

Image Processing for Industry 4.0

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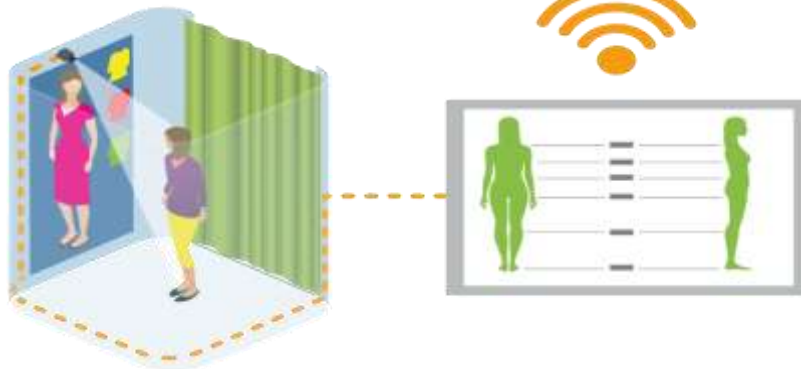
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ABSTRACT: Image processing technology is a popular practical technology in the computer field and has important research value for signal information processing. This article is aimed at studying the design and algorithm of image processing under cloud computing technology. This paper proposes cloud computing technology and image processing algorithms for image data processing. Machine Learning (ML) has become one of most widely used AI techniques for several companies, institutions and individuals who are in the business of automation. This is because of considerable improvements in the access to data and increases in computational power, which allow practitioners to achieve meaningful results across

several areas. Today, when it comes to image data, ML algorithms can interpret images the same way our brains do. These are used almost everywhere, right from face recognition while capturing images on our smartphones, automating tedious manual work, self-driving cars.

INTRODUCTION

Looking for a new pair of pants? Right now you're likely to go to a store or order a pair online in a standardized size, typically one of four variants ranging from S to XL. Low unit costs are achieved through mass production.



Textile production in the world of Industry 4.0 may instead deliver customized individual pieces by taking advantage of efficient data processing. Once a customer decides on a model, their dimensions could be determined via an image processing system (machine vision system). This might take the form of a small changing room with four cameras to take a picture of each side of the body. Software handles the measurements and the subsequent cutting pattern for production. The remainder of production runs automatically right up through shipping. Fashion houses of the future will thus no longer sell their services based around full shelves with huge offerings, but rather through a large virtual selection and quick, reliable production.

New Opportunities for Small Batches

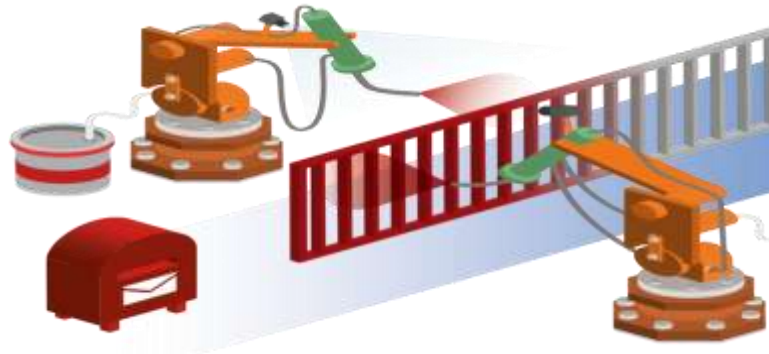
One important effect of Industry 4.0 is the fact that due to using control automation many work pieces can be produced cost-effectively not just in large quantities, but also in much smaller lots — a 'batch size of 1' is the buzzword here. One example of this comes in the production of textiles mentioned above; another might be in the production of individually designed metal pieces to customer spec, such as post boxes or railings.

But how can precise industrial camera systems support in this effort?

It's conceivable for example that this kind of system might be used for the coating of newly produced metal parts. Automatic spray nozzles

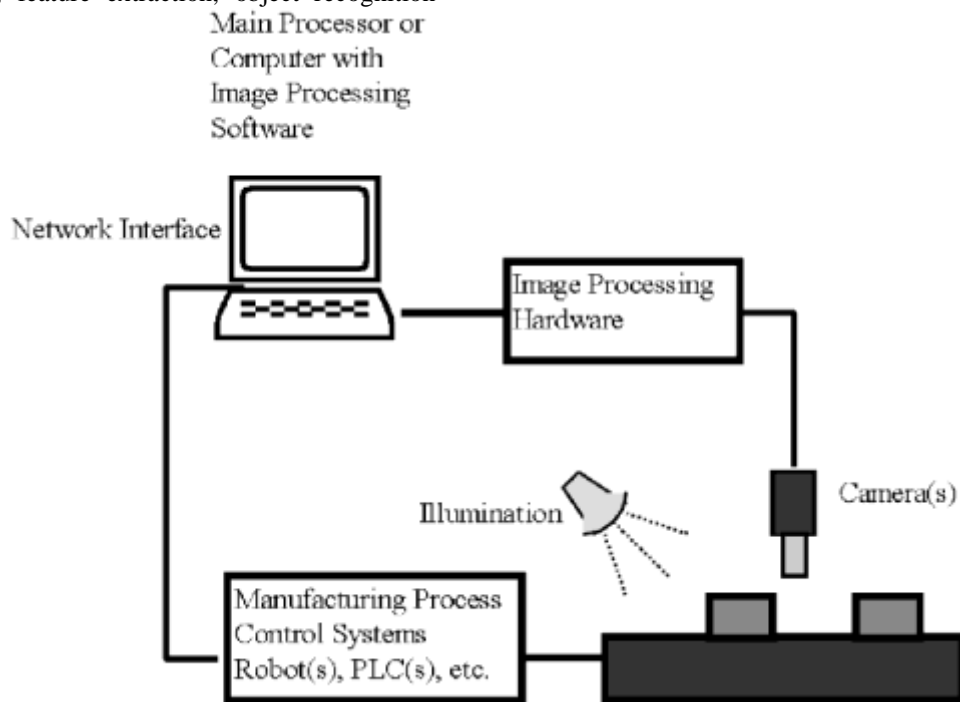
normally work based on pre-programmed painting movements. Such pre-programmed movements are difficult to plan in advance for custom work. Determining them from design specs could be possible in principle. However, to calculate the final spray pattern is highly complex and imprecise. Industrial cameras by contrast can make precise measurements of the component on the spot, determining its individual shape and position and instructing the spray arms accordingly. At the same

time, the painting results can also be controlled optically, either through assessment of the coloring or by measuring more complex reflective properties on the coating. This control data can flow in real time into the control unit. As such, a system for automated coating can become a self-learning system. New but similar components could then be processed more efficiently based on the prior experience.



The recent advances in sensors quality and processing power provide us with excellent tools for designing more complex image processing and pattern recognition tasks. In this paper we review the existing applications of image processing and pattern recognition in industrial engineering. First we define the role of vision in an industrial. Then a dissemination of some image processing techniques, feature extraction, object recognition

and industrial robotic guidance is presented. Moreover, examples of implementations of such techniques in industry are presented. Such implementations include automated visual inspection, process control, part identification, robots control. Finally, we present some conclusions regarding the investigated topics and directions for future investigation



Imaging applications plays important role in Industry-4.0 ecosystem:

- autonomous robots, self-driving cars and drones
- augmented reality
- artificial intelligence systems, big data and analytics

Cameras are eyes in many modern industrial applications and with the further progress of neural networks and AI systems, performance of machine vision systems will eventually overcome human abilities. In a new era, cameras will see much better than humans, understand images better and faster, will be able to work continuously and precisely. Literary, computers with cameras will be able to see everything and that will greatly affect different levels of our everyday life.

Current progress in imaging applications is based on new achievements in the following fields: image sensors, electronics, interfaces, illumination, lens, software and hardware. We see a tremendous boost in all these fields and now you can't be surprised with 8K video processing in realtime. Moreover, you can expect to get that data processed and analyzed as well. That could already be done with contemporary imaging systems.

GPU-based image processing can significantly improve both performance and image quality in industrial vision applications. This is important step towards faster imaging solutions. Such a processing could be boosted by AI software which could run on the same GPU. Quite often, modern GPUs have hardware-based cores for AI applications and we can build the whole pipeline on GPU to accomplish full task in realtime, starting from raw data acquisition to final AI task. Success in today's Industry-4.0 market requires a unique combination of hardware, software and AI solutions working together. Our GPU-based image processing solutions are constituent parts of imaging products. We cooperate with many companies in different fields and we see increasing demand for high performance imaging applications on the market.

Intelligent Image Processing for Industry 4.0

Industry 4.0 essentially encompasses networking and extensive data communication as a core element. As cameras have become central in many modern industrial applications, deploying smart cameras and sensors can help digitize and transfer information, interpreting what they capture and confiscating the need of human analysis. With further progress of neural networks and AI systems,

image processing or machine vision systems will eventually outpace human abilities.

Image processing based on the graphicprocessingunit (GPU) can significantly enhance both performance and image quality in industrial vision applications. This is a vital step towards faster imaging solutions, and such processing could be empowered by AI software which could run on the same GPU. Smart factories increasingly rely on machine vision systems, enabling communication between networks and the intelligent exchange of information among sensors, devices and machines. Previously, informationgathering and computation were performed by humans that were prone to errors. But with advances in technology, especially in image processing, these processes are now being done by industrial cameras, minimizing errors and enabling automated technology such as robots to react flexibly to production control requirements. In the Industry 4.0 ecosystem, applications of image processing are autonomous robots, self-driving cars and unmanned aerial vehicles (UAVs or drones), immersive technology such as augmented reality, and digital technology includes artificial intelligence, big data and analytics and others. We must bear in mind that automated visual inspection falls under the general heading of computeraided manufacture (CAM), of which computer-aided design (CAD) is part of. Today many manufactured parts can be designed on a computer, visualized on screen, made by computer-controlled machines, and inspected by the very same computer — all without human intervention in handling the parts themselves.

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