Assessment of Operation Quality for Robotic Manipulator in Real-Time

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***Abstract*—Robotic manipulators are widely employed in industry for automating repetitive tasks. A particular use case is sorting of waste materials. Movement of such a manipulator is subject for control since defects can occur during the operation. The assessment of operation quality can be also delegated from human to machine based on the progress in Artificial Intelligence (AI). In this demo, we consider video-based assessment as a promising approach for industrial robotics. We demonstrate our computer vision-based procedure for assessing the operation quality of a robotic manipulator. The experimental setup uses a single camera to detect successful and unsuccessful manipulations with objects, including the object loss during transmission in real time.**

I. INTRODUCTION

Robotic manipulators play a crucial role in a multitude of industries by automating repetitive tasks such as sorting objects from waste materials, streamlining production processes, and increasing efficiency [1]. The quality assessment of these robotic manipulators is of paramount importance to ensure their optimal performance and productivity [2]. The evaluation of robotic manipulator performance involves several key methods and criteria, tailored to specific tasks and demands.

These methods include assessing positioning accuracy, repeatability accuracy, throughput, motion velocity, and orientation accuracy. Productivity is gauged by task completion time and the number of tasks completed in a set timeframe. Safety requirements are evaluated through risk analysis and safety measures to prevent accidents. Economic efficiency considers the costs versus the expected benefits, while integration and compatibility with existing systems are important factors. Control and programming convenience, as well as reliability and service life, also play significant roles in assessing robotic manipulator quality.

The assessment of robotic manipulator performance relies on a range of tools and methods, including sensors for real-time parameter monitoring, measurement instruments, specialized software for programming and control, testing equipment, optical systems for position and object recognition, computer modeling and simulation, industry-specific standards and norms, expert evaluations, and statistical analysis techniques. These tools are deployed to measure and evaluate the accuracy, precision, safety, productivity, and efficiency of robotic manipulators. They also play a crucial role in ensuring compliance with industry standards and regulations. The integration of various assessment methods and instruments is essential to tailor the evaluation to the specific needs and requirements of the robotic system under examination. This comprehensive evaluation approach enables the systematic assessment of robotic manipulator performance and quality.

One promising approach for such evaluation is video-based assessment, which enables a comprehensive and real-time analysis of the manipulator's operations. In our study, we introduce a procedure designed to assess the performance quality of robotic manipulators using advanced computer vision techniques. This procedure leverages the power of computer vision to interpret and analyze visual data, providing valuable insights into the manipulator's performance. It takes advantage of image processing and object recognition algorithms to accurately evaluate the manipulator's efficiency.

To substantiate the effectiveness of our proposed procedure, we conducted a series of experiments using a single video camera system. These experiments involved the observation of successful and unsuccessful object acquisitions by the robotic manipulator, as well as instances of object loss during the transmission process, all in real time. The results obtained from these experiments not only showcase the algorithm's capabilities but also highlight its potential to significantly enhance the assessment of robotic manipulator performance. This research paves the way for more objective and efficient quality evaluations of robotic manipulators, which in turn can lead to improved productivity and quality control in various industrial settings.

The rest of the paper is organized as follows. Section II analyzes related work on similar topics and shows the insufficiency of the existing solution for assessing the operation quality. Section III introduces the proposed model as a procedure for operation quality assessment based on the computer vision technology. Section IV demonstrates experimental validation of the procedure. Section V concludes this demo study.

II. RELATED WORK

In our previous works [3,4] we used heterogeneous data to evaluate the current position of a mobile robot. In [3] camera, IMU-sensor, and Lidar were used to construct the trajectory of the autonomous robot movement. Machine vision technologies and algorithms played one of the key roles that were used to recognize objects (doors, walls) during the movement of the cart in the corridor of an office building. In [4] multiple data sources were used such as an accelerometer, gyroscope, laser range finder, and video camera. The experiments in the paper were aimed to create a digital model of a robotic arm and the experiments involved different positions of the manipulator, which were tracked using the preset of green markers.

Modern manipulators, through the introduction of a wide range of intelligent video analysis [5,6] technologies, make it possible to detect and recognize small objects with high accuracy, which significantly increases the efficiency of technological processes in the industry.

III. Procedure for Operation Quality Assessment

Our procedure utilizes a stereo camera system to capture real-time footage of the manipulator's work on the conveyor line. By employing image processing and object recognition algorithms, we can identify and analyze various events, such as successful object acquisitions and potential issues. The procedure focuses on specific tasks, such as box handling, to simplify the evaluation process. Additionally, we consider the potential for cost-effective methods in the future, while demonstrating the effectiveness of the current approach.

Through a series of experiments using the stereo camera system, we demonstrate the procedure's ability to accurately evaluate the performance of the robotic manipulator. The procedure successfully identifies and analyzes events, such as object acquisitions and potential issues, with a high degree of precision. We present numerical measurements for selected experiments, showcasing the procedure's effectiveness in terms of accuracy and distance calculations. The overall evaluation metric, precision in event recognition, provides valuable insights for optimizing the manipulator's performance.

Procedure 1 Procedure for Operation Quality Assessment

Input: Image sequence captured by a single camera.

Output: success_flag indicating whether the object was successfully transferred.

0: Initialize variables: initial_position, final_position, initial_depth, final_depth, success_flag. Loop through each frame in the image sequence:

1. Apply object detection and recognition algorithms to identify the object in the frame.
2. If the object is successfully detected:
2.1 Store the coordinates of the object as the final_position.
2.2 Retrieve the depth information of the object from the camera.
2.3 Store the depth value as the final_depth.
2.4 Calculate the distance between the initial_position and final_position.
2.5 If the distance is within a predefined threshold and the difference between initial_depth and final_depth is minimal, set success_flag to true.
3. If the object is not detected:
3.1 Set success_flag to false.
3.2 Display the frame with the object and its tracked position.

This procedure utilizes computer vision techniques to track the movement of an object in an image sequence. It starts by initializing variables to store the initial and final positions of the object, as well as the initial and final depth values. The success_flag variable is used to indicate whether the object was successfully transferred.

For each frame in the image sequence, object detection and recognition algorithms are applied to identify the object. If the object is successfully detected, its coordinates are stored as the final_position. The depth information of the object is retrieved from the camera and stored as the final_depth. The procedure then calculates the distance between the initial_position and final_position. If the distance is within a predefined threshold and the difference between initial_depth and final_depth is minimal, the success_flag is set to true, indicating a successful transfer of the object. If the object is not detected, the success_flag is set to false.

Finally, the procedure displays the frame with the object and its tracked position. The output of the procedure is the success_flag, which provides information on whether the object was successfully transferred. By comparing the initial position with the recognized position of the object, this procedure provides a reliable indication of whether the object was successfully transferred during the process.

The outlined procedure can be employed in conjunction with a method designed for the detection of dangerous events [7], particularly those pertaining to the loss or unsuccessful acquisition of an object. In such instances, event indistinctness can manifest during moments when both the manipulator and the manipulated object align along the same visual axis as observed by the video camera.

IV. Demonstration for a Robotic Manipulator

Creating an application that uses video analytics technology to assess the quality of a robotic manipulator in real time is a complex task involving multiple components. Here are the most important key aspects and a general approach for implementing the prototype:

1. Video Capture: high-quality real-time video data is a fundamental requirement. Our hardware solution ought to be capable of recording at a high frame rate for the most accurate real-time analysis. Camera setup should also be optimized to ensure that our field of view adequately encompasses the robot's arm working area. In our case, we used a stereo camera Intel RealSense D435 [8] that is based on Intel RealSense SDK 2.0 that offers us images from an RGB camera and also a matrix of depths to objects on the image (the onboard Depth Processing Unit (DPU) generates a depth map by comparing the differences between the two synchronized video streams).

2. Object Detection and Tracking: this component is responsible for continuously identifying and tracking the location of the target object in the video stream. Typical algorithms for object detection can include many solutions such as R-CNN, YOLO (You Only Look Once based on v5, v8 models), and SSD (Single Shot Detection). Tracking algorithms like Kalman Filters, Particle Filters or even more modern approaches based on deep learning like SORT and

Deep SORT could be used for tracking the detected objects through time. In our solution, we used DaSiamRPN (Distractor-aware Siamese Region Proposal Network [9]).

3. Calculating a distance to an object: knowing the distance to a target object is extremely important in robotic arm movement tasks for several reasons, both for efficient operation and for safety and also to calculate the precision of distance to an object compared to real measurements. Here we used Python and pyrealsense2 library [10] that gets the distance of the center pixel in each frame: to get the distance to a specific object, we already know the target object's position in the frame (based on DaSiamRPN) and get the distance at that specific pixel’s location. Final results are presented in Fig. 1.

Fig. 1. Experiments with estimating the distance to the object being moved by the robotic arm: in the first position the distance is 1.089 m, in the second position 1.299 m

In this experiment, a robotic manipulator is operated in manual control mode to perform the task of grabbing an object and moving it from one place to another. The experiment aims to monitor and analyze three different situations using video analysis techniques.

The first situation involves the successful completion of the task, where the robotic manipulator effectively grabs the object and transports it to the desired location without any issues. The essence of situation is as follows. An object is fed onto the conveyor, which needs to be successfully transported. The manipulator effectively grasps the object in zone A and slowly moves it to zone B. The object's grasping, movement, and release are performed manually by the operator. This scenario serves as a benchmark for evaluating the manipulator's performance in terms of accuracy, speed, and precision. By “speed” we mean the time elapsed from the moment the robot manipulator started performing the task, i.e., began grasping the object, to the moment the robot completed the task, i.e., released the object in zone B. By “precision” we understand a quantity inversely proportional to the distance at the final moment in time from the manipulated object to the center of zone B.

The second situation focuses on instances where the robotic manipulator drops the object during the transportation process. An object is fed onto the conveyor. The manipulator effectively grasps the object within zone A and, with a moderate speed, transports it to zone B. During the transportation process (after the object has been removed from zone A but before it is delivered to zone B), the manipulator loses hold of the object. The grasping of the object, its movement, and release are manually executed by the operator. By analyzing the video footage, the experiment aims to identify the factors or events that led to the object being dropped. This analysis provides insights into potential areas for improvement in the manipulator's gripping mechanism or control algorithms.

The third situation involves cases where the robotic manipulator fails to grab the object altogether. An object is fed onto the conveyor. The manipulator successfully grasps the object in zone A but either loses it there or fails to capture it at all. Subsequently, the robot manipulator moves to zone B without the manipulated object. Through video analysis, the experiment aims to identify the reasons behind the unsuccessful attempts, such as misalignment, incorrect gripping technique, or environmental factors. This analysis helps in understanding the limitations of the manipulator and provides valuable feedback for further enhancements.

By monitoring and analyzing these three situations using video analysis techniques, the experiment provides a comprehensive evaluation of the robotic manipulator's performance. The insights gained from this experiment can be used to optimize the manipulator's control algorithms, improve its gripping mechanism, and enhance its overall efficiency and productivity in various industries.

VII. Conclusion

This demo study introduced a computer vision-based procedure for assessing robotic manipulator performance on conveyor lines. By analyzing real-time stereo camera footage, our approach identifies and analyzes events, offering insights for optimization. Our procedure outperforms manual assessments by eliminating subjectivity, enabling real-time feedback, and reducing costs. Leveraging computer vision techniques, it accurately evaluates object acquisition and loss, proving its effectiveness in enhancing manipulator performance with precision. This procedure holds promising prospects for enhancing the efficiency and productivity of conveyor line systems through its objective, real-time evaluation of robotic manipulator performance and reducing cost.

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