Trucks Operation where one of the tasks to perform is to apply two strings of glue on a frame to mount the engine cover. Results from the case study shows that it is possible to realize automatic quality inspections through the integration of a collaborative robot and state-of-the-art machine learning, but also that there are some challenges that need to be further addressed in order to achieve a top-performing system.

References

[1] Soini, A., 2001. Machine vision technology take-up in industrial applications. Pula, IEEE..
[2] Brosnan, T. & Sun, D.-W., 2004. Improving quality inspection of food products by computer vision-a review. Dublin, Elsevier.
[3] Vithu, P. & Moses, J., 2016. Machine vision system for food grain quality evaluation: A review. Trends in food science & technology , Volume 56, pp. 13-20.
[4] Davies, R. E., 2012. Machine vision: Theory, Algorithms, Practicalities. 4th ed. London: Elsevier.
[5] Michalos, G. et al., 2014. ROBO-PARTNER: Seamless Human-Robot Cooperation for Intelligent, Flexible and Safe Operations in the Assembly Factories of the Future. Procedia CIRP.
[6] Goodfellow, I., Bengio, Y. & Courville, A., 2016. Deep learning. First ed. Cambridge: MIT press