3D Object Recognition based on the Reference Point Ensemble

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Abstract: In the present paper, we have proposed a high-performance 3D recognition method based on the reference point ensemble, which is a natural extension of the generalized Hough transform. The reference point ensemble consists of several reference points, each of which is color-coded by green or red, where the red reference points are used to verify the hypothesis, and the green reference points are used for Hough voting. The configuration of the reference points in the reference point ensemble is designed depending on the model shape. In the proposed method, a set of reference point ensembles is generated by the local features of a given 3D scene. Each generated reference point ensemble is a hypothetical 3D pose of a given object in the scene. Hypotheses passing through the verification by the red reference points are used for Hough voting. Hough voting is performed independently in each green point space, which reduces the voting space to three dimensions. Although a six-dimensional voting space is generally needed for 3D recognition, in the proposed method, the six-dimensional voting space is decomposed into a few three-dimensional spaces. This decomposition and the verification using green or red reference points have been demonstrated experimentally to be effective for 3D recognition. In other words, the effective recognition has been achieved by skillfully switching the following two different modes. (A) Individual mode: Voting of the hypothesis independently in each green Hough space and verifying of hypothesis with red reference points are done in this mode. (B) Ensemble mode : Verifying of registration into PHL(promising hypothesis list) and aggregating of total votes are done in this mode. This mode switching mechanism is the most significant characteristic of the proposed method.

1 INTRODUCTION

3D object recognition is core technology for use in a bin picking system. Recently, 3D object recognition for complex scenes, such as irregularly arranged homogeneous objects, has attracted a great deal of attention. Robot vision that can function in real environments is expected, and high-performance robot vision is needed in order to develop intelligent robots that will work on behalf of people in real environments.(Rusu, 2010) 3D object recognition methods are generally classified into two types, depending on the characteristics of the local feature used.

(I) 3D recognition using high-dimensional local features: Recognition by constructing a reliable correspondence between model and scene.(Johnson and Hebert, 1999; Chua and Jarvis, 1997; Mian et al., 2006; Sun et al., 2003; Tombari et al., 2010; Mian et al., 2010; Rusu et al., 2009)

(II) 3D recognition using several simple local features and their combination: Recognition by generating several hypotheses (poses) using the majority rule (by Hough transformation).(Rabbani and Heuvel, 2005; Tombari and Stefano, 2010; Drost et al., 2010; Kim and Medioni, 2011)

Type I features are composed of key points and descriptors. Spin Image (Johnson and Hebert, 1999), Point fingerprint (Tombari et al., 2010), and SHOT (Mian et al., 2010) have been proposed for using Type I features. Each of these features is a high-dimensional feature derived from 3D points of objects. After establishing the correspondences between the model and the scene by matching features of the model, a plurality of correspondences with high reliability are used for 3D recognition. This approach is excellent in terms of efficiency because recognition is possible using only a few correspondences of the local feature. On the other hand, there is a need to

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ensure robustness with respect to background noise, such as occlusion or clutter.

Methods for Type II features recognize 3D poses based on the Hough transform using a large number of hypotheses that are generated from low-dimensional features. Low-dimensional features are less susceptible to both occlusion and clutter. On the other hand, since the recognition performance is weak, numerous features are needed in order to obtain a reliable hypothesis.

We herein propose a high-performance 3D recognition method for a bin picking system intended for a pile of industrial parts. The proposed recognition method is especially robust to occlusion or clutter, while suppressing the amount of computation required and incorporates new ideas from the perspective of reducing computation time while guaranteeing robustness with respect to noise (occlusion or clutter). In the proposed method, the voting space is reduced to a few three-dimensional spaces from the six-dimensional space (three for position and three for orientation). Whereas a smaller voting space reduces the computational cost, it also provides interference between two different voting sessions, which decreases the accuracy. In the present paper, the following two strategies are proposed in order to suppress interference.

(a) Removing useless hypotheses through a verification process.

(b) Reducing interference effects by voting on the redundancy space.

The above two strategies are designed based on the reference point ensemble, which is proposed in the proposed paper with the framework of the generalized Hough transform (Ballard, 1981). A set of reference point ensembles is generated by local features of a given 3D scene. Each generated reference point ensemble is a hypothesis about the 3D pose of a given object in the scene. Based on the reference point ensemble, new devices for quickly eliminating useless hypotheses and efficiently selecting promising hypotheses are incorporated into the proposed method.

2 LABELED-SURFLET-PAIR (L-SURFLET-PAIR)

Surflet-Pair(Wahl et al., 2003; Drost et al., 2010) is a point pair feature that describes the relative position and orientation of two oriented points. In the present paper, we introduce a new feature called the Labeled-Surflet-Pair (L-Surflet-Pair) that extends the Surflet-Pair as the basic feature describing 3D shapes.

2.1 Labeled Surflet (L-Surflet)

In the present paper, the labeled surflet is defined as follows:

$$\Delta(p) =< p, \Omega(p) > \tag{1}$$

$$\Omega(p) =< L, d > \tag{2}$$

where L is a label, which is 'F' or 'E'. If the point p belongs to a smooth curved surface (including planes), then L = 'F' (flat). On the other hand, if the point p belongs to a rapidly changing surface (including edges), then L = 'E' (edge). In Equation (2), d represents a direction vector. If L = 'F', d represents the direction of normal n to the surface to which the point p belongs ($d = n$) (in Figure 1). On the other hand, if L = 'E', d represents the direction of gradient g of the edge to which the point belongs ($d = g$) (in Figure 2).

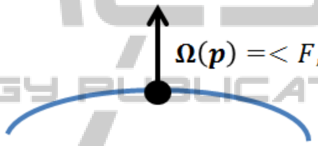


Figure 1: Flat L-Surflet.

Figure 2: Edge L-Surflet.

2.2 Labeled-Surflet-Pair (L-Surflet-Pair)

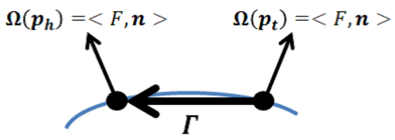
The L-Surflet-Pair Γ is defined as a set of two ordered L-Surflets as follows:

$$\Gamma =< \Delta(p_h), \Delta(p_t) > \tag{3}$$

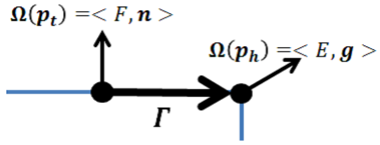
where p_h and p_t represent the head L-Surflet point and the tail L-Surflet point, respectively. In the definition of the L-Surflet-Pair Γ, the label of the tail point is always flat (L='F'):

$$\Omega(p_t) =< F, n > \tag{4}$$

There are two types of L-Surflet-Pairs: F-Type (Figure 3(a)) and E-Type (Figure 3(b)). When the head label of the L-Surflet-Pair is F, the L-Surflet-Pair is referred to as an F-type L-Surflet-Pair, and when the head label of the L-Surflet-Pair is E, the L-Surflet-Pair is referred to as an E-type L-Surflet-Pair.



(a) F-Type



(b) E-Type

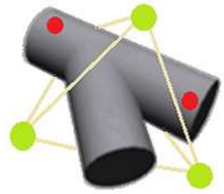
Figure 3: Two Types of L-Surflet-Pairs.

3 3D Object Recognition based on the Reference Point Ensemble

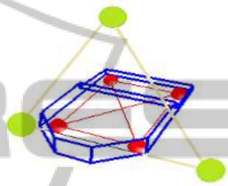
In this section, the reference point ensemble, which is a natural extension of the reference point in the generalized Hough transform, is proposed for 3D recognition. The geometric relation between the reference point ensemble and local features, referred to as the L-Surflet-Pair, are registered in the R-table as the C-matrix. Using the L-Surflet-Pair and the R-table, Hough voting is performed in a few three-dimensional spaces rather than a six-dimensional space. A fast ranking method using a promising hypothesis list is also proposed.

3.1 Reference Point Ensemble

The reference point ensemble consists of several reference points, each of which is color-coded (see Figure 4). The number of reference points in the reference point ensemble is denoted by K, and the number of green and red reference points are denoted by K_g and K_r, respectively ($K = K_g + K_r$). The configuration of reference points in the reference point ensemble is designed depending on the model shape. Two examples are shown in Figure 4. The green reference points in the reference point ensemble indicate vertices of an equilateral triangle (K_g=3, Figure 4(b)) and a tetrahedron (K_g=4, Figure 4(a)). The centers of gravity of the green reference points is set to approximately match the center of gravity of a given object model (see the Figure 4). The orientation of each green reference point with respect to the center of gravity of the model differs greatly from the orientations of the other green reference points. This type of configuration leads to reduced interference in the 3D Hough space. The distance between the center of gravity and each green reference point is set to approximately half the maximum length of the given object model. On the other hand, red reference points are placed on the model surface or inside the model in order to check the consistency with a 3D point cloud (scene data) (see Figs. 4 and 8).



(a) K=6, K_g=4, K_r=2
(Tube with reference points)



(b) K=7, K_g=3, K_r=4
(Plate with reference points)

Figure 4: Examples of reference point ensembles. The green reference points are used for Hough voting, and the red reference points are used for verification.

3.2 Reference Table (R-Table)

Let $\Gamma =< \Delta(p_h), \Delta(p_t) >$ be an L-Surflet-Pair of a given object model, and let f be the following vector:

$$f = p_h - p_t \tag{5}$$

A local coordinate system determined from the L-Surflet-Pair is defined as follows in terms of the vector f:

$$\begin{aligned} e_1 &= n_t \\ e_2 &= \frac{n_t \times f}{\|n_t \times f\|} \\ e_3 &= e_2 \times e_1 \end{aligned} \tag{6}$$

where n_t is the normal of the tail surflet of the L-Surflet-Pair. The k-th reference point ($k = 1, 2, \cdots, K$) in the reference point ensemble can be described in the local coordinate system as follows:

$$c_k = \begin{pmatrix} c_{k1} \\ c_{k2} \\ c_{k3} \end{pmatrix} \tag{7}$$

Next, we express K reference points together as matrix C (referred to herein as the C-matrix):

$$C = (c_1 \;\; c_2 \;\; \cdots \;\; c_k \;\; \cdots \;\; c_K)\,. \tag{8}$$

The R-Table, which is shown in Table 1, is created using the C-matrix and hash key H. Here, hash key H is constructed from an L-Surflet-Pair of the given model as follows:

Table 1: R-table.

Hash Key	C-matrix
H_1	$C_1^{(1)}, C_1^{(2)}, \cdots$
$\vdots$	$\vdots$
H_i	$C_i^{(1)}, \cdots, C_i^{(m)}, \cdots, C_i^{(M_i)}$
$\vdots$	$\vdots$

$$H = \langle L, \|f\|, \angle(d_t, f), \angle(d_h, f), \angle(d_t, d_h) \rangle \quad (9)$$

where L, $\|f\|$, and $\angle(d_t, f)$ are the head label of the L-Surflet, the length of vector f, and the angle between vectors d_t and f, respectively. M_i denotes the number of C-matrices derived from hash key H_i.

In general, there are many L-Surflet-Pairs having the same hash key H. Since each L-Surflet-Pair provides a hypothetical 3D pose, mutual information between hash key H_i and the 3D pose is approximately $\log(M_{max} / M_i)$, where M_{max} is the number of possible 3D poses for a given object model. Accordingly, the discrimination ability of hash key H_i is proportional to $\log(M_{max} / M_i)$. A hash key having a large number of C-matrices in the R-table is not a suitable feature for 3D recognition, whereas a hash key having a small number of C-matrices is advantageous for 3D recognition. In the proposed method, no hash key having a large number of C-matrices is used for 3D recognition.

3.3 Generation of the Reference Point Ensemble

Let the 3D point cloud (scene) be given. An appropriate number of L-Surflet-Pairs is randomly sampled from the scene. Let the local coordinate system defined by a L-Surflet-Pair be defined as follows:

$$B = (e_1 \ \ e_2 \ \ e_3) \quad (10)$$

Let the C-matrix retrieved by hash key H of the L-Surflet-Pair be defined as follows:

$$C^{(m)} = (c_1^{(m)} \ c_2^{(m)} \ \cdots \ c_K^{(m)}) \quad (11)$$
$$(m = 1, 2, \cdots, M).$$

Next, the reference matrix is defined as follows:

$$R^{(m)} = (r_1^{(m)} \ \ r_2^{(m)} \ \ \cdots \ \ r_K^{(m)}) \quad (12)$$
$$(m = 1, 2, \cdots, M)$$

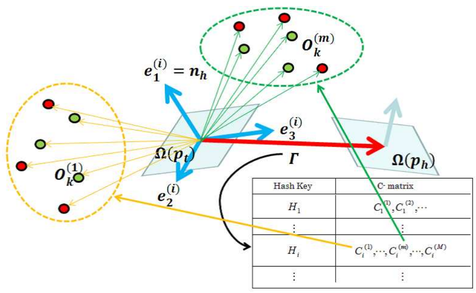


Figure 5: Generation of the reference point ensemble.

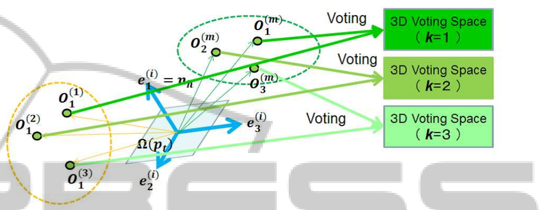


Figure 6: Hough voting in the proposed method.

Each column of $R^{(m)}$ represents the coordinates of each reference point when p_t (tail point of the L-Surflet-Pair) is placed at origin in the global coordinate system. Reference matrix $R^{(m)}$ can be calculated using B and $C^{(m)}$ as follows:

$$\begin{aligned} R^{(m)} &= BC^{(m)} \\ &= (e_1 \ \ e_2 \ \ e_3)(c_1^{(m)} \ \ \cdots \ \ c_K^{(m)}) \\ &(m = 1, 2, \cdots, M) \end{aligned} \quad (13)$$

Calculation of $r_k^{(m)}$ can be written as follows:

$$r_k^{(m)} = c_{k1}^{(m)} e_1 + c_{k2}^{(m)} e_2 + c_{k3}^{(m)} e_3 \quad (14)$$
$$(k = 1, 2, \cdots, K; m = 1, 2, \cdots, M)$$

Accordingly, the coordinates of the k-th reference point $o_k^{(m)}$ in the global coordinate system is as follows:

$$o_k^{(m)} = p_t + r_k^{(m)} \quad (15)$$
$$(k = 1, 2, \cdots, K; m = 1, 2, \cdots, M)$$

where p_t is the tail point of the L-Surflet-Pair.

A set of reference point ensembles is generated by an L-Surflet-Pair of a given 3D scene (see Figure 5). Each generated reference point ensemble is a hypothetical 3D pose of a given object in the scene. Red reference points are used for the verification of the hypothetical pose, while green reference points are used for voting on the hypothetical pose in 3D Hough space. Since three or more points are needed

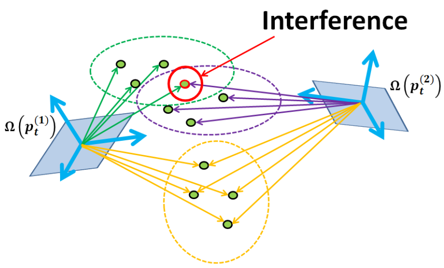


Figure 7: Interference in Hough voting.

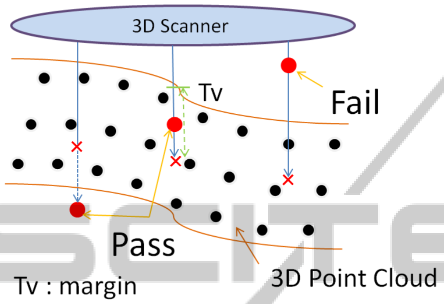


Figure 8: Verification process.

in order to represent the 3D pose, the number of green reference points must be three or more, i.e., $K_g \geqq 3$. Hough voting is performed independently in each green Hough space, which is reduced to three dimensions (see Figure 6). Hough voting is performed for the *m-th* reference point ensemble as follows:

$$V_k(o_k^{(m)}) = V_k(o_k^{(m)}) + 1 \qquad (16)$$
$$(k = 1, 2, \cdots, K_g)$$

where $V_k(o_k^{(m)})$ denotes the counter value at position $o_k^{(m)}$ in the *k-th* green Hough space.

Although a six-dimensional voting space is generally needed for 3D recognition, the six-dimensional voting space has been decomposed into K_g three-dimensional spaces in the proposed method. In other words, the space complexity is reduced from $O(J^6)$ to $O(K_g J^3)$, where J denotes the dimension of one side of the Hough space. However, interference occurs as a reaction to the dimensionality reduction. Even though two poses are different, some (although not all) green reference points would be the same position in 3D Hough space (see Figure 7). This phenomenon is referred to as interference, which causes a degradation in recognition accuracy. A simple method by which to suppress the decrease in recognition accuracy due to interference is to increase the number of reference points in the reference point ensemble.

Verification is performed using red reference points before Hough voting. In other words, only the reference point ensemble passing through the verification is used for Hough voting. Since every red reference point in the reference point ensemble is set on the model surface or inside the model, the generated hypothesis should fail when observed outside the object. The proposed verification process is shown in Figure 8. When a red reference point is observed closer to the scanner than the 3D point cloud, the hypothetical pose is set as Fail. Otherwise, the hypothetical pose is set as Pass.

The decomposition of the voting space as well as the verification of the generated hypothetical pose by green or red reference points has been shown experimentally to be effective for 3D recognition (as described in the next section). In other words, in an experiment involving industrial component recognition, the computational costs as well as the robustness with respect to occlusion and clutter are improved by a well-designed reference point ensemble.

3.4 Ranking of Generated Hypotheses

A generated reference point ensemble is a hypothetical 3D pose of a given object. Based on the generated hypothetical pose, Hough voting is performed using Equation (16). The number of votes by the generated reference point ensemble thus far is estimated to be as follows:

$$V_{min} = \min_k \{V_k(o_k)\} \qquad (17)$$

where o_k $(k = 1, 2, \cdots, K_g)$ is the position of the *k-th* green reference point. In Equation (17), the *min* operation is the best way to suppress the influence of interference caused by dimensionality reduction. The proposed ranking method of generated hypotheses is shown in Figure 9. When V_{min} is just beyond the threshold T_c, the generated reference point ensemble is registered in the promising hypothesis list (PHL). After all votes have been cast, the hypotheses in PHL are ranked according to the final vote results. In other word, each hypothesis in the PHL is re-evaluated using Equation (17), and is ranked according to its re-evaluated value combined with non-maximum suppression technique. The top of the ranking is used as 3D recognition result. The PHL not only suppresses the influence of interference but also improves the processing speed. The proposed ranking method is shown to work very efficiently in the next section.

4 EXPERIMENTS

We applied the proposed method to two different types of industrial components, namely, (a) a tube-shaped Y branch (tube) and (b) a plate-shaped bracket

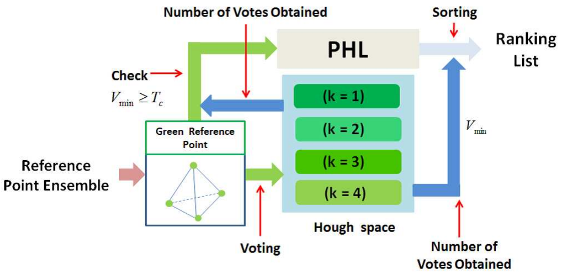


Figure 9: Fast ranking using the promising hypothesis list (PHL).

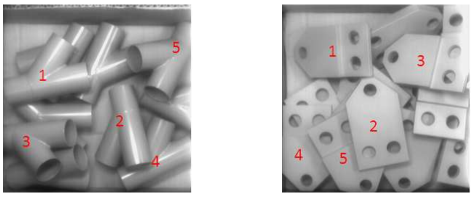
(plate) (see Figures 4 and 10), and evaluated its performance. While the tube in Figure 4(a) consists of curved surfaces, the plate in Figure 4(b) consists of planar surfaces.

In the first experiment, a single tube is used as an object for 3D recognition (see Figure 4(a)). The proposed method has been applied to 41 scenes, each of which includes a single tube in a unique pose. For the case of using three green reference points (K=3, K_g=3, K_r=0) with an F-type L-Surflet-Pair, the accuracy of 3D recognition is 75.6%, i.e., among the 41 scenes, the pose is not correctly recognized 10 times. On the other hand, the accuracy is 100% for the case of using four green reference points (K=4, K_g=4, K_r=0) with an F-type L-Surflet-Pair. This experiment shows that a small increase in the number of green reference points significantly improves the accuracy of 3D recognition. In other words, a small increase in redundancy suppresses the influence of interference resulting from a dimensionality reduction. The maximum length of the tube used in the experiment is 120 [mm]. Pose errors of less than 5 [mm] and 5 [deg] are acceptable. Otherwise, the 3D recognition is regarded as having failed.

In the second experiment, a pile of tubes is used as objects for 3D recognition (see Figure 10(a)). The last six of the eighteen scenes are shown in Figure 12. Each scene includes approximately six tubes. Among them, tubes indicated by numbers are for experiment of 3D recognition. The total number of tubes to be recognized is 110. The number of green reference points used in this experiment is four (K=4, K_g=4, K_r=0) and an F-type L-Surflet-Pair is used. The experimental results are shown in Table 2. For tube recognition, the proposed method has high recognition performance without the need for verification.

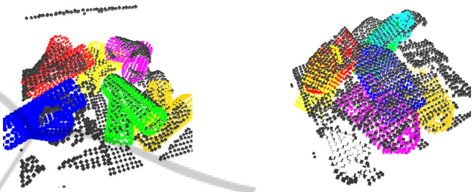
In the third experiment, the proposed method with ICP (Besl and Mckay, 1992) has been applied so as to pick up each tube shown in Figure 13(a), which shows 18 tubes in a box. In this experiment, the number of green and red reference points are four and two, respectively (K=6, K_g=4, K_r=2), and an F-type L-Surflet-Pair is used. The experimental results are shown in Table 3. We successfully picked up every tube in just 18 trials (see Figure 14). In this experiment, two red reference points (K_r=2) were used in order to ensure the precision of 3D recognition.

In addition to the tubes, the proposed method was applied to picking up bolts, as shown in Figure 13(b). Fifty bolts of four different sizes each were used in



(a) Tubes (b) Plates

Figure 10: Examples of input scenes.



(a) Tubes (b) Plates

Figure 11: Examples of 3D recognition.

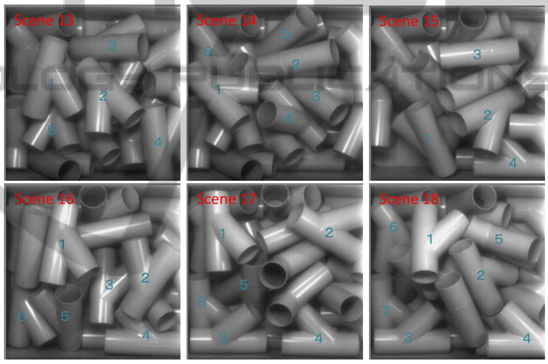
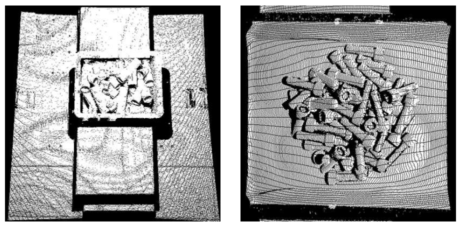


Figure 12: The last six of the eighteen scenes of a pile of tubes. In each scene, tubes indicated by numbers are for experimet of 3D recognition.



(a) Tubes (b) Bolts

Figure 13: Two piles of parts for bin picking.

Table 2: Experimental results for tubes. (The total number of parts to be recognized is 110, as shown in Figure 10.)

Threshold	Recall[%]	Precision[%]
$T1$	87.3	100
$T2$	100	76.9

Table 3: 3D recognition results for tube picking. (The processing time includes the ICP processing time.)

Part	#Trials	Success Rate	Processing Time
Tube	18	100 [%]	0.32 [s]

Table 4: 3D recognition results for bolt picking. (The processing time includes the ICP processing time.)

Bolt Size	#Trial	Success Rate	Processing Time
M12x40	50	100 [%]	0.28 [s]
M10x70	50	100 [%]	0.24 [s]
M8x30	51	98.0 [%]	0.26 [s]
M6x20	55	90.9 [%]	0.40 [s]

this bin picking experiment (see Figure 15). The configuration of the reference points is shown in Figure 16, where K=5, K_g=4, and K_r=1. The experimental results for the bolts are shown in Table 4. Although a few trials have failed for small bolts, we have succeeded in picking up every bolt of every size as shown in Figure 15. These results indicate that a well-designed reference point ensemble ensures a sufficient success rate for bin picking. In the bin picking experiment, pose errors, which are not perceived almost visually, are acceptable. Otherwise, the 3D recognition is regarded as having failed and an additional trial is performed. The experiment is performed using Visual Studio C++ 2010 Express OpenMP on a Xeon 3.5-GHz (quad-core) processor with 8 GB of memory running on Windows 7 (64 bit).

Finally, we applied the proposed method to the plate shown in Figure 17 and evaluated the performance of the proposed method in the same manner as for the tube. Figure 17 shows the last six of the eighteen scenes, each of which includes approximately six plates. Among them, plates indicated by numbers are for experiment of 3D recognition (103 plates in total). Three green reference points and two or zero red reference points are used in the final experiment, i.e., K=3 (K_g=3, K_r=0) or K=5 (K_g=3, K_r=2). Two types of L-Surflet-Pairs (F-type or E-type) are used, and the performances of the F-type or E-type pairs are compared.

The experimental results are shown in Figure 18. Both recall and precision when using an E-type L-Surflet-Pair are greatly improved compared to the use of an F-Type L-Surflet-Pair because the mutual information of the E-type L-Surflet-Pair is much greater

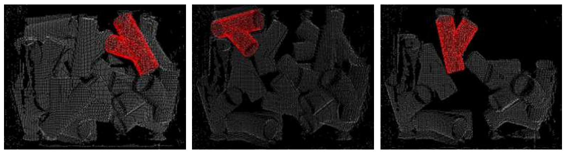
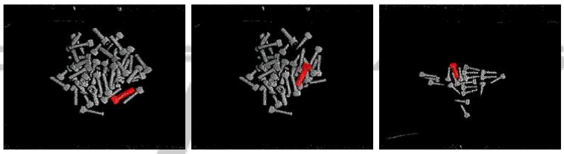


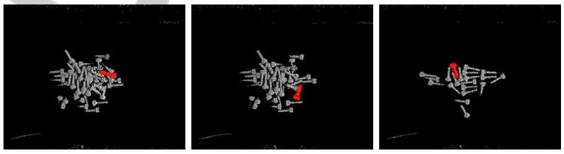
Figure 14: Images of tubes used in the bin picking process.

(a) M12x40 bolts

(b) M10x70 bolts



(c) M8x30 bolts



(d) M6x20 bolts

Figure 15: Images of bolts used in the bin picking process.

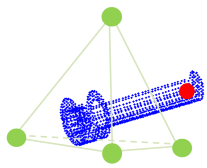


Figure 16: The reference point ensemble designed for bolt (K=5, K_g=4, K_r=1).

than that of an F-type L-Surflet-Pair with respect to the plate. The total number of C-matrices listed in the R-table for the F-type L-Surflet-Pair is much greater than that for the E-type L-Surflet-Pair. This means that the F-type surflet pair is not suitable for planar shaped parts but works very well for cylindrical parts. The performance is also confirmed o be improved through verification using red reference points (see Figure 15: E-V is better than E-N). This is because wrong votes are suppressed by the verification process. For bin picking of the plate, an E-type L-

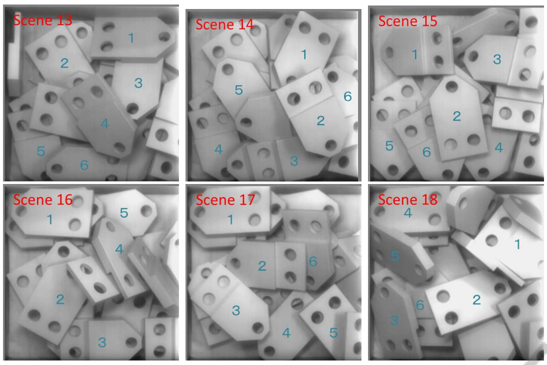


Figure 17: The last six of the eighteen scenes of a pile of plates. In each scene, plates indicated by numbers are for experiment of 3D recognition.

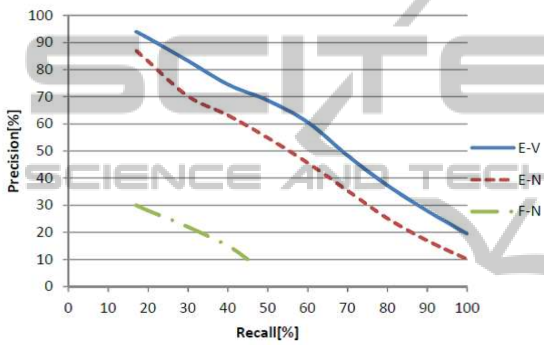


Figure 18: Experimental results for the plate. F-N shows the results obtained using the F-type L-Surflet-Pair without verification (K=3, K_g=3, K_r=0). E-N shows the results obtained using the E-type L-Surflet-Pair without verification (K=3, K_g=3, K_r=0). E-V shows the results obtained using the E-type L-Surflet-Pair with verification (K=5, K_g=3, K_r=2).

Surflet-Pair with a reference point ensemble consisting of four green reference points and more than two red reference points (K=6, K_g=4, $K_r \geqq 2$) is recommended. For bin picking a mixture of the plate and the tube, the proposed method can be applied@same as in the homogeneous case.

5 CONCLUSIONS

In the present paper, we have proposed a high-performance 3D recognition method based on the reference point ensemble, which is a natural extension of the generalized Hough transform. The reference point ensemble consists of several color-coded reference points. Red reference points are used for verification of the hypothesis, and green reference points are used for voting of the hypothesis in the 3D Hough space. The proposed method has the following two different modes:

(A) Individual mode: Voting of the hypothesis independently in each green Hough space and verifying of hypothesis with red reference points are done in this mode.

(B) Ensemble mode: Verifying of registration into PHL and aggregating of total votes are done in this mode.

The efficient recognition has been achieved by skillfully switching the above two modes. This mechanism is the most significant characteristic of the proposed method. In the proposed method, a set of reference point ensembles is generated by a local feature referred to as the L-Surflet-Pair. Each generated reference point ensemble is a hypothetical 3D pose of given object in the scene. Effective recognition of the reference point ensemble has led to robust 3D recognition of a pile of industrial parts. An experiment involving industrial parts recognition has revealed that both robustness with respect to noise and computational cost are improved by a well-designed reference point ensemble. Interference suppression and hypothesis verification, which are designed by the reference point ensemble, are also demonstrated to improve 3D object recognition performance. Moreover, the L-Surflet-Pair is newly proposed as an extension of the Surflet-Pair. This extension was especially successful for planar-shaped part recognition, although challenges remain. For the case in which the image area of a given part is relatively small, the reference point ensemble is difficult to generate stably based on the L-Surflet-Pair. Furthermore, the proposed method has difficulty in recognizing certain shapes, such as needle-shaped objects, string-shaped objects, and combinations thereof. This remains a challenge for future research.

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