

APPLICATIONS OF MACHINE AUTOMATION WITH ROBOTICS AND COMPUTER VISION IN CLEANROOM ASSEMBLIES*

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Abstract

Modern linear particle accelerators use superconducting radio frequency (SRF) cavities for achieving extremely high-quality factors (Q) and higher beam stability. The assembly process of the system, although with a much more stringent cleanliness requirement, is very similar to the ultrahigh vacuum (UHV) system operation procedure. Humans, who are conventionally the operators in this procedure, can only avoid contaminating the system by wearing proper sterile personal protection equipment to avoid direct skin contact with the systems, or dropping particulates. However, humans unavoidably make unintentional mistakes that can contaminate the environment: cross contamination of the coverall suits during wearing, slippage of masks or goggles, damaged gloves, and so forth. Besides, humans are limited when operating heavy weights, which may lead to incorrect procedures, or even worse, injury. In this paper, we present our recent work on a viable and cost-effective machine automation system composed of a robotic arm and a computer vision system for the assembly process in a cleanroom environment, for example for SRF string assemblies, and more.

INTRODUCTION

Background

Modern particle accelerators use superconducting radiofrequency (SRF) cavities to achieve extremely high quality factors (Q) and higher beam stabilities [1–3]. Most of the SRF cavities and their associated systems need to be assembled in a dedicated cleanroom space and at a custom SRF test stand. The assembly process of the system, although with a much more stringent cleanliness requirement, is very similar to the ultrahigh vacuum (UHV) system operation procedure.

Humans, who are conventionally the operators in this procedure, can only avoid contaminating the system by wearing proper sterile personal protection equipment, such as coveralls, gloves, facial masks, goggles, etc., in order to avoid any direct skin contact with the system. The operators also need to pay special attention to avoid dropping lints or dander in the system [4]. The reasons why humans are needed in the assembly process are unquestionably clear: the ability to identify and solve problems *in operando*, and to evaluate the assembly quality and make adjustments based on rich experience. However, the disadvantages of having humans in the process are often ignored: humans make unintentional

mistakes that can contaminate the system - cross contamination of the coverall suits during wearing, slippage of masks or goggles, damaged gloves, and so forth.

High energy physics, nuclear physics and basic energy sciences experimental researchers have recently been investigating solutions in which the assembly can be done or at least dominated by robotic arms instead. Robotic arm manufacturers, such as Yaskawa, FANUC and KUKA have been actively developing robot systems that are suitable for cleanroom operations. The industrial arms can have their repeatability as high as $\pm 30 \mu\text{m}$ and maximum payloads of tens of kg. Although the convenience and benefits of using robotic arms in assembly processes have been widely recognized, the acceptance of robotic automation systems is still relatively low in R&D environments, compared to other industries like automotive manufacturing, welding, chemical processing, etc.

Our Methods

Under a grant from the DOE SBIR program, we were awarded for the development of a viable and fully automated robotics system equipped with computer vision hardware and AI/ML algorithms for the assembly process in a cleanroom environment, for SRF systems and other cleanroom assembly processes. Our computer vision system is powered by 3D cameras and image processing to identify arbitrary structures for robotic arms to mate parts together. Our solution provides the versatile integration of object recognition and repeatable specialized control of industrial grade robotic arms. It is capable of reducing or eliminating human interventions in the assembly procedure. Our system runs on high-level programming languages, which allows for both user customization and hassle-free operations without the need for controlling the arms using teaching pendants.

In our finalized product, for which the workflow is shown in Fig. 1, our system will first automatically detect a target object (object-of-interest) using a 3D camera mounted on the arm (“eye-in-hand”) and advanced vision algorithms. The computer vision system then registers the “pose”, which contains both the position and orientation, of the target object and passes that information to a robotic arm, on which the camera is mounted. Then, the arm will grab another object (object-in-hand) that needs to be assembled onto the object-of-interest, and mate the two objects together, based on a calculated path and instructions for the arm. In cases where fasteners are needed to tighten flanges or similar interfaces together, another robotic arm that is also equipped with an eye locates the mated objects, places the fasteners through the holes, and tightens them.

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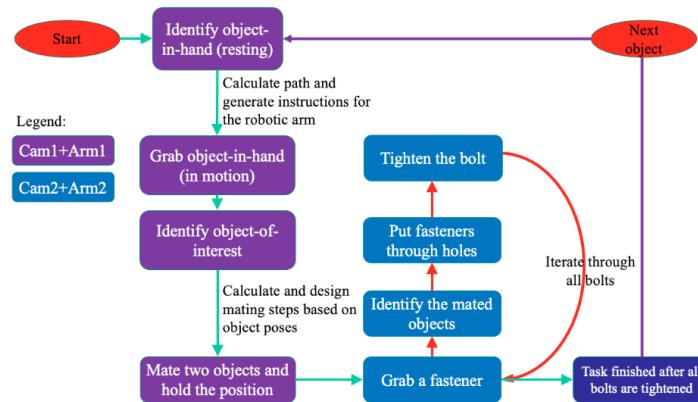


Figure 1: The workflow of our ultimate fully automated robotic system for machine-aided assembly processes.

In this paper, we discuss the preliminary but extremely promising results obtained in the 9-month project. We successfully implemented image segmentation and pose registration algorithms to isolate an object-of-interest from the background and recognize its position and orientation using images collected by a 3D camera. We also managed to calibrate, program and operate an industrial robotic arm from Yaskawa Motoman to manipulate objects both in a simulation software RoboDK and in real-life operations. The computer vision and robotic control systems were integrated together to demonstrate the mating of two vacuum components: a tee and nipple with both 2.75" conflat flanges. The demonstration video is available online. Our results delivered the most important milestones for our concept and confirmed the feasibility of our machine-aided assembly automation.

COMPUTER VISION SYSTEM

For the computer vision system, the main and ultimate goal is to obtain accurate information about the pose of an object-of-interest with respect to the camera (“eye”) of the system. The pose of an object consists of both the position and orientation of the object. The pose information is then passed on to the robotic control system to instruct the robot to move an object-in-hand, which is to be mated with the object-of-interest, to a certain destination based on the geometry. To get the accurate object pose, we implemented a two-steps approach. The first step is to get a global pose estimation of the object-of-interest from a 3D camera; the second step is to refine the object pose by local registration, for which there is a mature algorithm called ICP [5]. In case of a rotatable flange (discussed later in this section), an additional step with registration can be added to align holes and leak grooves.

We carried out two approaches for the global registration. In the first approach, we used a “pose estimation” from a 2D-keypoints neural network (NN) and PnP [6]. An algorithm “*singleshotpose*” [7], which was based on the YOLOv2 [8] algorithm, was used and the model was trained with “ground truth” pose information with the help from ArUco markers. Our ArUco markers were precisely painted on a flat

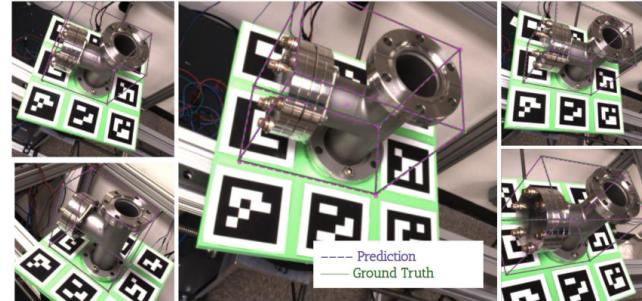


Figure 2: Examples of our NN-predicted and ground truth bounding boxes overlaid with test images of real image dataset for global registration.

Aluminum plate and work well as a rough estimate for the object’s pose. The NN is then able to determine the key control points from any 2D RGB image that has the object-of-interest in it, as shown in Fig. 2.

The second approach does not rely on an ArUco plate or markers, which makes it more flexible with the size of the object-of-interest and the camera angles because the markers could possibly be blocked. Two steps are needed. First, a 2D (RGB) image segmentation based on NN algorithms, where the object-of-interest is selected and separated from the rest of the image, is done to work as a “filter” for the point cloud data of the same image. Another NN-based algorithm is used to do the registration with the isolated point cloud of the object. We have successfully demonstrated segmentation with multiple algorithms, using a CF tee as an example. However, for the global registration with the segmented point cloud, we had tried several popular algorithms, such as Deep Global Registration [9], and MS-SVConv [10]. However the results were not sufficiently good to be used in the ICP local registration algorithm. Further studies are required for this task.

Examples of the segmentation results and the workflow of the pose registration are shown in Fig. 3. Our vision algorithms were robust enough to work with various geometries of SRF/UHV components.

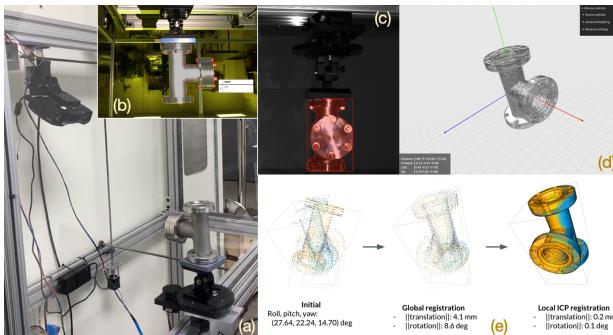


Figure 3: (a): Image data collection for segmentation NN training. (b): Manual labeling for the training dataset. (c): Segmentation done with MaskRCNN. (d): A “Tee” coordinate frame constructed after the global and local (ICP) registrations. (e): Workflow and accuracy achieved with the full pose registration.

ROBOTIC ARM SETUP AND CONTROL

After comparing the strength and weakness of more than five robotic arm manufacturers and their products, we eventually selected the Yaskawa Motoman GP series for our machine automation purposes. For our project, GP8 that has a maximum payload of 8 kg was sufficient for our proof-of-principle experiments. Most industrial robotic arms and their controllers do not ship with the best programming support, such as an API. As our computer vision algorithms are developed in Python, for which the API doesn’t exist in the arm control system, we wrapped the low-level control of the arm using the Yaskawa Fast Ethernet in Python and created the API. The API allows one to set local coordinate frames and control the arm to move along an arbitrarily defined trajectory in the frames. The computer vision and robotic arm control programs are seamlessly connected in Python as an integrated package.

The “destination” frame of an object mounted on or held by the arm can be defined by a series of transformation matrices. With the matrices known for both from the object-in-hand to the eye, and the eye to the destination, the object-in-hand and object-of-interest can be mated together following a planned path. The illustrative coordinate frames and matrices are shown in Fig. 4.

INTEGRATION OF THE VISION AND ROBOTIC SYSTEMS

We demonstrated the feasibility of our robotics-based machine automation and the integration of the two systems aforementioned by mating two 2.75” CF flanges together. The two flanges were on a CF Tee, which was the object-of-interest and mounted on the ArUco plate, and on a CF nipple, which was the object-in-hand and mounted on the arm. In the demonstration, we started with an arbitrary robotic arm pose, took a picture of the object-of-interest with the eye-in-hand, calculated the destination for the object-in-hand (a.k.a. the tool) and controlled the arm to move the object-in-

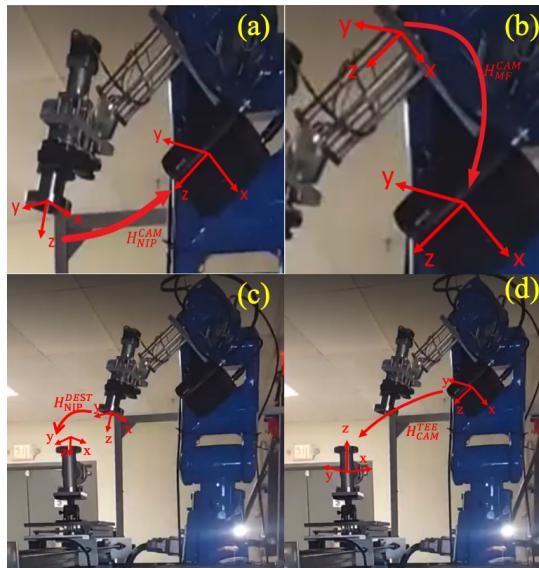


Figure 4: Transformation matrices used in calculating the coordinate frames for the robotic arm control.

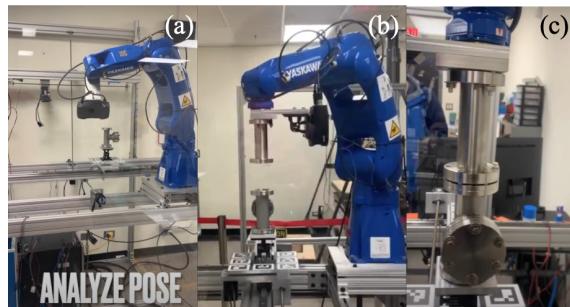


Figure 5: The key poses of the robotic arm during our flange mating demonstration.

hand. The destination frame was set to be millimeters above the Tee. The full demonstration was recorded in a video [11], for which the key screenshots are shown in Fig. 5. Since the alignment errors could be from multiple sources, the resultant alignment for each mating trial could be slightly different. Among the best cases, both the translational and rotational errors were sufficiently small for dropping the bolts through the CF holes.

CONCLUSION AND FUTURE WORK

We demonstrated the critical steps of realizing the full machine automation with our computer vision and robotic arm systems. The results were extremely promising and laid the foundation for future work, such as the global registration with segmented point cloud images, robotic calibration for accuracy improvement, ICP improvements, and so forth.

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