Fine localization of complex components for bin picking

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***Abstract*—The aim of this paper is to present verified parameters of a particular approach to one sub-procedure of the bin picking problem. To successfully implement an automatic bin picking application using a robotic arm, it is necessary, among others, to detect the precise position and rotation angle of a selected object. In this approach, the procedure is considered as a two step operation. The first step provides an initial guess of both position and rotation angle, while the second one should specify the pose as exactly as required for following operations. The goal of the paper is to determine a correct relation between those two mentioned steps, i.e. to specify the maximal possible degree of uncertainty provided by the first step so that the second step works correctly. The proposed problem is dealt with as an industrial contract and the results are clearly dependent on specific conditions. However, it can be plainly used as a first insight into the problematics of bin picking, and provide a good starting point for deeper investigations.**

Keywords*—*Bin Picking; Point Clouds; Pose Estimation; Robotic Arm.

I. Introduction

'Bin Picking Problem', a generalization of 'Pick and Place Problem', has been a very attractive field of research for many years. Although being a very popularized phenomenon among the public nowadays, it is still able to cause great interest to scientists and engineers for its complexity and variability. In simple words, a solution of the 'Bin Picking Problem' should allow the robotic arm (or group of them) to grab a particularly shaped object, located randomly in a box with other items, and place it in a defined position.

The industrial bin picking applications often include sets of two-and three-dimensional cameras, conveyor belt with containers and and a group of robotic manipulators - see Fig. 1.

From the engineering point of view, two main challenges are set. On the one hand, the object has to be precisely positioned (its position and rotation angle has to be estimated), the grab coordinates have to be computed considering various constraints and, eventually, the object has to be robustly grasped. On the other hand, motion planning has to be performed, considering both robotic manipulator limitations and the surroundings of the station. Then, the object can be placed in its desired position - see [2] for a nice review of the whole process.

In this contribution, the first mentioned challenge is discussed. In order to securely implement it, three comprehensive technical issues have to be dealt with [3]:

- the nimble robot grippers that are able to firmly handle a variety of parts in boxes;
- the real-time 6 degree-of-freedom positioning system that can locate a particular object in its container among others;
- the real-time grip planner that is able to estimate a firm and robust grasp.

Within those three points, let us focus on the second one. Considering object detection/identification and pose estimation, many approaches have been proposed during the last decades [4], [5], [6]. Almost every proposed approach uses computer vision of some sort.

Recently, due to an increasing availability of advanced laser 3D scanners, point cloud processing has often been implemented for pose estimation [7]. With point clouds, a new family of pose estimation algorithms becomes available to implement, and an Iterative Closest Point (ICP) algorithm is one of them [8]. An ICP algorithm can be implemented very efficiently and it has been used for bin picking applications many times [9], [10].

One of the key features of an ICP algorithm is its sensitivity to an initial guess of a position and rotation angle of the searched object [11]. Clearly, the sensitivity rate depends on a very complex set of features, including size and complexity of

Fig. 1. Bin picking in industry [1].

Fig. 2. UR3 and PhoXi 3D scanner M.

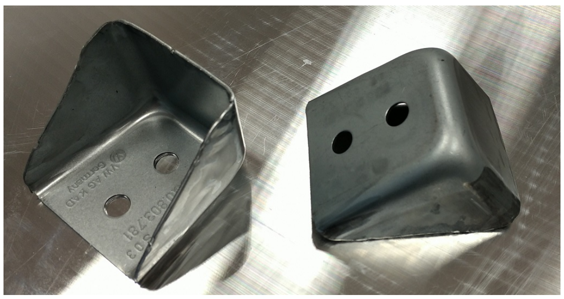

Fig. 3. Object of interest.

the object or the resolution of the point cloud [12]. Therefore, a sensitivity rate relevant to the particular conditions of the application should be estimated in order to develop a robust bin picking application.

In the following paragraphs, the procedure of the sensitivity rate for one bin picking application is presented. The aim of the contribution is properly defined in section II. Then, the experiments with the results are presented and, finally, the paper is concluded with some discussion.

II. Problem formulation

A long-term contractor of our local University ordered the improvement for an existing bin picking system. A UR3 type robotic arm by Universal Robots (see Fig. 2) is used to pick objects and place them to a defined position for future processing. PhoXi 3D scanner M by Photoneo is used for point cloud acquisition. This scanner provides point clouds with absolute accuracy of less than 100μm.

The aim of the setting is to find a position of an optimally located object (see Fig. 3) in a bin with randomly loaded components (see Fig. 4), grab it and move to a desired position. The pose estimation, as a part of the bin picking procedure, is used as follows.

- Get the 3D point cloud of the object and the 3D point cloud of the scene using PhoXi 3D scanner as the inputs to the procedure;
- get the initial guess of the optimal position and rotation angle of the searched object using an in-house approach - this approach is proposed by the contracting authority and we are not allowed to publish it;
- use the ICP algorithm to fine localization of the object.

Fig. 4. Bin with components.

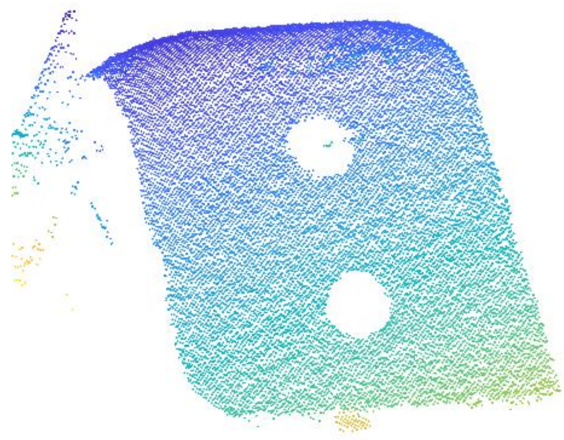

Fig. 5. Point cloud of the object.

An example of the point cloud of the searched object is in Fig. 5 and the point cloud of the scene is in Fig. 6.

The ICP algorithm is a straightforward method to align two shapes. Hence, if the position and orientation of one shape is set (in this case, the shape of the scene in Fig. 6) it iteratively tries to find a particular operation composed of translation and rotation, which transforms the other shape (in this case, the object in Fig. 5) to the pose which minimizes differences between each couple of corresponding points found in both shapes.

As the iterative algorithm, it requires an initial guess to be set. The issue of the algorithm is, that it diverges with an

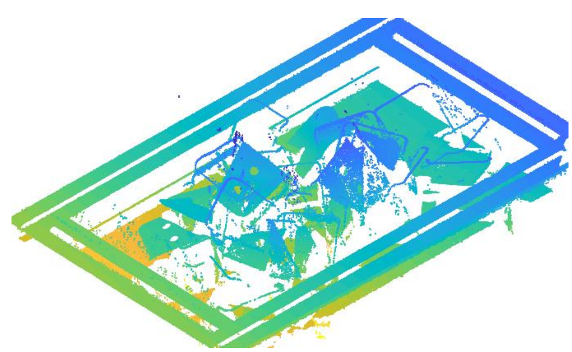

Fig. 6. Point cloud of the scene.

Fig. 7. Experimental device.

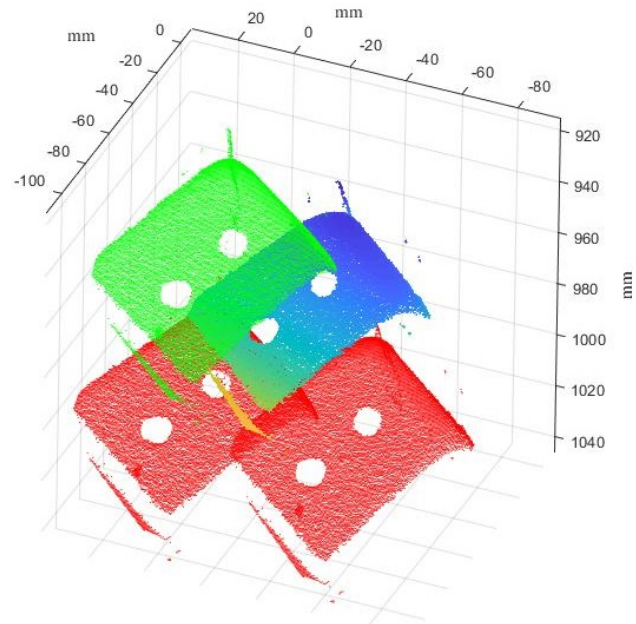

Fig. 8. Example of initial guesses; green objects converge, while red objects do not. Blue object is the desired position.

inappropriately selected initial guess. Thus, it is necessary to determine a sensitivity rate relevant to the conditions defined by the situation. Therefore, a set of experiments is necessary to perform in order to detect the maximal difference in both position and rotation angle suitable enough for the ICP algorithm to converge. In other words, the aim is to detect the acceptable rate of error provided by the in-house approach for initial guess estimation.

III. Experiment Setting

An experimental stand was prepared to perform a testing procedure - see Fig. 7. It was designed to emulate the conditions in an industrial environment; at least in terms of geometric dimensions. Using this device, a set of experiments was performed. A blind search approach was implemented as a search algorithm. To be more specific, a set of initial guesses was prepared using translation and rotation of the object - see Table I for detailed information. The ICP algorithm was then used for fine localization. Three different initial guesses are shown in Fig. 8 as an example. Red clouds represent the situation, where the ICP algorithm did not converge, while the green cloud indicates convergence.

TABLE I. Parameters of testing set

Number of samples	100000
Translation in X-axis	±100 mm
Translation in Y-axis	±100 mm
Translation in Z-axis	±100 mm
Rotation in X-axis	±30°
Rotation in Y-axis	±30°
Rotation in Z-axis	±30°

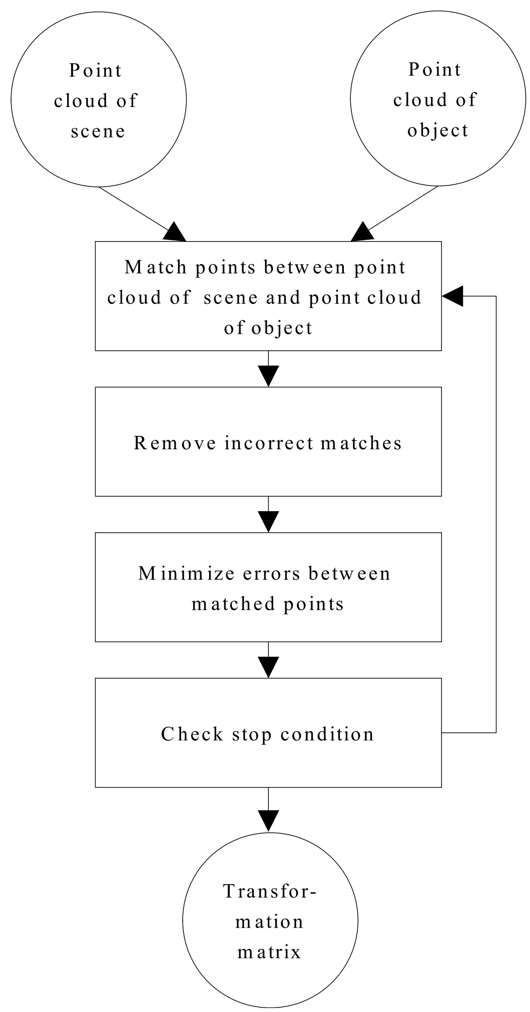

Fig. 9. ICP algorithm.

The procedure of the ICP algorithm is summarized in Fig. 9, see [8] for a detailed description of each step. In our implementation of the algorithm, the maximum number of iterations is set to 1 000 epochs and the stopping criterion is defined as the 2-element vector $D = [\delta_1, \delta_2] = [0.001, 0.001]$, that represents the absolute difference in translation and rotation estimated in two consecutive iterations. δ_1 measures the Euclidean distance between two translation vectors, δ_2 represents the angular difference in radians.

TABLE II. LIMITING VALUES OF POSITIONS, WHICH STILL CONVERGE TO CORRECT POSE

Translation in X-axis	$[-30; 30]$ mm
Translation in Y-axis	$[-30; 30]$ mm
Translation in Z-axis	$[-30; 30]$ mm
Rotation in X-axis	$[-15; 15]^\circ$
Rotation in Y-axis	$[-15; 15]^\circ$
Rotation in Z-axis	$[-15; 15]^\circ$

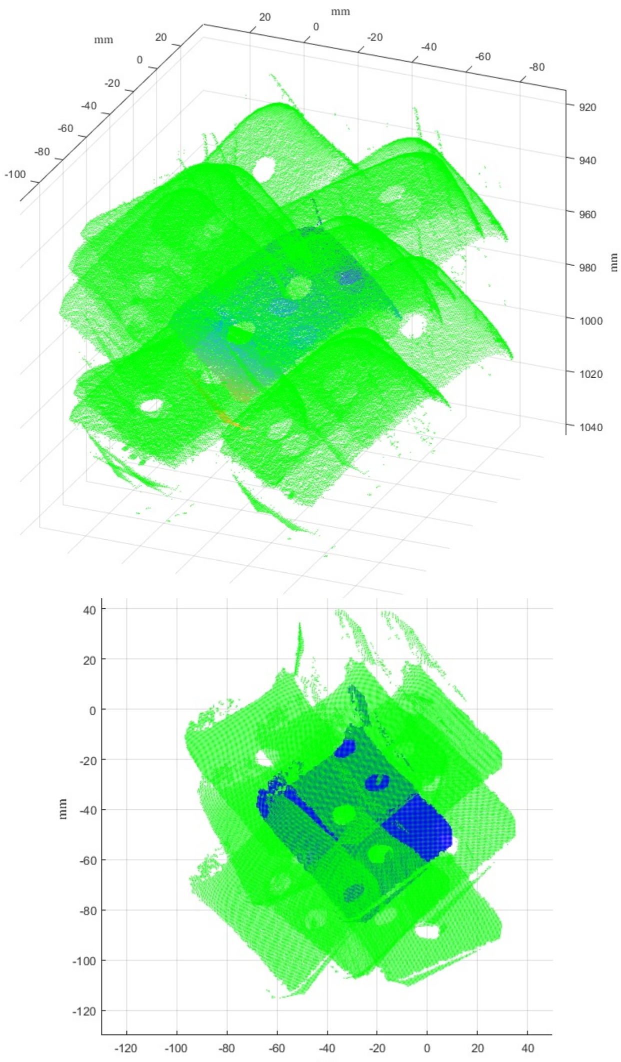

Fig. 10. Perimeter of positions, which still converge to correct pose

IV. RESULTS

According to the performed testings, the safe tolerance of the initial guess of a pose is summarized in Table II. Clearly those results are significantly dependent on the experiment conditions, especially the shape and complexity of the object and the density of the point cloud. The visualization of the perimeter of positions, which still indicate convergence to the correct pose, is shown in Fig. 10.

Apparently, related to specific conditions of the experiment, the initial guess setting significantly affects the overall hit rate, and it is recommended to keep the initial guess uncertainty within a few centimeters and degrees of rotation angle.

V. CONCLUSION

An accurate localization of complex components depending on the initial guess of the position and the rotation angle is discussed in this paper. Although the issue is related to a specific demand from a contracting authority, the results can be roughly generalized into a group of similar situations. To be more specific, dealing with the positioning of complex components using point clouds, the ICP algorithm is significantly sensitive to an initial guess. Thus, special care must be taken to select the appropriate method for choosing the initial guess. In our specific case, the dominant dimension of the object is about 60 mm, while the tolerance of initial guess uncertainty is about 30 mm. The knowledge of the absolute tolerance in an initial guess procedure can significantly help with the overall stability of the solution.

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