Object Recognition in Terrestrial Laser Scan Data using Spin Images

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ABSTRACT

This paper describes a method of object recognition in terrestrial laser scan data of complex scenes. By local 3D shape matching between the CAD model mesh of the object and the laser scan data of the scene, the existence of the object is recognized and its location and orientation in the scene are extracted. Spin-images are used for shape matching. In this paper, some techniques for applying spin-image matching to the terrestrial laser scan data are proposed. They include robustness improvements for the scan noise and the differences in vertex densities by normal averaging and uniform point sampling, and efficient calculation by using multi-resolution images and geometric point filtering.

Keywords: object recognition, terrestrial laser scan, spin images, shape matching.
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1 INTRODUCTION

Middle and long range laser scanning technology has been growing in this decade and it has become popular in recent years. Currently, three types of scans are available to acquire the scan data of several objects and environments. A terrestrial laser scan (TLS) is often used for scanning rooms, inside plant facilities, cultural property and remains, buildings and so on. A mobile mapping system (MMS) is used for scanning objects around the road of an urban area. An aerial laser scan (ALS) acquires scan data of the building and the city from the above. With the progress of scanning technology, useful and novel applications of laser scan data are strongly required for the efficient analysis, modeling, and management of small scale objects such as industrial products, to large scale environments including people's work space, buildings and cities. The scan data applications are in wide ranging fields, including mechanical engineering, civil engineering, architecture, and GIS. However, it is still difficult to efficiently extract the meaningful and useful information from the scan data because of its low level representation (generally the scan data is a point cloud), enormous quantity (from a few to hundred million points in one scan), high level scanning noise (sometimes the data includes unexpected creatures), and the lack of data by occlusion or the reflectance property of the object's surfaces. Therefore, enormous time and effort is spent for scan data processing such as filtering, registration, classification and object recognition, although the laser scan becomes familiar and scan data have been accurate and high density.

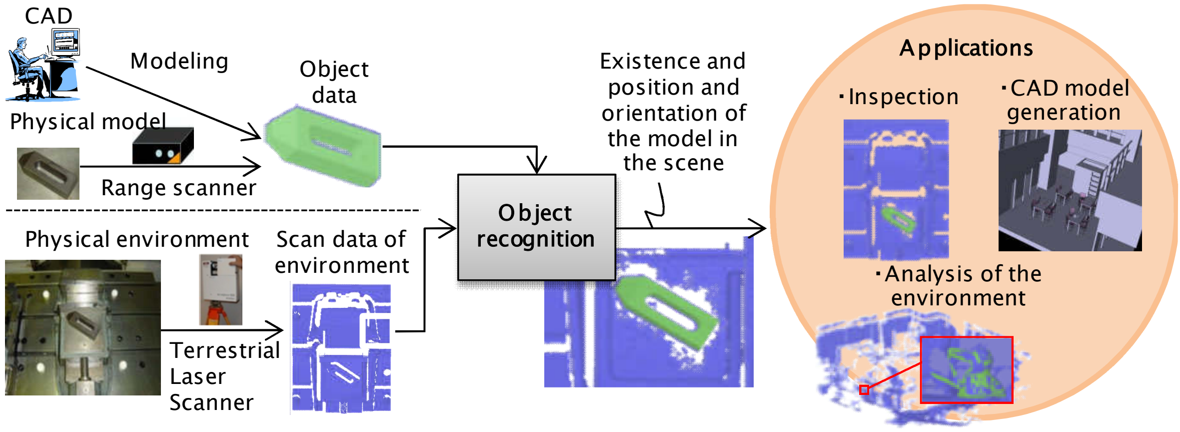


Fig. 1: Object recognition using laser scan data and its applications.

The purpose of our research is to efficiently find an object and to extract its position and orientation in complex environments using terrestrial scan data and geometric models of objects as shown in Fig. 1. An input is the terrestrial scan data of a cluttered large physical environment (scene), and another input is the geometric model of the object to be recognized. As a result of the object recognition, the existence of the object is confirmed, and if it exists, its position and orientation in the scene is extracted. Several applications of this kind of object recognition can be considered, for example, efficient modeling of environments by embedding the CAD model data into scan data according to the result of object recognition, inspection of the work space which checks the existence of undesired and desired objects in the environment, and analysis of the environment which checks the existence of the objects in the scene and creates a parts list of the environment. In order to realize these applications, an efficient object recognition algorithm using scan data and model data is necessary.

In this paper, a method of object recognition using the scan data obtained by terrestrial laser scan and object data is described. The input scan and object data are represented by triangular meshes, and our method of the object recognition is based on spin-image matching [6,7]. Some techniques for applying spin-image matching to the terrestrial laser scan data are proposed in this paper. They include robustness improvements for the scan noise and the differences in vertex densities by normal smoothing and uniform point sampling, and efficient calculation by using multi-resolution images and geometric point filtering. The effectiveness of our method was evaluated by experiments using some terrestrial scan data.

The rest of the paper is organized as follows. In section 2, related works of object recognition are introduced. The basic algorithm of object recognition using spin images is described in section 3. In section 4, the extension method for applying the basic method to terrestrial laser scan data is described, and the effectiveness of the method is evaluated by experiments in section 5.

2 RELATED WORKS

Many local shape descriptors and shape matching methods have been proposed for object recognition and 3D model retrievals [6,7,9,14]. Several good results of the object recognition were shown in the previous works, but there is no example of the object recognition from terrestrial laser scan of large environments and small object in the environments. In order to realize this type of object recognition, in our research, we focused on the spin images proposed by Johnson [6,7], because several results and analyses of object recognition using the scan data of cluttered scenes show the high ability and applicability of the spin image based object recognition. Our method is the extension of Johnson's method [6], which is designed for applying the spin image based method to the terrestrial laser scan data of large environments, especially for the robustness related to the noise and differences in vertex density, and efficient calculation. For efficient calculation of object recognition, using principal component analysis of the spin images is proposed [7], but it causes low object recognition. Therefore, we propose other approaches based on standard spin image matching. Johnson [6] also discussed the problem of the spin images for data with differences in the vertex density. They use mesh modification to obtain uniform density of the vertices. In order to solve the same problem, we propose simple point sampling based on fast marching, which is easily applicable to large scan data.

On the other hand, registration techniques can also be used for finding matches between the objects in some cases. For example, ICP algorithm [3,11,17] can find the matching position and orientation of two objects using iterative minimization of the error function, such as the sum of distances between the closest points. However, the results of registration depend on the initial position and orientation. Therefore, a certain method for giving the appropriate initial conditions is required (One of the methods is the spin image matching). A registration method using four-points congruent sets resisters two models efficiently using the ratio of the intersection of diagonals of the co-planar four points [1] without the initial conditions. However, the method is not appropriate for finding small objects in large scan data, and an adjustment of the parameters is difficult.

Classification is also useful to find objects in the scan data, and it is important topic for the efficient use of laser scan data. Many methods for the classification of the laser scan data have been proposed, for example, region growing for finding roads and walls [16], and support vector machines for classifying several ground objects [5]. They are effective for finding specific classes of the objects, but they are not suitable for recognizing arbitrary objects required by the user. From this point, object recognition based on shape matching by inputting object data, i.e., our settings, is appropriate for many applications as described in section 1.

3 SPIN-IMAGES AND OBJECT RECOGNITION

3.1 Spin Images

Spin image is one of the shape descriptors of polygonal meshes proposed by Andrew Johnson in 1997[6]. A spin image is created for a vertex (base vertex) by projecting vertices in the mesh to a local 2D coordinate system defined by the base vertex position and its normal. The pixel value of the image is the density of projected vertices. Given the base vertex *i*, the projection S_i of other vertex *j* is defined by Eq. (1).

$$S_i(j) \rightarrow (\alpha_j^i, \beta_j^i) = \left(\sqrt{\left\|\mathbf{p}_j - \mathbf{p}_i\right\|^2 - (\mathbf{n}_i \cdot (\mathbf{p}_j - \mathbf{p}_i))^2}, \mathbf{n}_i \cdot (\mathbf{p}_j - \mathbf{p}_i)\right) \tag{1}$$

Where, $\mathbf{p}_i$ and $\mathbf{n}_i$ are the position and unit normal vector of the vertex *i*, respectively.

In spin image generation for base vertex *i*, first, the projections of other vertices in the mesh are calculated. Then, a two dimensional grid is defined on the projected 2D coordinate system so that it covers all projected points. Next, the weights of each projected point are calculated for four grid points of the cell which includes the projected point. The weight is a normalized distance between the projected point and grid point. Finally, the spin image is obtained by converting each grid point to the pixel, and sum of the weights of the grid point to the pixel value. The projection is only dependent on the normal of the base vertex and relative position between the base vertex and the vertex to be projected. Therefore, spin-image does not depend on the position and orientation of the object, that is, object recognition using spin images is not affected by them.

3.2 Object Recognition Using Spin-images

In this section, the basic algorithm of object recognition using spin-images [6] is briefly described. First, the spin-images are created for all vertices in the object data *Mo* and for randomly selected vertices in the scene data *Ms*. Then the candidates of correspondences (vertex pairs) between the object and scene data are extracted by thresholding of a similarity measure. For the thresholding, a histogram of the similarity measures is created by comparing a spin image of the model data with all spin images of the scene data as shown in Fig. 2. Similarity measure calculation is based on the correlation coefficients between two images. Outliers in the histogram, which have extremely large similarity measures, are extracted as the candidates of the correspondences (vertex pairs). The outliers are founded based on quartiles, as shown in Fig. 2. This process is applied for all spin images in the object data, and the multiple correspondences are obtained. Finally, the candidates of correspondences which have a similarity larger than the similarity threshold are extracted as the final correspondences.

After the correspondence extraction, a set of groups of correspondences is created. Correspondences (vertex pairs) which have a geometric consistency, that is, the relative locations of the corresponding vertices have no inconsistency, are grouped. Each group is created by selecting a base correspondence from the extracted correspondences and by adding other correspondences with geometric consistency to the group, and therefore, the number of the groups is equal to the number of extracted correspondences. For each group which has more than three correspondences, registration is applied using correspondences (vertex pairs) in the group. After registration, the degree of adaptation is evaluated using the resulting position and orientation. In this evaluation, the following measure is used.

$$d(i,j) = \sqrt{\|\mathbf{p}_i - \mathbf{p}_j\| + v\|\mathbf{n}_i - \mathbf{n}_j\|} \tag{2}$$

Where, v is a weight defined by the user. Measure $d\ (i, j)$ is calculated for each vertex pair (i, j) ($i \in Ms$, $j \in Mo$) of the correspondences in the group. If the $d\ (i, j)$ is smaller than the threshold, each vertex is marked as valid. If pair (i, j) is valid, the neighboring vertex k of vertex i, which has a smaller $d\ (k, j)$ is founded and $d\ (k, j)$ is compared with the threshold. The same operation is done by changing the evaluating vertices to its neighbors in each mesh. If the number of valid vertices are larger than the threshold, the object exists in the scene, and the modified ICP algorithm is applied to the object and model data for determining the final object's orientation and location.

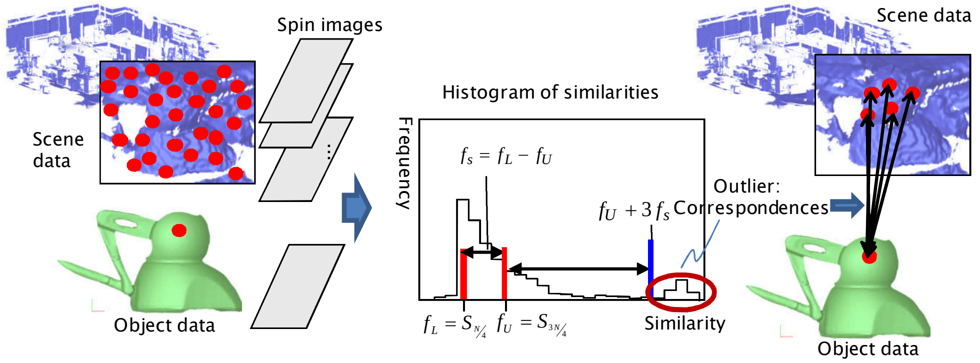


Fig. 2: Correspondences extraction using spin images.

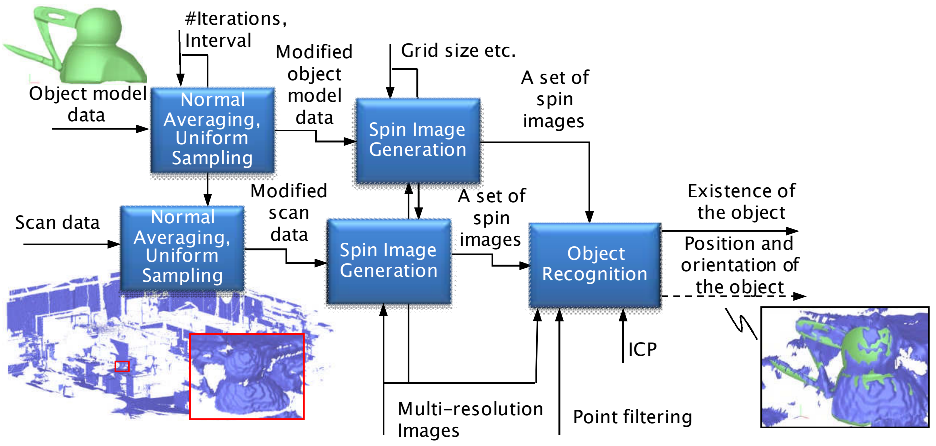


Fig. 3: Our algorithm of object recognition using spin images.

4 OBJECT RECOGNITION FROM TERRESTRIAL LASER SCAN DATA

4.1 Terrestrial Laser Scan Data and Extension of the Algorithm

Our algorithm of object recognition is shown in Fig. 3. First, normal averaging and uniform point sampling is applied to the input data for improving the robustness of the scanning noise and differences in the vertex densities. Then, spin images are generated and object recognition is done using the method described in the previous section. In the object recognition process, the hierarchical image comparison using multi-resolution images and point filtering is adopted for shortening calculation time.

The problems of the application of spin image based method to object recognition using the terrestrial scan data are 1) uncertainty of the normal directions, 2) different vertex density, and 3) high-computational cost in image comparison.

The scan data generally has scanning noise, which affects the evaluations of several geometric properties, such as normals and curvatures. The influence of the scanning noise on normal has to be reduced, because spin images are greatly depending on the normal directions. To solve this problem, normal averaging is used in our algorithm.

Spin images depends on the density of the vertices. Generally, terrestrial scan data have a different vertex density depending on the distance from the scanner. It is high near the scanner and low at distant locations from the scanner, and is in inverse proportion to the squared distance from the scanner. Therefore, spin images at a distant position have low pixel values. In our algorithm, uniform point sampling is used for averaging the vertex density of the scan data and object data.

Terrestrial scan data generally includes several millions or hundreds of millions of points. The computational time of object recognition using spin images depends on the number of vertices in the scan data, therefore it should be reduced. In our implementation, comparing spin images using correlation coefficients was the most time-consuming process (about 90% of all process). It depends on the number of vertices which have a spin image in the model and scan data, and the number of the pixels of the spin images. In order to reduce the computational time, in our algorithm, multiresolution images based on wavelet transform are used. In this method, low resolution images are used to extract candidates of correspondences efficiently. Point filtering is also proposed to shorten the computational time. In this method, the regions where the object does not exist are founded and the spin image comparison is not applied to the points in the regions. In the following sections, their details are described.

4.2 Normal Averaging

In order to reduce the influence of scanning noise, normal averaging is applied. Since spin images are created depending on the vertex normals, the images are greatly influenced by scanning noise. Robust normal estimation is one of the solutions for maintaining the robustness for the noise, but the density of the points differ from the distance between the objects and scanners, and therefore, their techniques often do not work well. Geometry smoothing [10,15] may be used to obtain better normals. However, the purpose of the modification of the normals is to bring the normal directions closer at the same position on the object in the object data and scan data. In spin image based recognition, it is not important to calculate exact normals, because it is enough to create similar spin images at the same position of the object. Therefore, in our algorithm, the normal averaging is applied both to the scan data and object model data. A normal of a vertex is replaced with the average normal of its neighboring vertices in one step, $\mathbf{n}_i \leftarrow \sum_{j\in i^*} \mathbf{n}_j / \| \sum_{j\in i^*} \mathbf{n}_j \|$, where $\mathbf{n}_i$ is a normal of vertex i, and i^* is a set of neighboring vertices of i. This is iteratively applied to the given meshes.

4.3 Uniform Point Sampling

Differences in the vertex densities cause low object recognition rate, because the spin image greatly depends on vertex density. In the laser scan data, the point densities differ depending on the distance between the scanned object and laser scanner as described in section 4.1. Fig. 7(a) shows spin images created at similar positions of the same object at different distances. The images differ greatly and it causes failure of object recognition. In order to solve this problem, some techniques can be used, for

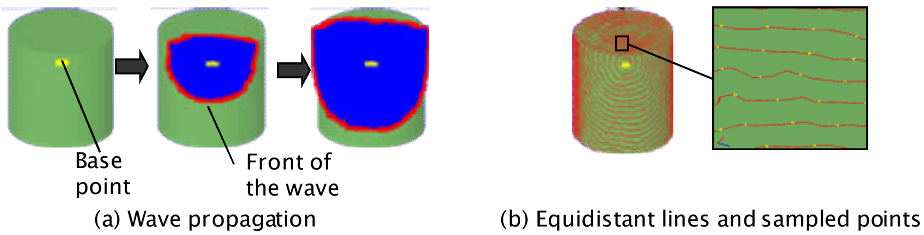


Fig. 4: Uniform re-sampling of triangular mesh.

example, mesh resolution control [6]. Surface fitting based sampling techniques [2] are also useful for uniform point sampling. In our research, simple uniform point sampling of the triangular mesh is proposed. The advantage of this method is its low computational cost and the applicability of massive complex meshes.

In our method, first, the fast marching method [12] is applied to each connected meshes in order to calculate geodesic distances. Then the equidistant lines are calculated in each of the connected meshes. Finally, the points are uniformly sampled on the equidistant lines.

The fast marching method is one of the methods for calculating geodesic distances of surfaces by solving an Eikonal equation, which represents a propagation of wave [12]. The wave is propagated from a vertex to its neighboring vertices iteratively. As a result, geodesic distances from the vertex are obtained as arrival times of the wave at each vertex as shown in Fig. 4(a). The arrival time of the wave at a vertex is calculated using the arrival times of its neighboring vertices based on a gradient. We used a method for calculating the time of a vertex from the other vertices proposed by Kimmel [8].

In fast marching method, first, tags are assigned to each vertex. A vertex (base vertex) is tagged in the initial conditions as *alive*. The *close* tag is assigned to its neighboring vertices. The other vertices are tagged as *far*. For each close vertex, time t is calculated. The following process is repeated until all vertices become alive. 1) finding a close vertex which has smallest t, and changing its tag from close to alive. 2) changing the tag of far vertex to close, if its neighboring triangle has two alive vertices. 3) recalculating the time t of the close vertices.

Then, the equidistant lines from the base vertex are created at specific intervals. According to the interval d specified by the user, new points n whose distance from base vertex are nd (n is integer number) are newly generated as $\mathbf{p}_n = \alpha\, \mathbf{p}_i + (1 - \alpha)\, \mathbf{p}_j$, where $\alpha = (nd - t_j) / (t_i - t_j)$, on the edges (i, j) whose one end point i has a larger time t_i than nd and the other point j has a smaller time t_j than nd ($t_j \le nd \le t_i$). Then by connecting points having the same distances, equidistant lines at interval d are obtained as shown in Fig. 4(b). Finally, by sampling the equidistant lines at interval d, uniform points are obtained.

For spin image generation, the normal at each point is required. Since all sampled points are on the triangles, the normal of a sampled point can be calculated by the area coordinate interpolation of the averaged vertex normals of the triangle in which the sampled point exists. In object recognition, uniform point sampling is applied to both the scan and model data using same interval d, and spin images are created for the sampled points with normal.

4.4 Correspondence Extraction Using Multi-resolution Images

Computational time of object recognition depends on the resolution (number of pixels) of the spin images, because similarities of spin images are calculated using the correlation coefficients of two images. Therefore, reducing the resolution of the images shortens the computational time of the object recognition. In our method, wavelet transform [13] is applied to the spin images for obtaining lower resolution images.

In our approach, first, candidates of correspondences are obtained using low-resolution spin images. Then, the final correspondences are extracted from the candidates using high-resolution spin images. In our implementation, Haar wavelet [13] is used. After wavelet transform, the multi-resolution representation (MRR) of the image is obtained, which consists of three high frequency components HL_j, LH_j, HH_j at each decomposition level j and the lowest resolution component LL. From the MMR, a high-

		case1	case2	case3
Object data	Name	corrugated carton	jig	Force feedback device
	size(wxhxd)]mm]	500x130x150	120x40x24	200x170x180 (body)
	#v,#t (original)	4.7k, 9.4k	1.5k, 3.0k	4.1k, 7.7k
	#points after sampling	11.8k	4.2k	2.3k
Scan data	Name	Four corrugated cartons	Machine tool table	Laboratory office
	size(wxdxh)]mm]	3400x265x1544	351x227x469	11267x3087x10634
	#v,#t (original)	141.5k, 277.7k	81.2k, 148.9k	3.7M, 7.1M
	#points after sampling	189.1k	60.0k	4.8M
	#objects	4	1	1
Sampling interval [mm]		5	2	4
#recognized object		2	1	1
Recognition time [sec]*		175	559	780

* CPU: Core 2Quad 2.4GHz, RAM:8GB, OS: WinXP64bit

Tab.1: Scan data and object data and object recognition.

resolution image is quickly reconstructed by inverse wavelet transform. Therefore, in our system, all spin images are stored by MRR.

4.5 Point Filtering

Point filtering is used to reduce the number of spin image comparisons. In this process, the regions in which the object does not exist are founded, and the spin image comparison is not applied to the points in the regions. In our method, we focused on the area of the planar region. First, the largest area *Sm* of the planar region of the object data and each area *Si* of the planar regions *i* in the scene data are calculated. The object does not exist in regions *i* which satisfy the condition *Sm*<*Si*, therefore the spin images of the points in the regions are not compared in the correspondence extraction.

The algorithm of planar region extraction is as follows: Step1: extracting connected mesh in the scene data. Step2: for each connected mesh, making clusters of vertices based on k-means clustering of normal vectors (details are described next paragraph). Step3: extracting connected triangles consisting of vertices in same cluster as the planar region.

In step2, k-means clustering of vertices are used to find a set of vertices which has similar normals. This process is done as follows: Step2.1: clusters and seed unit vectors of each cluster are defined (80 clusters in our implementation). Step2.2: each vertex i is added to the cluster whose seed vector ns is closest to its normal. Step2.3: If the cluster does not change from the cluster of the previous iteration, the clustering process finishes. Otherwise, new seed vectors are calculated as the average vector of the normal vectors of the vertices in the cluster. Step2.4: Seed vectors and clusters are merged, if the angle between two seed vectors less than the angle threshold *t* (1 degree in our implementation). Step2.5: Go back to step2.2.

5 RESULTS

5.1 Scanner, Data, and Examples of Object Recognition

A scanner, delta sphere 3000 [4], was used in our experiments. Fig.5 shows the scan data and object data used in our experiments. We apply our method to three scan data and object data. The information of the scan and model data are summarized in Table 1. Object recognition using our algorithm is done for each scan data and the results are also shown in Fig. 5 (right). In case 1, two objects near the scanner were recognized. In other cases, each object was correctly found in the scan data. Results of registration are shown in the right of Fig.5. Processing times are shown in Table 1.

5.2 Effects of Normal Averaging and Uniform Point Sampling

First, spin images are visually compared before and after normal averaging and uniform point sampling. Fig. 6 shows the spin images at a similar position on the object in the object and scene data. By applying normal averaging, spin images become similar as shown in Fig. 6 (right). Fig. 7 shows the result of the uniform sampling of the laser scan data and generated spin images. In order to investigate the effects of uniform point sampling, we scanned the scene including the same objects (force feedback devices) at 2m to 7m at 1m intervals, and we applied our method to the scan data. Using uniform point sampling, similar spin images can be obtained from objects at different distances as shown in Fig. 7. Table 2 shows the number of extracted correspondences. By applying the point sampling, the number of correspondences increased for each object.

In the object recognition without normal averaging and point sampling, the objects at 2m, 3m, and 4m were recognized. After point sampling and normal averaging, the objects at 5m and 6m were able to be recognized (but the object at 7m was not recognized). This shows that the recognition ability increases by normal averaging and uniform point sampling.

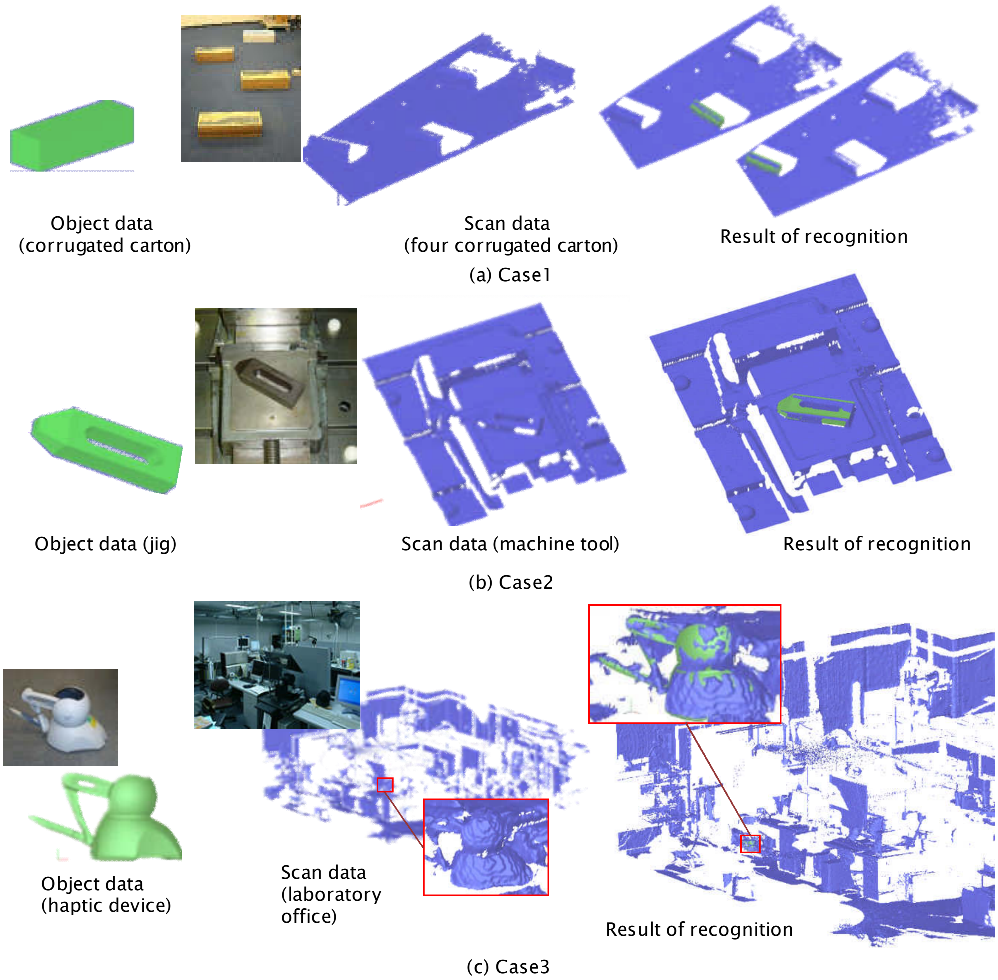


Fig. 5: Results of object recognition.

5.3 Effects of Multi-resolution Images and Point Filtering

The effects of the use of multi-resolution images and point filtering were individually investigated. First, the effect of the use of multi-resolution images was evaluated for case 3 in Fig. 5. The candidates of correspondences (top 20% of resulting correspondences) were extracted using low-resolution images (decomposition level is two). After that, final correspondences extraction was done using candidates of correspondences and their high-resolution (original) spin images. The recognition time was reduced to 18.7% of the original method using multi-resolution images. In our experiments, final correspondences differed from the one without the use of multi-resolution images, but the recognition results were same.

Planar regions extracted by our method are shown in Fig. 8(a,b), and filtered points are shown in Fig. 8(c). Using point filtering, the numbers of spin-image comparisons reduce to 54%. The rate will depend on the complexity scene and object. As a result, object recognition time is shortened to 63%. The results of recognition were not changed in our experiments. However, the point filtering has possibility to change the results of object recognition.

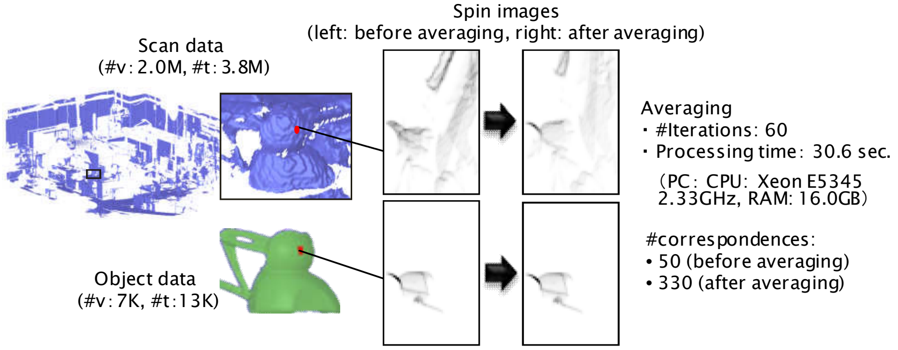


Fig. 6: Normal averaging and spin images.

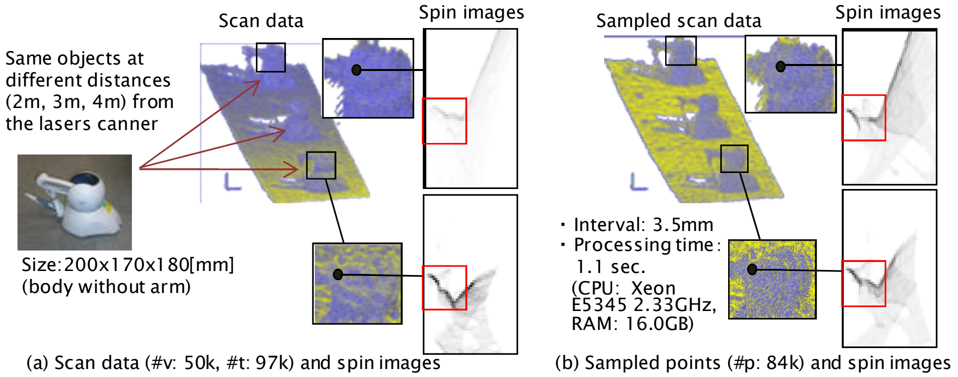
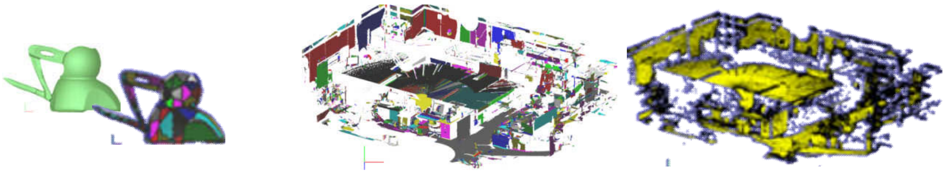


Fig. 7: Uniform point sampling and spin images.

Distance from scanner [m]	2	3	4	5	6	7
#correspondences (original)	71	51	88	25	0	1
#correspondences after point sampling	385	245	215	260	142	68

Tab. 2: Number of extracted correspondences before and after uniform point sampling.



(a) Planar regions of object data (a) Planar regions of scan data (c) Filtered points (yellow)

Fig. 8: Planar region extraction and point filtering.

6 CONCLUSION

This paper describes a method of object recognition using terrestrial laser scan data and object data. First, spin images and the object recognition method using spin images are described. Then, extension methods for applying spin image based object recognition to terrestrial laser scan data are proposed. They include normal averaging for improving robustness to the scan noise, uniform point sampling based on the fast marching method for improving robustness to the difference in the vertex densities, the use of multi-resolution images for efficiently finding the correspondences, and point filtering based on comparing the area of planar regions for reducing the number of spin image comparisons. Some experiments showed that our method can improve the recognition rate of objects and can shorten the calculation time of object recognition. Future works include object recognition from point clouds, and the application of object recognition to the modeling of environments by embedding the CAD model data into scan data.

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