FRAUNHOFER-INSTITUTE FOR MACHINE TOOLS AND FORMING TECHNOLOGY (IWU)

MULTI-SENSOR DATA FUSION FOR IN-LINE VISUAL INSPECTION

Interview on practical experiences

Alexander Pierer, Thomas Wiener, Leutrim Gjakova, Sven Barthel, Martin Naumann, Mattias Mende, Michael Hoffmann, Dieter Weise

Fraunhofer-Institute for Machine Tools and Forming Technology IWU in Chemnitz, Dresden und Zittau.

Jiri Koziorek, Petr Bilik

VŠB – TU Ostrava in Ostrava.

Amy Groth

The Imaging Source Europe GmbH in Bremen.

Link to the application report:
https://www.theimagingsource.com/media/blog/archive/20201207/

Content

Introduction

Visual inspection is the cornerstone of most quality control workflows. When performed by humans the process is expensive, prone to error, and inefficient: a 10%-20% pseudo scrap and slippage rate and production bottlenecks are not uncommon. Under the name IQZeProd (***I**nline **Q**uality control for **Ze**ro-error **Prod**ucts)*, researchers at Fraunhofer IWU are developing new, inline monitoring solutions to recognize defects as early in the production process as possible for a variety of materials such as wood, plastics, metals, and painted surfaces. The system uses multi-sensor data fusion from a variety of sensors to recognize structural and surface defects as the components travel the production line. The goal is to make industrial manufacturing processes more robust and sustainable by increasing process reliability and improving defect detection. At the heart of the system is the researchers' own Xeidana® software framework and a matrix of twenty industrial cameras. The researchers had very specific camera criteria: global-shutter monochrome sensor; low-jitter real-time triggering; reliable data transmission at very high data rates and straightforward integration into their software framework. They selected GigE **Vision-**standard industrial cameras from The Imaging Source.

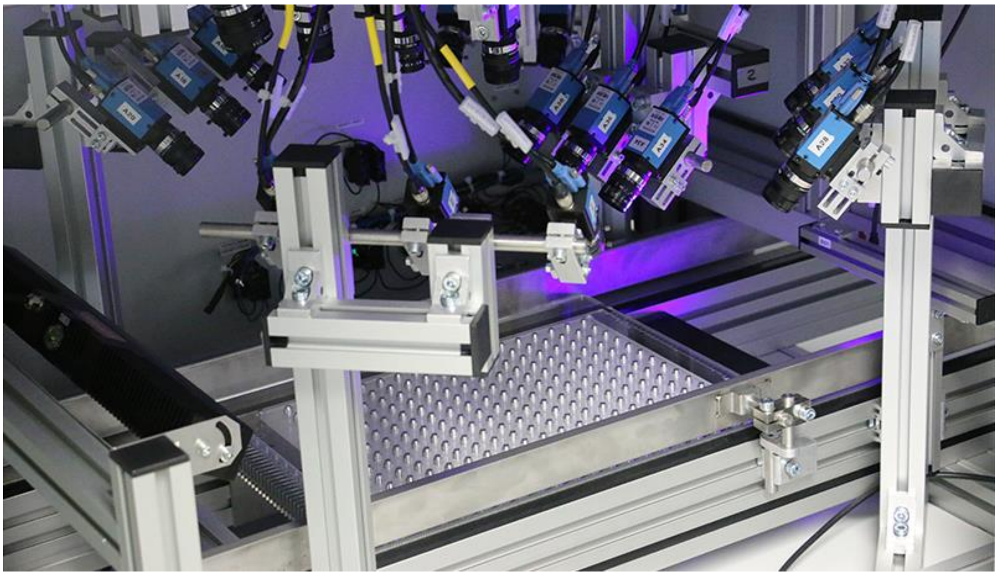

Fig. 01 Image data from IQZeProd's twenty TIS GigE industrial cameras as well as data from hyperspectral and non-optical sensors are fused using the Xeidana software framework to enable an inline QC system with zero errors. *Image: Fraunhofer IWU ©*

While Xeidana's framework approach offers the flexibility necessary to process data from optical, thermal, multi-spectral, polarization or non-optical sensors (e.g. eddy current), many inspection tasks are completed using the data delivered by standard optical sensors. Project manager, Alexander Pierer, commented, "We often use data fusion to redundantly scan critical component areas. On the one hand, this redundancy can consist in the fact that we capture one and the same region under different perspectives, which mimics the so-called manual mirroring of the human visual inspection. Or we combine different sensor principles, e.g. classical image processing with hyper-spectral analysis, polarization analysis or non-optical methods such as eddy current." To acquire the visual data needed to complete these tasks, the researchers created a camera matrix consisting of twenty GigE industrial cameras: nineteen monochrome and one color.

Fig. 02 **Nineteen monochrome industrial cameras gather data from critical component areas. Xeidana processes the redundant data to imitate the process known as 'mirroring' - a technique commonly used for manual inspection.** ***Image: Fraunhofer IWU ©***

Fig. 03 **Color testing of plastic toys with a hyperspectral line scan camera (type: Specim FX10).** ***Image: Fraunhofer IWU ©***

Monochrome Sensors - Optimal for Defect Detection

Monochrome Sensors - Optimal for Defect Detection

Due to their intrinsic physical properties, monochrome sensors deliver higher detail, improved sensitivity, and less noise than their color counterparts. Pierer notes: "monochrome sensors are sufficient for detecting defects that appear as differences in brightness on the surface. While color data is very important for us humans, in technical applications the color data very often does not provide additional information. We use the color camera for color tone analysis, by means of HSI-Transformation, to detect color deviations that may indicate a problem with paint coating thickness."
Task requirements and short exposure times meant that the engineers had very precise camera criteria: Pierer continues, "The main selection criteria were global shutter and real-time triggering with very low jitter, because we shoot the parts in motion with very short exposure times in the 10µs range. The exposure between the camera and the Lumimax illumination (iiM AG), which is also triggered via hardware input, must be absolutely synchronous. We tested some of your competitors here and many of them had problems. It was also important to us that the ROI could already be limited to relevant areas in the camera's firmware in order to optimize the network load for image transmission. Furthermore, we are dependent on reliable data transmission at very high data rates. Since the parts are inspected in throughput, image failures or fragmented image transmissions must not occur."

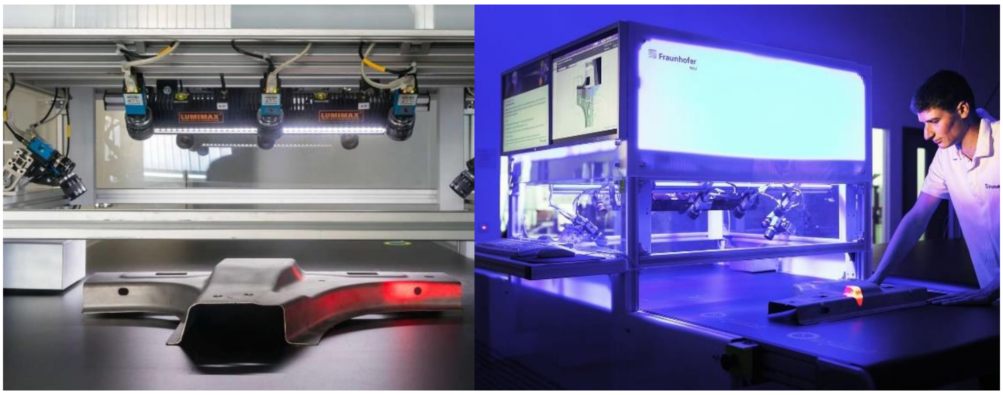

Fig. 04 **Mobile demonstrator for inline quality control of sheet metal formed parts (here B-pillar-foot from a vehicle) with patented defect projection onto the moving part (right). The demonstrator can be used flexibly for live demonstrations or in production at the customer's site.** ***Image: Fraunhofer IWU ©***

Motorized Zoom Cameras Allow for Quick Adjustments to FOV

Over the course of the project, the team built several systems: for industrial settings as well as for demonstration and testing purposes. In the typical industrial setting where the components under inspection remain constant, the imaging provided by the fixed-focus industrial cameras met the team's requirements. For the demo/test system, however, the researchers were using a number of diverse components including metal parts, wooden blanks and 3D-printed plastics which required cameras with an adjustable field of view (FOV). The Imaging Source's monochrome zoom cameras with integrated, motorized zoom offered this functionality.

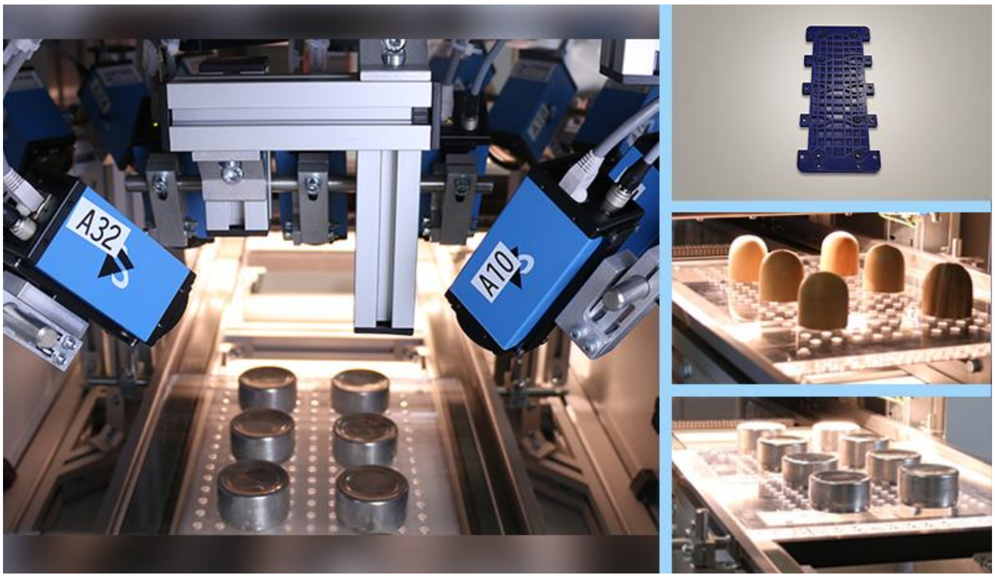

Fig. 05 Zoom cameras provide a rapidly adjustable field of view (FOV), allowing the demo system to scan components of diverse size and shape. ***Images: Fraunhofer IWU ©***

Due to vibrations during the inspection process and tolerances in the placement of the components, position and orientation can vary from part to part. For an actual-target comparison, the actual component position in relation to the reference position must be known in the form of an affine transformation (displacement, rotation, scaling, shear). The approximate calculation of the transformation matrix is performed using an image registration procedure. "This allows us to compensate for placement tolerances caused by handling systems - such as feeders or robots - in the range of a few millimeters by software. Currently, a system is being commissioned in which components fall from a press onto a transportation belt, which makes the component position for the inspection very indeterminate. Initial tests have already gone very well, so we are very confident that we will also be able to reliably monitor randomly oriented components," notes Pierer.

Massively Parallel Processing Keeps Pace with Data Transmission and enables Deep Learning

With over 20 sensors of varying kinds delivering data to the system, there is a data stream on the order of 400 MB/s to contend with. Pierer explains, "The system is designed for throughput speeds of up to 1 m/s. [...] Every three to four seconds, the twenty-camera matrix creates 400 images. Added to this is the data coming from the hyperspectral line camera and the roughness measurement system (developed BIMAQ, University of Bremen), all of which must be processed and evaluated within the 10 second cycle time. In order to meet this requirement, so-called massively parallel data processing is necessary, involving 28 computing cores (CPU) and the graphics processing unit (GPU). This parallelization enables the inspection system to keep pace with the production cycle, delivering an inline-capable system with 100% control." Optimized for modern multi-core systems to enable massively parallel processing, Xeidana's modular framework approach allows application engineers to quickly realize a massively parallel, application-specific, quality control program using a system of plug-ins that can be extended with new functionalities via a variety of imaging libraries.

The system's data fusion capabilities can be used in several ways depending on what information is likely to provide the soundest results. In addition to the more standard machine vision inspection tasks, the team of researchers are currently working on integrating other non-destructive evaluation techniques such as 3D vision as well as additional sensors from the non-visible spectrum (e.g. x-ray, radar, UV, terahertz) to detect other types of surface and internal defects.

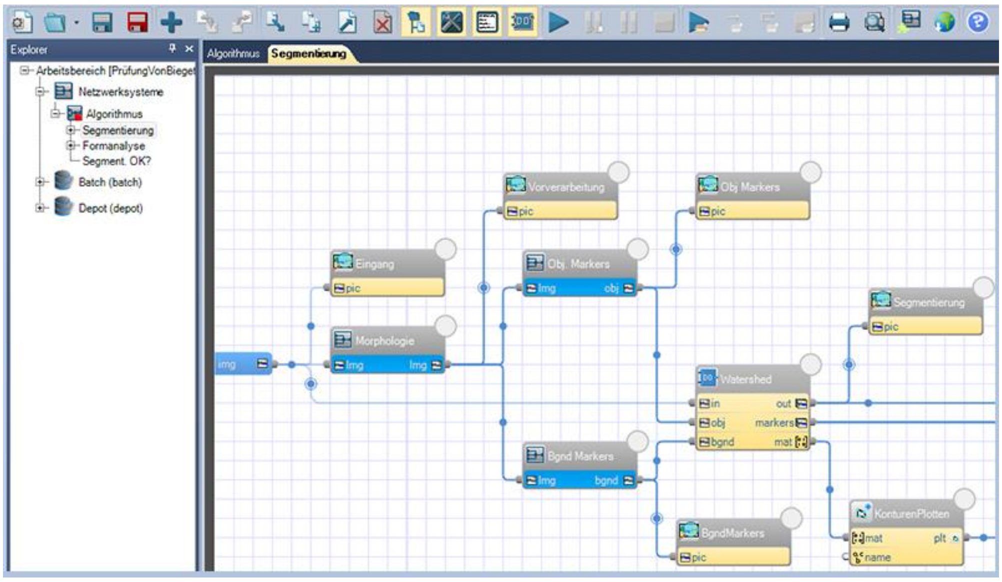

Fig. 06 Processing network. Blue and yellow modules execute individual image processing tasks in parallel. ***Image: Fraunhofer IWU ©***

Since Xeidana supports massively parallel processing, deep learning techniques can also be applied to defect detection of components whose inspection criteria are not clearly quantified or defined. Pierer clarifies, "These methods are particularly important for organic components with an irregular texture, such as wood and leather, as well as textiles. In close cooperation with our partners from the VSB-TU Ostrava, we succeeded in coupling the Xeidana framework with the well-known Deep Learning libraries from Google® and Microsoft®. Whereby we mostly use pre-trained networks, such as VGG16, and re-train the final layers task-specifically. Fault localization is very well possible via the so-called class activation maps when using Convolutional Neural

Massively Parallel Processing Keeps Pace with Data Transmission and enables Deep Learning

Networks (CNNs). A major drawback of machine learning (ML) approaches is the limited traceability of the classification decision. Furthermore, the ML algorithms can hardly be readjusted manually during the commissioning phase if increased test slippage or pseudo-rejects occur. Here, the only thing that can really be done is to retrain or to manipulate something in the preprocessing." Pierer adds.

Pierer summarizes: "We therefore mostly rely on classical image processing algorithms and statistical signal processing methods in our projects. Classical image processing methods, on the other hand, usually have sufficient sensitivity parameters with a clear, explainable cause-and-effect relation that we can specifically modify when problems arise in practical use. Only when we reach limits here do we switch to machine learning."

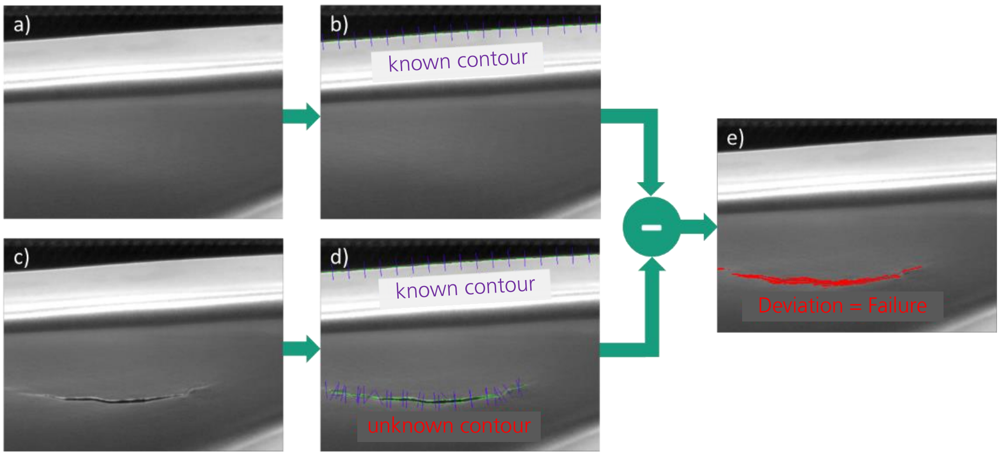

Fig. 07 **a) Reference image of an area on a formed sheet metal part; b) reference image after automatic detection of inner and outer contours; c) crack image recorded during inline monitoring; d) automatic detection of inner and outer contours, whereby the crack is classified as an inner contour; e) Comparison of reference contour and inline detected contour, where the detected inner contour represents a deviation from the known contour and is thus visualized as a defect.** ***Image: Fraunhofer IWU ©***

Acknowledgement: *The Imaging Source Europe GmbH is an active member of the industry working group of the IQZeProd project and is in close professional exchange with the research partners. The IGF project IQZeProd (232 EBG) of the German Research Association for Measurement, Control and Systems Engineering - DFMRS, Linzer Str. 13, 28359 Bremen was funded by the AiF within the framework of the program for the promotion of joint industrial research (IGF) by the Federal Ministry of Economics and Energy based on a resolution of the German Bundestag. Please note that the final report of the IGF project 232 EBG is available to the interested public in the Federal Republic of Germany. The final report can be obtained from The German Research Association for Measurement, Control and Systems Technology - DFMRS, Linzer Str. 13, 28359 Bremen and the Fraunhofer IWU, Reichenhainer Straße 88, 09126 Chemnitz. Supported by the Federal Ministry of Economics and Energy on the basis of a resolution of the German Federal Parliament.*

Bundesministerium
für Wirtschaft
und Energie

This work has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N°856670.

GeoUS

Contact:

Dipl.-Ing. Alexander Pierer
E-Mail: Alexander.Pierer(at)iwu.fraunhofer.de

Dipl.-Inf. Thomas Wiener
E-Mail: Thomas.Wiener(at)iwu.fraunhofer.de

Dipl.-Ing. Michael Hoffmann
E-Mail: Michael.Hoffmann(at)iwu.fraunhofer.de

Fraunhofer IWU
Department Monitoring and Automation
Reichenhainer Str. 88
09126 Chemnitz
Germany

www.iwu.fraunhofer.de