PROPHET: PReference-based OPtimization for Human-cEnTric visual inspection

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Abstract. Nowadays, complex inspection processes rely heavily on human operators, while automatic systems handle simpler tasks. However, these tasks are highly repetitive and demand consistent high-quality performance throughout, leading to significant stress for human workers. In contrast, automatic systems can help alleviate this burden. Nevertheless, configuring automatic inspection systems is challenging due to numerous parameters that require extensive time and trial-and-error adjustments. To address these issues, this project aims to introduce an optimization approach based on user preferences for configuring visual inspection systems. Preference-based optimization is a potent method for enhancing system performance in an intuitive manner. This methodology enables the resolution of optimization problems when the decision-maker cannot directly assess the objective function tied to the problem at hand. Instead, they can only express preferences, such as "this option is better than that" when comparing different decision choices.

Keywords: Human-centric production, human-robot collaboration, human-robot interaction, knowledge transfer, preference-based optimization, artificial intelligence.

1 Introduction

Robotics is increasingly being used to assist humans in various fields such as rehabilitation, rescue missions, and medical applications. In these applications, robotic systems need to support and enhance human tasks by utilizing intelligent tools to understand human needs, requirements, instructions, feedback, and satisfaction [1, 3].
One significant domain where robotics plays a crucial role is industrial workplaces, particularly in the context of Industry 4.0 and its evolution into Industry 5.0 [4, 6]. Industry 5.0 aims to improve the working conditions of industrial operators while harnessing human knowledge, adaptability, and intelligence. A central goal of this new industrial revolution is to shift the focus from connected cyber-physical systems to the operators themselves, creating human-centric production environments that leverage human expertise to enhance industrial processes [5]. Instead of performing repetitive manual tasks, humans are placed at the core of the production environment, taking on a leading
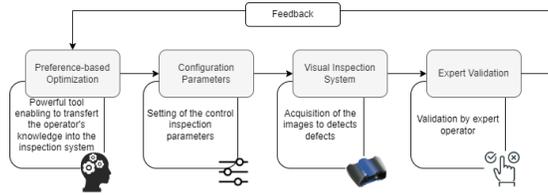
Fig. 1: PROPHET overview.

role. They are involved in high-value operations where their expertise can optimize the production process, leaving easily automatable tasks to robotic systems [7]. Thus, tools are needed to effectively and naturally transfer operator expertise to robotic systems.

The primary objective of the PROPHET project is to introduce and validate a human-centric approach for transferring human knowledge of a task to robotic systems, relying solely on qualitative feedback. This approach utilizes preference-based optimization (PBO) to enable non-expert programmers to impart their expertise to robotic systems, specifically for fine-tuning a target task. The project focuses on a visual inspection task, aiming to develop a system capable of automatically configuring control parameters by learning from the choices made by expert operators. The resulting system facilitates the adoption of automated visual inspection, even in complex tasks, by reducing setup time through the incorporation of skilled operators' inspection results and their valuable experience.

2 Methodology

As previously discussed, the goal of this project is to enhance the efficiency of inspection software by automating the parameter optimization process. Up until now, this task had been performed by a skilled user who relied on a trial-and-error approach to fine-tune the machine's settings until reaching the optimal configuration. This process solely relied on the user's expertise, lacking any mathematical criteria for selecting the parameters to test. Additionally, this operation was quite time-consuming, taking the user approximately 1-working day to identify the machine's optimal parameters. The solution chosen for this problem involves employing preference-based optimization (PBO). This optimization technique leverages a surrogate function to approximate the behaviour of the inspection machine, guided by user preferences. In simpler terms, it helps determine the best machine parameters by considering user experience and preferences. An overview of the PROPHET architecture is depicted in Fig. 1. The optimization algorithm utilized in this study is founded on the methodology outlined in a prior work by one of the authors [2], where the GLISp algorithm was introduced. The algorithm is not summarized in this paper, for a comprehensive understanding please consult the original paper [2].

3 Use case

An evaluation of the preference-based visual inspection system was conducted using three real-world case studies, each involving a dataset of workpieces with and without

Fig. 2: Workpieces used for evaluating the system. On the left the RGB image, on the right the PointCloud.

defects. Fig. 2 depicts an example of the three objects used to evaluate the system: use case 1 is a brass component (object in the center), while cases 2 and 3 are plastic pieces (objects on the side). The goal was to assess the system's performance in detecting various types of defects, including obvious and subtle ones. The evaluation protocol for each case study follows:

– **Configuration of Vision System**: The first phase involved setting up the vision system, including configuring camera parameters and acquiring a reference image of a defect-free workpiece (referred to as the "master"). This master serves as the benchmark for identifying defects in other workpieces. Additionally, masks were created to define specific Regions of Interest (ROIs) within the master image. These masks are used to align the master with the current workpiece image for defect detection.
– **Optimization of Inspection Parameters**: In the second phase, a workpiece with significant defects was chosen to fine-tune the inspection parameters using the preference-based optimization module. Initially, a set of parameter guesses was selected, and operators used the preference-based module to refine these parameters. Once optimization was completed, the best parameters were chosen based on operator preferences.
– **Validation of Parameters**: The third phase involved validating the optimized parameters using a variety of workpieces, both defective and defect-free, to ensure that the system accurately detected defects.

This project was focused on optimizing three key inspection algorithm parameters:

– **Control Threshold**: This parameter determines the minimum defect surface area (in square millimeters) that the system should identify.
– **Correlation Threshold**: It represented a multiplier applied to the resolution, setting the minimum distance (in millimeters) from the master image that a point must be to be considered a defect.
– **Cluster Defects Resolution Multiplier**: This parameter acted as a multiplier factor to the resolution, enabling the system to identify two nearby points as part of the same defect cluster.

To conduct the experiments, a workcell was set up in the IT+Robotics laboratory, consisting of the EyeT+ Inspect vision system and a template for positioning the three types of workpieces. The template ensured that experiments were repeatable, replicable, and comparable.

Table 1: Technical KPIs and results obtained.

KPI No	Description of Technical KPI	Starting value	Results
KPI-1	Configuration time	1 working day	[0.5, 1] h
KPI-2	Inspection mistakes	0.1%	0.02%
KPI-3	Productivity	-	500%
KPI-4	Reduced number of optimization iterations	-	20 iterations

4   Result

The KPIs described in Table 1 are used to evaluate the preference-based visual inspection system. Since three different use cases are used for the validation phase, each case study is evaluated through the KPIs. Following the protocol and steps described in the previous paragraphs, this section presents the results achieved at the end of the project. Configuration time (**KPI-1**) is one of the most important KPIs because it describes the amount of time spent configuring the inspection parameters of the system. At the beginning of the project, the time spent on this activity was 1 working day, i.e., 8 hours. At the end of the project, the time was reduced between 30 minutes and 1 hour at most for each use cases. In particular, use case 1 and 3 required at most 30 minutes to find a suitable set of values, while use case 2 needed at most 1 hour. During the experiments, it was noted that these values depended on both the size of the chosen domain and the optimiser mode, i.e., whether continuous or discrete mode is used. A large domain with the continuous mode requires lots of time, while a small domain with discrete mode requires less time. In fact, for the evaluation a continuous mode with a large domain [0, 10] were used. In order to improve the system, the discrete mode was added and tested with a small domain [0, 5] and incremental step 0.1. The number of iterations is partially related to the optimization time and the domain size and mode used: with a continuous mode at least 50 iterations were needed, while with a discrete mode only 15/20 iterations were needed. The difference between the continuous and discrete modes highlights that the discrete optimization approach was able to converge on the optimal solution more efficiently than its continuous counterpart. This knowledge can be leveraged to guide future optimization efforts and enhance the efficiency of optimization algorithms. The best parameters obtained from the optimiser were then used to inspect all the other objects in the dataset and to evaluate **KPI-3** and **KPI-4**. As summarized in Table 1, both KPIs are achieved. These results show that the preference-based optimization module can best configure the parameters of the inspection system, and the values obtained are more accurate than those found through trial and error. Fig. 3 depicts an example for the use cases: the non-defective object and two pieces with defects. The non-defective object is on the right of the image, the heavy fault object is in the middle, and the lighter defective object is on the left.

5   Conclusions

Preference-based Optimization represents a highly potent methodology for optimizing variables across various applications, including industrial machines and robots. One
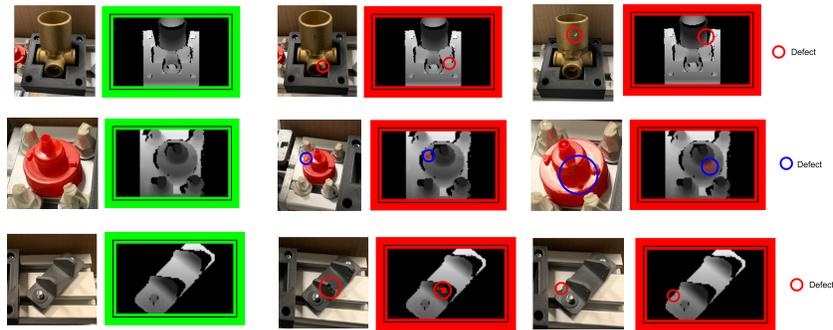
Fig. 3: Example of defects and non-defect recognition.

key advantage of PBO is its ability to leverage user experience as an added value to the optimization process. This aspect is crucial for enhancing efficiency and from a social perspective, as human-centric considerations are always paramount. By prioritizing the human element and considering the user's preferences, PBO can optimize the outcomes in a manner that is not only highly effective but also highly ethical, thus providing a more holistic approach to Optimization that considers both the technological and social aspects of the problem at hand. The application of preference-learning technologies in visual inspection has a strong impact from many points of view, such as simplifying and accelerating the deployment, allowing non-skilled operators to train the system, and increasing production efficiency, enabling wide adoption of such technology. The proof-of-concept developed within this project demonstrates the applicability of the PBO component to a visual inspection system. The designed component could be easily adaptable to various applications and rapidly transferred to other industrial fields, thus significantly improving its potential impact.

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