Title:
Development of a Low-Cost Vision System for CAD-Based Guidance of Industrial Robots

Authors:
Jacopo Lettori, jacopo.lettori@unimore.it, InterMech-DIEF, UNIMORE
Roberto Raffaeli, roberto.raffaeli@unimore.it, InterMech-DISMI, UNIMORE
Pietro Bilancia, pietro.bilancia@unimore.it, InterMech-DISMI, UNIMORE
Marcello Pellicciari, marcello.pellicciari@unimore.it, InterMech-DISMI, UNIMORE

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Introduction

Nowadays, the ability of vision systems to automate robot operations such as picking and placing or machining, which require good positioning accuracy, is a topic of strong interest both for scientific research and industry. Vision systems integrated with robotic arms [10] can be adopted to check the actual position of components and act accordingly [4]. For example, aircraft parts are analyzed for inspection in [7]. Similarly, it is possible to control the movement of robots by calculating the distance of a given target in real time thanks to the information received from cameras or 3D sensors.

This approach is called Visual Servoing (VS), and it splits into two types, i.e., Image-Based Visual Servoing (IBVS) and Position-Based Visual Servoing (PBVS) [6]. In IBVS, the image acquired by a camera is compared with the image of the target. A positioning error is calculated to be provided as input to correct the imposed trajectory [1]. On the contrary, PBVS control implements depth cameras to obtain the pose in 6 dimensions in the space of the target point. In this context, it is possible to calculate the transformation matrix that superposes the target reference system to the one obtained from the camera [5]. Although IBVS systems are less prone to calibration errors, it is possible to define robot tasks with less effort with PBVS systems because there is no need to map position and relative velocity between the camera reference system and object position. Moreover, two types of configurations can be distinguished according to the camera location. The first configuration is called eye-in-hand, and the camera is attached to the robot. On the contrary, in the eye-to-hand configuration, the camera is fixed and performs an external observation of the robot's working space [2].

The VS is crucial in automated drilling [17], welding [14], and assembly [12] to increase the stability and reliability of those processes. In this context, a light plane is used in [9] to detect deviations and calculate the tool position according to a given part. Also, the VS technique is often implemented in pick-and-place operations. Indeed, it is possible to identify strategies that use an initial transformation of approximation and then the Iterative Closest Point (ICP) algorithm [8] with a PBVS system. A depth camera is required for this type of application.

In flexible robotic manufacturing cells [13], where several operations are performed, the tool attached to the flange of the robot needs to be changed from time to time. For example, clamps, drillers, and other manufacturing tools are required in production lines [11] and should be interchanged as robot end effectors when needed. However, calibrating the robot with the exact position to find the tool is necessary. In the current industrial practice, the definition and the recording of the robot tool positions involve the manual coupling of the robot flange with the required tool recovered in storage. This procedure is called teach by showing, and it is time-consuming, especially for a 6 degree of freedom manipulator, leading to production downtime. Furthermore, this process must be repeated when cell reorganization occurs, resulting in additional downtime that corresponds to a reduction of productivity for the company. A vision system to get the correct tool position can be used in the change procedure along with a VS technique, thus reducing operator intervention and time inefficiency. For instance, the tool change procedure based on vision systems has been experimented in some works in the literature [16]. However, these works mainly focus on the robot control architecture.

In this context, this paper proposes the development of a vision system based on low-cost depth cameras which are spreading in the market. In particular, an eye-in-hand configuration was selected to be applied to a 6 degrees of freedom anthropomorphic robot, a KUKA KR210 R2700 prime. The alignment of the real target to the nominal one is based on the Iterative Closest Point (ICP) algorithm [15]. At first, pick-and-place tests were conducted to verify the behavior of a depth camera under different operation conditions, varying the brightness, the distance from the focal point, and the object orientation. The tests were carried out using a small block to evaluate the performance reachable with the developed application. Subsequently, this setup was tested on a more complex case study of industrial interest. In particular, the system was used to guide the robot to the position of a tool changer. This position is used as a target for the robot, identifying the correction necessary to pick the tool. Fig. 1 depicts the main phases of the proposed work.

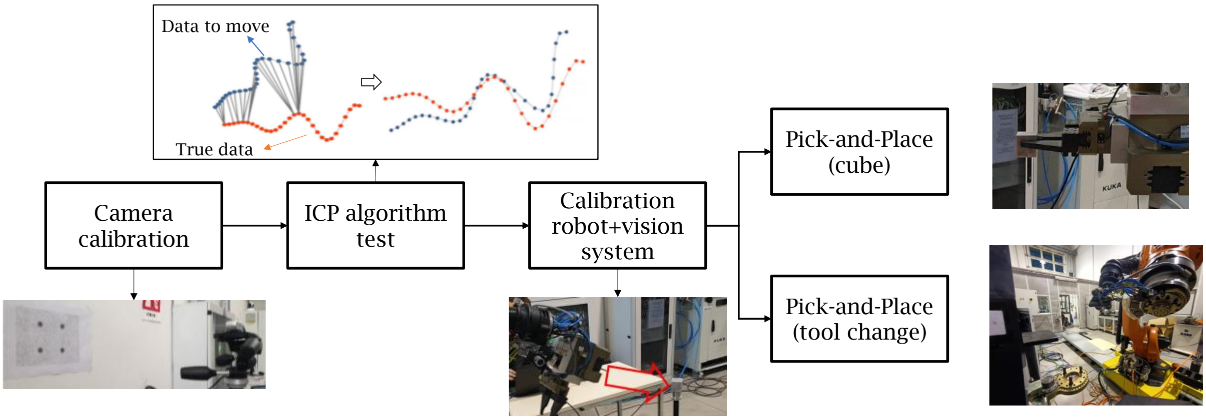

Fig. 1: Main phases of the proposed approach.

Approach to the application development

The development of the vision system is based on low-cost devices that correct the picking position of components in robotic cells automatically. The selected camera for the first part of the experiment is an IntelRealSense D435i, and two types of parameter tuning were performed to optimize the acquisition.

The first calibration involves an adjustment of the extrinsic and intrinsic parameters of the device to minimize the difference between the measured distance value and the real distance. The considered extrinsic parameters are: 1) RotationLeftRight, which expresses the rotation matrix between the reference system of the right camera and that of the left camera; 2) TranslationLeftRight, which is the translation between the reference system of the right camera with respect to that of the left camera; 3) RotationLeftRGB that expresses the rotation matrix of the RGB module with respect to the left camera; 4) TranslationLeftRGB that is the translation between the RGB module and the camera on the left. Then, the intrinsic camera parameters have been identified as follows: 1) Focal point; 2) Main point; 3) Distortion, which is described through Brown's model. In this case, the Depth Quality Tool provided by Intel was used to calibrate the camera.

The selected parameters to evaluate the image acquisition are: 1) Plane Fit RMS Error, that is the RMS error expressed as a percentage with respect to the mean plane (plane fit) passing through the acquired points; 2) Subpixel RMS Error that represents the RMS error expressed in pixel units with respect to the mean plane passing through the acquired points; 3) Fill-Rate that is the percentage of pixels with a depth value considered correct; 4) Z Accuracy that is the percentage disparity between the distance of the plane fit and the actual distance of the target called Ground Truth (measured with the Faro laser tracker). So, tests were conducted at different target distances to verify the behavior of the camera. As a result, it is noted that the Z accuracy error tends to increase with the distance from the target. Specific parameters were adjusted to reduce the acquisition error (estimated points), i.e., camera resolution, frames per second, sampling step and the infrared lighting option.

Then, as second step, an experimental campaign was developed to evaluate the camera performance considering a cube as reference geometry. First, the cube was placed on graph paper at known positions, ensuring that at least three faces were visible from the camera, as depicted in

Fig. 2. In this context, an ICP algorithm was used to superimpose the obtained point cloud with the actual 3D geometry. The algorithm was tested by evaluating its repeatability, execution parameters, the first iteration approximation, and the point cloud density. After these initial steps, the complete system was tested, considering the repeatability and the approximation error. As a result, the system is found to be repeatable with predictable errors.

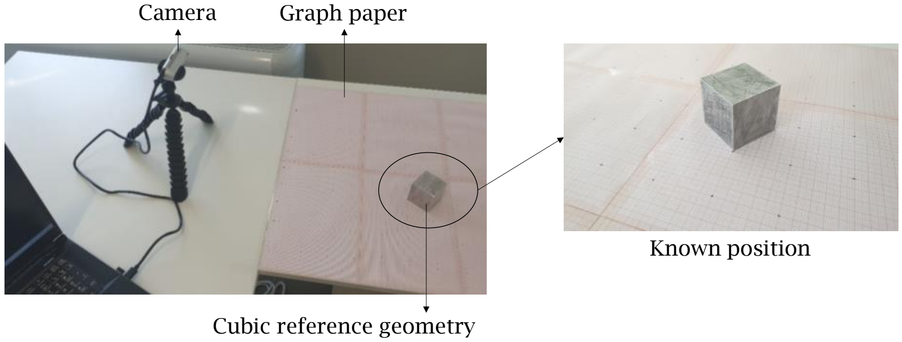

Fig. 2: Testing the ICP algorithm.

Next, the camera was placed on a robot arm (KUKA KR210 R2700 prime) equipped with a two fingers gripper to perform pick-and-place operations. Note that a calibration between the reference system of the camera and that of the robot is necessary, which was performed using the laser tracker FARO Vantage E following a procedure described in detail in a previous work [3]. After, the test was performed using the ICP algorithm to generate the pick-and-place orienting transformation, as shown in Fig. 3. Despite the limited accuracy of the scan point cloud resulting from the vision system, the commanded position has been accurate enough to pick the object.

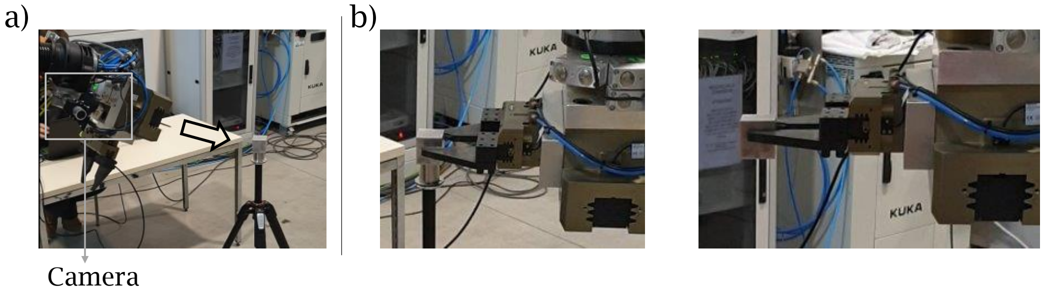

Fig. 3: Pick-and-place operation: a) Detection of the object; b) Pick task.

Subsequently, the procedure was tested in a more realistic industrial scenario. Like the previous test, a pick-and-place operation of robot tools was evaluated. In particular, the considered robotic system was equipped with a tool changer composed of a master part that is mounted on the robot flange and a slave part that is fixed on the tool to be grasped. Such a solution allows more than one slave to be applied to different tools and picked by the same master counterpart so that the robot can change the tool according to the required operation. In this case, a ZED 2i depth camera has been chosen and calibrated according to its specific intrinsic and extrinsic parameters, i.e., texture confidence, minimum and maximum detected depth, depth stabilization, depth mode, fill mode, and the initial position of the object. The limited performance of the camera does not allow a very detailed and accurate point cloud of the inspected part to be collected, resulting in a noisy and smoothed shape.

Again, the ICP algorithm was used to compute the overlapping transformation between the scanned point cloud and the set of points sampled from the nominal geometry. To improve the overall performance of the algorithm, the ICP was performed in two steps to increase its performance. A high approximation value was used for the first run, i.e., also, couples of relatively distant corresponding couples of points between the two clouds were considered. This procedure brings the scanned point cloud close to the reference CAD geometry. In the second run, the approximation value is lowered to reach a higher overlapping accuracy, increasing the success rate of the approach compared to a single ICP step.

A typical result is shown in Fig. 4 (left). Next, the camera was connected to the robot with a specially developed stand. The device was placed so that the camera was parallel to the flange of the robot, as depicted on the right of Fig. 4. Despite the limited quality of the acquired point cloud, the presence of a certain number of characteristic features of the tool changer, i.e. holes and pins, guarantees a good overlap between the two geometries and, consequently, the possibility to grasp the tool.

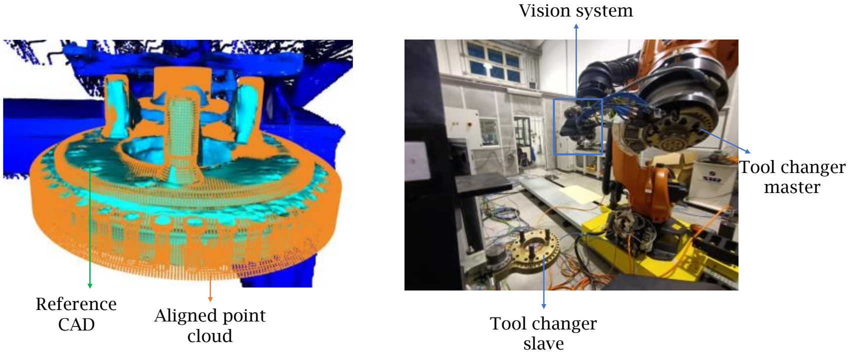

Fig. 4: Left: Alignment of the acquisition result (point cloud in orange) and the reference CAD geometry (green mesh); Right: Final robot configuration with the vision system.

Results and conclusions

The goal of the presented work was the development of a low-cost depth vision application to provide flexibility and absorb positioning errors in pick-and-place operations with industrial anthropomorphic robots. As a first step, an IntelRealSense D435i depth camera was selected for an initial problem exploration. Afterward, the procedure was applied to an industrial scenario involving the coupling of the two halves of a tool changer and using a ZED 2i depth camera. In this second case, a two-step ICP process has been devised.

Despite the low accuracy of the scans of the adopted cameras the results in robot positioning are promising even if a considerable level of error remains. In fact, in both the cases the alignment tasks were executed, ensuring a sufficient degree of precision. As future work, the substitution of the cameras with more advanced 3D scanning systems can considerably improve accuracy. In addition, the ICP algorithm can be further tuned to reach a higher level of reliability and to avoid falling in local minima solutions, leading to wrong orientations and potential collision. Finally, further applications would ensure an effective validation of the proposed system.

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