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A cloud-based 3D real-time inspection platform for industry: a case-study focusing automotive cast iron parts

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Abstract

In this work, a 3D real-time quality inspection platform for industry is presented, with a specific focus on automotive cast iron parts. It is supported by a cloud-based platform, which combines recent software and hardware advances to deal with large amounts of information related to the acquisition process and the computational power needed to execute the computer vision platform algorithms (e.g., point cloud filtering, alignment, and comparison). This platform introduces modifications in the current workflow through the digitalization of the inspection process, promoting the reduction of human related inspection errors as well as ergonomic issues, while making available a solution for automatically gathering and storing data in a cloud-like environment for further access and advanced data analytics.

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Keywords: 3D real-time inspection, cloud, computer vision, cast iron, automotive industry

Nomenclature

CAD	Computer Aided Design
QI	Quality Inspection
PCL:	Point Cloud Library
TLS:	Terrestrial Laser Scanning
RANSAC:	Random Sample Consensus
FCSOR:	Fast Statistical Outlier Removal
ICP:	Iterative Closest Point
NDT:	Normal Distribution Transform
ECMPR:	Expectation Conditional Maximization for Point Registration
SVR:	Support Vector Registration
CPD:	Coherent Point Drift

1. Introduction

Currently, quality inspection (QI) procedures in industry in general, and in the context of automotive parts assessment in particular, are still carried out mainly manually, in spite of being known the benefits of converting traditional QI procedures into more automated digital pipelines (reduced human errors, improved ergonomic conditions, possibility of reallocating professionals to activities in which they will be more needed, etc.). Among the approaches that have been allowing such digitalization outstands computer vision, which has been progressing towards zero-defect solutions, due to continuous advances in hardware and software. More specifically, recent advances in laser line scanners using laser triangulation (e.g., high resolution, wider field of view) along with the capacity of computer systems to handle large more and more amounts of data (e.g., more powerful graphics processing unit) and more advanced logical/numerical strategies to manipulate data efficiently underly as arguments to sustain the QI digital journey.

Regarding the 3D QI process, many are the works that can be found in this field, such as [1], which addresses the metrological suitability of a laser line scanner to evaluate the quality of the 3D metal prints comparatively to computer aided design (CAD) models, as well as the accuracy of the obtained measurements using such type of scanner. The method resorts to the standard deviation of the point cloud acquired from objects laser scanning to measure errors. Filters that eliminate those points responsible for the difference between the measured and the reference values are also proposed.

Another proposal [2] includes the construction of a theoretical point cloud of the 3D digital model considering the generated G-code and the computation of the dimensional deviations between the theoretical 3D point cloud and the corresponding printed model. The method uses a high-resolution point cloud data of the physical printed part with the digital 3D model and introduces a vision-based method to scan, filter, segment, and correlate in real-time, as well as to evaluate the performance of the additive manufacturing process. This approach allows to decide whether or not to continue the additive manufacturing process.

In [3], authors proposed another framework to automatically monitor the visual surface defects inside of the wire arc additive manufacturing technology. It includes libraries such as: Point Cloud Library (PCL) and Open-Source Computer Vision Library (OpenCV). The method includes three steps: 1) Point cloud pre-processing, using a statistical outlier removal algorithm; 2) topographic image conversion, transforming the filtered 3D point cloud into a 2D heightmap, with each pixel corresponding to a height value, for further analysis; and 3) defects detection, employing the Support Vector Machine (SVM) classifier with the input variables of 12 features (e.g., intensity, maximum, minimum, mean, contrast, standard deviation, entropy, flatness, homogeneity, skewness, distance to boundary, Laplace filtered). To improve accuracy, they applied the minimum redundancy maximum relevance

(MRMR) algorithm as a feature selection method that quantifies the relevance between the features and response variable and achieved the accuracy of 99.8%.

In [4], authors focused on industrial plant piping system inspection, wherein an improved technique relying on terrestrial laser scanning (TLS) for data acquisition, normal-based region growing and efficient random sample consensus (RANSAC) for point cloud data processing was proposed. Two main stages are involved: 1) point cloud data processing, with a point-to-mesh Iterative Closest Point (ICP) algorithm for a fine registration, and an octree-based down sampling algorithm to reduce the number of points; efficient RANSAC is then used to detect and remove the planar objects and apply normal-based region growing algorithm to segment the pre-processed point cloud; and 2) performance assessment of results, relying on distance-based deviation analysis and geometric parameter comparison.

In this paper, we propose a cloud-based 3D real-time inspection platform for assessing the quality of vehicle cast iron parts, using 3D line scan sensors, computer vision, and cloud systems. The size of the part to inspect should be restricted according to the field of view and the measurement range of the sensor.

The paper is structured with 4 sections. Besides section 1, wherein an introduction and a literature review is provided, section 2 describes the proposed platform. Section 3 presents the platform implementation along with preliminary results. Finally, section 4 ends this paper with a few conclusions as well as remarks for future work.

2. Platform proposal

A platform for 3D cast iron parts inspection that can however be extended to other contexts is presented in Fig. 1. It is composed of two main components: computer vision component and cloud component. The computer vision component, which can be instantiated according to the number of part surfaces to inspect, includes a laser line sensor to acquire the top surface as a 3D point cloud, in synchronization with the movement induced by a conveyor belt, and also a processing unit that manages a collection of algorithms to compute cast iron parts point clouds, to measure surface deviations and to build CAD model representations of the scanned elements. On the other hand, the cloud component is a layer of dynamic and secured REST-based services for storing and retrieving scanned parts and respective associated data. It includes functionalities such as computer vision component(s) configuration (e.g., acquisition and evaluation parameters), as well as methods to save and consult inspection results.

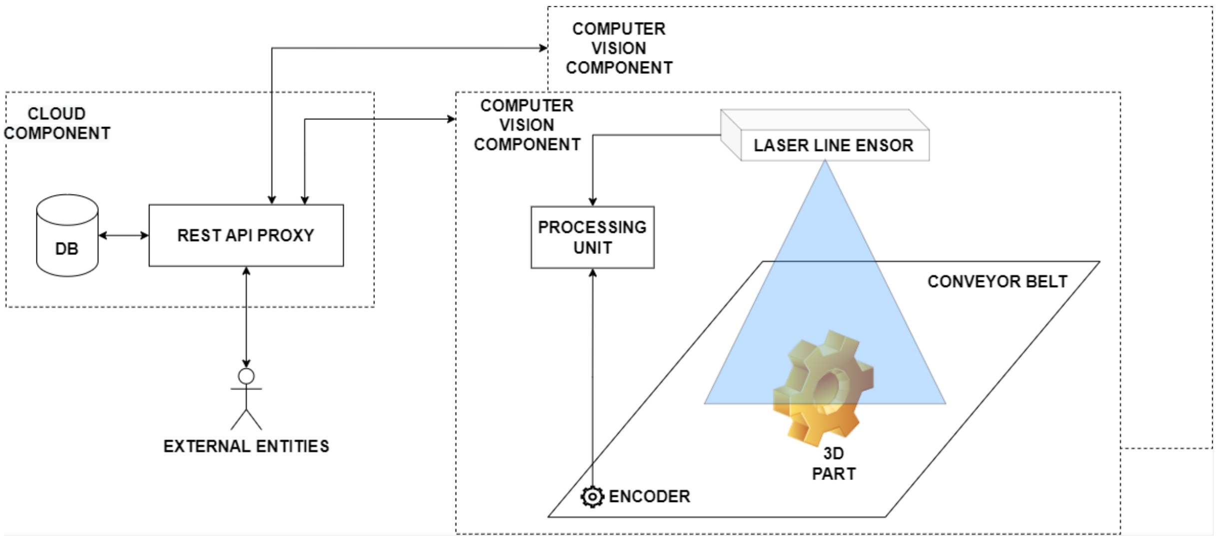

Fig. 1 Diagram of the platform including two main components: computer vision component and cloud component.

For each type of cast iron part, the system supports the adjustment of a related setup of configuration parameters: the acquisition resolution, exposition time, timeouts, the speed of the inspection process, error thresholds (th_1 and th_2), clusters size, down-sampling thresholds, among others. This way, the platform allows to carry out experiments while ensuring the flexibility to select the most proper configuration to perform QI. Selected parameters are stored in the cloud component ensuring that configurations are accessible to the group of computer vision components inspecting the different perspectives/surfaces of a given type of cast iron part.

3. Implementation and preliminary results

Our platform performs inspection in six stages: I) CAD model enhancement, II) point cloud capture, III) filtering, IV) alignment, V) evaluation and VI) upload result to the cloud – summarized in Fig. 2. Firstly, the CAD model is transformed into a dense 3D point cloud, considering a specific resolution threshold for detection. This stage uses parallel programming algorithms based on the CUDA library to estimate the point's positions from the polygons and vertices of the CAD model. The second stage is a non-invasive capture process using 3D line scan sensors (such as Gocator or Automation Technology devices) to obtain a 3D point cloud of the cast iron part that is formed from assembling each captured measurement profile (surface), with the support of an incremental encoder.

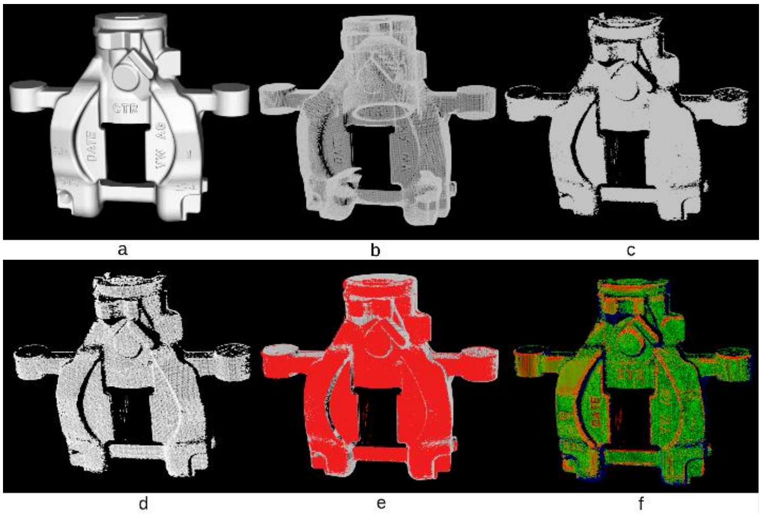

Fig. 2 Platform stages. From left to right: a) original CAD model; b) enhanced CAD; c) captured point cloud; d) filtered point cloud; e) alignment result; and f) evaluation result.

The third stage carries out the reduction of noise (i.e., outliers) related to the 3D point cloud acquisition process, which can be defined as a cleaning task to remove groups of erroneously generated points that usually result from diverse factors regarding sensor capture operation [5]. It aims to avoid errors in measurements and disturbances affecting subsequent processing steps. To tackle outliers in general and, in particular, the mixed noise that rarely comes isolated from the main point cloud [6], there are several filtering algorithms and techniques based on statistics, neighborhood search, projection, signal processing, differential equations, or a hybrid filtering (i.e., combination of methods). In the proposed approach, a Fast-Statistical Outlier Removal (FCSOR) algorithm was employed, which reduces the 3D space, thereby decreasing the computational complexity using the voxel-subsampling subprocesses, known as clustering [7].

The fourth stage handles the alignment of the filtered acquired 3D point cloud (stage III) with the 3D point cloud obtained from the CAD model enhancement stage (stage II). Among the available algorithms specialized in alignment (e.g., ICP [8][9], Normal Distribution Transform (NDT) [8][10], Expectation Conditional Maximization for Point Registration (ECMPR) [8][11], Support Vector Registration (SVR) [8][12], Coherent Point Drift (CPD) [8][13]) - i.e., iterative transformation methods that aim the convergence between acquired data and reference sample, following close neighborhood strategies -, in this proposal, a process that includes rigid transformation estimated with the centroids of both point clouds, followed by an iterative coarse (less density) to fine (full density) alignment process using the ICP algorithm was adopted, towards the attainment of optimal convergence values in real-time.

The evaluation stage (stage V) quantifies the surface deviation between the aligned point cloud of the part and the enhanced computer CAD model (Fig. 3). This stage involves two steps:

- to determine surface deviation between the filtered 3D point cloud and the mesh of the CAD model, by measuring the Euclidean distance between 3D points and, then, classifying each point according to a pair of constraint thresholds (th_1 and th_2);
- and to detect missing regions in the cast iron part comparatively to a reference sample using a near-neighborhood algorithm that considers (1) the point cloud of both scanned element and inferred from a CAD model representing a defect-free part as well as (2) a configuration parameter for delimitation purposes.

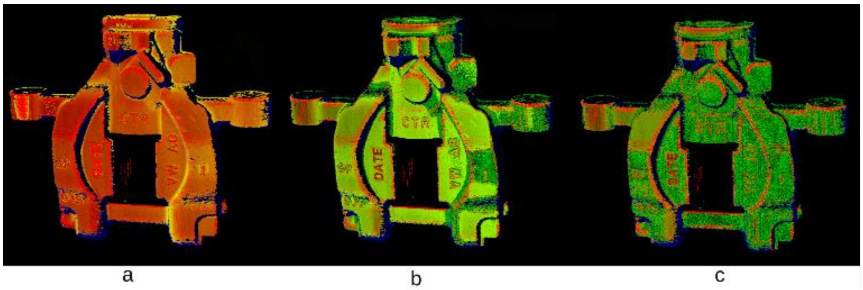

Fig. 3 Distance deviations considering two thresholds: a) th_1=0.1mm, th_2=2.5mm; b) th_1=1.5mm, th_2=3.0mm and c) th_1=2.0mm, th_2=3.5mm

According to (Fig. 3), the tuning of parameters th_1 and th_2 produce different results in the product quality control process for the same cast iron part. Just like a heatmap, the color of the points is associated with the distance deviations. wherein red corresponds to a distance greater than th_2, distances lower than th_1 are represented in green, while all the other distances between th1 and th_2, are highlighted at yellow. Those values should be defined according to the resolution requirements to detect distance deviations. Fig. 3 a) shows a low threshold for an inspection that is more demanding in terms of tolerances, visually confirmable through the merge of red and yellow colors. Fig. 3 b) and c) depict results of inspection procedures configured to be less sensitive to deviations, with a complaint combination of displayed colors, more specifically, scales of red/yellow/green and green/red, respectively. The levels of detail and tolerances must be parametrically adjusted according to the requirements established for the inspection of a given cast iron part type (considering the dimensions of the elements to be scanned, supported camera´s field-of-view, distance and resolution, etc.).

4. Conclusions and future works

This work presents an innovative platform for the 3D quality control inspection oriented to the automotive industry, although, expansible to other areas and sectors (e.g., moulds industry). The platform introduces alterations in the current workflow of the cast iron inspection process, making it more digital, reducing the human-related ergonomic issues and inspection errors while gathering and storing data in the cloud, foreseeing the application of advanced techniques for data analytics. Configuring cast iron part inspection procedures are supported by the proposed solution, according with the required quality inspection resolution. Lower thresholds imply inspections more sensitive to errors, and, thus, more demanding in terms of quality control preciseness, while higher thresholds are more prone to ignore smoother defects. A color system provides visual feedback of the deviances, in which red identifies erroneous points, yellow is for medium scale perturbations still inside the defined error tolerance, and green indicates pixels that practically match the reference sample.

Future work will focus on the refinement of the current data analytics techniques to make the predictions more precise in what regards to information related to defects' location and probability of occurrence. Moreover, these optimizations will allow to specify and implement labeling techniques for building models capable of distinguishing defect types. Such upgrades can bring the industry sector closer to enhanced decision making and, ultimately, defect-free production lines.

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