Fast and Robust Bin-picking System for Densely Piled Industrial Objects*

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Abstract—Objects grasping, also known as the bin-picking, is one of the most common tasks faced by industrial robots. While much work has been done in related topics, grasping randomly piled objects still remains a challenge because much of the existing work either lacks in robustness or costs too much resource. In this paper, we develop a fast and robust bin-picking system for grasping densely piled objects adaptively and safely. The proposed system starts with point cloud segmentation using improved density-based spatial clustering of application with noise (DBSCAN) algorithm, which is improved by combining the region growing algorithm and using Octree to speed up the calculation. The system then uses principle component analysis (PCA) for coarse registration and iterative closest point (ICP) for fine registration. We propose grasp risk score (GRS) to evaluate each object by the collision probability, the stability of object and the whole pile's stability. Through real test with Anno robot, our method is verified to be advanced in speed and robustness.

Index Terms—Bin-picking, Robot Arm, DBSCAN, Registration, Point Cloud

I. INTRODUCTION

Humdrum works, such as bin-picking, met the first wave of robots in job. Traditional bin-picking robots have limited ability sensing the environment, making it hard to meet the requirements of the complicated real-situation in plants. Recent studies focus on improving visual approaches of robots. Point cloud, with its richness in 3D information, is born to be among the best choices for object sensing. Generally, bin-picking problems are solved by a common pipeline, which basically contains plane segmentation, correspondence grouping, coarse registration and fine registration.

Previous researches about pipeline usually focus on some specific procedures. Random sample consensus (RANSAC) works well in solving plane segmentation problems, and some more modified algorithms are proposed recently. Bastian Oehler et al. present an efficient multi-resolution approach to segment a 3D point cloud into planar components, combining the Hough transform with robust RANSAC [1]. Lin Li et al. propose an improved RANSAC method based on Normal Distribution Transformation (NDT) cells to avoid spurious planes for 3D point-cloud plane segmentation [2]. Credit to Xian-Feng Han et al., filter algorithms are categorized into four classifications [3], statistical-based [4] [5] [6], neighborhood-based [7] [8] [9], projection-based [10] [11] [12] and PDEs-based filtering [13] [14]. Sample consensus initial alignment (SAC-IA) is one of the basic coarse registration approaches, with different modified versions specifically designed for different situations [15] [16]. Besides, S Zhang et al. use frequency domain point cloud registration based on the Fourier transform to detect the side data of the whole part [17]. For fine registration, a few new approaches are proposed recently. Weimin Li et al. propose a modified iterative closest point (ICP) algorithm with high speed [18]. Brayan S Zapata-Impata et al. propose a method to find the best pair of grasping points given a three-dimensional point cloud with the partial view of an unknown object. In order to autonomously perform grasps, the robot must calculate where to place its robotic hand to ensure that the grasp is stable [19]. For object pose estimation, modified algorithms like using adaptive threshold for bin-picking are proposed [20].

The pipeline as a whole has also been covered by a handful of researches. Dirk Buchholz et al. show an applicable solution for the bin-picking problem, focusing on robustness against noise and object occlusions [21] [22]. Ales Pochyly et al. present a functional case study of a bin-picking system based on a modified revolving vision system, in which they admit it remains hard to implement in industry environment and give a few analysis [23]. While above studies are verified under simulation, there are some papers give pretty results using real robot. Carlos Martinez et al. prove their pick-policy and basic visual system to be robust using ABB IRB2400 robot, and give a practical test method [24] [25]. In addition to eye-to-hand robots, eye-in-hand is also capable to deal with bin-picking problem according to Wen-Chung Chang’s vision-based robotic bin-picking system in which CCP approach is proposed [26]. Some patents are also applied, for example, Kye-Kyung Kim’s patent about bin-picking system using top-down camera with bin-picking box [27].

However, though bin picking has been a research topic for years, regarding the problem of randomly-piled-objects bin-picking problem which is a more general scenario in real industry application, only a few papers have been published. One example is inward-region-growing-based accurate partitioning...
of closely stacked objects for bin-picking proposed by Zaixing He et al. Focusing on segmentation of piled objects, they give no result on real-robot [28].

We make two main contributions in this paper:

- An Improved density-based spatial clustering of application with noise (DBSCAN) segmentation algorithm is designed.
- An efficient and adaptive grasp-policy evaluation function is proposed.

The rest of the article is organized as follows. Section 2 presents an overview of our point-cloud-based bin-picking algorithm. In Section 3, our methods are described in detail. And then in Section 4, results and discussion of experiments are illustrated. Conclusions are drawn in Section 5.

II. OVERVIEW

The goal of our research is to develop a fast bin-picking system for grasping dense and stacked objects adaptively, safely and fast. Here we outline the given information, the potential challenges and the desired capabilities of the proposed method.

Our system is expected to get depth images from RGB-D camera and convert it into 2.5D point cloud for pose estimation. 2.5D point cloud has insufficient dimensionality for the single viewpoint of camera. As we focus on grasping general industrial objects like three-way-pipes etc. which have similar textures and features, the objects’ computer-aided design models with their 3D point cloud can be assumed as priori knowledge. Simple as their shapes are, it becomes a big challenge to estimate their 6-DoF pose accurately when they are randomly and densely piled. In that case, some traditional segmentation methods are not suitable and robust for this scene, some feature-based registration methods are accurate but slow and some deep learning methods are robust but have too much calculating and time cost.

Our approach is shown in Fig[1] We propose a DBSCAN-based point cloud segmentation algorithm improved through combining the Region Growing algorithm and using Octree to speed up the calculation. Our segmentation algorithm is verified to perform well in dense point cloud segmentation and noise point cloud filtering. To reduce cost in features calculation, we use principle component analysis (PCA) to estimate the principle component of the segmented point cloud for coarse registration, then use ICP for fine registration. For the safety goal, we focus on a novel policy of grasping for the objects to avoid the collision while improve the grasping efficiency. We consider three factors to evaluate the collision probability, the stability of object and the whole system. According to the factors, we define the grasp risk score (GRS) to evaluate each object. From the rank of GRS, we get the optimal sequence of grasping. In the end of a grasping round, the program will check if the objects moved by the change of segmented centroids. The program will do registration and calculate GRS again only when a significant displacement has occurred, otherwise will continue grasping without data process to improve efficiency.

III. METHODS

A. Preprocessing

In our approach, after using RGB-D camera to get point cloud of grasping area, it is necessary to preprocess the point cloud to remove the noise and get the point cloud of target objects. The implementation procedure of preprocessing is as following:

- Convert the depth image to point cloud.
- Extract the grasping area and remove the noise by using the passthrough filter.
- Use voxel grid filter to downsample, that is to reduce the number of point cloud but retain the detailed information of original point cloud.
- Use RANSAC to remove the plane of the point cloud rapidly [29].

The preprocessing result is shown in Fig[2]

B. Improved DBSCAN algorithm for segmentation

There has been many point cloud segmentation algorithms, like Region growing, Euclidean Clustering, RANSAC and so on. However, they are not robust for piled and dense objects, which have arbitrary poses and overlapping point cloud. To overcome this problem, the paper proposes an improved DBSCAN algorithm for point cloud segmentation of stacked
and dense objects, combining Region Growing with DBSCAN and using Octree to improve the efficiency of algorithm.

DBSCAN algorithm is a simple and effective density based clustering algorithm which has ability to find arbitrary shaped clusters and remove noise without any prior knowledge \cite{DBSCAN}. DBSCAN requires two parameters, Eps and MinPts. Firstly, DBSCAN evaluates the density of points by defining a cluster as a group of points that have their neighbor points within Eps. Secondly, MinPts is the minimum number of neighbor points around core points to form a cluster. The border point is not core point but is contained in the Eps-neighborhood of the other core point. The noise point is the point not belonging to any cluster.

Here are some important definitions of DBSCAN.

**Definition 1:** (directly density-reachable) A point \( p \) is directly density-reachable from a point \( q \) wrt. Eps, MinPts if:

\[
p \in N_{Eps}(q) \\
|N_{Eps}(q)| \geq MinPts
\]  

(1)\hspace{1cm} (2)

Directly density-reachable is symmetric for pairs of core points, but not for the pair of a core point and a border point.

**Definition 2:** (density-reachable) A point \( p \) is density-reachable from a point \( q \) wrt. Eps and MinPts if there is a chain of points \( p_1, p_2, ..., p_n, p_1 = q, p_n = p \), such that \( p_{i+1} \) is directly density-reachable from \( p_i \).

**Definition 3:** (density-connected) A point \( p \) is density-connected to a point \( q \) wrt. Eps and MinPts if there is a point \( o \) such that both \( p \) and \( q \) are density-reachable from \( o \) wrt. Eps and MinPts.

Density-connectivity is a symmetric relation. For density reachable points, the relation of density-connectivity is also reflexive.

**Definition 4:** (cluster) Let \( D \) be a dataset of points. A cluster \( C \) wrt. Eps and MinPts is a non-empty subset of \( D \) satisfying the following conditions:

1) \( \forall p, q, \) if \( p \in C \) and \( q \) is density-reachable from \( p \) wrt. Eps and MinPts, then \( q \in C \). (Maximality)
2) \( \forall p, q \in C : p \) is density-connected to \( q \) wrt. Eps and MinPts. (Connectivity)

To find a cluster, DBSCAN starts with an arbitrary point \( p \) and retrieves all points density-reachable from \( p \) wrt. Eps and MinPts. If \( p \) is a core point, this procedure yields a cluster wrt. Eps and MinPts. If \( p \) is a border point, DBSCAN visits the next point.

There are some deficiencies of DBSCAN. First, it costs a lot when finding the neighbor points to form clusters. It’s necessary to speed up the calculation to improve the efficiency. Second, DBSCAN algorithm only merges the Eps-neighborhood points of core points, which means lots of border points are lost in this proceeding. It causes a loss of the objects’ edge and some detailed point cloud, which may lead to a bad registration of following proceedings.

**Improved DBSCAN:**

1) Use Octree to speed up:

To improve the efficiency of DBSCAN for finding the nearest neighbors, it is necessary to use relevant algorithms to speed up the calculation. As a dynamic partition algorithm, K-d tree is efficient and has been widely implemented for handling point cloud. However, all of the child nodes should be retrieved to traverse from a node to its child node where the 3D boundary satisfies a positional query. Inspired by Soohee Han’s work \cite{IndexStructure}, Octree is adopted in this paper.

An Octree is defined as a tree data structure in which each internal node has exactly eight children. A 3D space is created by recursively subdividing it into eight octants. When using Octree for point cloud, the 3D boundary is divided into eight octants, which will be further subdivided recursively only when they bear points within themselves until the sequence reaches a given threshold value \( \text{depth} \). In Octree, only one child node in each depth is traversed for the 3D boundary of each node is known by positional query. And a leaf node can be advantageously retrieved to improve the index efficiency.

By using Octree to find the nearest points, the accuracy and efficiency of DBSCAN are improved to deal with 3D point cloud data.

2) Combine with Region Growing algorithm

To avoid the loss of some details and bounds, this paper proposes a method to combine the DBSCAN with Region Growing algorithm \cite{RegionGrowing}. Firstly, Region Growing sorts the points by their curvature value and picks points with minimum curvature value as seeds to start the growth of the region. Secondly, Region Growing algorithm uses surface normals as a measure of local geometry, which are estimated by fitting a plane to the neighborhood of the point. The algorithm also approximates the local curvature by the residual of plane fitting. The method has two parameters \( \theta_{th} \) and \( r_{th} \), which mean curvature threshold and smoothness threshold. Region Growing focuses on using the point normals and residuals to group points to the smooth surfaces, according to the two parameters.

DBSCAN usually results in over segmented point clouds and lost borders, but Region Growing tends to extend for more points from the growing seeds. To enhance the DBSCAN algorithm for solving the problems, we combine the Region Growing method with DBSCAN algorithm, which can take DBSCAN clusters as region growing seeds to start growing. Instead of only merging the clusters of core points into one, we also merge the border point cluster to the core point cluster according to some rules:

- The border point and core point are directly density-reachable.
- The Eps neighborhoods of two points have the most in common.
- The normal for each point is estimated by fitting a plane to some neighboring points. The normal and curve features of two points’ Eps neighborhood can be matched, which means the two clusters have similar surface properties.
Coarse Registration: PCA algorithm is used mainly to reduce the dimensions of data sets by retaining the greatest feature of the data which contribute to variance at most. For point sets $P(x_1, x_2, ..., x_n)$, $x_i$ is n-dimensions data, and the algorithm calculate the mean and variance \[\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i\] \[\text{cov}P = \frac{1}{n}\sum_{i=1}^{n} (x_i - \bar{x})(x_i - \bar{x})^T\]

The feature vectors of the covariance matrix $\text{cov}P$ is the principle component of the point cloud $P$. For point cloud which has three dimension data, we use $\overline{x}$ as the origin of the coordinate system, and the three feature vectors as the XYZ axes, which represent the principle component of the data. By adjusting the coordinate systems of target point cloud and model point cloud, the coarse registration can be achieved.

Fine Registration: To improve the accuracy of registration, the paper uses point-to-point ICP for fine registration to estimate the pose of object. And ICP algorithm needs an iterative initial transformation matrix $T$, which can be set by the result of coarse registration. And point-to-point ICP updates the transformation $T$ by minimizing an objective function $E(T)$:

\[E(T) = \sum_{(p,q) \in D} ||p - Tq||^2\]

The registration results are shown in Fig. 4.

![Fig. 3. Segmentation results of different algorithms. The centroids of each cluster are calculated and shown as red points.](image)

![Algorithm 1 Improved DBSCAN](algorithm)

D. Policy of grasping

Grasp policy involves grasp order, grasp position, grasp angle and gripper opening width. Inspired by Kentaro Kozai’s work [34], we propose Grasp Risk Score(GRS) to optimize above parameters in case to avoid collision and improve the grasping efficiency.

1) Grasp order selection: We consider three factors in grasp order selection. $P_{\text{self}}(i)$ represents the unstability of object $i$ itself. We use $P_{\text{grasp}}(i)$ to describe the possibility of collision while grasping object $i$. $P_{\text{system}}(i)$ tells the contribution to the system’s stability of object $i$, that is, if the system would tend to collapse without object $i$, then the $P_{\text{system}}(i)$ would be pretty large in value.

We define the Grasp Risk Score(GRS) of object $i$ in equation: \[\text{GRS}(i) = (\alpha P_{\text{self}}(i) + \beta P_{\text{grasp}}(i)) \cdot P_{\text{system}}(i)\]
with $\alpha, \beta$ to be tuned. The GRS expresses the possibility of object $i$ to be safely picked up. By formulating the Grasp Policy as a function of the grasping order, it is possible to solve the problem of optimizing the grasp order. The optimal grasping parameter $\tilde{i}$ can be determined by maximizing GRS, as in equation $[7]$

$$\tilde{i} = \arg \min_{i \in P} \text{GRS}(N)$$

with $N$ being the number of objects.

$P_{self}(i)$ expresses the unstability of the object $i$ itself. We consider the height of the object $i$'s barycenter $z_{oi}$ and the principal axis angle $\theta_i$ to be the main factors that determine the stability of the object. Generally, a large $z_{oi}$ means object $i$ is on the top of the pile, while a small one means it’s lying on the ground, which is obviously more stable. And a slant principal axis means it tends to topple over. $P_{self}(i)$ is defined as equation $[8]$

$$P_{self}(i) = k_1 \cdot z_i + k_2 \cdot \sin \theta$$

with $k_1$ and $k_2$ to be tuned.

$P_{grasp}(i)$ represents the possibility of collision while grasping object $i$. Since the grasp parameters are uncertain, we just calculate the density of objects around object $i$ by using KD-Tree to find the distance of $K$ nearest neighbors as an estimate. Denote the centroid position of object $i$ as $(x_i, y_i, z_i)$, the centroid position of other object as $(x_j, y_j, z_j)$. $P_{grasp}(i)$ is defined as formula $[9]$

$$P_{grasp}(i) = \frac{1}{K} \sum_{k \in K} \{(x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2 \}$$

$P_{system}(i)$ expresses object $i$'s contribution to the system’s stability. An object can count a lot if it’s supporting or propping against another object. As point cloud data is gained from an overhead camera, it contains only the information of the top layer of the object pile, thus above situations would be presented as overlap. Through advanced segmentation and registration, the dependencies information could be gained.

Replace the origin point cloud $Q_i$ with the template point cloud $\tilde{Q}_i$ introduced during the registration. For target object $O_{target}$, we have formula $[10]$

$$P_{system}(i) = \begin{cases} 
0 & \text{threshold \lt \text{COUNT}(\hat{Q}_{target} \cap \tilde{Q}_i)} \\
1 & \text{threshold \geq \text{COUNT}(\hat{Q}_{target} \cap \tilde{Q}_i)}
\end{cases}$$

with $N$ being the number of detected objects and COUNT($Q$) meaning count the points’ number of point cloud $Q$.

2) Grasp position determination: As Brayan S et al. proposed, the grasp point should on the object’s principle axis $l_{axis}$ $[19]$. We consider the distance between the grasp point and the barycenter to be as small as possible, while the distance between the grasp point and the nearby objects to be as large as possible. Denote the distance between the grasp point and the lower endpoint of the principle axis as $x$, the distance between the barycenter and the grasp point as $de(x)$, the distance between the nearest object and the grasp point as $dn(x)$. The grasp point’s position $\tilde{x}$ is determined by formula $[11]$

$$\tilde{x} = \arg \min_{x} k_3 \cdot de(x) + k_4 \cdot dn(x)$$

$k_3$ and $k_4$ to be tuned.

### IV. Experiments and Results

The performance of our algorithm and conventional algorithms is evaluated by using an Anno robotic arm. We use robot operating system (ROS) to enable cooperation between all methods and the operation of the robot arm.

After validating the algorithms on the “Randomly Piled Industrial Objects” dataset, the results of segmentation are listed in Table I. Improved DBSCAN is capable of segmenting point cloud of dense and randomly piled industrial objects, reducing noise and removing some bottom objects.

Our grasp system is deployed to an Anno robotic arm with a Kinect V2 camera, as shown in fig. 5. Performance of our method is evaluated by grasp-success-rate and collapse-rate. Former is defined as the ratio of the number of objects successfully moved out of the box to the total number of the objects, while the latter is defined as the ratio of the number of collisions to the total number of grasp. The results of the experiment with the proposed and comparative pipelines are listed in Table II. Our method gained the best performance among the methods tested in the experiments.

Photograph of the working robot is shown in Fig. 5. The gesture of the robot when it’s grasping the object in corner is particularly presented in Fig. 5.
based algorithm, which is improved by combining the Region Growing algorithm and using Octree to speed up the calculation. Then we use PCA for coarse registration and ICP for fine registration. We proposed Grasp Risk Score to evaluate each object by the collision probability, the stability of object and the whole system’s stability. Through real test with Anno robot, our method is verified to be advanced in speed and robustness.

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