Hanging Work of T-Shirt in Consideration of Deformability and Stretchability *

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***Abstract*— This paper describes a hanging work, which is one of the work related to cloth products. By using deformability and stretchability of clothes successfully, it is possible to efficiently proceed with a hanging work. We focus on cloth wrinkles and superimposed relation of objects, and propose a method to recognize the progress of hanging work on-line. In a detection processing of wrinkles, after using edge detection filters, clustering is applied, and the direction and inclination of the wrinkle are extracted. By statistically observing the large number of wrinkles, we can estimate the current tension state of cloth. The effectiveness of the proposed method was proven through experiments using a dual-armed robot.**

***Index Terms*— Hanging work, wrinkles, deformability and strechability**

I. Introduction

Cloth product is an important tool supporting human social life. Therefore, there are also many work related to cloth product in daily life. Many of them are nonproductive, such as cleaning and drying, therefore it is considered useful if they can be replaced by automated machines.

In this paper, we focus on hanging clothes, which is one of the work related to cloth products. In this work, it is necessary to consider not only the deformability of the cloth but also the fact that the cloth streches. Especially, stretchability is helpful characteristic that makes it possible to widen a hole originally small. By using it successfully, it is possible to efficiently proceed with a hanging work.

We can find studies on automatic operation of cloth products [1-4]. Rectangular cloth products and clothing were used, and their folding or unfolding tasks have been targetted. Cuén-Rochín et al. [5] 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. As actions that fold cloth products has also been noted, it is possible to transfer cloth products that are placed casually into the desired form. Kita et al. [6] used a 3D deformable model, and obtained a correspondence between the model and an input pointcloud that was captured by a trinocular stereo camera. Doumanoglou et al. [7] succeeded in recognizing the type and shape of clothing items during the unfolding process, using a 3D range camera. Their framework also provided the next grasping point for subsequent manipulation. Stria et al. [8] unfolded a clothing item by means of shape estimation using a polygonal model. As their main manipulation was pick-and-place, they designed recognition functions to find feasible grasping points for the next step in the unfolding process.

In these studies, even though the authors assumed the deformation of the cloth, but they did not assume strechability. Therefore, when considering the work of inserting something into an empty hole in a cloth product, if the size of the insert is larger than the hole not pulled, it is judged that the insertion work can not be performed. However, many cloth products are elastic materials, and depending on how they are handled, the above-described insertion work is also possible. In this study, we aim to automate such work, and focus on hanging work as an example. Besides this, we consider that there is similar development such as assisting work of clothes wearing, packing work at logistics sites, assembling work at the manufacturing site.

In this paper, we combine two kinds of state recognition methods; one is a method of confirming that a hanger can be moved to a desired arrangement with respect to the cloth, and another is a method of estimating the tension state of the cloth. Also consideration is given to high-speed processing, making it possible to observe the state of tension during hanger manipulation.

The paper is organized as follows: Section II presents related work. Section III explaines our approach. Section IV and V explains the proposed method. Section VI shows experimental results, and Section VII presents the conclusions of this paper.

II. Related work

It is important to observe the tension state of cloth in the hanging work. In that sense, information processing about wrinkles is an important element. Even in automatic operation of cloth products in intelligent robotics, there are several studies focusing on the state of wrinkles. Yamazaki and Inaba [9] devised a wrinkle-specific image feature expression and proposed a method to detect clothing captured in daily

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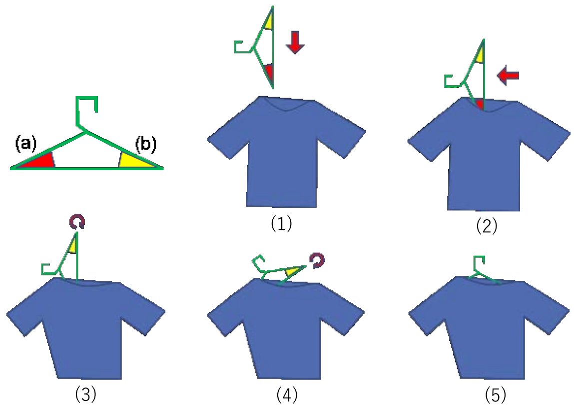

Fig. 1. hang clothes on hangers

images. Also, by combining several characteristic expressions unique to cloth, including wrinkles, individual identification of cloth products was performed with high accuracy [10]. A filter bank with dozens of edge detection filters was used. Then, after integrating the filtering results, shape-invariant feature representation was generated.

Sun et al. [11] achieved the work of spreading an item of clothing into flat. After conducting relatively high-precision three-dimensional measurement, the existence and direction of wrinkles were determined, and then the direction to elongate wrinkles were identified. Li et al. [12] addressed the topic of robotic ironing, proposing a procedure of wrinkle detection followed by flattening. In their work, the initial state of the cloth is assumed to be in an unarranged shape, but the unfolding phase was skipped. The above-mentioned studies recognized the shape state of clothing using wrinkles as a clue. Also in our study wrinkles are important information for shape recognition. In this research, we use the time series change of wrinkles and recognize the elongation of cloth.

III. Our approach

Fig. 1 shows the procedure of the hanging work we assume. First, one end of a hanger is inserted into the inside of a T-shirt from above, and the end part pulls out the hole of the neck portion of the T-shirt. Then, after inserting the other end, the work is finished.

We focus on two types of state recognition on hanging work as follows:

1) Prediction of shape condition of clothing accompanying insertion operation of hanger, and
2) Detection of viewable area of hanger accompanying insertion operation of hanger.

For item 1), we use wrinkles of cloth. When stretchable cloth is grasped by a part and pulled in a predetermined direction, wrinkles tend to form in the same direction as the tension. Therefore, by observing the inclination of wrinkles, we can know the state of tension. For this reason, wrinkle information is extracted from a color image sequence of the fabric photographed during the operation, thereby estimating the state.

On the other hand, item 2) is done by observing hiding situation of the hanger. The appearance of the hanger might change in the case where it was able to be put in the hole of the clothing and the case where it was not so. If the hanger got down on the front side of the clothing, the whole hanger remains visible. Otherwise, the visible portion is reduced by the amount that entered. This can be determined by looking at the overlapping relationship. The authors focused on the previous study [13] and introduce this concept.

IV. State recognition from wrinkle distribution

A. Edge detection processing for wrinkle emphasis

In grasping wrinkles of cloth by image processing, we think that there is a high possibility that wrinkle is a part where the edge of gentle shading changes. In order to detect wrinkles, we apply the filter bank framework [14][15] to detect wrinkles. In our case, dozens of two-dimensinal Gabor filters are used [10].

A Gabor filter [16] is a filter in which the direction and frequency can be arbitrarily changed. The filter has often been applied to scale space analysis. The corresponding equation is as follows:

$$g(\mathbf{x}, \theta, \sigma_x, \sigma_y) = \frac{1}{\sqrt{2\pi}\sigma_x\sigma_y} e^a \cos(2\pi f x_\theta + p), \quad (1)$$

where

$$\begin{aligned} a =& \quad -\frac{1}{2}\left(\frac{x_\theta^2}{\sigma_x^2} + \frac{y_\theta^2}{\sigma_y^2}\right), \\ x_\theta =& \quad (x - u_x)\cos\theta + (y - u_y)\sin\theta, \\ y_\theta =& \quad -(x - u_x)\sin\theta + (y - u_y)\cos\theta. \end{aligned} \quad (2)$$

The f is frequency domain, which depends on the variance value σ. The variables x and y are the coordinates of the present pixel, and u_x and u_y are the center coordinates of the Gaussian distribution. The variables σ_x^2 and σ_y^2 are the variances; both of them are represented as σ in the rest of this paper. Thus, $g(\mathbf{x}, \theta, \sigma_x, \sigma_y)$ is represented as $g(\mathbf{x}, \theta, \sigma)$. p is a variable of the phase, and we substitute $\pi/2$ into it because the edge detector should be generated in our case.

Because a Gabor filter has directionality, the resulting images contain various edges that rely on the θ setting. In order to describe wrinkles from this result, a maximum orientation image $I_{ori}(\mathbf{x})$ is generated from these results. The pixel information is written as follows:

$$I_{ori}(\mathbf{x}) = argmax F(\mathbf{x}, \theta), \quad (3)$$

where $\mathbf{x}$ denotes the pixel coordinates and θ denotes the inclination angle of a kernel function in equation (2). The $F(\cdot)$ is a continuous function concerning θ and the neighboring pixels.

$$F(\mathbf{x}, \theta) = \int_w f(\mathbf{x}) g(\mathbf{x} + \mathbf{x}_0, \theta) d\mathbf{x}_0, \quad (4)$$

where $f(\mathbf{x})$ indicates an input image and w denotes the window size of the convolution.

In practice, $I_{ori}(\cdot)$ is calculated from the discrete values $(\theta_1, \theta_2, \cdots, \theta_K)$. After pre-processing with varying θ, an image is generated by collecting the highest radiance value at the same pixel coordinates in the set of filtered images. In the case of clothing, ellipse-like regions are extracted along wrinkle directions.

If $\mathbf{x}$ is the pixel coordinate of the wrinkle portion, it should have the same direction component as the surrounding pixels. Therefore, after generating the direction component, a grayscale image having different illuminance for each angular direction is generated. When comparing this image before and after pulling, if little change is seen, it can be judged that the work has failed.

B. Acceleration of edge detection processing

In the method using the filter bank described above, it takes time to process because it is necessary to apply a large number of filters to the original image. Therefore, it is replaced by the following processing to achieve high speed. First, smoothing processing is applied to the image. Since this smoothing is aimed at detecting wrinkles, the size of the window of the convolution is set to be as large as about tens of pixels on a side. For this, a box filter is used. Since the box filter is a method that does not require convolution processing, when a large filter kernel is required, it is particularly effective as a means for speeding up.

Next, the differences between the pixels in the vertical direction and the horizontal direction are taken. That is,

$$\begin{aligned} D_x(\mathbf{x}) &= I(x + \Delta x, y) - I(x, y) \\ D_y(\mathbf{x}) &= I(x, y + \Delta y) - I(x, y). \end{aligned} \tag{5}$$

Here, $\mathbf{x}$ is the coordinates of the pixel for which the difference result is to be obtained. I is the smoothed image. Δx and Δy are parallel movement components in the horizontal direction and the vertical direction, respectively. They are values determined in conjunction with the window size for smoothing.

Finally, direction component $\theta(\mathbf{x}) = \tan^{-1}(D_y(\mathbf{x})/D_x(\mathbf{x}))$ at each pixel is obtained from these two difference values. By discretizing this value at arbitrary intervals, the same effect as equation (3) is obtained.

In our experience, the result calculated in this way is similar to the method described in the previous section. Therefore, the result is also effective in detection of wrinkle elements described in the next section.

C. Extraction of wrinkle elements

By using the processing described in the previous section, we can know the existence and inclination of wrinkles. From here, the following processing is performed on the processed image in order to know the situation of pulling.

Fig. 2. Wrinkles caused at the time of pulling and its detection result. The wrinkle element was detected for the red frame portion of the left image. As indicated by the yellow ellipse in the right image, the direction of the wrinkle elements is divided into two directions: gravity direction and pulling direction.

First, clustering of pixels is performed using the region growing method. Here, with the similarity of the direction components as the evaluation criterion, when adjacent pixels satisfy the following, these pixels are set as one group.

$$|I'_{ori}(x, y) - I'_{ori}(x + \delta x, y + \delta y)| < \theta_{thre}, \tag{6}$$

where I'_{ori} is the image after wrinkle emphasis mentioned the above, θ_{thre} is a threshold value. δx and δy represent the amount of displacement to four neighboring pixels up, down, left, and right. As the area of pixels satisfying this equation is expanded, many elongeted clusters can be obtained from wrinkle area.

Next, referring to each cluster, ellipse approximation is performed. Specifically, average coordinates and a distributed covariance matrix of pixel coordinates constituting a cluster are obtained, and eigenvalue decomposition is applied to the matrix to obtain information on axes needed for describing ellipse equation. When the long axis component obtained is superimposed and displayed on the original image, the tendency of wrinkle direction can be seen. Hereinafter, the line segment indicating the long axis of the ellipse is referred to as “wrinkle element”.

D. Estimation of tensile state based on temporal change of wrinkle element

It can be said that the arrangement of wrinkle elements is one index representing the current state of cloth. The authors focus on descriptive possibilities of the stretching state, in particular. That is, since there is a clear difference in the arrangement of the wrinkle elements before and after the pulling, Our consideration is that the tension state can be measured by observing the time series change.

Therefore, a frequency histogram based on the inclination angle of the wrinkle element is generated. Prepare bins separated every 10 degrees and vote on the bins according to the angle of each wrinkle element. By observing the shape of this histogram, the tensile state is statistically described.

In our experience, if we observe a hanging work from a bird’s-eye viewpoint, histograms that were a single peak in

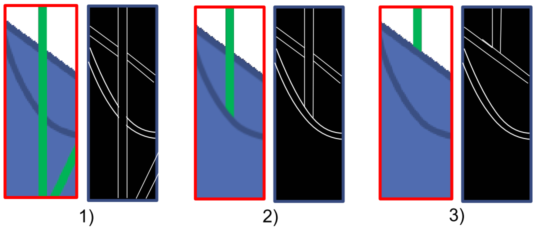

Fig. 3. Three types of overlapping relationship

the absence of tension will become bimodal as a result of pulling. The reason for this is that wrinkles were originally created only by pulling in the direction of gravity, but cloths become to have wrinkles in another direction because they are also pulled laterally by the hanger. Fig. 2 shows an example when pulling clothes with a hanger. The right panel is the result of detecting the wrinkle element with respect to the red frame portion of the image on the left panel. A white line segment shows a wrinkle element. We can see that long wrinkle elements are divided into two branches.

V. Insertion state estimation based on superimposition relation

Let's lower a hanger vertically downwards and consider a situation where it put in the hole around the neck of clothing. At this time, the bottom portion of the hanger is hidden by the cloth on the front side of the clothing, and compared with the case where the hanger comes to the front of the clothing, the visible portion is reduced. Furthermore, in a situation where the hanger comes to the back of the clothing, the bottom portion of the hanger is also hidden by the cloth on the back side of the clothing, so that the visible portion is higher than the state. Then, the visible part is further reduced than the state in which the hanger is put in the hole around the neck of the clothing. From the above, by observing the position of the hanger, it is possible to distinguish the following three types: when the hanger comes to the front of the clothes without entering the hole, (Fig. 3, 1)), when the hanger enters the hole (Fig. 3, 2)), and the hanger does not enter the hole and exists on the back of the clothes (Fig. 3, 3)).

The discrimination method is as follows. Suppose that there is an image taken from a point of view where a robot can observe a hanger overhang from the front. First, edge extraction is performed by applying convolution integral to the original image using Sobel filter. An edge having a direction of 50 to 70 [deg] with respect to the horizontal line is extracted as an edge of a hole around the neck of the clothing. On the other hand, an edge having a direction of 80 to 95 [deg] is extracted as an edge of the hanger bottom. After that, observing both extracted edges and judging the present condition of the hanger according to the relation between the edge of the bottom of the hanger and the edge of the hole around the neck of the clothing. That is,

1) If the bottom of the hanger completely separetes the extracted edge, the hanger is present in front of the clothing.
2) If the bottom of the hanger separates only a part of the extracted edge, the hanger is present in the clothing.
3) If the bottom of the hanger does not break the extracted edge at all, the hanger will be on the back of the clothing.

In this classification, depending on the state of the neck around the garment, it may be difficult to determine the state of being lowered to the back side and the state of being placed in the clothing. However, in that case, when the robot starts the action to pull the nape of the neck afterwards, it will observe the change in the shape of the wrinkle of clothing during that process. If no big change is seen, it can be judged that the work has failed because the hanger was lowered to the back side.

VI. Experiments and results

A. Experimental settings

Experiments of placing a long sleeve shirt on a hanger with a dual-armed robot were carried out. The robot used was HIRO manufactured by Kawada Industries, Inc. It was a joint structure with six degrees of freedom in one arm, one degree of freedom in the waist and two degrees of freedom in the neck. The end effector was an opposed two finger hand of one finger with two joint. A Microsoft Kinect was installed on the head.

First, on the right hand of the robot, a part between the neck and shoulder of the shirt was grasped. At this time, we put the shirt so that the neck hanged in a natural state. The initial position of the left hand shall be taken at the position of $(x, y, z) = (0.5, 0.1, 0.4)$ [m] from the origin of the robot and shall not be moved thereafter. The initial posture of the right hand shall be taken at the position of $(x, y, z) = (0.5, -0.1, 0.3)$ [m] from the origin of the robot. Based on the procedure introduced in Section III, the subsequent hand trajectory was created by moving the tensile extension motion $0.07[m]$ in the y axis direction. It is assumed that the x axis in the depth direction from the origin of the robot, the y axis in the left hand direction, and the z axis in the height direction.

Fig. 4 shows snapshots of a hanging experiment. The initial posture and subsequent hand trajectory was given manually.

B. Wrinkle element detection

Fig. 5 is an example of a result of describing a shape state by detection of wrinkle elements. The left is the original image and the two images on the right are the results after processing. The processing was applied only to Region Of Interest (ROI) shown in the red frame. Since the position of the hanger visible from the robot viewpoint was known, the ROI was able to be set in advance.

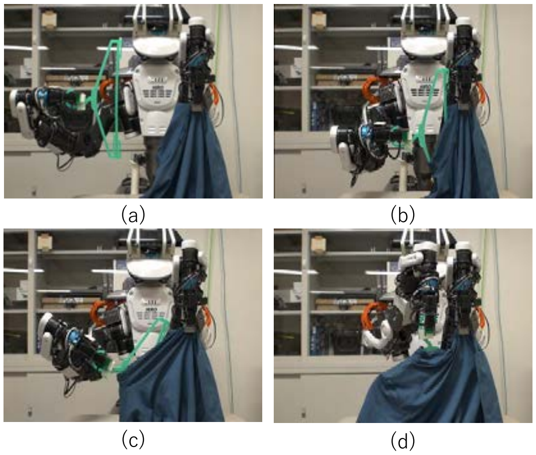

Fig. 4. Snapshots of an experiment using a dual-armed robot. (a) Before insertion, (b) Inserting one side of the hanger, (c) Pulling, (d) Inserting the other side of the hanger.

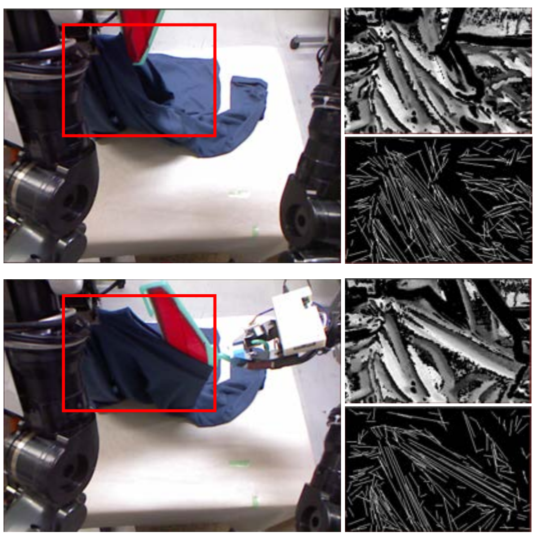

Fig. 5. State description of clothing based on wrinkle elements

The upper image shown in left column is a Maximum Orientation Image, which is an image displayed by varying the density of each pixel depending on the edge direction. The bottom row shows plotting the long axis when clustering results were elliptically approximated.

C. Recognition of hanger insertion

Regarding the discrimination method described in Section V, verification experiments were conducted to determine how accurately three states can be identified. As shown in Fig. 4 (b), when moving the hanger downward in the vertical direction, the initial posture was registered so that it would be one of the three states shown in Section V, and after the operation to lower the hanger, discrimination was made.

TABLE I

THE RESULTS OF HANGER INSERTION STATE DETERMINATION. IT WAS IDENTIFIED WITH MORE THAN 92 % ACCURACY.

		Estimation results		
		Inside	Near side	Back side
Actual state	Inside	27	0	3
	Near side	0	30	0
	Back side	4	0	26

TABLE II

THE RESULT OF STATE DETERMINATION COMBINING WITH ROBOT MOTION. BY COMBINING WITH THE MOTION OF ROBOT, MISRECOGNITION WAS REDUCED.

		Estimation results		
		Inside	Near side	Back side
Actual state	Inside	10	0	0
	Near side	0	10	0
	Back side	1	0	9

Validation was done 30 times for each of the three states.

Table I shows the results of discrimination. All cases where the hanger came to the front of the clothing were all accurately determined. Approximately three to four misjudgments occurred in the case that the hanger entered the hole and the case where the hanger came to the back of the clothes. The reason for this is as follows. The neck part of the clothing should originally look double. However, when viewed from the robot, there was a case where the cloth on the near side existed at a higher position than the cloth on the back side. That is, it can be thought that erroneous judgment has occurred because cloth on the back side can not be visually recognized.

As a countermeasure against this misjudgment, it can be considered that accurate judgment can be made by observing the change in the shape of the wrinkle in the course of starting the action of pulling the neck afterward. Therefore, in addition to the judgment method using the image visualizing the wrinkle portion described in Section IV-D, three states were re-verified ten times in each case. Table I shows the results of revalidation. It is confirmed that the judgment accuracy is improved from the above verification result although the erroneous judgment is found once in the discrimination when the hanger comes to the back of the clothing.

D. Recognition of tension state

The effectiveness of the tensile state estimation method described in III-D was verified. Fig. 6 shows an example of frequency histogram of wrinkle elements. The horizontal axis shows the angle of the wrinkle element and the vertical axis shows the frequency, and the time series data are shown divided into 4 stages. Before pulling, immediately after touching clothes, during pulling, after pulling. From this

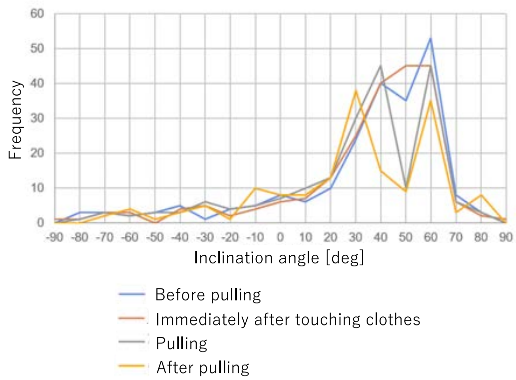

Fig. 6. Pulling state recognition during the experiment

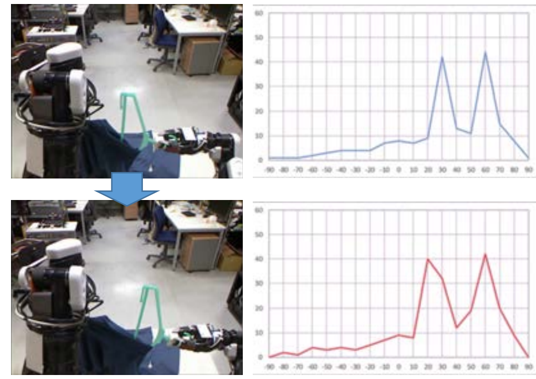

Fig. 7. Implementation of alert function for excessive pulling.

result, it can be seen that when the amount of pulling exceeds a certain level, the peak of the histogram becomes two, and as the pulling amount increases, the width between the peaks increases.

Therefore, it was decided to judge the state of excessive tension by the following method. First, a frequency value equal to or more than a certain threshold was obtained from the histogram, and it was set as the peak. If the peak becomes two and the width exceeds a predetermined threshold value, it is assumed that it exceeds the allowable amount of tension.

By this method, it became possible to prevent situations where the force of pulling is too great to disengage the hanger from the hand. Fig. 7 shows an example. As the processing up to the extraction of the wrinkle element can be implemented at about 5 fps, the shape change of the wrinkle can be observed on-line. In the case of using a force sensor, the situation is unknown unless the tension is more than a certain level, but by using the above visual processing, it was found that state recognition is possible even from a state where little force is applied.

VII. Conclusion

In this paper, we describe a sensor information processing method for manipulating stretchy cloths with the subject of hanging clothes as a theme. Focusing on changes in the wrinkles of the clothing and changes in the appearance of the hanger, we proposed methods of state description for each. In addition, we confirmed that the proposed method works effectively using image data acquired during actual hanging work by a dual-armed robot.

In the future, verification experiments are performed on various shirts, and the generality of the proposed method is confirmed. We also extend the method for various tasks using stretchy cloth.

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