Zero-error-production through inline-quality control of press-hardened automotive parts by multi-camera systems

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Abstract. Visual inspection often represents a bottleneck in the production chain due to limited receptivity and human fatigue. Depending on the inspection task, human classification error decisions greater than 10% are not uncommon. In order to make the manufacturing process more robust and sustainable, this paper presents innovative automated inline monitoring to realize a zero-error strategy in the field of industrial manufacturing. The central idea is to detect surface defects in the running production process by data fusion of a multi-camera system. Due to the required data analysis in conjunction with the targeted high throughput rates in production, this generates large amounts of data to process. Massively parallel hardware structures are used to enable defect detection within the production cycle. The paper especially addresses how to tackle boundary conditions in productive press-lines like the software-based mitigation of placement tolerances of parts and real-time capabilities. As a result, benefits could be achieved in terms of minimum detectable failure sizes and inspection speed, enabling 100% inline inspection of produced parts. The feasibility of the presented approach is demonstrated on realistic press-hardened deep-drawn automotive parts.

1. Introduction

Quality control in production is usually carried out at the end of the process chain. At that time, considerable costs and energy were already invested in the components in the preceding production steps. Since quality control is often still carried out by appropriately trained personnel, visual inspection often represents a bottleneck in the production chain due to limited receptivity and human fatigue. During visual inspection, errors can always be easily overlooked. Depending on the inspection task, classification error rates including false-negatives (inspection slippage) and false-positive (pseudo errors) greater than 10% are not uncommon [1]. In order to make the manufacturing process more robust and sustainable, this paper is developing and implementing innovative inline inspection solutions to realize a zero-error strategy for industrial press-line applications. This paper will attempt to address zero-defect manufacturing more systematically by developing a scalable multi-camera monitoring approach that can be applied to a variety of manufacturing technologies. In order to define the range of components to be considered, a selection of different component groups and families was initially analysed and the focus was placed on structural components in car body construction. The nodal structured B-pillar base (figure 1, left) was selected as the demonstrator component for the area of cell structures. The nodal structure is found in all passenger cars and has similar requirements for all vehicles. The geometric design of the B-pillar base takes into account transferability to other vehicles such as
buses or trucks [2][3]. In order to meet the growing demands on structural components in terms of lightweight design, complexity, strength and crash safety, press hardening is used to manufacture the B-pillar base. The B-pillar base is made of 22MnB5 with a thickness of 1.5 mm. The forming die (figure 1, right) is made of EN-JS1070 by casting. The cast-in cooling channels are made of 1.4571 stainless steel pipes. The melting temperature of the stainless steel used is approx. 1500 °C, which is higher than the melting temperature of the cast material used. Only under this condition it can be ensured that the pipes do not collapse in the casting process. The cooling system consists of several individual cooling channels that can be controlled separately with a counter-flow principle [4][5].

![Figure 1. Demonstrator component B-pillar base (left) and press hardening die (right).](image)

Due to the complex structure of flow channels with small radii and recesses, which are created by means of forming and cutting processes, cracks, necking and burr formation cannot be completely avoided during production. In order to prevent the transfer of defective parts to the assembly line, an automated 100% inline inspection is mandatory. One possible approach for full-surface monitoring is to capture the surface using matrix cameras under high optical magnification and then detect defects by applying various image processing techniques. Since defects, such as cracks, have to be detected in the 0.1 mm range, correspondingly high camera resolutions are required. As a consequence, extensive amounts of data have to be transmitted and processed for each part to be monitored.

2. Inspection system hardware

For the experimental evaluation, an inline monitoring system was designed as a modular camera-based measuring bridge for the inspection of sheet metal parts (figure 2). The inline monitoring system comprises 13 monochrome cameras (type TheImagingSource DMK 33G445 with a resolution of 1280 pixel x 960 pixel, global shutter, GigE-interface) and four high-power LED-illumination-bars. For instance, such a system can be installed above the outlet conveyor belt of a multi-stage press and monitors each produced part. As assistance for the workers, a beamer was coupled to the inspection system to highlight the detected failures directly on parts on the moving conveyor belt [6]. A second option for such an assistance, is a multi-colour LEDstripe (type WS2811) along the conveyor belt that indicates the failure classification result in the vicinity of the part synchronized to its movement.

The captured images are processed by software developed for Windows systems. Due to the lack of real-time capability of Windows systems, an additional real-time controller is required to trigger the cameras and the associated illuminations at defined positions of the part. This additional real-time controller is based on a Controllino® Mega hardware. Figure 3 depicts the general topology of the hardware system. Over a LAN-interface the Windows system can define a trigger program which is list of positions and associated cameras and illuminations to be triggered at the designated positions. In order to measure the part position, a rotary encoder and light barrier are attached to the conveyor belt and connected to the real-time controller as inputs. To ensure the real-time capability of the triggering, the trigger-sequence is handled within the interrupt routine for the decoding of the encoder. If a new part is entering the inspection system, the light barrier is triggered and the part position in the coordinate system of the inspection system is reset to zero. Over digital 24V-outputs the real-time controller can trigger the cameras and illuminations according to the defined trigger programme.
Due to the planned throughput speed of up to 1.5 m/s, a special requirement arose in the selection of the illuminations. Since the designed image processing system should not interrupt the running production process, the images are captured and evaluated directly in motion. For this reason, the choice fell on high-power LED-illuminators with integrated flash technology (type LUMIMAX from iiM AG). These flash illuminators react enormously fast to the trigger pulse of the real-time controller, so that the maximum light output is available within 5 µs. A very short exposure time is therefore no problem at all. The movement of the object can be virtually frozen and thus acts as a standstill for the camera. Thus, image evaluation is possible without any motion blur. The illuminations light individual surface regions of the parts from different angles in order to make defects visible. In this way, the so-called “mirroring” of manual inspection was imitated. Illumination without diffuser attachments were used, so that a quasi-structured lighting was present. Overall, the image processing system generates very high data volumes of up to approx. 550 Mbyte/s, which must be processed. To meet this requirement, so-called massively parallel data processing [7] involving 14 CPU-cores (Intel® Xeon® E5-2690v4, 2.6GHz) and a graphics processor is necessary. This parallelization enables the inspection system to keep pace with the production cycle and ensure inline 100% inspection.

3. Inspection system software
To enable rapid development of application-specific, massively parallel quality monitoring programs, the framework XEIDANA® with a visual programming interface was developed. To build a data analysis program, functional modules from a library of data analysis methods (e.g. image processing methods, machine learning methods, statistical analysis methods) and data source connections (e.g. sensors, camera links, database interfaces) are placed via drag-and-drop and interconnected at their input and output nodes. The result is a processing network that solves the application-specific task (see figure...
4). In the background, the framework manages the optimal parallelization of data processing and the synchronization of data streams. The parallel data processing enables optimal utilization of the performance of multi-core processors. Each module generates at least one separate CPU-thread in which the corresponding algorithms are processed. This allows, for example, the simultaneous pre-processing of different sensor signals before the signals are fed to a common execution. Additionally, modules interconnected as daisy-chain can be processed in the so-called pipeline mode. This means that while a module is still calculating the output for an incoming data packet, its predecessor module can already be processing a new data packet at the same time.

![Image](image.png)

**Figure 4.** Example network built by visual network programming.

The demonstrator inspection system is used for the gapless acquisition of the part’s surface. The required camera resolution and thus resulting amount of data depends on the size of the smallest defects to be detected. In order to reliably detect defects with an extension of 0.1 mm on a part surface of approx. 500mm x 500mm, image resolutions of at least 100 megapixels are required. With a dynamic range of 12 bits, this corresponds to a data volume of 150 Mbyte per part. With industrial cameras currently available on the market, this amount of data can be recorded within a few seconds. Due to the limited camera resolutions, several overlapping images must be recorded per part in an equidistant grid in order to cover the entire surface. The recorded images are evaluated by using model-based methods. These enable inner and outer contour inspection as well as the detection of cracks, necking and burrs. This involves an actual-target comparison between the live images recorded during production and a model, which can be in the form of a CAD file or a reference image from a good-quality part.

In detail, the image processing is described by the following steps, which are performed for each of the recorded images of a part:

1. **Lens distortion correction and image enhancement**
   The lens of the camera usually results in a distorted representation of straight lines. Using calibration and correction methods, the distortion in the recorded images is corrected [8]. Even global image enhancements such as edge-preserving denoising with median or bilateral filters can be performed [9].

2. **Pose correction**
   Due to vibrations during the test process and tolerances during the placement of the part, position and orientation can vary from part to part up to ±5mm and ±3°. For an actual-target comparison, the actual part image \( I_{\text{Live}} \) in relation to the reference image \( I_{\text{Ref}} \) must be known in the form of a transformation matrix \( T \) as shown in figure 5. Thereby, the variables \( I \) associated with the respective images are considered as homogeneous pixel-coordinate vectors \( (x_k, y_k, 1)^T \) whereby \( k \) sequentially indexes the \( N \) pixels of the image \( I \).
The approximate calculation of the transformation matrix $T$ is performed using an image registration method called enhanced correlation coefficient (ECC) based on a maximized normalized cross correlation as objective function [10]. The resulting transformation matrix $T$ delivers a subpixel-precise estimation for an optimal aligned live image $I'_{\text{Live}}$ in relation to the reference image $I_{\text{Ref}}$:

$$I'_{\text{Live}} = T \cdot I_{\text{Live}}$$

$$T = \begin{pmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ 0 & 0 & 1 \end{pmatrix}, I = \begin{pmatrix} x_k \\ y_k \\ 1 \end{pmatrix}_{k=1,2,\ldots,N}$$

The ECC is operated in Euclidean mode and delivers a normalized notation where $h_{33}$ is set to 1. In the Euclidean case the transformation matrix $T$ delivers 6 degrees of freedom $h_{ij}$. Hence this mode only considers rotational misalignments $\phi$, lateral displacements $\Delta x, \Delta y$ in the camera plane which can easily be re-calculated by a parameter comparison between the delivered matrix parameters $h_{12}, h_{13}$ and $h_{23}$ with the transformation parameters of a sub-sequent rotation and translation according to equation (2).

$$T = \begin{pmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ 0 & 0 & 1 \end{pmatrix} = \begin{pmatrix} \cos \phi & -\sin \phi & \Delta x \\ \sin \phi & \cos \phi & \Delta y \\ 0 & 0 & 1 \end{pmatrix}$$

Figure 6 demonstrates the Euclidean ECC-based transformation of a live image taken by one camera of the inspection system to the pose of a reference image. One path of the data-processing network overlays the original monochrome live and reference image to the green and red channel of the coloured output images without any pose correction. The yellow areas indicate matches between the two images. The visible green and red shadows are mismatches that could cause additional pseudo-errors if kept uncorrected. The second network path below shows the result of the performed pose correction. The pose of the live image is registered to the pose of the reference image allowing a direct region or pixel-wise feature comparison between both images.

3. Feature generation
Component quality is often described by a set of critical-to-quality (CTQ) metrics [11]. However, an automatic inspection system can only make decisions based on the available sensor data. Therefore,
features must be found in the sensor data that optimally represent the given CTQ. For sheet metal parts, anomalies are expected to be detectable by contrast edges in the monochrome camera image. For the live image $I_{\text{live}}$ to be evaluated, inner and outer contours are first extracted using Canny algorithm [12]. Subsequently, the extracted edges are tracked using depth search [13] and divided into segments. In addition, gaps in the tracing are closed.

4. Feature comparison

In the final step, a distinction must be made between edge segments associated with specific geometric features and the normal texture of the part and edges caused by failures. To separate failure edges from the normal texture of the part, the actual position of the part is virtually transformed back to the reference position of the part (step 3) and compared to the known good state of the part. To perform this comparison, the distance and angle of the part's edge segments to the closest contours of the good state model are calculated. If the distance or angle exceeds a specified threshold (e.g. $>0.5$ mm, $10^\circ$), it means that there is no similar edge of the good state model in its vicinity. As a consequence, such edges are identified as failures. This step could also detect larger deformations or geometric inaccuracies as anomalies with respect to the reference part model. Since the cameras are not equipped with telecentric lenses and not all cameras are aligned perpendicular to the part surface, precise dimensional measurements of features in the range of 0.1 mm or below are not possible and are subject to further optimization of the optical setup and its accurate calibration if required in the specific application.

4. Experimental evaluation

The described method is already used for inline monitoring of formed sheets in the press shop and allows the detection of cracks, local necking, geometrical defects and surface anomalies. Figure 7 illustrates the failure detection. Reference image (a) and a live image with a crack recorded (b) are taken from an area of a formed sheet metal part. Subsequently, the inner and outer contours are extracted from the reference (c) and live (d) image whereby the crack is classified as an inner contour. Comparison (e) of reference contour and detected contour in the live image yields the inner contour of the crack represents as deviation from the known contour and is thus visualized as a failure.

![Figure 7. Failure detection by feature comparison.](image-url)

For inline monitoring of parts of size 500mm x 500mm, the whole-area evaluation can be performed in a time span under 3 s. The rate of evaluated images per second is limited by the computational complexity of the algorithms, the portion of parallel code and underlying hardware. To investigate the computational performance of the implemented software, a test scenario was created in which the number of active cameras varied from 1 to 13. The frame rates of the cameras were set to the maximum rate of 30 frames per second. For each camera the processing steps described in section 2 have been carried out simultaneously in a monitoring network for a period of 100 s. The mean rate of evaluated images per second was documented for different numbers of active cameras. To show the scalability of the implemented monitoring network, the test scenario was executed on two different hardware
platforms. The first hardware platform uses a CPU with four cores (Intel® Core™ i7 CPU 860, 2.4GHz) and the second platform uses a CPU with 14 cores (Intel® Xeon® E5-2690v4, 2.6GHz). Figure 8 presents the relationship between the minimum detectable failure size, number of cameras and the highest possible velocities $v$ of the moving parts during monitoring. The cameras were triggered with an image overlapping of 50% and at least 4 pixels for the detection of a minimum sized failure.

![Figure 8](image.png)

Figure 8. Performance of two different hardware platforms for failure monitoring in dependency of maximum velocity of parts and detectable failure size.

The experiment has shown that the evaluation of camera images is up to four times faster using a 14-core instead of a 4-core CPU. Lower speedup-factors are a consequence of the division of parallel code and sequential code as anticipated theoretically by the Amdahl’s Law [14]. The lower the count of cameras, the lower the portion of program code that benefits from parallel hardware. Depending on the size and complexity of the monitored part as well as the minimum size of the detectable failures, the accumulated number of images from all cameras varies for a specific part. The smaller the size of the failures, the smaller the monitored camera field must be at a constant camera resolution. Consequently, if the size of camera fields decreases, the number of required images increases for complete coverage of the part surface.

5. Summary and outlook

A multi-camera inspection system for sheet metal parts was presented which can master non-ideal part placements occurring in real industrial applications. Using parallelization, smaller failure sizes are detectable and shorter inspection cycle times are feasible. Since the used Euclidean pose correction preserves parallelism of linear features, it cannot fully compensate three-dimensional perspective distortions raising from a rotation of the part out of the camera plane. In the inspection application this occurs if the part can jiggle on the conveyor belt or the camera is non-perpendicular aligned to the part surface in combination with a rotational respective lateral displacements. To take these effects into account, ongoing research must deal with affine and homographic pose corrections and the handling if the associated increased computational efforts. The utilization of colour and hyperspectral cameras will be one focus for future developments, especially for the inspection of coated parts. Therefore dedicated feature generation methods must be developed. Two approaches the authors are currently working on, are hue analysis based on HSI-transformation and coating thickness analysis in the infrared spectrum.
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