Grasping Point Selection on an Item of Crumpled Clothing Based on Relational Shape Description

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***Abstract*— This paper describes grasp point selection on an item of clothing randomly placed on a table. The input data for our proposed method is a range image captured from a fixed, 3D range camera. Hem elements are extracted from the data, and their relationships are characterized for both similarity measures and grasp point evaluation. Experiments using real images, targeting a piece of clothing, show the effectiveness of the proposed method.**

I. Introduction

People use various types of clothing in the course of their daily lives. One of the effective contributions of robots will the ability to doing laundry, to relieve people from tedious housework. When we fold washed laundry, there are several things we need to do: (i) decide which item of clothing to target, (ii) recognize its type, (iii) search for grasp point(s), (iv) spread the clothes out, and (v) handle it for folding. In this paper, we propose a method to search for grasp points to spread a clothing item effectively.

As mentioned above, folding an item of clothing is divided into several stages, there has been research into achieving item recognition or manipulation by an autonomous robot. Kakikura et al. [3] targeted an “Isolation task” to pick up a single target item from a pile of clothing. They assumed that every clothing item is a different color. Willimon et al. [14] proposed a classification method that consists of an isolation and classification phase. In the isolation phase, one grasping point is selected, based on the result from image-based segmentation and stereo disparity. Cuén-Rochín et al. [1] proposed an action selection method for handling a planar cloth. The recognition method is based on matching between a 3D point cloud and a physical model, and the result is used to spread a square cloth. In a similar approach, Kita et al. [4] used a deformable model, which corresponded with the range data by means of trinocular stereo.

Because clothes are soft objects, their shapes get changed after picking up, depending on the grasp position. To cope with this uncertainty, almost all existing research has taken the approach where the primary hanging up behavior is performed by picking up one grasp point. After the first manipulation, another grasp point is sought, and then the cloth is spread using the other hand. In previous studies, Osawa et al. [10] and Abbeel et al. [7] achieved a cloth classification method by shifting an item of clothing from one arm to another. Their methods focused on clothing contours extracted from an image.

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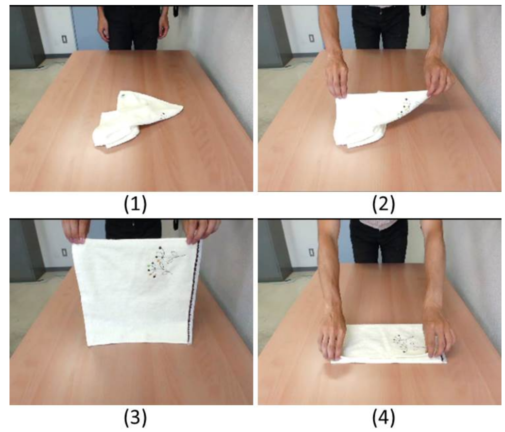

Fig. 1. Picking up a piece of cloth with both hands

One advantage of the manipulation-based approach is its certainty, it is possible to get the assumed shape condition eventually by continuing to select several motion primitives for shifting the grasping arms. However it is a time-consuming approach.

In this paper, we propose a method to select two grasp points from an item of clothing that is randomly placed. Selecting grasp positions for both hands simultaneously enables a dual-armed robot to spread a piece of cloth directly into planar state, as shown in Fig. 1. Input data is a range image captured from a 3D range camera such as Kinect. 3D hem elements extracted from the input data play a key part in the proposed method. Both shape description and grasp point representation are based on the hem elements.

The main characteristics of the proposed method are as follows:

1) The method is not influenced by any variety of appearance such as color or texture. One learning dataset can be applied to various clothing appearances, as long as the target cloth is the same type as the item of clothing that was used to generate the learning data.
2) The method makes it possible to simplify the manipulation procedure for picking up and spreading a wrinkled cloth. Compared to conventional methods, the proposed method makes it possible to reduce the amount of handling that shifts the cloth from one arm to the other.

For this latter task, the result of the proposed method should be used selectively with conventional one-armed manipulation. That is, if two grasp positions are found by the proposed method, a spreading manipulation will be achieved effectively. Otherwise, the conventional approach to shifting the grasping hand should be applied. This will enable the robot to manipulate the item of clothing more intelligently.

The paper is organized as follows: Section II explains issues and our approach. Section III and IV explains the proposed method. Section V introduces an efficiency technique for searching process. Section VI shows experimental results, and Section VII presents the conclusions of this paper.

II. Issues and approach

A. Issues of grasp point selection

Fig. 1 (1) shows an example of cloth that we target. It is placed on a horizontal plane, such as a table or the floor. The purpose of this study is to find two grasp points. As shown in Figs. 1 (2) and (3), the "grasping points" indicates the places where they are picked up to enable them to be spread into a planar state.

The shape of clothes casually placed down can have various bend patterns. In some patterns, it is difficult to find the hem edge. In a study related to this problem, Ono et al. [8] proposed a shape estimation method. They targeted a neatly-spread square cloth, and several bend patterns were given in advance. Shape estimation was performed by matching the existing bend patterns with the given patterns by using image edges. In a recent study, Ramisa et al. [12] targeted more wrinkled clothes, and demonstrated an application to detect the collar on crumpled polo shirts.

The above study aimed to find specific parts, such as a corner hem or collar directly. However, it means that less distinguishable parts have difficulty becoming candidates for grasping positions in case of highly crumpled clothes. Furthermore, image features may lead to an adverse result if we target a set of the same category of clothes but with different stitching, so that each seam appears different.

B. Approach

Our input sensor data is a range image captured by a 3D range camera that observes an item of clothing from a bird's-eye view. The 3D range camera can provide us with a color image, but we do not use it, color images are influenced by the different texture patterns on clothes. The proposed method takes the approach according to which learning data are prepared in advance, and it is desirable that one learning dataset for an item of clothing be used for others, even if they have different textures. By using only range images, such universality is maintained.

C. Outline of the proposed method

To extract grasp points from an item of clothing randomly dropped, both local and global shape information are needed. Local shape information indicates candidate positions where the robot hands will make contact. The information should include its feasibility as a grasping point. For instance, the hem of a hand towel is an applicable grasping position. The global shape information indicates the shape of the target clothing, which is used to judge whether the target clothing will be properly spread after being picked up using the selected grasp points.

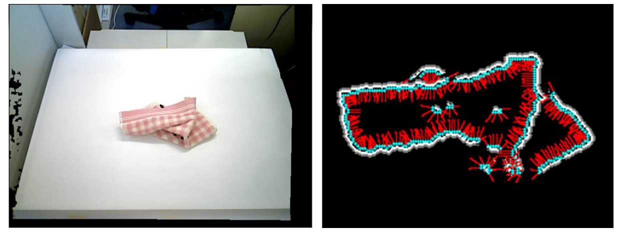

Fig. 2. Hem detection result

To avoid complicating procedure, only the "hem element" is used to describe both local and global shape information. The hem element is extracted from an input range image. Fig. 2 shows an example of hem element extraction. Right figure shows an enlarged image of the extraction result with regard to the left figure. The aqua color point shows the center of the hem element, and the red line segment shows the main direction of the element. In this paper, local shape information is represented by each hem element, while global shape information is the geometry of the hem elements that are extracted from the item of clothing.

To select grasp points from this information, we take the following steps. As prior preparation, we take a set of range images that capture an item of clothing with a variously changed shape. From each range image, hem elements are extracted. Appropriate grasp points are assigned manually. From this, we obtain our learning dataset.

In the process of grasp point selection, hem elements are first detected from input data. By identifying the global shape information from them, similar shape information included in the learning dataset is detected. Then, appropriate hem element grasp points are selected from the input data.

D. Difficulty of grasp points selection from a range image

One method to extract grasp points from sensor data is to use distinctive feature descriptions [6] [9] [11] that can find feasible grasp points directly. In this subsection, we describe the difficulty of such an approach.

Fig. 3 shows an example of sensor data. The lower graph shows a plot of depth values along the black line drawn on Fig. 3 (1). Here, we can find three uneven places where the depth values are changed considerably. In Fig. 3 (1), the red circle shows the hemmed edge, the green circle shows the part that is banked up, and the blue circle shows the trough of the wrinkle. It is difficult for us to find significant differences among these parts, meaning that distinctive description is also difficult. For this reason, we do not directly extract grasp positions from a range image, but take an implicit approach by means of recommendations from a few hundred points around the hem elements.

III. State description of clothes by using hem element

As mentioned in section II-A, the input data is a range image. Based on our assumption that the range image in-

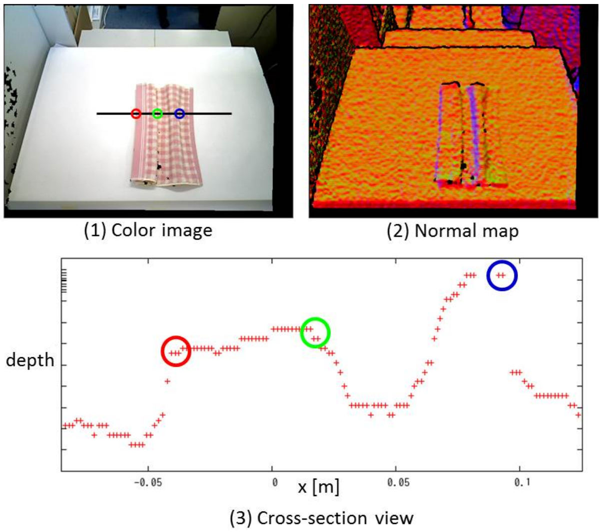

Fig. 3. 3D points from the clothing surface

cludes appropriate grasp points, a process to find probable positions is implemented, whereby grasp position candidates are narrowed down from the input data by extracting hem elements.

A hem element is one that is divided from the boundary of a 3D shape. In case of clothes, there are used to identify hem edge and any creases. Because this study aims to find grasp positions, we consider that either of the two hem elements detected from the input data is a position to grasp. Each hem element is represented as a 3D coordinate system. This representation has a high affinity with the grasp planning of a robot hand.

A. Extraction of hem elements

As mentioned in section II, the hem element is used to represent local shape information. The extraction procedure is as follows. Pixels that are a large distance from several neighboring pixels are regarded as a hem element. Around each of the pixels, the following calculations are performed to define the coordinate system. First, a single hem element is selected, and an area of a dozen millimeter diameter is defined, centered on the 3D position of the element. From the 3D points contained in the spherical region, ellipsoidal approximation is performed, and then a plane is defined from the two major axes of the ellipsoid. Next, the axis that is perpendicular to the hem line is defined on the plane, followed by the axis that is in parallel with the hem line. A third axis is calculated by cross product from the above two axes. From this procedure, we obtain a 3D coordinate system. Fig. 4 shows an example. Only pixels on upper side of the boundary are used to make the coordinate system. An example of the hem elements is already shown in Fig. 2.

B. Description of global shape information

Because the procedure described above produces hundreds of hem elements from one range image, the result is used to describe global shape information. In the proposed method, to achieve invariance to rotation and translation, relative posture between two hem elements is used for the description.

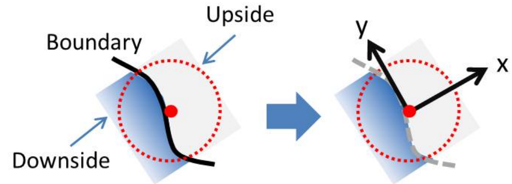

Fig. 4. Hem detection method

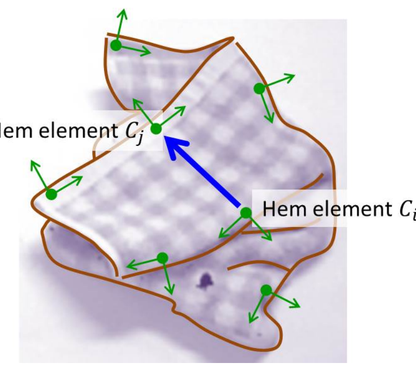

Fig. 5. Making hem element pair

Let hundreds of hem elements be a result of the procedure described in Section III-A. Because each hem element is represented as a coordinates system, we represent the i th coordinate system as C_i. $\mathbf{r}_i$ and $\mathbf{t}_i$ are rotation matrix and translation vector respectively, which are transformed from world coordinates O to C_i. A 4×4 matrix ${}^o\mathbf{T}_i$, which is called the transformation matrix, is composed of $\mathbf{r}_i$ and $\mathbf{t}_i$:

$$ {}^o\mathbf{T}_i = \begin{pmatrix} \mathbf{r}_i & \mathbf{t}_i \\ \mathbf{0}^T & 1 \end{pmatrix}. \tag{1} $$

If there is another j th coordinate system C_j whose posture is represented by a transformation matrix ${}^o\mathbf{T}_j$, their relative relationship is calculated as follows:

$$ {}^i\mathbf{T}_j = ({}^o\mathbf{T}_i)^{-1}({}^o\mathbf{T}_j). \tag{2} $$

Fig. 5 illustrates an example of the relative relationship.

Global shape information is described by a collection of relative relationships. That is, two hem elements are selected and their relative relationships is described as a transformation matrix by using Eq. (2). One shape description has the same number of possible combination of hem elements extracted from one range image.

IV. Grasp points selection

A. Outline

A list of learning data is prepared in advance. As described in section II-C, each learning data block is composed of the arrangement of hem elements and two recommended grasp points.

Let $X = \{\mathbf{x}_1, \cdots, \mathbf{x}_K\}$, and $H = \{h_1, \cdots, h_K\}$ be information extracted from the input data. $\mathbf{x}_k$ indicates a posture variable vector of kth hem element. In particular, $\mathbf{x}_k = (x_k, y_k, z_k, \phi_k, \theta_k, \psi_k)$ and these six parameters are calculated from a transformation matrix $\mathbf{T}_k$. h_k is a representation of the kth hem element. Let ${}_nI$ be hem element information registered as nth learning data, and let ${}_g\mathbf{x}$ be the recommended grasp points embedded among the nth data as ${}_nI = \{{}_nX,\ {}_nH\}$.

When we get X and H, which correspond to nth learning data, a posterior distribution of the probability that we can get correct grasp points ${}_g\mathbf{x}$ is represented as follows:

$$p({}_nI, {}_g\mathbf{x}|X, H). \tag{3}$$

The purpose of the proposed method is to find grasping points on input data, based on Eq. (3). Therefore, learning data similar to the input data are first detected, and then grasp points are selected from the input data by using the recommended grasp points registered in the learning data.

We embody the method by equation deformation. The policy to calculate the adequacy of grasp points is based on majority voting from the K hem elements. That is,

$$p({}_nI, {}_g\mathbf{x}|X, H) \propto \sum_{k \in K} p({}_nI, {}_g\mathbf{x}|\mathbf{x}_k, h_k). \tag{4}$$

By means of the definition of conditional probability, this equation is convertible into the following equation:

$$\sum_{k \in K} p({}_nI, {}_g\mathbf{x}|\mathbf{x}_k, h_k) = \sum_{k \in K} p({}_g\mathbf{x}|{}_nI, \mathbf{x}_k, h_k) p({}_nI|\mathbf{x}_k, h_k) \tag{5}$$

where the left side of the right member indicates an operation to calculate a posterior probability from hem elements of nth training data and input data. For this purpose, a voting-based approach similar to the implicit shape model [5] is applied (see section IV-C). The right side of the right member indicates an operation to search training data similar to the input data (see next subsection).

B. The method for shape similarity evaluation

Let $\mathbf{x}, h$ be a pair of a posture variable vector and a hem element representation that are extracted from the input data. To calculate a posterior probability which shows that ${}_nI$ is the most similar to the input data, $p({}_nI|\mathbf{x}, h)$ is used as shown in Eq. (5). According to Bayes' theorem, it will be translated into the following equation:

$$\begin{aligned} p({}_nI|\mathbf{x}, h) &= \frac{f(\mathbf{x}, h|{}_nI) p({}_nI)}{p(\mathbf{x}, h)} \\ &\propto f(\mathbf{x}, h|{}_nI) p({}_nI). \end{aligned} \tag{6}$$

We assume that prior distribution $p({}_nI)$ is uniformly distributed. Therefore, the only part we have to know is the likelihood $f(\mathbf{x}, h|{}_nI)$. The method to calculate the likelihood is to evaluate the correspondence of hem elements' information $\{\mathbf{x}, h\}$ between input data and ${}_nI$. The equation is as follows:

$$f(\mathbf{x}, h|{}_nI) \propto \sum_{a \in A} \max_{b \in B} S(\mathbf{T}_a, \mathbf{T}_b), \tag{7}$$

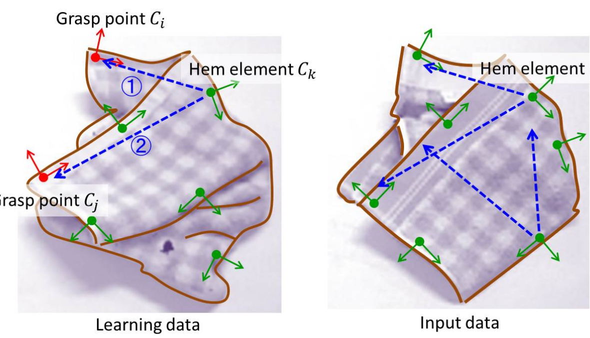

Fig. 6. Voting for grasp point detection

where A is the number of hem element pairs generated from the input data, and B is that of the learning data. $S(\mathbf{T}_a \cdot \mathbf{T}_b)$ indicates a similarity calculation between two relative postures (shown in Eq. (2)), which will be explained in section V-A in detail.

Eq. (7) describes a searching operation for a relative posture that is the most similar to that of the input data from n learning data. The higher the similarity value, the better evaluation is acquired.

C. Detection of plausible grasp points

To explain the detection procedure, we consider that two grasp points C_i, C_j extracted from the learning data are given. In addition, a hem element C_k that is not a candidate for a grasp point is used to calculate ${}^k\mathbf{T}_i, {}^k\mathbf{T}_j$ by means of Eq. (2). The right figure of Fig.6 indicates relative relationship between C_i, C_j where the kth hem element seems to originate. This relationship calculation is performed by changing the kth element, and their results are listed as the relational information for grasp points.

The method to select grasp point candidates from input data is as follows: first, hem elements are extracted from the input data, and then one element C_l is selected from them in order. For each C_l, the following transformation matrix calculation is performed.

$$\begin{aligned} {}^o\hat{\mathbf{T}}_i &= {}^o\mathbf{T}_l\ {}^k\mathbf{T}_i, \\ {}^o\hat{\mathbf{T}}_j &= {}^o\mathbf{T}_l\ {}^k\mathbf{T}_j, \end{aligned} \tag{8}$$

That is, the present C_l is regarded as C_k which is the learning data, and tentative C_i and C_j are generated. In the hem elements of the input data, if there are other coordinate systems that are near the tentative C_i and C_j, their degrees of correspondence are evaluated along the difference of position and direction. This evaluation is performed for all of the hem elements, and the final result is represented by a likelihood map that describes the position of the plausible grasp points.

The proposed method is based on majority voting from around hem elements in the input data by means of their relative relationships. That is, it assumes that there are learning data where the clothes' shape is similar to that of the present data.

V. Speeding up the searching process

A. Similar data search and evaluation calculation

As mentioned in section IV-C, to select feasible grasp points, a set of hem element pairs is first generated from the input data, and then the pairs are compared with the learning data. The comparison can be performed simply by the following method.

Let $\mathbf{x}$ be a posture variable vector that shows a relative relationship between two hem elements. $Y = \{\mathbf{x}_1, \cdots, \mathbf{x}_A\}$ denotes a set of hem element pairs derived from the input data, and ${}_nY = \{{}_n\mathbf{x}_1, \cdots, {}_n\mathbf{x}_B\}$ denotes a set of hem element pairs of nth learning data. In general, A and B, which show that the number of pairs are not the same because the number depends on the clothes shape and sensor data.

A posture variable vector is represented by six parameters: $\mathbf{x}' = (\alpha x, \alpha y, \alpha z, \phi, \theta, \psi)$, where α is a weight coefficient for adjusting the ratio between position and direction elements. In this state, it is experimentally defined. Following is the procedure of a search algorithm: a posture variable vector $\mathbf{x}_a$ is selected from Y, and the most similar vector ${}_n\mathbf{x}_b$ is selected from ${}_nY$ by means of cosine similarity. That is,

$$S(\mathbf{x}_a, {}_n\mathbf{x}_b) = \sum_{a \in A} \max_{b \in B} (Dist(\mathbf{x}_a, {}_n\mathbf{x}_b)), \tag{9}$$

where

$$Dist(\mathbf{x}_a, {}_n\mathbf{x}_b) = \frac{\mathbf{x}_a \cdot {}_n\mathbf{x}_b}{|\mathbf{x}_a||{}_n\mathbf{x}_b|}. \tag{10}$$

The correspondence of the equation with Eq. (7) is

$$S(\mathbf{x}_a, {}_n\mathbf{x}_b) = \sum_{a \in A} \max_{b \in B} S(\mathbf{T}_a, \mathbf{T}_b). \tag{11}$$

Similarity calculation by Eq. (9) provides good evaluation between two similar shapes in satisfying the invariance to rotation and translation.

However, this approach requires considerable calculation. For instance, if several hundreds of hem elements are acquired from one sensor data, the number of hem element pairs becomes several tens of thousands. When there are five hundred blocks of learning data, the number of calculations of Eq. (10) becomes several tens of thousands multiplied by five hundred. This number might be decreased by means of parallel computing and search trees such as kd-tree, but in our implementation, it took over 90 s for one input data.

B. Representation transformation based on unsupervised clustering

To overcome the problem of computation time described above, we propose the transformation of global shape information. Unsupervised clustering by means of k-means algorithm is applied to several tens of thousands of hem elements that are extracted from one sensor data.

Through the clustering procedure, several tens of thousands of vectors are reduced to k vectors. Because this enables a reduction in the number of comparisons, the speed of the search process is drastically improved. Also note that the number of elements for global shape information is pegged at $k \times 6$. As another characteristic, because clustering calculations for each learning data can be applied in advance, all we have to do for the similarity evaluation process is to cluster input data and to calculate the similarity against a set of learning data whose clustering has already been finished.

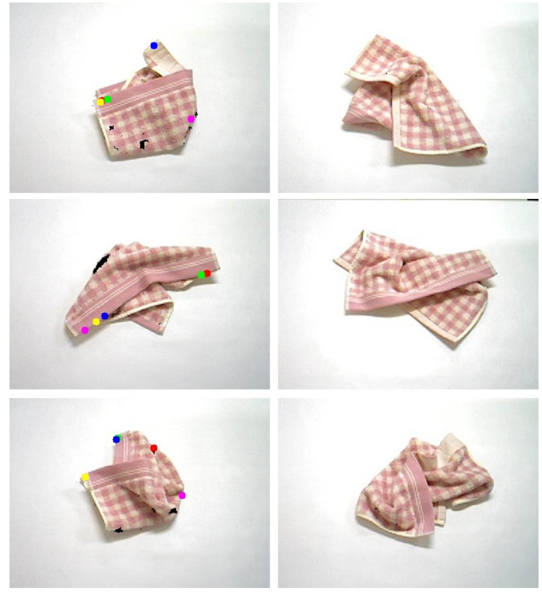

Fig. 7. Examples of the results of grasping point selection

VI. Experiments

A. Experimental settings

A hand towel was selected as the target object, and grasp position selection was performed. The cloth was placed on a horizontal plane. A color image and a range image were captured by a 3D range camera “Xtion PRO LIVE” made by ASUS. Hem elements were extracted from each sensor data, and then an operator manually selected feasible hem elements as grasp points. In this experiment, only sensor data that had at least two hem elements suitable for grasp points were registered as learning data.

The output of this experiment was a 2D position map that quantified the distribution of grasp point adequacy. The map was same size as the input range image, and each element of the map corresponded to a pixel in the range image. The left column of Fig.7 shows some examples, illustrating the top five candidates by different colors (red, green, blue, pink, and yellow). The right column shows learning data that were the most similar to the input data shown in each left figure. That is, the right figure was first searched using similarity calculation between input and learning data. Next, using the relationship of hem elements of the most similar learning data, feasible grasp points were selected.

To evaluate the success rate, leave-one-out cross validation was applied. That is, if we prepared 500 patterns of sensor data, one block of data was selected as input data, and the remainder was used as learning data.

Two patterns of representation are applied to calculate the success rate.

TABLE I

RESULTS OF GRASPING POINT ESTIMATION

Method	(1) Best 5 [%]	(2) Best 3 [%]	Time [sec]
(a) Original	47.8	29.2	94.8
(b) k=10	53.1	39.3	1.53
(b) k=100	65.6	49.5	1.64
(b) k=200	67.1	52.6	1.67
(b) k=500	66.4	48.6	1.74
(b) k=1000	69.0	53.3	1.78
(c) SPRH[13]	23.5	10.5	0.57
(d) SpinImage[2]	21.0	10.0	0.61

1) Target cloth can be spread by picking two grasp points out of five candidates (a best of five pattern),
2) target cloth can be spread by picking two grasp points out of three candidates (a best of three pattern).

Based on these criteria, the evaluator judged the quality of 499 selection results, and the success rate was calculated.

B. Comparison of global shape information

500 patterns of sensor data were prepared, and grasp point selection was performed. For comparison, we applied several methods of shape-based feature descriptor: (a) directly comparing hem element pairs (described in section V-A), (b) improvement by using k-means (described in section V-B), (c) Suflet Pair Relation Histogram (SPRH) [13], and (d) SpinImage [2]. (c) and (d) are conventional description methods that uses 3D position and orientation. In (b), five patterns, where $k = 10, 100, 200, 500$, and 1000, were tried.

Table I shows the experimental results. The second and third columns show a probability that feasible grasp points were found, and the fourth column shows processing time. In these experiments, similarity calculation between input data and learning data was parallelized by means of multi-thread programming. As shown in the table, the proposed method with $k = 1000$ provided about 70% success rate in finding grasp points. In addition, its processing time had practicality because there was significant remediation from straightforward comparison (a).

C. Number of learning data

Success rates against the number of learning data were investigated. In this experiment, the number of data blocks was changed to $50, 100, 300$, and 400, and the description method of global shape information was standardized on (b) k=1000, as explained in the above subsection.

The success rate was as follows:

- Best 5 = 39.5 [%] , Best 3 = 23.9 [%] in 50 data
- Best 5 = 47.8 [%] , Best 3 = 29.2 [%] in 100 data
- Best 5 = 44.4 [%] , Best 3 = 36.5 [%] in 300 data
- Best 5 = 70.0 [%] , Best 3 = 48.2 [%] in 400 data

These results show that 400 data can be a criterion in this condition because its result was almost same as the result shown in table I.

VII. CONCLUSIONS

In this paper, we proposed a method to select grasp points from an item of clothing placed randomly. In the proposed method, the clothing shape was described using hem elements extracted from a range image. Grasp point selection was also proposed, based on global shape similarity with a list of training data. Unsupervised clustering was applied to improve similar shape search. These methods were proven by experiments conducted with some types of clothing.

In our future work, the detection success rate will be revised. Using overlaps of cloth is an additional approach. Application to dual-arm manipulation is also needed to show the value of the proposed method.

ACKNOWLEGEMENT

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