Object Recognition: Bin-Picking For Industrial Use

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***Abstract*-- This paper shows a method for object pose detection and gripping point determination that is successfully applied to industrial applications running a three-shift system. The industrial applications are fully automated feeding systems, commonly known as bin-picking. The proposed method for object detection is a generic approach to detect 6 degrees of freedom of any solid objects with arbitrary geometry. The proposed method is using 3D range data and is based on a heuristic tree search using a 6D pose voting scheme. For gripping point determination the object removal is simulated using the range data and a CAD model of the gripper in order to avoid any kind of collisions. During long-term operations in different use-cases, the method showed its usability regarding the crucial requirements, such as robustness, accuracy, portability and speed.**

***Index Terms*—Automated feeding system, object pose detection, gripping point determination**

I. Introduction

Work pieces are usually stored in carriers in order to move them from one stage of production to another. Although the work pieces lose their state of order, these carriers, e.g. lattice boxes, in general can be seen as a standard for manufacturing internal material flow systems. They can be filled easily with different objects and transported comfortably with forklifts or lift trucks. In addition, their stackability ensures ideal stocking.

Task of an automated feeding system, commonly called bin-picking, is to restore the work piece location and orientation by removing it from the carrier and placing it onto a transfer station.

The picking of chaotically stored objects is an ongoing subject for years in automation particularly in robotics. There exist various numbers of approaches to solve this problem. When it comes to real life implementation, most approaches struggle with cycle time or reliability.

The considered handling tasks are one of the last not yet automated gaps in material flow chains. A strong market growth could be observed making robot supported intralogistics a key industry for modern processes in economics and production.

II. System

To localize and grip the objects, the first step is to capture the situation inside the bin. This is done by a 3D sensor which is usually mounted over the bin. Different kinds of 3D sensors can be used, e.g. time-of-flight, stereo cameras or laser triangulation. The system uses this sensor data to detect the objects and calculate a suitable path for the robot to grip the object. Figure 1 visualizes the entire setting and the frames which will be referenced in this paper.

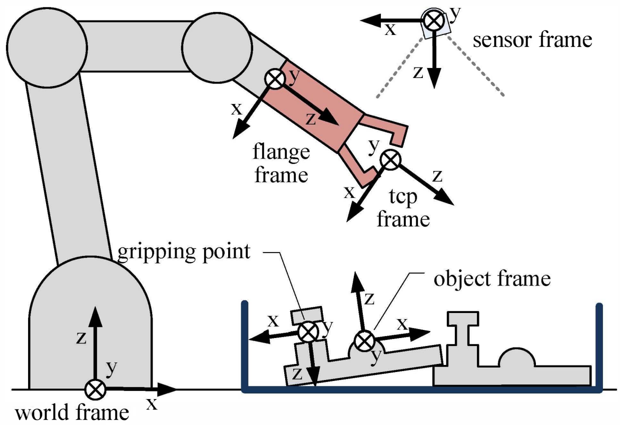

Fig. 1. Visualization of the various frames used in the system

The entire bin picking application is divided into five modules (Figure 2):

- Sensor module: Responsible for communicating with the actual sensor and creating a point cloud (transformed into the world frame) representing the surface of the objects and the bin.
- Recognition module: Localizes the objects inside the bin
- Gripping module: Determines a suitable gripping point for given object poses
- Robot module: Communicates with the robot
- Control module: Responsible for the entire program coordination

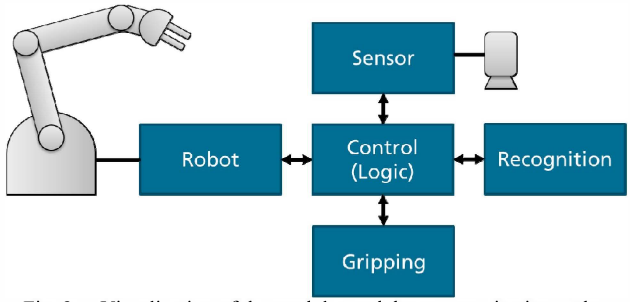

Fig. 2. Visualization of the modules and the communication paths

III. Calibration

For the sensor to transform the measured distances into a 3D point cloud in the world frame, the transformation from the sensor frame to the world frame has to be known. This is determined by using a calibration pattern. First, the pattern (i.e. the reference frame) is teached in as a user frame by the robot to make its position known in the world frame. Then, the position of the frame is measured by the sensor, making it known in the sensor frame. By using these two informations, the required transformation can be calculated. Figure 3 visualizes the entire process.

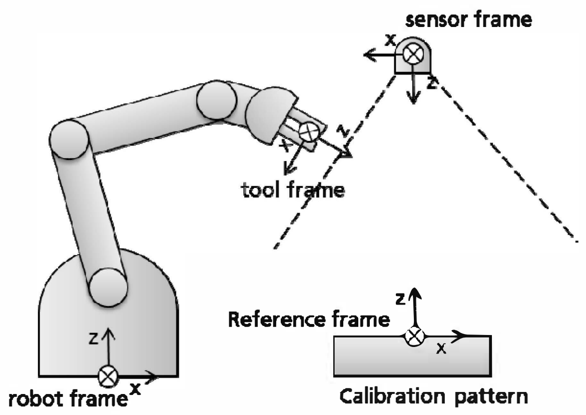

Fig. 3. Calibration method

Since a setup with a laser scanner needs an additional swivel or translation unit, there may be errors between the sensor itself and the moving unit. By using a calibration pattern, which covers the entire gripping area, this problem can be reduced. A simple way to achieve an improvement is to calculate a different transformation from the sensor frame to the robot frame for each area inside the bin. Figure 4 shows the visualization of a possible calibration pattern.

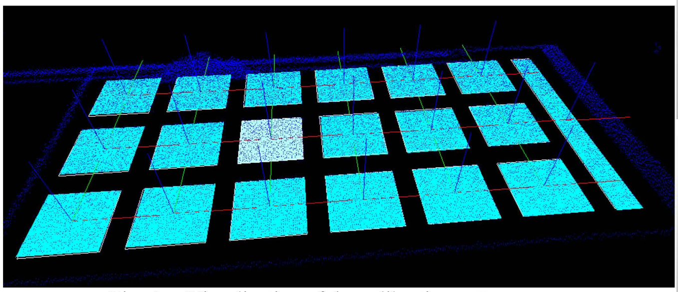

Fig. 4. Visualization of the calibration pattern

IV. Recognition

The object recognition is considered as a combinatorial optimization problem, for which a construction heuristic is applied. For this heuristic tree search, a finite set of possible work piece poses is initially derived from the continuous search space. The object itself is defined by a CAD-model, preferably using a triangulated surface.

To apply a decision tree, the elements of the search set are divided into two components. The first component describes interesting points in search space, which is part of the work piece surface. The second component describes possible work piece poses relative to interesting points. The resulting partial search quantities thereby have a significant lower complexity compared to the original search set. The reason is that interesting points can provide a constraint on the relative work piece poses, thus restricting its freedom of movement.

The applied tree search strategy is best-first search. Best-first search explores the search tree by always expanding the most promising nodes first and is similar to popular greedy-search. The promising nodes are chosen according to a heuristic evaluation score, representing the estimated distance from the node to a solution.

Final evaluation of work piece poses is provided by a six-dimensional Hough voting procedure, which is also known as Generalized Hough Transform [1]. The required features being used for Hough voting are sensor measurements, which are considered relatively to interesting points. For all possible constellations of sensor measurements relative to interesting points, a probabilistic statement about possible work piece poses can be made. Through the superposition of all probability statements, solution candidates can be formed, which are subjected to a statistical test based on a quality rating. The obtained quality rating along with a given level of significance is used in order to decide about the acceptance of a work piece pose.

The complete scheme can be seen in Figure 5.

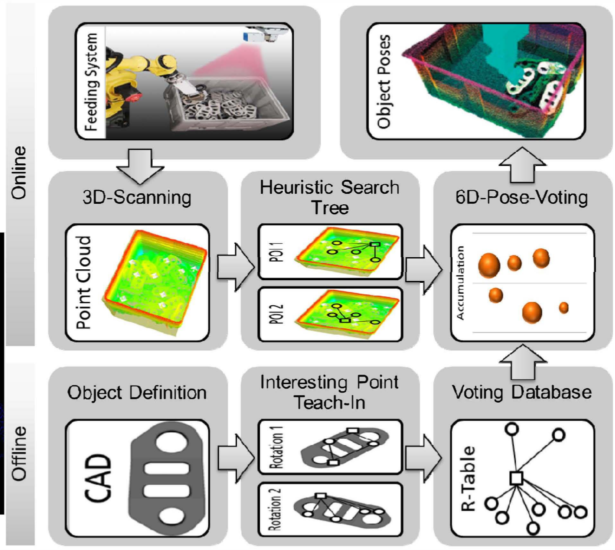

Fig. 5. Object recognition scheme

V. Gripping Point Determination

Once the object poses are known, the software needs to determine where to move the gripper to actually grip the object. To perform this task, we use predefined gripping points on the objects, so the system can choose the best gripping point for a given situation, by analyzing all gripping points on all localized objects.

The primary consideration to determine which gripping point is best suited for gripping, is the avoidance of collisions. Therefore, a collision test is performed using a simplified CAD model of the gripper. First, the gripper model is positioned inside the point cloud, by attaching its tcp frame to the gripping point frame (in world frame) of the localized object. Then, the collision test is performed. For such a collision test, several approaches have been proposed [2, 3]. Since our main consideration is speed, we use a simple and fast approach.

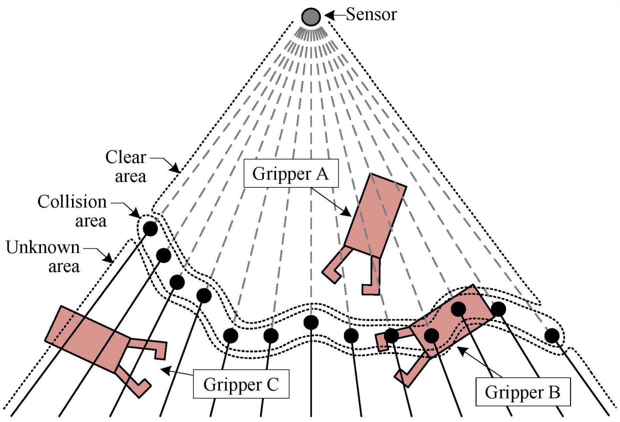

Fig. 6 Relevant areas for the collision test used by the gripping point determination

The entire area under the sensor is divided into three areas:

- Clear area: The area under the sensor known to be free of objects
- Collision area: The area around the sensor data, where objects are known to be
- Unknown area: The area under the sensor data. Since the sensor cannot detect anything in this area, it is unknown, where there are objects inside this area

To perform a safe collision test, it is not necessary to distinguish between the collision area and the unknown area, so we can use a fast algorithm for collision testing: We construct a line for each point inside the point cloud starting from the point itself towards the opposite direction of the sensor (Figure 6). By performing an intersection test of these lines with all the triangles of the gripper model, we can then detect, if a gripper is inside either the collision area or the unknown area.

VI. Conclusions

The proposed method is able to find and simulate removal of three to four work pieces on average within 0.5 and 3 seconds, using a standard desktop computer. It could be tested at ten automated feeding systems, with three families of parts and a total of 15 types of work pieces on which the algorithm is used in three-shift operation.

References

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