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Robotic Picking of Cylindrical Fuel Pellets from a Boat Using 3D Range Sensor

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Abstract

Fabrication of nuclear fuels comprises many intricate tasks that are difficult to automate. One such task is picking of cylindrical pellets from a container, called a boat. In the boat, pellets can be randomly oriented, touching and partly or wholly occluded. They have poor contrast with respect to each other and the boat. Hence, vision based techniques with either monocular or stereo camera configurations are not suitable for identification of pellet poses. This paper describes a novel technique in which 3D point cloud data is acquired by a 3D range sensor, and processed with optimized RANSAC (O-RANSAC) algorithm for estimating pellet poses for the robot to pick. First, cylinders are identified from point cloud data, and thereafter scores indicating the extent of matching is computed. We also present the improvement in processing time for O-RANSAC algorithm as compared to RANSAC. We demonstrate that O-RANSAC algorithm is robust even in presence of outliers and noise by testing in simulation with synthetic data. Proposed method was tested in an experimental setup consisting of an articulated robot, a 3D range sensor and dummy densely packed pellets in multilayer.

Keywords: *Bin picking, Robot, 3D point cloud, RANSAC*.

1. Introduction

Pose estimation of objects is an essential requirement for robotic bin picking applications. Until recently, poses were estimated by using cameras by processing 2D images. However, pose estimation by using camera images becomes challenging for densely packed featureless objects. Furthermore, occlusion along with ambiguous pose estimation for some views causes additional uncertainty in estimation of pose. In order to overcome above challenges, sensors that can generate 3D point cloud with high resolution have been developed by the researchers, and are now commercially available. Thus, now main challenge is to develop robust algorithm for processing the 3D point cloud for estimating the poses accurately for reliable picking by robot. Furthermore, estimation shall be invariant to rigid body transformation, sensor noise and occlusion. In this paper, we present a robotic bin-picking system that uses 3D point cloud data for detection of object poses. The system performs detection of 3D poses of cylindrical objects that are stacked in multiple layers in a part container, picks up the objects using an industrial robot, and place on rod trays for further processing. In order to achieve fast, reliable and accurate operation, imaging hardware that uses stereo cameras and structured light is used. Point cloud thus generated is processed by optimized RANSAC algorithm for faster pose estimation. This paper is organized as follows. Related literature is briefly overviewed in Section 2. Robotic bin picking system is described in Section 3. Thereafter, in Section 4, we present pose estimation algorithm and its optimization. Experimental results and discussion are presented in Section 5.

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2. Related work

Pose estimation methods can be generally classified as either segmentation or point clouds based. Segmentation based method generally fit the model to set of segmented points. Therefore, this method depends on the quality of segmentation which is affected by noise and outliers. In the second approach, data points are directly processed by using RANSAC, where a model is fit by using random sampling of minimum number of points.

In recent years, there has been considerable work on using 3D vision techniques for industrial bin picking problem [2]. In order to detect multiple objects, key point detection along with RANSAC has been used [5]. A probabilistic approach for picking objects that do not fit into a shape primitive was proposed [6]. Also, in order to get depth information, multi flash camera for estimating poses of objects was used [7]. Further, pair features were used for detection of object poses for bin picking applications [3].

However, for our problem, pellets are feature less. Hence, techniques like key point or pair features are not suitable. Furthermore, probabilistic approach is not required as described objects fit into shape primitive. In the experimental setup, commercially available point cloud sensor is used instead of multi flash sensor as it provides robust high resolution depth data for accurate pose estimation.

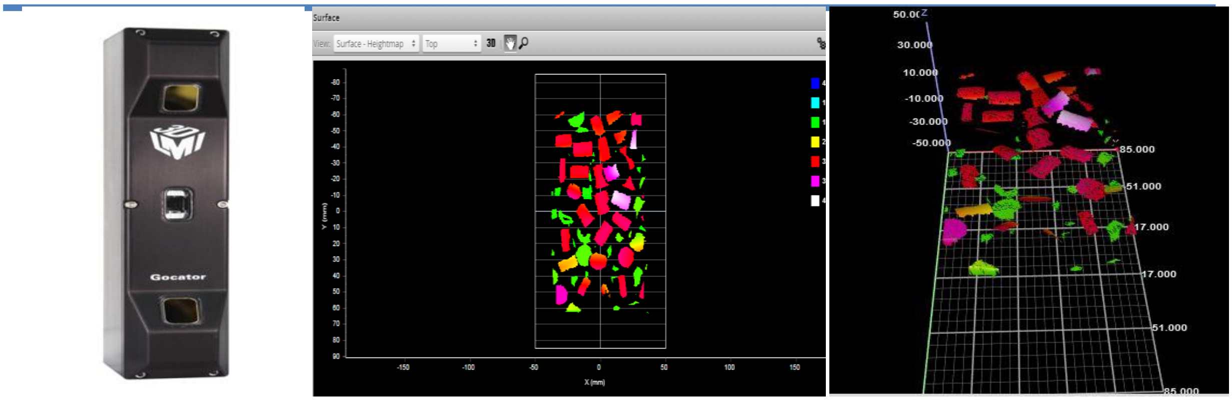
Figure 1: Robotic system for picking randomly oriented texture less cylindrical objects in multiple layers.

3. Description of bin picking system

Figure 1 shows the setup of bin picking system. It uses a 6-axis industrial robot arm for picking the objects by using suction gripper. Here, pose estimation is performed by processing the 3D point cloud data generated by sensor mounted on robot arm. In order to estimate 3d pose, it is essential to have depth data along with point location. Presently, many commercial sensors with such capability are available. However, for bin picking application with small objects it is desired to have sub millimeter resolution. In this paper, scanner from LMI Technologies with projection source and stereo scanning technology is used to acquire 3D point cloud data. This sensor is mounted on robot end effecter for performing bin picking experiments. Figure 2 shows the 3D range sensor used for experimentation along with top and side view of a typical set of pellets arranged in multilayer. Here, distance of pellet from sensor is indicated by color. In this case, violet and green depict the nearest and farthest objects respectively from the sensor.

4. Methodology for pose estimation

Point cloud generated by sensors needs to be processed for estimating the poses which is an essential requirement for a robust bin picking. In order to do this, these points are fitted into cylinder model. Among the various methods, RANSAC (Random Sample Consensus) algorithm [1] is widely used for estimating model parameters from point clouds. Cylindrical pellet which is a small cylinder is



(a) (b) (c)

Figure 2: (a) 3D point cloud sensor, (b) Top view of multilayer pellets displayed by sensor, (c) Side view of same pellet configuration
Violet color indicate pellet closer to sensor followed by red, yellow and green

described by a set of three parameters: axis orientation, a point on the axis and radius. Figure 3 shows the sequence of steps required for estimating the pose of cylinder from point cloud data.

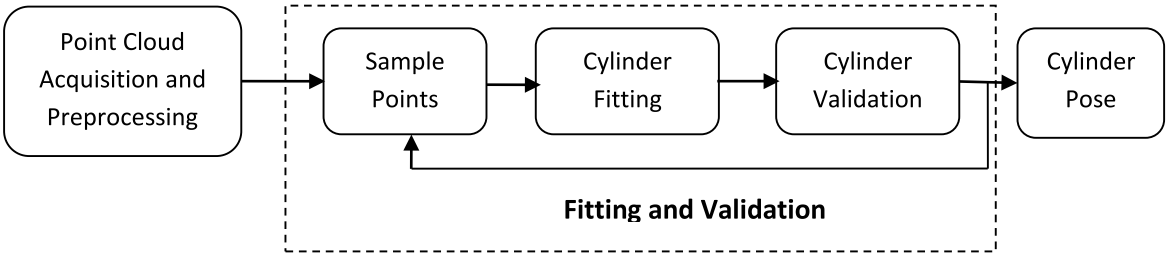


Figure 3: Cylinder pose estimation for bin picking

4.1. Building cylinder with two sample points

In 3-dimensional space, a cylinder can be defined by orientation vector and radius. These parameters can be estimated from two points (*p1, p2*) from the cylindrical surface.

$$[p1, p2] \rightarrow [\overline{ax},\ r] \tag{1}$$

One of the important steps in estimation of pose is computation of normal. For a point *O* on the surface, we can estimate normal as follows: find all the points inside a sphere of radius *r* centered at *O*, and then compute the least square plane fitting those points. The normal vector to fitting plane is our estimate of normal at *O*. After computation of normal, next step is finding the cross product of normal of two points. This gives the direction of cylinder axis ($\overline{ax}$). Once axis projection is known, the radius of the cylinder can be found as a distance from point to the axis.

4.2. RANSAC and O-RANSAC algorithms

Input to the RANSAC and O-RANSAC algorithms are set of measurements, called point cloud. Proportion of these points will be consistent with a model with parameters from parameter space and are referred as inliers. Rests of the points are outliers. These algorithms also estimate the quality of estimated pose. The score is based on the number of points that lie within small band outside the cylinder. Out of these points only points whose normal do not deviate from the normal of shape are considered. Additionally, among the points that fulfill the previous two conditions, only those are considered that can constitute largest possible cylinder. Algorithm-1 outlines the steps of RANSAC algorithm for cylinder fitting.

Algorithm-1: RANSAC

1. Calculate the normal at the individual points in the cloud.
2. Pick 2 random points from the point cloud.
3. Use above points to fit a cylinder. If the radius is beyond the range, discard the cylinder. Calculate the score of the current cylinder, i.e., the no. of points that are consistent with the current cylinder. Call this as the score of that cylinder. Add this cylinder among the list of candidates.
4. Repeat 2 & 3 for the calculated number of iterations (using probability estimate).
5. Extract the best candidate which achieves the highest score.

In order to reduce the computational cost, O-RANSAC algorithm [8] is used. It is based on hierarchical structured sampling strategy which significantly reduces the sample size. Pseudo code for O-RANSAC algorithm for cylinder fitting is described in Algorithm-2.

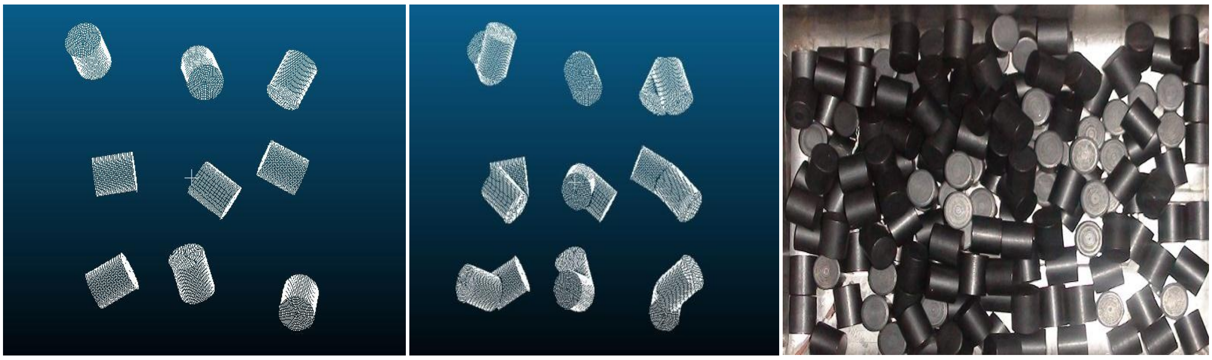
Algorithm 2: O-RANSAC

1. Calculate the normal at the individual points in the cloud.
2. Subdivide 3d point cloud space into eight equal octants by using octree data structure.
3. Above cells are further partitioned into multiple levels using octree data structure thus creating a hierarchical data structure. Each node in the octree is referred as the cell. Initially the probability of a cell getting selected from each of the level is the same. This probability is then updated according to the scores obtained by the candidates chosen from a cell chosen from that level. The higher the score, the higher is the probability of a cell getting selected from that particular level [8].
4. Select 2 points from the selected cell to fit a cylinder. If this radius is more than the tolerance then discard the cylinder. Else, add this cylinder to the list of candidates.
5. Partition the point cloud into random subsets.
6. Calculate the score on the first subset instead of computing on the entire point cloud. Use induction [8] to extrapolate and get the score for the entire cloud. This is done to reduce the computations for score calculation.
7. Extract the best candidate which achieves the highest score among all and the points belonging to it.
8. Calculate probability that no undetected cylinder is larger than the current best candidate. If yes, extract the largest connected component for each candidate and recalculate size for each candidate. If no, then repeat 2 if max iterations have not been reached.
9. Extract the best candidate and the points belonging to it.

Described methods are iterative in nature. Therefore, these can produce a result only with certain probability. If *p(n)* is probability of detecting the model in single pass from *N* points, and p_t is the desired probability of successful detection, then desired number of candidates (*T*) required to detect shape of size *n* can be given by following expression.

$$T \geq \ln(1 - p_t)/\ln\big(1 - p(n)\big) \tag{2}$$

Probability of detecting model *p(n)* is more for O-RANSAC method.



(a) (b) (c)

Figure 4: (a) Single layer point cloud (synthetic data) (b) Multilayer point cloud (synthetic data) (c) Image from experimental setup

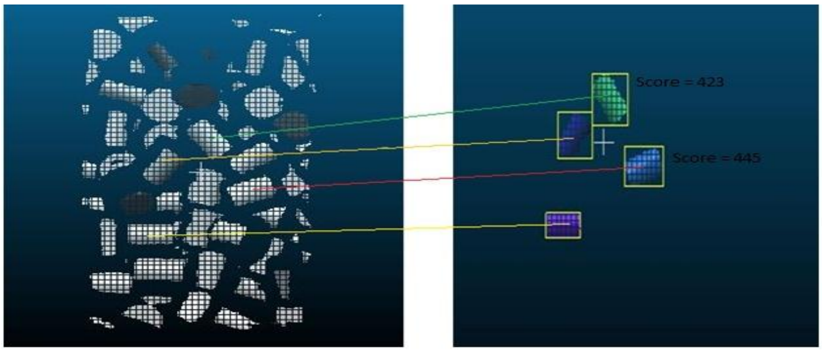
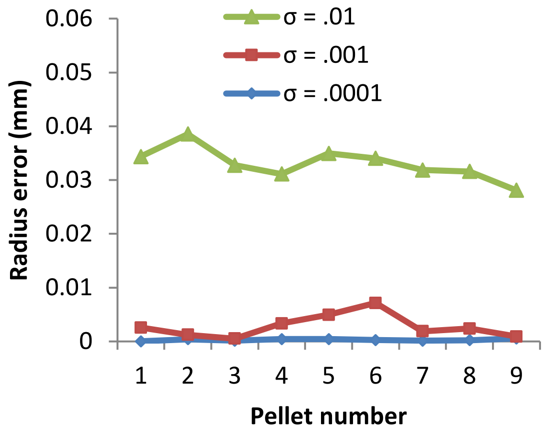


Figure 5: (a) Sensor view of multilayer pellets (b) Detection of pellets with score higher than threshold

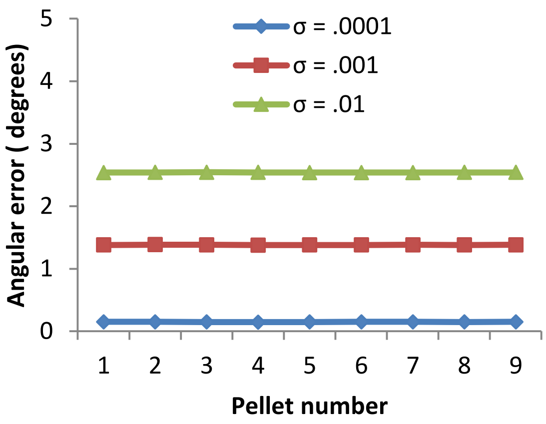
5. Results and discussion

In order to verify the accuracy of pose estimation, it is essential to measure the reference poses accurately. However, this is a complex task for densely packed pellets, as ensuring same orientation after measurement is complicated. Hence, initial verification is performed with synthetic data consisting of predefined pellet poses. Further, in order to test robustness of algorithm synthetic data is mixed with Gaussian noise.

Figure 4 shows the point cloud data for single and multiple layers along with image of pellets from the experimental setup. In this paper, point clouds from multiple layers with different Gaussian noises are used for estimating the accuracy of poses. Figure 5 shows successful detection of pellets using O-RANSAC algorithm. In order to estimate the accuracy of radial and angular error, O-RANSAC algorithm, with different Gaussian noise, is applied on synthetic point cloud of multiple layers (Figure 6). The results show reliable detection of cylindrical pellets even in the presence of outliers. Further use of localized sampling and revised score calculation strategy substantially improves the processing time (Figure 7). Described algorithms are tested both in simulation and on experimental setup with variable sample length (14-18 mm) and fix radius. It is to be noted that performance of described algorithms is generally invariant to dimensional variance given the number of points in the point cloud remain same. However, time required for computation of connected components depends on the surface area of samples.



(a)



(b)

Figure 6: Errors after estimation with O-RANSAC algorithm with synthetic data for multiple layers using different Gaussian noise (a) Radius errors (b) Angular errors

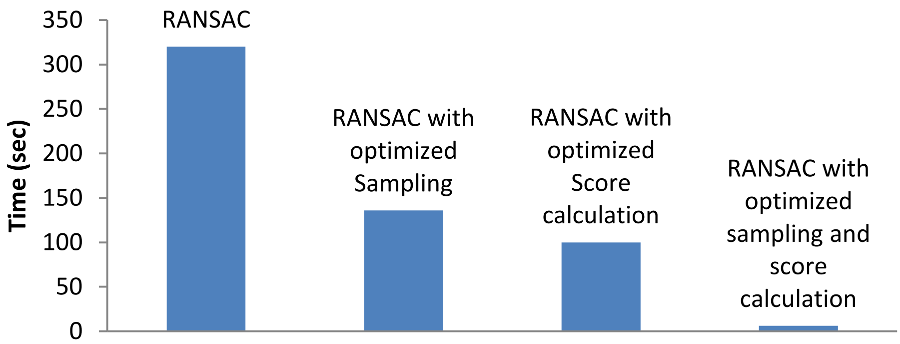


Figure 7: Improvement of processing time with optimized sampling and score calculation using 18 cylinders from multilayer layer synthetic point cloud of Figure 4. Nine cylinders of top layer along with few cylinders from lower layer were detected during 5 trials. Processing time presented here is average of time taken during these trials.

Conclusion

In this paper pose estimation of cylinders from point cloud by using RANSAC and O-RANSAC algorithms has been presented. It is observed that RANSAC and O-RANSAC takes around 316 sec and 6 sec respectively for processing of 1,00,000 points. Gaussian noises with different standard deviations are used for evaluating the accuracy of radius and orientation measurement. Simulation results with multiple layer pellets show that radial and angular error increases with increase in standard deviation of Gaussian noise. Maximum error of .04 mm in radius and 2.5° in angle is observed. Experimental results show success rate of around 80%. Currently, we are investigating the robot and sensor calibration errors for more promising results. In addition, it is proposed to apply refitting on the estimated model for further improving the accuracy of robotic bin picking.

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