Fast detection method for Baggage pallet based on multi-layer

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Abstract

In self-service baggage check-in and sorting for civil aviation, automatically detecting whether pallets are added to self-dropped baggage is an essential function; however, the pallets are largely obscured by the embedded baggage, which poses a challenging problem. To address this issue, a fast detection method for embedded baggage pallets based on multi-layer skeleton model registration is proposed. To describe the characteristics of the pallet, a point cloud skeleton model and a point-line model are constructed from the 3D point cloud model. During online detection, the designed banded feature description and extraction method is used to capture the border point cloud, and the proposed point-line potential energy iterative algorithm is employed to register the point-line model with the horizontal border points. Subsequently, point cloud iterative closest point registration based on random sample consensus is utilized to achieve accurate registration and pose estimation. Consequently, the possibility of the pallet' s existence is determined. The effectiveness of the algorithm is verified through various actual pallet detection experiments. A variety of typical comparative experimental results demonstrate that when up to 70% of the pallet point cloud is missing, the algorithm can still maintain 94% accuracy, and its speed exceeds that of typical algorithms by more than six times.

Full Text

Graphical Abstract

Fast detection method for baggage pallets based on multi-layer skeleton model registration

Highlights - Designed description and extraction method for point cloud banded features - Registration algorithm for point-line model based on iterative gravitational potential energy - Proposed modeling and registration algorithm of multi-layer skeleton model

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Abstract

In civil aviation baggage consignment and sorting, automatically detecting whether a pallet is present beneath passenger baggage is a necessary function. However, pallets are largely obscured by the baggage placed on top, making pallet detection a challenging problem. To address this issue, we propose a fast detection algorithm for embedded baggage pallets based on multi-layer skeleton model registration. To describe the characteristics of pallets, we construct both point cloud skeleton models and point-line models from 3D point cloud data. During online detection, we first employ our designed feature description and banded point extraction method to capture border point clouds, then use the proposed point-line potential energy adaptive iterative algorithm to register the point-line model with the horizontal border point set. Next, point cloud iterative nearest point registration based on random sampling consistency is used to achieve accurate registration and pose calculation, thereby determining the likelihood of pallet existence. The effectiveness of the algorithm is verified through various actual pallet detection experiments. Comparative experimental results demonstrate that the algorithm maintains 94% accuracy even when up to 70% of the pallet point cloud is missing, while achieving speeds more than six times faster than typical algorithms.

Keywords: 3D object detection, baggage pallet, multi-layer skeleton model, point clouds registration

1. Introduction

The self-service baggage check-in system frees airport attendants from heavy-duty service tasks and significantly improves the efficiency and quality of airport operations. The system must automatically detect the shape of baggage delivered by passengers, including the number, size, shape, and type of items, as well as whether soft baggage is placed on pallets and the number of baggage pieces on each pallet. Automatic detection of whether passenger-delivered soft baggage is equipped with pallets is key to ensuring the safety of both passenger baggage and the baggage sorting system.

Detection of objects such as baggage pallets typically uses industrial cameras or LiDAR to obtain surface images or three-dimensional point clouds, with object recognition performed by extracting and matching color, texture, and structural characteristics [1]. In the open baggage drop area, the reliability of pallet detection methods based on image analysis is reduced due to complex ambient lighting, interference from luggage surface textures, and uncertainty in drop positions. In contrast, object detection methods based on point clouds are less affected by environmental factors. Therefore, using a three-dimensional

(3D) object detection method based on point cloud analysis is a more reliable solution for pallet detection in embedded baggage scenarios.

3D object detection based on point clouds generally first extracts local or global features of the object from the point cloud to match scene features, then judges whether the object exists in the scene according to matching evaluation results. The precise pose of the target is estimated through point cloud registration [2, 3, 4] or pose clustering [5, 6, 7]. However, air baggage pallets are embedded and occluded by baggage during self-service shipment, with only the border or partial border exposed, making it difficult for traditional 3D object detection methods to work effectively.

To address this issue, this paper investigates a 3D detection method for embedded occluded objects with partially missing point clouds. Based on the known structure of the pallet and considering its rectangular characteristics and horizontal upward placement orientation, we design a specific three-layer skeleton model and adopt a step-by-step refinement registration approach to achieve fast and accurate detection of baggage pallets. The main contributions of this study are:

1. The established multi-layer skeleton model can effectively describe the morphological characteristics of baggage pallets.
2. The designed banded point cloud description and extraction method can effectively extract banded borders from the target scene, enabling separation of pallets and baggage.
3. The proposed point-line model registration algorithm based on iterative gravitational potential energy can map and match horizontal point sets to rectangles, completing registration between the pallet point-line model and horizontal banded point sets.
4. The proposed point cloud registration algorithm based on multi-layer skeleton model enables fast and accurate detection of baggage pallets under conditions of large-area missing point clouds.

The main structure of this paper is as follows: Section 2 briefly introduces related work. Section 3 presents the principle of the multi-layer skeleton model registration method. Section 4 provides analysis and experiments. Section 5 concludes the work of this paper.

2. Related Work

Many different methods have been proposed for 3D object detection and recognition based on point clouds [8, 9], including 3D feature descriptor-based methods, graph matching-based methods, and machine learning-based methods. Typically, 3D feature descriptor-based methods extract local keypoint neighborhood features or global statistical features of objects and scenes, completing object discrimination through feature matching [10, 11, 12, 13]. Graph matching-based methods [14] decompose point cloud data into basic shapes, use adjacency relationships between shapes to represent three-dimensional objects, and obtain object positions through matching. Machine learning-based methods [15] use samples to train classifiers to complete object detection and classification. Among these, 3D object detection methods based on deep learning [16, 17], through large numbers of labeled samples and training of multi-layer deep neural networks, can achieve good generalization performance and high detection accuracy, such as PointNet [18] and LiDAR R-CNN [19].

However, when objects are occluded, the accuracy of traditional methods decreases significantly. Registration with local descriptors such as Fast Point Feature Histograms (FPFH) [10] and Signature of Histogram of Orientation (SHOT) [11] can overcome the influence of small occlusion and background interference. Point Pair Feature (PPF) [7] and its improvements [20] perform object recognition and pose estimation through correspondence between point pairs, remaining effective when the target is partially occluded. Detection methods based on three-dimensional Hough voting [21], Rotational Subgroup Voting [22], and clutter-oriented detection methods [23] further solved the problem of target occlusion and achieved good results on various datasets. When object occlusion is severe and the proportion of incomplete point cloud exceeds 50%, 3D object detection becomes more difficult, requiring more target feature information or multi-sensor information fusion to complete detection.

In summary, to overcome the impact of incomplete point clouds on 3D object detection, many scholars have conducted extensive research. Pallets loaded with baggage only show their borders, sometimes with occlusion reaching over 70%. Additionally, due to cost limitations, the accuracy of 3D target point clouds obtained by sensors is not high, resulting in traditional 3D target detection methods failing to meet practical requirements. In contrast, this paper proposes a multi-layer skeleton model description and registration method to effectively overcome baggage occlusion of pallets, meeting the actual needs of self-service luggage check-in systems.

3. Methods

The fundamental reason why traditional point cloud target detection methods are prone to mismatch under occlusion conditions is that features of occluded targets are not obvious. If the object model is known, establishing a specific model based on the object's structure or local characteristics and adopting model registration can improve target detection success rates [24]. Point cloud skeleton models have simple and obvious topological structures, and using skeleton model registration can effectively utilize object structural features, helping to overcome misregistration caused by occlusion. The algorithm flow is shown in Fig. 1.

3.1. Pallet Modeling

The shape and size of air baggage pallets across airports are not significantly different, and the specifications of baggage pallets at the same terminal are always identical. Therefore, a three-layer skeleton model of the pallet can be established offline.

In the same airport application scenario, Fig. 2(a) shows one type of baggage pallet in the airport. First, the empty pallet is scanned by a 3D laser scanner, ignoring the bottom, to obtain the point cloud model M_L, as shown in Fig. 2(b).

Direct use of point cloud model registration and detection can easily lead to mismatches and errors when pallets are obscured by loaded luggage. The pallet border, especially the upper surface of the border, is basically visible in the scene cloud, and the border can fully demonstrate the morphological characteristics of the pallet. Therefore, the L1 center skeleton extraction algorithm [25] is used to establish the border skeleton model. The skeleton modeling process is as follows:

1. Manually select the upper surface points from the point cloud model.
2. Randomly select a certain number of sampling points to determine the appropriate neighborhood and construct the initial skeleton model.
3. Expand the neighborhood scope, use local L1 median to shrink sampling points, and iteratively construct different regional skeletons.
4. After skeleton smoothing and concentration, the border-skeleton model M_S of the pallet is obtained, as shown in Fig. 2(c).

It is difficult to extract the complete pallet border when the baggage frame shields parts of it, and the skeleton model is also prone to matching errors. The horizontal projection of the pallet frame is a rectangle, which can well describe the geometric information of the pallet. Therefore, the border skeleton model is mapped to a horizontal plane, forming a plane point-line model M_L, which is composed of four corner points and can be expressed as M_L = {(x_i, y_i) | i = 1, 2, 3, 4}, as shown in Fig. 2(d).

3.2. Banded Feature Description and Pallet Border Point Cloud Extraction

During online detection, due to the small number of occluded pallet points, it is difficult to maintain a high success rate by directly registering the scene point cloud with the pallet point cloud model. If baggage and pallet point clouds can be separated, the misregistration problem caused by embedded baggage can be effectively overcome by using only pallet point cloud to register with pallet model. Combined with the strip distribution characteristics and horizontal placement characteristics of the pallet, a strip feature description and extraction method is designed to capture the upper surface border points and realize separation of baggage and pallet point clouds.

(1) Banded Feature Description According to the relative position distribution of point clouds, three-dimensional scanning point clouds can be divided into two categories: non-banded points and banded points, as shown in Fig. 3. Non-banded points are located at edges and inside large-scale point cloud areas, generally representing point clouds on the upper surface of baggage. Banded points are distributed in linear bands, generally representing point clouds of the pallet border.

To distinguish between non-banded points and banded points, the covariance matrix of neighborhood points is defined to describe the relative position distribution characteristics within the point cloud. For a point q = (x, y, z)^T, the X-Y coordinate plane is horizontal, and the Z coordinate axis direction is vertical upward. In the k-neighborhood point set of q, Q_k contains n neighboring points, so the covariance matrix of Q_k can be defined by Formula (1):

$$C(q) = \sum_{i=1}^{n}(q_i - q)(q_i - q)^T$$

The eigenvalues of C(q) are λi*, i = 1, 2, with maximum eigenvalue* λ{max}. For point q, if λ_{max} » λ_i, then q is a banded point. For non-banded points, there is little difference between the eigenvalues.

(2) Pallet Border Point Cloud Extraction The pallet is horizontally placed in the baggage channel without suspension or inversion. The height range of point clouds in the border is known, so the banded point cloud extraction process for pallet border is as follows:

1. According to the known height range of the pallet border, select the pallet border candidate point cloud Q_{Sec} from the scene cloud Q_P.
2. For a planar mapping point q = {x, y} of any point q in Q_{Sec}, obtain a set of n neighborhood points by searching points in the k-neighborhood, denoted by: Q_{Mat} = {(x_i, y_i) | i = 1, 2, ···, n}
3. The covariance matrix C of Q_{Mat} is calculated by Formula (2), which is a two-dimensional square matrix yielding two eigenvalues λ_1, λ_2. Coefficient l is introduced, calculated by Formula (3):

$$l = \max(|\lambda_1/\lambda_2|, |\lambda_2/\lambda_1|)$$

Set a threshold (determined empirically). When l > , the corresponding point is a banded point. 4. Repeat the above steps, traverse Q_{Sec}, and obtain pallet banded border point cloud Q_S. After horizontal projection, the horizontal border point set Q_L is obtained.

3.3. Three-Layer Skeleton Model Registration

After obtaining the three-layer skeleton model and the banded points on the pallet border of the scene, online matching is needed to evaluate whether the scene contains the pallet and determine its exact pose. Therefore, according to the different structures of the three-layer skeleton model, a multi-level model registration method is designed to complete pallet model registration at the plane, border skeleton, and three-dimensional point cloud levels.

(1) Registration of Planar Point-Line Model The horizontal border point set Q_L is a discrete lattice, and the planar point-line model M_L is the fitted rectangular boundary. The registration process is essentially a mapping transformation from the point set to the rectangle. Therefore, an evaluation index called "point-line gravitational potential energy" is defined to measure the correctness of the mapping from point set to rectangle, and an adaptive iterative registration algorithm is designed based on this.

As shown in Fig. 4, a_i is a point in Q_L, b_i is the nearest point to a_i on M_L, O is the rotation center of M_L, and c_i is the foot of perpendicular from a_i to the line through O. M_L is continuously rotated and shifted by the traction of point a_i, and the gravity T_i and torque R_i are calculated by Formulas (4) and (5):

$$T_i = G \cdot \frac{\overrightarrow{a_i b_i}}{|\overrightarrow{a_i b_i}|}$$

$$R_i = \overrightarrow{Oa_i} \times T_i$$

where G is a constant. The average traction T_S and torque R_S of the planar point-line model M_L for all points in Q_L are obtained by Formulas (6) and (7):

$$T_S = \frac{1}{n}\sum_{i=1}^{n} T_i$$

$$R_S = \frac{1}{n}\sum_{i=1}^{n} R_i$$

where n is the number of points in Q_L. Under the traction of horizontal frame banded lattice Q_L, M_L gradually approaches Q_L. During this transformation process, the coincidence degree of the two can be evaluated by potential energy E, defined by Formula (8):

$$E = -\min\{l_{ij} | j = 1, 2, 3, 4\}$$

where l_{ij} is the distance from any point in Q_L to the four edges of the rectangle in the planar point-line model. The purpose of registration is to find a suitable transformation that minimizes the potential energy between the transformed plane point-line model and the horizontal border point set, with the objective function expressed as Formula (9):

$$f(R,T) = \arg\min E(Q_L, M_L(R,T))$$

where R is a rotation matrix and T is a translation vector.

In the registration process, under the constraints of potential energy E and the objective function, M_L is iteratively transformed. During iteration, the step length of transformation is adaptively adjusted by gravity. The relationship between translation T_i and rotation angle _i of the i-th transformation and the gravitation and torque is shown in Formulas (10) and (11):

$$T_i = step_T \cdot T_{S_i}$$

$$\theta_i = step_\theta \cdot R_{S_i}$$

where step_T and step_ are constants, T_{S_i} and R_{S_i} are the average traction and torque of the i-th transformation, and the corresponding transformation relationship R and T are solved by Formula (12):

$$M_{L_{i+1}} = R \cdot M_{L_i} + T = \begin{bmatrix} \cos\theta_i & -\sin\theta_i & 0 \\ \sin\theta_i & \cos\theta_i & 0 \\ 0 & 0 & 1 \end{bmatrix} M_{L_i} + \begin{bmatrix} tx_i \\ ty_i \\ 0 \end{bmatrix}$$

where M_{L_i} and M_{L_{i+1}} are the plane point-line models before and after the i-th transformation, and tx_i and ty_i are the components of R_{S_i} in x and y directions respectively. The potential energy is recalculated after each transformation to guide the next iteration. Iteration terminates when the number of iterations reaches the upper limit or the potential energy stabilizes.

In the registration process, the absolute value of potential energy |E| can reflect the coincidence degree between the horizontal border point set and the pallet point-line model. The higher the coincidence degree, the greater the probability of containing a pallet. Set a threshold E_{min} (E_{min} > 0, empirically set to 150). After iteration completes, if |E| > E_{min}, the existence of a pallet can be determined.

(2) Registration of Border-Skeleton Model The horizontal border point set loses some three-dimensional spatial characteristics, and the vertical position and orientation of the pallet need to be corrected at the border skeleton level. There are differences between the position and orientation of the pallet banded border point cloud Q_S and the border-skeleton model M_S, and their shapes also differ. RANSAC can be used to select corresponding point pairs to complete registration.

First, select the nearest neighbor points as corresponding point pairs from the pallet banded border point cloud and skeleton model after initial transformation by applying point-line model registration. The process is as follows:

For point m_i in M_S, search for the nearest point q_i from Q_S. Simultaneously, for point q_j in Q_S, search for the nearest point m_j from M_S. If m_i and q_j are the closest corresponding points to each other and the distance is less than the set threshold, then (m_i, q_j) is a pair of corresponding points.

After selecting corresponding points, randomly select n groups of corresponding points to estimate the transformation and calculate the distance d = ||R' m + T' - q|| after transformation for remaining points. If d is less than the given threshold, the point pair is called a pair of inliers.

Set the maximum number of iterations N, and count the number of interior points corresponding to each transformation until the maximum number of iterations is reached. After iteration, the transformation with the largest number of inliers is the best transformation of the model, representing the coarse position of the pallet.

(3) Registration of Point Clouds Model The point-line model registration and border-skeleton model registration match the extracted banded border at the plane and border-skeleton levels. The above registration only uses the point cloud of the pallet border, without involving point clouds of other pallet parts. To calculate the pallet pose more accurately and detect and extract all pallet point clouds, it is necessary to register the 3D point cloud model of the pallet with the field point cloud.

ICP [2] is a classical algorithm for point cloud registration. Its principle is to find the nearest points in target and source point clouds according to certain constraints, and calculate optimal transformation parameters R and T through iterative matching. However, civil aviation baggage pallets are embedded and occluded, with low weight in point clouds. Moreover, the characteristics of baggage surface and pallet side are similar, making direct ICP registration prone to mismatch. To prevent ICP from falling into local optimum, a certain distance threshold is set under the constraint of initial pose from skeleton registration. By extracting the nearest points, the overlapping area of two point clouds is obtained. The ICP algorithm is applied to the overlapping area to obtain the accurate pose of the pallet.

4. Experimental Results of Pallet Detection

The experimental hardware platform uses an Intel Core i5-7300HQ CPU with 8 GB memory. Under the Windows 10 operating system, the algorithm is implemented based on OpenCV and PCL development libraries using Visual Studio 2019. The experimental platform is shown in Fig. 5. A Hokuyo URG-04LX-UG01 is used as the 3D laser scanner. The scanning area of the sensor is 20–5600 mm, with accuracy of $±$30 mm. The experimental data consists of 490 sample data randomly selected from 5 million data points collected at a Guangzhou airport from 2019 to 2021.

Typical samples under various conditions are selected, as shown in Table 1. Sample 1 is a typical pallet sample embedded in baggage without border cover, sample 2 is an empty pallet, and samples 3 to 6 are pallet samples with different levels of completeness. In the experiment, to show the registration effect of point clouds more clearly, the point cloud is used to represent the pallet model, and the reconstructed mesh model is used to represent the scene point cloud of the test field.

4.1. Pallet Border Point Cloud Extraction

The effectiveness of the border point cloud extraction algorithm is verified using typical sample 1 with unshielded pallet border. The banded boundary of sample 1 is extracted using the banded point cloud extraction algorithm, with results shown in Fig. 6(a), which are projected onto the horizontal plane to obtain the horizontal boundary points of the pallet, as shown in Fig. 6(b). It can be seen that the banded point cloud mainly includes side points of the pallet border, but corner points and adjacent baggage points cannot be correctly extracted. The reason is that the distribution of corner points and luggage-adjacent points is relatively concentrated, causing them to be mistaken for non-banded points. In general, the proposed banded point cloud extraction algorithm can extract the pallet border point cloud from the scene point cloud and realize separation of baggage and pallet point clouds.

4.2. Three-Layer Skeleton Model Registration

The effectiveness of the three-layer skeleton model registration algorithm is verified using typical sample 1 with unshielded pallet border.

(1) Registration of Planar Point-Line Model To verify the effectiveness of the point-line gravitational potential energy registration algorithm, registration experiments are carried out using the pallet plane point-line model and the horizontal boundary point set extracted from sample 1. Before registration, the position of the pallet plane point-line model is quite different from the horizontal boundary point set of the scene to be tested, as shown in Fig. 7(a). After registration, the two are aligned, as shown in Fig. 7(b).

The process of potential energy change is shown in Fig. 8. Before registration, the absolute value of potential energy is relatively small. With increasing iterations, the point-line model of the pallet plane is continuously transformed under traction from the horizontal boundary point set, and the absolute value of potential energy gradually increases. When the two coincide, the absolute value of potential energy tends to be maximized and stabilizes. After registration, the absolute value of potential energy is greater than the set threshold, confirming pallet existence. It can be seen that the proposed adaptive iterative registration algorithm of point-line gravitational potential energy can effectively evaluate the possibility of pallet existence in the scene to be tested and complete matching at the horizontal plane, providing the initial pose for subsequent registration.

(2) Registration of Border-Skeleton Model To verify the effectiveness of the border-skeleton model registration algorithm, the pallet border skeleton model and sample 1 banded border point cloud are used for registration. Before registration, under the constraint of initial pose, the pallet border-skeleton model and the banded border point cloud overlap on the horizontal plane, but there are still deviations in the vertical direction, as shown in Fig. 9(a). After registration, the two also overlap in the vertical direction, as shown in Fig. 9(b). It can be seen that registration of the border-skeleton model can complete coarse registration of the pallet border-skeleton model and the banded border point cloud in the vertical direction.

(3) Registration of Point Clouds Model After border-skeleton model registration, the accurate pose of the pallet is determined through point cloud registration. The initial pose from point-line model registration and border skeleton model registration is used to transform the pallet point cloud model coarsely. After extracting the overlapping area, the ICP algorithm is used to fine-tune the registration. Before transformation, the position relationship between the pallet point cloud model and the scene point cloud to be measured is shown in Fig. 10(a), and the position relationship after registration is shown in Fig. 10(b). It can be seen that after multi-layer transformation and registration, the pallet point cloud model is basically at the same position as the pallet point cloud in the scene to be tested, though there are still slight differences. The reason is that the point cloud model established offline differs from the actual pallet point cloud in the scene to be tested, resulting in incomplete overlap. The overall experimental results show that the proposed three-layer skeleton model registration method can effectively detect the baggage pallet and mark its precise pose.

4.3. Results of Pallet Detection

Typical samples 1 to 6 were selected for pallet detection experiments to evaluate the influence of pallet point cloud defect ratio on the proposed method, and compared with other typical point cloud registration algorithms: ICP, SHOT-ICP, and FPFH. As shown in Table 2, experimental results demonstrate that each method can achieve good registration effects for samples 1 and 2 without pallet point missing. However, when the pallet point cloud is incomplete, typical algorithms become unsuitable. In sample 3, ICP and FPFH fail when a small part of the pallet point cloud is incomplete. When SHOT provides a good initial position for ICP, successful registration can be achieved. When pallet defects exceed 40%, SHOT-ICP cannot detect effectively, while the proposed method' s detection results remain stable. Under conditions of large-scale point cloud missing, registration can still succeed.

To quantitatively analyze registration accuracy, RMSE [26] is used as the evaluation index, as shown in Formula (13):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} \|(x_i, y_i, z_i) - (x_{MP_i}, y_{MP_i}, z_{MP_i})\|^2}$$

where n is the number of pallet points in the scene to be tested and m is the number of pallet point cloud model points. The registration accuracy is shown in Table 3. It can be seen that when the pallet is complete, the typical algorithm SHOT-ICP has the best registration effect, with the proposed algorithm' s accuracy not significantly different. When the pallet point cloud is missing, the proposed method' s accuracy is significantly better than other methods. These results show that the proposed method ensures detection accuracy when the pallet is complete and has obvious advantages for incomplete point clouds.

The practicability of the algorithm is verified through statistical analysis of point cloud samples with different integrity levels and without pallets. The results are shown in Table 4. All 268 groups of pallet-free samples were tested correctly. Among 222 groups of pallet-containing samples, all samples with pallet defect ratio less than 50% were tested correctly. In 17 groups of samples with pallet defect ratio of 50%-70%, only one group had detection errors, achieving 94.1% accuracy. When the incomplete ratio of pallet point cloud exceeds 70%, detection accuracy decreases significantly, with only one correct detection among 13 samples with high pallet integrity. The reason is that the banded point cloud of the pallet border becomes too sparse, resulting in a small absolute value of point-line model potential energy, causing misjudgment as no pallet. Overall, the detection accuracy of the proposed algorithm exceeds 94%, demonstrating obvious practical value.

4.4. Time Complexity Analysis

To verify the rapidity of the method, the registration time for a single typical point cloud sample is compared with other algorithms. The results are shown in Table 5. The average time for ICP registration is about 2.41 s, the average time for SHOT-ICP is about 23.97 s, and the average time for FPFH is about 42.67 s. The average time required for the proposed algorithm is less than 0.4 s, which is obviously faster than other algorithms. The reason is that the proposed three-layer skeleton model registration method only needs to calculate the distribution of neighborhood positions of the point cloud when extracting pallet features, reducing computational consumption, and greatly decreasing calculation amount through multi-level local point registration.

5. Conclusion

This paper studies a 3D object detection method based on a three-layer skeleton model to solve the problem of fast and accurate pallet detection when baggage causes large-area occlusion in self-service baggage consignment.

The constructed skeleton model can better describe the three-dimensional characteristics of baggage pallets. Through gradual refinement registration of the three-layer skeleton model at plane, skeleton, and point cloud levels, pallet detection accuracy can exceed 94% under conditions of 70% point cloud incompleteness. The banded point cloud feature description and extraction method and the adaptive iterative registration algorithm based on point-line gravitational potential energy can accurately extract the pallet border point cloud, avoid influence from baggage point clouds on pallet model registration, and effectively improve detection speed, which is more than six times faster than typical 3D target detection algorithms.

The method detects pallets based on the registration degree of a known three-dimensional structural skeleton model. When pallet types are known and limited in variety, it can be applied in civil aviation airports. However, for occlusion detection of other unknown structures, it has limitations and requires further improvement and optimization.

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Note: Figure translations are in progress. See original paper for figures.