Challenges in Automated Quality Assurance of Three-Dimensional Parts

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Introduction

Automation of image recognition-based quality assurance is commonly applied to manufacturing parts with well-defined geometries and predictable perspectives. However, capturing parts with irregular three-dimensional shapes presents significant challenges. These complex components are critical for industries such as manufacturing, automotive, and aerospace where custom designs drive functionality and innovation. Automation of quality assurance for such parts has become increasingly vital due to rising labor costs, the need for consistent inspection quality, and the growing importance of detailed process documentation. Traditional manual inspection methods are often slow, prone to inconsistency, and difficult to scale, making automation an increasingly attractive solution.

Despite the potential benefits, automating quality assurance for these parts presents unique challenges. The variability in shapes and surfaces complicates key tasks such as:

- definition of views: identifying optimal perspectives to capture all critical features of the part;
- handling for views: developing reliable handling systems to correctly position parts for inspection;
- camera selection: choosing appropriate imaging devices to capture high-quality data;
- model selection: selecting image processing or machine learning models capable of accurately interpreting complex and irregular data.

Naive approaches, such as those used for flat parts, fail because of the complexity and diversity of three-dimensional parts, which often require tailored solutions for effective inspection.

Related Work

Previous research and industrial implementations have focused on flat (Villalba-Diez et al., 2019) or standard parts, using traditional machine vision and fixed inspection setups (e. g., Tabernik et al., 2019; Vacho et al., 2018). Although effective for predictable geometries, these methods lack the flexibility to handle the variability of many more complex parts (Ornat et al., 2022). Attempts to apply generic AI-based solutions (Božič et al., 2021; Akcay et al., 2022) have faced limitations in adaptability and integration with real-world production environments. Comprehensive guidelines for addressing the specific challenges of automated quality assurance remain scarce.

Method

Our approach involves a systematic evaluation of options across multiple projects involving different types of three-dimensional parts. By focusing on practical challenges and using diverse datasets, our aim is to develop a holistic decision-making framework. This framework incorporates the following: standardized methods for view definition and handling; criteria for selecting appropriate cameras, image recognition, and AI models; context-specific trade-offs between performance, cost, and feasibility.

The presentation and the full abstract will discuss three use cases (which are abstracted from real-world use cases to ensure the anonymity of the project partners). We validate our approach using three distinct use cases, elaborated in Table 1:

1. *Customized medical implants (Use Case 1):* irregularly shaped three-dimensional parts that come in different series (i.e., ≈ 100 different geometries) and up to five distinct series per geometry.
2. *Metallic tubular assemblies:* reflecting metallic parts with different quality challenges such as sealing ends *(Use Case 2a)* and quality requirements for the non-functional visible surface *(Use Case 2b)*.

Table 1: Different requirements in use cases

Category	Use Case 1	Use Case 2a	Use Case 2b
Challenges	different textures	clearly defined relevant segments	unclear error classification
	numerous geometries	easy to locate critical areas	convex surfaces
	difficult to handle		surface irregularities
	large quantity of parts		
	unclear error classification		
Errors	diverse error types	any outlier is classified as an error	errors are poorly defined and require further investigation
	requires robust classification models		
Surface	irregular surfaces	clear and well-defined segments	convex surfaces with visual irregularities
Handling	complex handling systems due to diversity in geometry	simple handling; parts are easy to align	requires precise handling to manage convex forms

Results

In this presentation, we will discuss the key characteristics of parts that must be considered when selecting an approach to automating quality assurance. The results will highlight how these characteristics, such as geometry, surface defects, and part complexity, were addressed through tailored solutions for three distinct use cases. By consolidating insights from these real-world examples, we demonstrate the potential and constraints of automating quality assurance of parts, bridging the gap between theoretical methods and practical industrial applications. The use cases and corresponding solutions will be presented to show how automation can enhance quality assurance processes. In summary, we briefly discuss the three use cases.

Use Case 1 is well-suited for machine learning. The sheer number of configurations makes it challenging to define a static set of rules required for classical systems. Furthermore, the parts cannot be positioned reproducibly and, therefore, are not in a well-defined position when investigated. Both challenges are easier to address with machine learning than with classical methods. Nevertheless, classical methods are necessary to manage the complex geometry and ensure good quality of the images used for classification. The challenges listed in Table 1 outline that sufficient labeled data are required to create a robust classification.

Use Case 2a can be seen as an application in which machine learning does not outperform classical methods. Creating a classical method will simply be faster and more accurate. Here, the quality of the camera, the light source, and how well they are synchronized determine the quality of the image and, consequently, the ease of identifying defects. Parts are positioned in a reproducible way and static rules are well suited.

Use Case 2b, on the other hand, would require fuzzy computations with traditional methods, and machine learning is an excellent tool to account for these cases where reproducing human subjective judgment is necessary. The scoring functionality of machine learning algorithms which provides a range between erroneous and correct parts rather than a simple true/false classification can be utilized efficiently for these purposes.

Apart from these purely technical insights, the following project-based insights should be considered: Existing or easily available classical methods can be used as benchmarks to guide the development of appropriate machine learning methods. When working on automation tasks, it is essential to consider the entire workflow before starting to automate specific stages. Quite often full automation cannot be achieved, and the costs of introducing automation for only selected parts may not be justified. If not all stakeholders are involved from the outset of the project, it is unlikely to succeed as acceptance of machine learning-based automation is rooted in a guided process.

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