Unfolding an Item of Rectangular Clothing Using a Single Arm and an Assistant Instrument

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***Abstract*— This paper describes a method of unfolding an item of clothing by a single arm robot. The unfolding action is assumed to use a corner of a table so that a crumpled cloth is unfolded by pulled up while making contacts with the corner. Using this approach, two issues arose; overlapping problem and outward turnback problem. To solve the former, we proposed an instrument to prevent overlapping. To solve the latter, we built an algorithm that recognizes a warping form of clothing and added dissolving manipulation. Using four kinds of clothing, we confirmed the effectiveness of the proposed method by using a real single arm robot. Our experiments resulted at a success rate from 65 percent to 85 percent.**

I. INTRODUCTION

People use various types of clothing in the course of their daily lives. Therefore doing laundry is an essential task, and we already have automated machines such as washing matching and drying machine. Meanwhile, folding and unfolding an item of clothing are performed by manual in many cases. Because the work is also regarded as unproductive routine work, automation is desired. For this reason, clothing manipulation has been a research target in robotics field. Osawa et al. [9] proposed a clothing classification method, Kita et al. [6] and Willimon et al. [12] proposed methods to know a shape of clothing while manipulation by robot arms, Cuen-Rochin et al. [3] achieved a folding task for an item of rectangular cloth.

These studies assumes that a dual-arm robot was used; thus, two end-effectors were used to grasp an item of clothing individually, and the shape of the cloth is controlled. Because human having two arms makes excellent use of their arm for clothing manipulation, above-mentioned approach seems to be orthodox one. Meanwhile, a dual-arm robot is a costly machinery and needs careful motion planning to avoid self-collision while manipulation.

We are interested in a development of automated machine performing clothing manipulation that is familiar to everyday life. From above consideration, one point of our study is that the automated machine should have simple mechanism as much as possible to doing chores. For this reason, we impose a robot on clothing manipulation by a single arm, and engage in an unfolding task that target a rectangular cloth casually placed on a table. As other studies using a single arm robot, Hamajima et al. [4] achieved isolation task that imposes a robot on picking up a piece of clothing from a pile of laundry. Our result is available to collaborate with their result, and contributes to a progression of automated clothing manipulation.

Several approaches can be applied to unfold an item of clothing. Ono et al. [8] proposed one solution. In their study, an item of squared cloth that was almost unfolded but had one or more bending corners was placed on a table. The bending pattern was estimated from the result of image corner detection. After that, unfolding was completed by picking and moving each bending corner to outside. On the other hand, we aim to develop a generalized method that can unfold a crumpled cloth. That is, we target more complex shape which is difficult to generate bending pattern models as proposed in Ono et al.

In our approach, a robot grasps one corner of an item of clothing, and unfolds it using a corner of a table that is regarded as a common structure in daily environment. This enables the robot to use only one arm; thus, a simple mechanism than dual arm is needed to the robot.

Doing an unfolding task based on the approach, we faced two major problems about cloth shape control. The first was about unnecessary bending pattern that was newly formed while unfolding manipulation. We call the problem "overlapping problem". In the proposed method, this was solved by assistant instrument installed on a corner of a table. The second was that the manipulated cloth did not form intermediate shape that was needed for desired unfolding state. We call the problem "outward turnback problem". This was alleviated by a vision function confirming clothing shape before unfolding manipulation.

This paper is organized as follows: Section II explains two major problems for unfolding manipulation and proposes a method to unfold an item of rectangular cloth. Section III and IV explains the solution to the two problems. Section V shows experimental results, and Section VI presents the conclusion of this paper.

II. PROBLEM DEFINITION AND APPROACH TO CLOTHING UNFOLDING

A. A method of clothing unfolding using a corner of a table

An item of rectangular cloth is on a table with casually form, and more than one corner of the cloth can be observed. Under this assumption, we suggest the following procedure to unfold the cloth using a single arm.

1) A robot detects a corner of the cloth and grasps it,
2) holds up and then moves it to a corner of the table,
3) pulls it up contacting with the corner hem of the table.

In a situation that the robot has only one end effector, it is difficult to control the shape of the cloth sufficiently. For this

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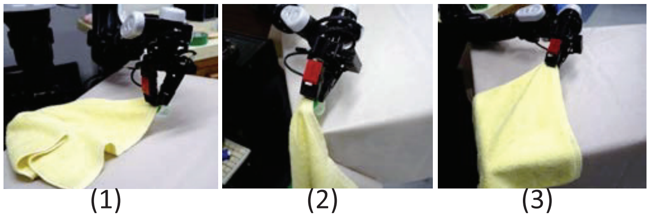

Fig. 1. Unfolding a clothing item

Fig. 2. Successful type of Unfolded results

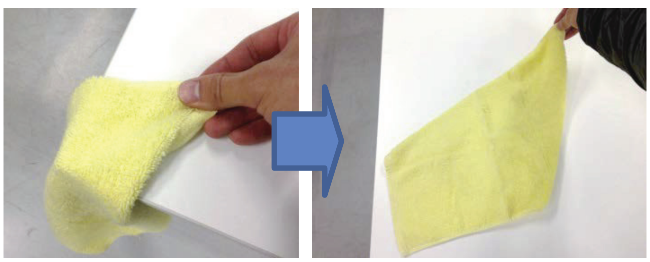

Fig. 3. Unfolding a clothing item using a corner of a table

reason, a corner of a table is used. Such part can mostly be seen in our living space; thus, a generality of this approach is not destroyed. Fig.1 shows an example that a robot performs an unfolding a clothing item.

We defined the success of unfolding as follows. Using the manipulation procedure mentioned above, sometimes the cloth is not quite unfolded as shown in the center and the right images in Fig.2. However, if two adjacent corners are visible without turnback, the robot can easily grasp them and unfold the cloth. In this research, we defined the success and failure of unfolding the cloth as follows.

- **Success**: Three or more corners can be observed without turnback, as shown in Fig.2.
- **Failure**: A state except for above-mentioned state.

B. Problems during unfolding

The previous section discussed how to unfold an item of rectangular cloth using a single arm robot. This section introduces two possible problems when the procedure is applied.

Overlapping problem: When a robot pulls up a clothing item while contacting it with the corner of the table, there are cases where undesirable turnback occur. That is, two different parts of the cloth directly contact, and a turnback derived from them cannot be dissolved. In this case, the shape of the cloth after the manipulation cannot be applicable because only two corners are found, as shown in the right panel in Fig.3. We call this problem the "overlapping problem" because the edges of the cloth is entrained inside.

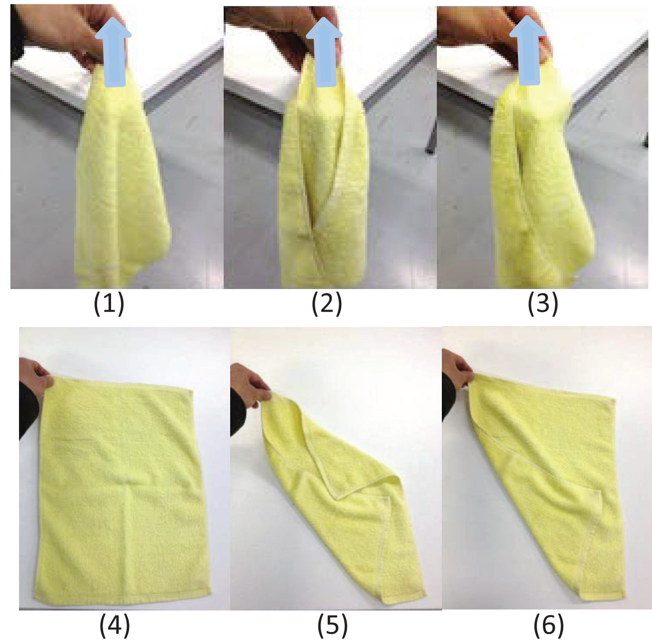

Fig. 4. Three patterns of unfolded clothing

Outward turn-back problem: The success rate of the unfolding is influenced by warping form of the cloth. There are three major shape patterns when a clothing item is brought to a corner of the table:

1) Both right and left side of clothing edges form inward turn-back.
2) Both clothing edges have turnbacks opposite sides against 1)
3) One side of the edge forms inward turn-back, whereas the other side forms outward turn-back.

Upper panels (1) to (3) shown in Fig.4 indicate the examples. The lower panels (4) to (6) shows the resulted shapes after pulling up on the table about each case. Based on the definition which is mentioned in section II-A, (4) and (6) are judged as successful unfolding whereas (5) is failure. For this reason, it is desirable that the clothing shape such as (5) should be detected and deformed in advance.

Based on the discussion, we distinguish two cases: The states of (1) and (3) belongs to "inward turnback" and The state (2) belongs to "outward turnback". As mentioned above, inward turnback often makes a success state whereas outward turnback is a causes of unfolding failure. We call that "outward turnback problem".

The following sections discuss the proposed approaches to overcome above-mentioned two problems.

III. Addressing the Overlapping Problem

Once overlapping occurs, its resolution is difficult because of friction between two different fabric parts. The proposed procedure to pull up the cloth using a corner of a table is one effective way to solve this problem. Comparing with a case using a straight hem of the table, we noticed that using a corner was more successful. For this reason, we

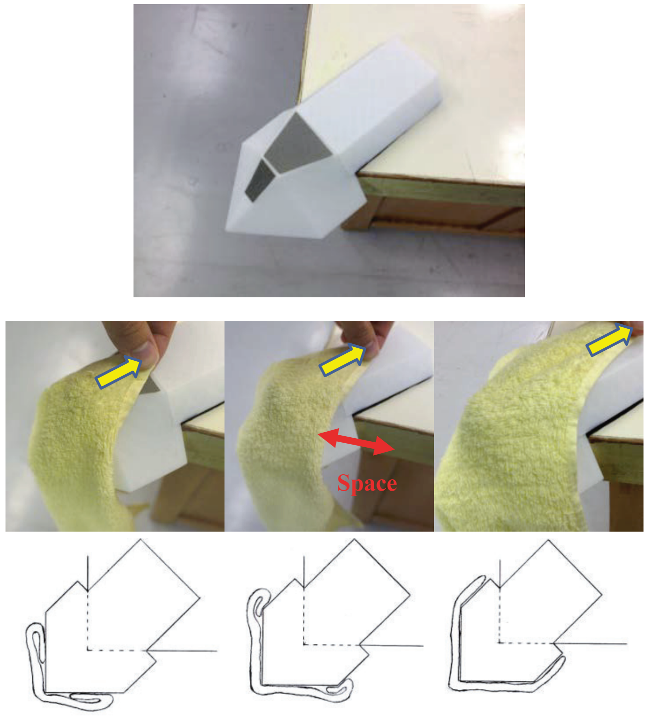

Fig. 5. Assistant instrument and its effectiveness

TABLE I

SIZE OF CLOTHING

Clothing type	Size [mm]
Hand towel	340×335
Face towel	330×450
Dishcloth	350×460
Napkin	420×395

take an approach to use such sharp-shaped part, and then try to improve the shape to resolve overlapping problem more effectively. In addition, it is desired that the improvement is simple as much as possible.

We designed the instrument as shown in top panel in Fig.5. The angle of the tip corner is 90 degrees, and nonskid rubber is cleated to the bottom surface. This means that we only have to put this instrument on the corner of the table. Furthermore, to coordinate clothing movement, waterproof sand paper is attached to the top surface.

The effectiveness of the instrument against overlapping problem is illustrated in the center panels in Fig.5. As shown in the center panel, this instrument generates gap between an edge of the table and an edge of the cloth. It prevents overlapping problem by decreasing friction between two different fabric parts; thus, it represents an effect to fall down the edge of the cloth by the force of gravity. The lower panels in Fig.5 show the sequence of their cross-section view.

The following is the background leading to the instrument. Fig.6 shows four instrument examples that we practically made. These were designed based on the following discussion.

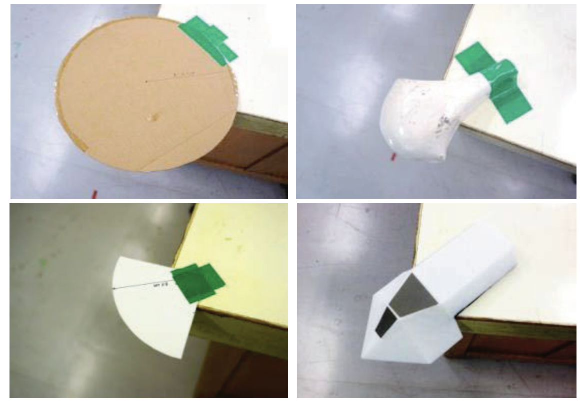

Fig. 6. Four types of assistant instruments

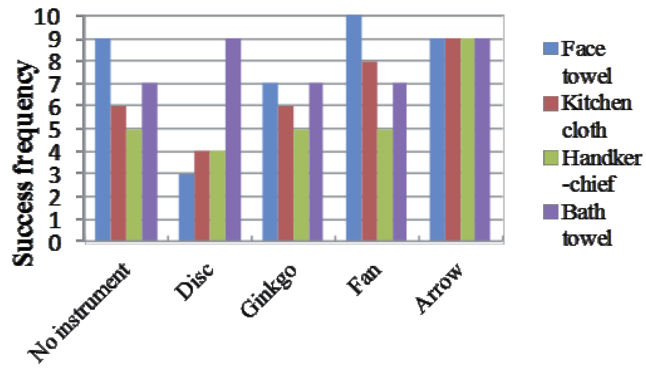

Fig. 7. Results of manually unfolding experiments

(a) Disc Shape: By making a smooth curve for contacting with cloth, it was expected to unfold the cloth while being pulled up to the table. However, this causes another problem that the cloth slips off to right or left. Although we experimented by two different radius disc, (100 [mm] and 50 [mm]), the problem was not resolved very well.

(b) Ginkgo Shape: By making the form with three-dimensional shape, the area to be contacted with a clothing item was increased. Furthermore, we tried to improve the overlapping problem by making hollows on the right and left sides.

(c) Fan Shape: To improve overlapping problem without increasing contact area between cloth and the instrument, hollows were added to right and left sides.

Fig.7 shows the unfolding success rate relevant to four types clothes which were shown in Table 1. Each of clothing item was tried 10 times at each instrument. The results of the experiments lead that Arrow type (d) showed the highest success rate which was 9 out of 10 about all clothes. So we decided to adopt the Arrow type to alleviate the overlapping problem.

IV. ADDRESSING THE OUTWARD TURNBACK PROBLEM

To address the outward turnback problem, we develop a vision function to judge whether or not the outward turnback occurs. If it occurs, a manipulation to remove the outward turnback is imposed to a robot.

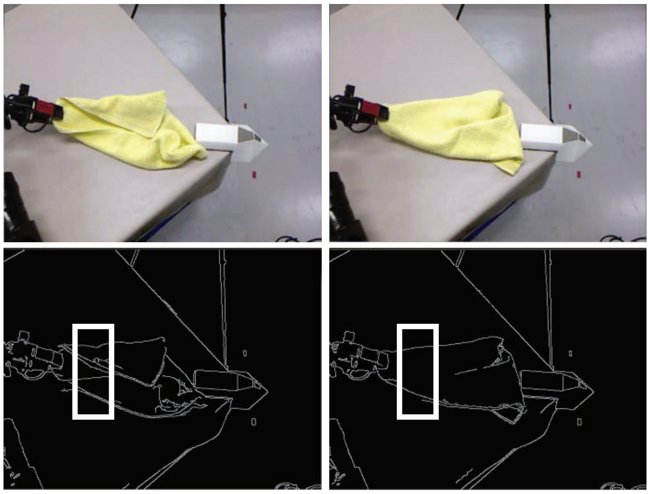

Fig. 8. Inward and outward turnback. White rectangular boxes depicted in lower panel shows region of interests where turnback type will be distinguished.

A. Detection of outward turnback

Upper two panels in Fig.8 show that a robot lays an item of cloth on the table with holding one corner of the cloth. If the next motion is to move the cloth to front of the instrument, inward warp show in right side figure is desirable. A clothing state shown in the left side figure has higher possibility to being outward turnback, whereas the right figure tends to be inward turnback. For this reason, we propose a vision function to classify above two states. First, Canny edge detection method [2] is applied to an input color image. Then image edges inner region of interest (ROI), shown as white rectangles in lower panels in Fig.9, defined near to the robot hand is focused on. Because a positional relationship between a hand and a sensor is assumed to be always the same, and the almost position of the clothing item can be controlled by the laying down manipulation. That is, we can fix the position and size of the ROI. In the region, inward turnback and outward turnback represent the following characteristics.

- Inward turnback: Several edges are observed between the uppermost edge and the lowermost edge.
- Outward turnback: Almost no edge between the two edges.

From this fact, we dealt with this problem as a binary identification problem to classify inward turnback and outward turnback. However, just counting the number of edges, we may have the possibility of erroneous determination. To improve it, the edges are used to generate feature description. First, the number of pixels belonging to image edges is counted. The value d shown in the following Eq. (1) is then calculated.

$$d = \frac{R_2 - R_1}{n}, \tag{1}$$

where R_1 represents the number of row that is the minimum in the range including edge pixels. R_2 represents the number of maximum row. n is a predefined number which means the dimension of a feature vector. If d does not result a natural number, it is rounded off to the first decimal place. Next, the area between R_1 *th* row to $R_1 + nd$ *th* row is divided into n equal parts, and edge pixels are then counted at each bins of N_1 *th* to N_n *th* bins. After normalization by $N (= \sum_{i=0}^{n} N_i)$, n dimensional vector $\mathbf{D}$ is obtained:

$$\mathbf{D} = \left[\frac{N_1}{N}, \frac{N_2}{N}, \cdots \frac{N_n}{N} \right]. \tag{2}$$

A feature vector $\mathbf{D}$ represents the distribution of edge densities. It can be predicted that many of elements have nonzero value when the cloth is in outward turnback state. Based on this prospect, we performed the machine learning using Support Vector Machine [11] (SVM). We prepared the learning data as a dozens of images capturing outward and inward turnback. A set of feature vectors was calculated from them, and binary label was added to each feature vector. SVM was applied to the vectors, and a discriminative function was generated. If outward turnback state is found by the function, a robot performs a pre-defined motion to resolve it.

B. Resolving outward turnback state

If a present cloth state is classified into outward turnback, a robot grasping the cloth swings its arm for bringing the state from the outward turnback to inward turnback. In order to generate the motion, a reference coordinate system is defined at the trunk of the robot. The directions of each axis are: x to the front, y to the left, z to vertically up, respectively.

The motion sequence is described as follows:

1) The robot raises the grasping hand to a predetermined height z, and then brings the hand down to $z - \Delta z$,
2) moves the hand relatively to $(0, -\Delta y, 0)$,
3) moves the hand relatively to $(0, 0, \Delta z)$, and
4) moves the hand relatively to $(0, \Delta y, 0)$.

There is a little trick to make a success of the second action: it should be performed while keeping the bottom of the cloth contacting with the table. Due to the manipulation, the outward turnback can transform into inward turnback. After finishing the actions 1) to 4), the robot recognizes again the state of the cloth. If the state was changed to inward turnback, the robot moves clothing manipulation into unfolding phase that uses the abovementioned instrument.

V. Experiments

A. Settings

A life-sized robot named HIRO manufactured by Kawada Inc. was used for experiments. The robot had two manipulators, but only left arm was used. A 3D range image sensor, Microsoft Kinect, was mounted on the head of the robot. This sensor provided both a color image and a depth image with VGA (640×480) size. They were used to detect clothing corner, to classify bending pattern and so on. We assumed that at least one corner of a clothing item could be observed and its shape is suited for grasping in easily.

B. Experimental procedure

One unfolding manipulation consisted of the following five phases:

1) A corner of an item of clothing placed on a table is determined as a grasping position.
2) The robot grasps the corner, and picks the clothing item up ((1) to (3) in Fig. 9).
3) If outward turnback is found, the motion sequence described in Section IV-B is performed. Otherwise, the robot brings the clothing item near a corner of a table ((4) to (6)).
4) The robot unfolds the cloth by pulling up on the table ((7) and (8)).
5) An evaluator confirms the manipulated clothing whether the unfolded shape has three or more visible corners without turnback.

Fig. 9 shows an example of the unfolding procedure. Similar experiments were performed 80 times, which was a sum of 20 times by four types of clothing shown in Table II. A success rate was calculated by the number of success in the 20 trials.

Fig. 10 shows the processing flow of one unfolding manipulation. The input is a pair of color image and depth image captured from the Kinect sensor. The output is a set of joint angles that should be sent to a robot arm. Above-mentioned items 1) to 4) are explained below in detail. In the procedure 1), edge detection by means of Canny filter is first performed, and the position of a corner is then identified in the color image. Three dimensional position of the corner is calculated using the depth image. The result is used to calculate inverse kinematics for generating joint angles of the arm of the robot. Based on the angle, the robot grasps the corner and picks up the clothing item. In the procedure 3), the clothing item is first put on the table. Canny filter is applied to an image capturing the lying cloth, inward turnback or outside turnback is classified as explained in Section V-A. If outward turnback is found, the motion sequence to bring the outward turnback to inward turnback is performed. After that, the classification process is performed again. These are repeated unless the classification process detects inward turnback state. In the procedure 4), the robot pulls up the cloth that initially placed on the front of the corner of the table. The pulling trajectory is set as a horizontal line directing 45 degrees from a hem of the table.

The number of division in Eq.(2) was experimentally set to 10. The number of training data used for SVM was 40, which was divided into 20 outward and 20 inward turnback images. Parameters for swinging arm described in Section IV-B were set as $\Delta y = \Delta z = 400$ [mm].

C. Experimental results

Table II shows the experimental results. 16 successful unfolding were obtained on the hand towel. 15, 13 and 15 successful unfolding were obtained on face towel, dishcloth and napkin, respectively. The major situation of unfolding failure was that the cloth sideslipped while pulling it up on the table, as shown in Fig.11. The situation was observed 11 times. Although a countermeasure had already been applied by attaching a sanding sheet on the top of the instrument, it was insufficient to completely prevent the sideslipping. Other failures were as follows: a classification of outward or inward turnback was wrong (four times), the robot dropped off a grasping cloth (three times), and overlapping did not resolved (two times).

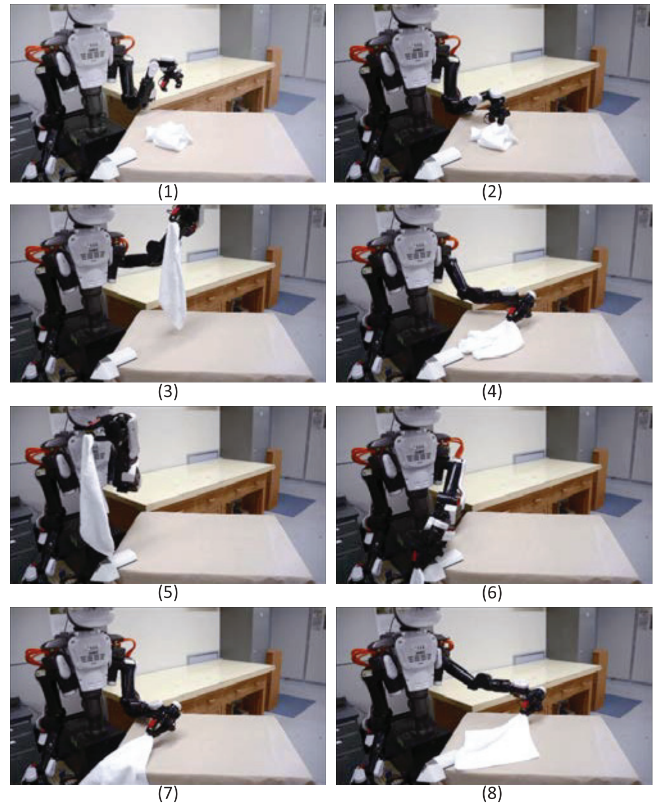

Fig. 9. An unfolding experiment

TABLE II
EXPERIMENTAL RESULTS

Clothing type	No. of Success	Success rate
Hand towel	17	75 %
Face towel	15	85 %
Dishcloth	13	65 %
Napkin	15	75 %

D. Discussion

Overlapping problem occurred only two times out of 80 trials. The result suggests that the proposed assistant instrument have a beneficial effect on preventing overlapping. Although there is still room for improvement about the shape and surface material, we could confirm a certain level of the usefulness of the instrument. Further improvement is our future work.

On the other hand, one major problem is already mentioned above: how to cope with a situation that a clothing item sideslips while pulling it up on a table. Pasting sandpa-

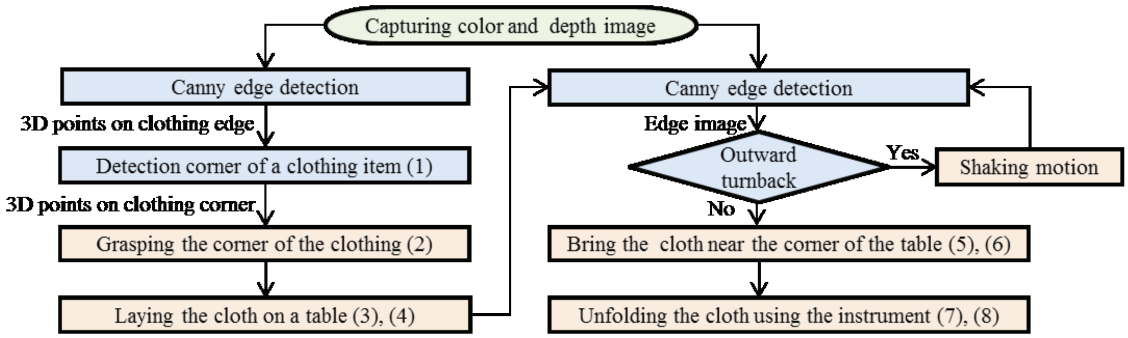

Fig. 10. The procedure flow of unfolding. Blue blocks indicate vision and decision making functions, whereas red blocks indicates motion functions. The numbers written in the blocks correspond to the number depicted in Fig.9

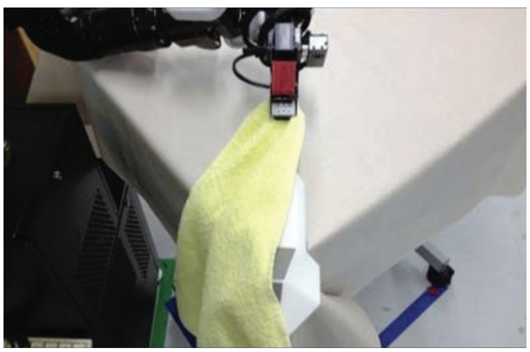

Fig. 11. Sideslipping while unfolding

per on the top of the assistant instrument had some efficacy in the problem, but insufficient to resolve the incomplete unfolding. An important idea is to modify end-effector trajectory in online. To achieve this, a higher level clothing state estimation is essential.

Other remaining problems are related to classification error and grasping error. For the former problem, we can have several recipes: e.g. using a classification function trained from more number of sample data, assembling assistant claw into the robot hand, and so on. These ideas are effective because they do not affect the amount of manipulation procedure. Present vision functions assumes only plain cloth. In general, it is desired that clothing state estimation should work for both textureless and textured clothing. This is also our future work.

VI. Conclusions

In this paper, we reported an unfolding of an item of rectangular clothing by a single arm robot. The proposed approach to perform unfolding assumed the use of a structural corner part. Based on the approach, we faced two major problems: overlapping problem and outward turnback problem. To overcome them, improvement methods were proposed and proven. In experiments using a real robot, several rectangular clothing items were selected, and their unfolding were performed with more than 80% success rate. We also discussed about failure case to improve the proposed approach.

Acknowlegement

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References

[1] D. Comaniciu, V. Ramesh, P. Meer: “Real-Time Tracking of Non-Rigid Objects using Mean Shift,” in Proc. of IEEE Conf. on Computer Vision and Pattern Recognition, Vol. 2, 142-149, 2000.

[2] Canny, J.: “Computational approach to edge detection,” IEEE Trans. Pattern Analysis and Machine Intelligence, Vol. 8, No. 6 (1986), pp. 679-698.

[3] Cuen-Rochin, S., Andrade-Cetto, A and Torras, C.: “Action selection for robotic manipulation of deformable planar objects,” in Proceedings of Frontier Science Conference Series for Young Researchers: Experimental Cognitive Robotics (2008), pp. 1-6.

[4] Hamajima, K. and Kakikura, M.: “Planning strategy for unfolding task of clothes - Isolation of clothes from washed mass -,” in Proceedings of International. Conference on Robots and Systems (2000), pp. 1237-1242.

[5] Hashimoto, K., Saito, F., Yamamoto, T. and Ikeda, K.: “A field study of the human support robot in the home environment,” in Proceedings of IEEE Workshop on Advanced Robotics and its Social Impacts (2013), pp. 143-150.

[6] Kita, Y., Saito, F. and Kita, N.: “A deformable model driven method for handling clothes,” in Proceedings of International Conference on Pattern Recognition (2004), pp.1425-1431.

[7] Maitin-Shepard, J., Cusumano-Towner, M., Lei, J. and Abbeel, P.: “Cloth grasp point detection based on multiple-view geometric cues with application to robotic towel folding,” in Proceedings of IEEE International Conference on Robotics and Automation, Vol.3 (2010), pp.2308 - 2315.

[8] Ono., E., Kita, K., and Sakane, T.: “Unfolding a folded fabric using information of outline with vision and touch sensor,” Journal of Japan Roborics Society, Vol . 15, No. 2 (1997), pp. 275 - 283.

[9] F. Osawa, H. Seki, and Y. Kamiya: “Unfolding of Massive Laundry and Classification Types by Dual Manipulator,” Journal of Advanced Computational Intelligence and Intelligent Informatics, Vol.11 No.5, pp. 457– , 2007.

[10] Shibata, M., Ota, T. and Hirai, S.: “Fablic unfolding using pinching slip motion,” Journal of Japan Roborics Society, Vol.27, No.9 (2009), pp.67-74 (in Japanese).

[11] Vapnik, Vladimir N.: “The nature of statistical learning theory,” Springer-Verlag (1995).

[12] Willimon, B., Birchfleld and S., Walker I.: “Classification of clothing using interactive perception,” in Proceedings of IEEE International Conference on Robotics and Automation (2011), pp. 1862 - 1868.

[13] Yamazaki, K.: “Grasping point detection for a piece of clothing casually placed on daily environment,” in Proc. of International Confference on Intelligent Robots and Systems, 2014(to appear)

[14] UBR-1, http://unboundedrobotics.com/ubr-1/ (accessed on 14 April, 2014)