Bottom Dressing by a Life-sized Humanoid Robot Provided Failure Detection and Recovery Functions

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***Abstract*— This paper describes dressing assistance by an autonomous robot. We especially focus on a dressing action that is particularly problematic for disabled people: the pulling of a bottom along the legs. To avoid injuring the subject's legs, the robot should recognize the state of the manipulated clothing. Therefore, while handling the clothing, the robot is supplied with both visual and force sensory information. Based on the them, dressing failure is detected and recovery from the failure is planned automatically. The effectiveness of the proposed approach is implemented and validated in a life-sized humanoid robot.**

I. Introduction

Dressing is an essential part of humans' daily routine. Because clothing should appropriately be changed to suit the time and circumstances, we can also regard dressing is important for social activity. However, elderly individuals or those with physical disabilities frequently require assistance while dressing, placing additional burden on helpers. Automated dressing would improve the quality of life for this group of people [3].

The purpose of this study is to achieve dressing assistance by an autonomous robot. We especially focus on a dressing action that is particularly problematic for disabled people: the pulling of lower clothing items along the legs. For the purpose, the robot requires both recognition skills and manipulation skills.

In the recognition skills, clothing state estimation is a challenging issue because clothes are soft objects whose shape largely changes while manipulation. However, the robot must understand the state of fabrics to avoid injuring the subject's legs. To achieve this recognition, we take an approach that the robot mainly uses image streams capturing dressed clothing, and supplementally uses force sensors mounted on the wrists of the robot.

As the manipulation skills, the robot must create an end-effector trajectory for pulling up a bottom clothing item. Because leg length differs among individuals, the trajectory planning should be adjustable on site. To accommodate leg differences, we create a set of trajectory segments corresponding to standard leg size in advance. These trajectory segments are then fitted to the size and position of the subject's legs using depth information captured by a range camera just before dressing. Modification for the fitting is based on a statistical human model.

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Collectively, clothing state estimation and on-site trajectory modification enables failure detection and recovery function. In other words, if the estimation function detects an unforeseen situation, such as snagging of the toe on the cloth, the original trajectory alters sequence to restore the previous trouble-free condition. Once the failure is corrected, the dressing procedure continues. The effectiveness of the function was confirmed in experiments on a real humanoid robot.

This paper is organized as follows: In the next section, related work was introduced. Section III describes our approaches. Section IV describe clothing state description and estimation based on optical flow. Section V describes end-effector trajectory planning. Section VI introduce experimental results, and section VII concludes this paper.

II. Related work

A. Recognition and manipulation of a clothing item

Robotics researches concerning clothing have been widely reported in the literature [6] [9] [19] [21]. Because clothing objects are so flexible, observing their motions during manipulation is essential.

Ono et al. [17] estimated the state of a rectangular cloth from its contour information. Knowledge was provided as groups of planar states, some with bent corners. Other researches have used silhouette information to estimate the state of an item of cloth hung by a robot [12] [18]. As more general approach, three-dimensional databases created by a physical engine were used. Kita et al. [8] fitted the three-dimensional cloth model to a three-dimensional point cloud capturing a hanged clothing. Maitin-Shepard et al. [12] proposed action selection for manipulating deformable planar objects. Implementing a physical model, they achieved the straightening of a square-shaped cloth by a robot. Recently, Doumanoglou et al. [2] succeeded to recognize clothing type and shape using a 3D range camera while unfolding. Their framework was also provide a next grasping point.

These previous studies assumed static conditions of the cloth during the recognition process; thus, clothing manipulation must be stopped to apply above-mentioned methods. Another problem is processing time for state estimation; e.g. a single estimation required several tens of seconds [14]. For practical application, the efficiency of state estimation must be markedly improved.

To overcome the issue, we proposed a clothing estimation method based on optical flow [22]. The input of the method is an image stream that captures the progress of the dressing action. It outputs whether clothing state is in a successful

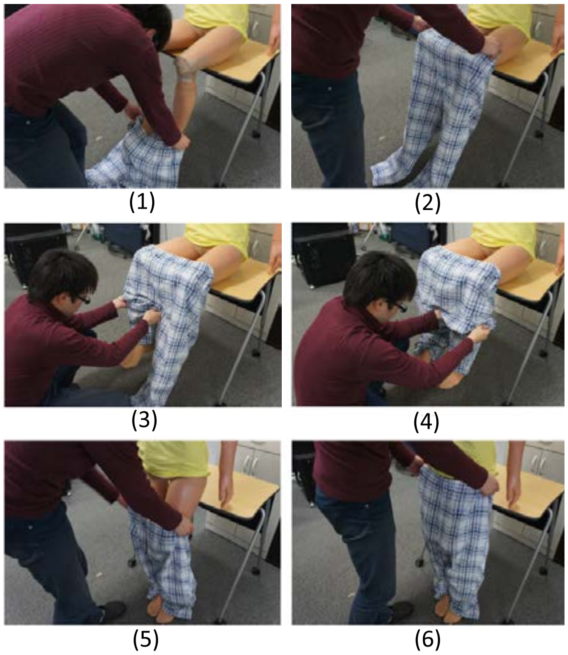

Fig. 1. Dressing sequence assumed in this study

situation or not, and if in failure, what type it is. In this study, we use this method to achieve on site clothing state estimation.

B. Dressing assistance by an automated machine

Unfortunately, dressing assistance has received slight attention in robotics research. Among the few relevant studies, Matsubara et al. [13] proposed the reinforcement learning of t-shirt dressing. They found a feasible end-effector trajectory after dozens of wearing trials. Several machines that provide daily assistance relevant to clothing have also been developed. To operate the toilet support machine, the subject needs to only stand at the center of the machine, and the bottom clothing item is manipulated by robot arms equipped with custom-designed actuators.

Dressing actions by these robotic systems are based on grasping points and motion trajectories. Manipulation failures during dressing are not considered, and recognition functions that provide information about the dressing state are lacking. However, these functions are crucial in practical application because of the difficulty in controlling the fluid motions of clothing.

III. Issues and approaches

A. Assumed dressing procedure

The purpose of this study is to dress a person seated on a bedside. The person is presumed to possess partial control over his limbs. Under the assumption, the dressing task is divided into several phases. Fig. 1 shows the sequence of dressing: (i) insert both toes into the bottom (Fig. 1, (1)), (ii) pull the item up to cover the knees (Fig. 1, (2)), (iii) pull up the dangling hem on one side (Fig 1, (3)), (iv) repeat (iii) for the other side (Fig. 1, (4)), and (v) pull the item over the hips (Fig. 1, (5) and (6)). In this study, the robot performs motion sequences (i)-(iv).

B. Approach to dressing

During the dressing action outlined above, there are possibilities to have several undesirable situations. For example, the feet may snag on the cloth, or a leg may not enter the desired hole. To avoid these undesirable situations, the progress of the dressing action should be monitored by external sensors.

We summarize our approach by the following three articles.

(A) Estimating the clothing state by an online process: Clothing state estimation is imposed to decide whether the present clothing state is appropriate to the dressing process. In such a purpose, we require only the irregular region of the fabric, i.e., the entire clothing shape is not needed. As another point, online performance is essential for realizing a practical robotic application. For the reasons, we use two-dimensional optical flow calculated from image streams that capture the dynamics of the manipulated clothing.

To construct prior knowledge, a series of optical flows measured from various dressing patterns are preregistered, and labeled according to their dressing phase. In the state estimation process, the current optical flow is compared with the registered optical flow, and represented by the label of the most similar flow in the registry.

(B) Estimating the shape and pose of the subject's legs: The subject's legs are an important recognition target because their size and pose varies among individuals and situations. If the legs are not recognized, the dressing action is more likely to fail. Thus, the identification of the subject's legs is needed.

A point cloud data generated by a 3D range image sensor is used for the identification. Before dressing, the robot measures the size and pose of the legs, and then line segments representing leg's parts are extracted. The leg size and pose is estimated from the lengths, inclinations, and the positions of these lines. Because this identification provides the shape of parts not facing the sensor (e.g., heel position), it is based on statistical frame data archived in a public database.

(C) Creating the trajectory of the end-effector: Once the subject's legs have been recognized, the end-effector trajectory of dressing should be planned. Manipulation sequence explained in Fig.1 must be managed by a set of end-effector trajectories that switch the grasping points of the fabric. The trajectories should also be adaptable to different clothing items and leg states.

One method to avoid otiose dressing failure such as getting a bottom hung up, to plan a trajectory that enables to tangle-free clothing handling is important. In our approach, a basic trajectory is empirically defined in advance. The trajectory is a good record with dressing to legs shape of a particular subject. If the robot dresses a bottom into another person, end-effector trajectory is created by modifying the basic trajectory.

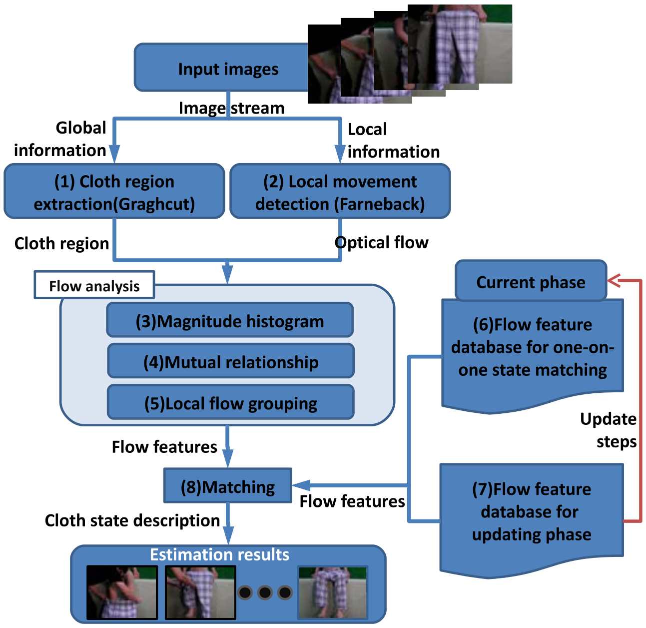

Fig. 2. A framework of the estimation of dressing clothes [22]

In addition to above three articles, we also cope with the correction of dressing failures. Failures are detected by force sensors and a vision function. The vision function returns the type of failure, which can be evaluated and canceled by the next end-effector trajectory.

IV. Clothing state estimation from image sequence

Our previous work, a clothing estimation method [22] was proposed. In this section, the method is introduced. The input is an image stream that captures the progress of the dressing action.

A. Framework overview

Fig. 2 is a flowchart of the method. The major procedures are outlined below:

Preprocessing (Fig. 2(1), (2)): First, each image in an input image stream is divided into cloth and background regions. The optical flow is calculated in the cloth region. Thus, the cloth states are extracted as a set of tiny local movements.

Feature extraction (Fig. 2(3), (4), (5)): Because cloth is very flexible, the flow transition is nonuniform. To represent the variety of cloth movement, three features are calculated. These are introduced in next subsection.

Database (Fig. 2 (6), (7)): The database is generated from image streams that capture several dressing patterns. A consecutive set of optical flows is calculated from each image stream, flow features are calculated, and then they are added to the database.

State matching (Fig. 2 (8)): The current state is estimated by searching for a matching optical flow in the database. If a failure is found, the type of failure is also identified.

B. Feature descriptors

To describe clothing state, three features are calculated from a pair of images.

Flow magnitude $\mathbf{f}_m$: The global motion characteristics of a piece of fabric can be expressed by the magnitude of the flows. After removing flows whose magnitude is excessively large or small, the remaining flows are normalized by their average magnitude. $\mathbf{f}_m$ is generated by calculating the density histogram of them.

Mutual relationship between flow pairs $\mathbf{f}_r$: Two flows are selected, and a mutual relationship between them is calculated. It is performed for many randomly sampled flow pairs, and the results are voted into the three dimensional parameter space to generate a frequency histogram. This description is inspired by the Surflet Pair Relation Histogram proposed by Wahl et al [20].

Local flow movement $\mathbf{f}_l$: To generate a feature describing partial movement of the cloth, only regions of dense flows are selected. $\mathbf{f}_l$ is generated by calculating the relationships between the central position of the cloth and that of the dense flows.

C. Clothing state estimation

There are three kinds of estimation targets that describe clothing state: (i) Dressing clothes is in success or in failure, (ii) if in success, which state it is in the present, or (iii) if in failure, what kind of failure it is.

Using flow database described in Section IV-A, the estimation of dressing clothes is achieved by searching features that is the most similar to features calculated from current image pairs. Let $\mathbf{F} = \{\mathbf{F}_m, \mathbf{F}_r, \mathbf{F}_l\}$ be a feature set calculated from an image stream , and let each $\mathbf{F}_*$ be a time-series feature set, for instance, $\mathbf{F}_m = \{\mathbf{f}_m^1, \mathbf{f}_m^2, \cdots, \mathbf{f}_m^T\}$, where T denotes a serial number of clock time, and each $\mathbf{f}_m$ comprises a feature calculated from a pair of images.

We express the similarity as follows:

$$P_{s_k} = \prod_{i=\{m,r,l\}} dist(\mathbf{F}_i, \mathbf{F}_i^{s_k}), \qquad (1)$$

where P_{s_k} represents the similarity with state s_k in the database. A matching result is a result that shows the smallest value in the Eq. (1).

Let k be a serial number of phases, and $\mathbf{s}_k$ be a group of state s_k^t, which we try to represent by using three features $\mathbf{f}_m^t$, $\mathbf{f}_r^t$ and $\mathbf{f}_l^t$. $\mathbf{s}_k = \{s_k^t, \cdots, s_k^{t+1}, \cdots, s_k^{t+a}\}$ (where t is a serial number of clock time, and a is positive number). If any one of s_k^* included in $\mathbf{s}_k$ is well matched with current features, the current phase is estimated as k. The $dist$ function varies by feature type. Hellinger distance [1] is applied for $\mathbf{F}_m$. Meanwhile, Euclidean distance is used for $\mathbf{F}_r$ and $\mathbf{F}_l$.

For improving the effectiveness and robustness of state matching, we bring in a state transition model. The transition model is based on dressing phases. For instance, if the present phase describes a situation where both legs are inserted into a bottom clothing item that is pulled up by both hands, the next phase can be limited to a manipulation that

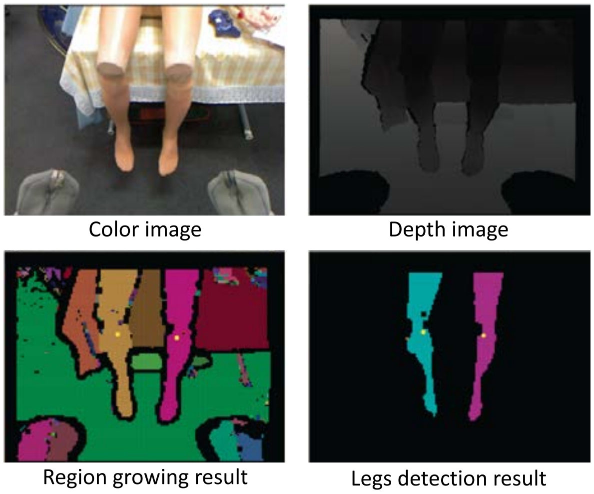

Fig. 3. An example of legs detection. Upper left and right images: color image and depth image captured from Xtion sensor. Lower left: a region growing result. Pixels with same color represent that they belong same cluster. Lower right: a legs detection result. Two clusters regarded as legs are extracted using the region growing result. Yellow points show the gravity center of each cluster.

inserts one foot into the bottom. If such a transition is not detected, the present manipulation is regarded as a failure.

V. Online dressing motion generation for a dual-arm robot

Our approach assumes a basic end-effector trajectory, and it adaptively modifies this trajectory to fit individual subjects. This section explains how the state of the subject's legs is measured, and introduces a strategy for modifying the end-effector trajectory.

A. The estimation of joint positions of legs

The state of the legs is evaluated from images acquired by a three-dimensional range camera, Xtion PRO LIVE. Immediately before the dressing action, the robot stands ahead of the subject and acquires a depth image of the two legs. The subject's legs captured by the sensor and the preprocessing result are shown in Fig. 3.

1) Legs extraction by the region growing algorithm: To extract two legs from the depth image, region growing algorithm is applied. In the algorithm, an initial point $\mathbf{p}_0$ is first given, neighboring points whose similarity to $\mathbf{p}_0$ exceeds the predefined threshold are selected as homologous points. Our similarity measure is calculated by the angular difference between the normal to $\mathbf{p}_0$ and that of a neighboring point.

Normal vectors are first calculated from the depth image. Let the pixel of interest be p. The depth value of p and that of its neighbors are collected, and then the positional average and covariance matrix are calculated from these points. After that, the directions and lengths of three orthogonal axes are obtained by eigenvalue decomposition. The normal vector is the axis of shortest length among the three axes. Thus, each pixel is assigned four variables, i.e., depth d, and the components of a normal vector $\mathbf{n} = (n_x, n_y, n_z)$.

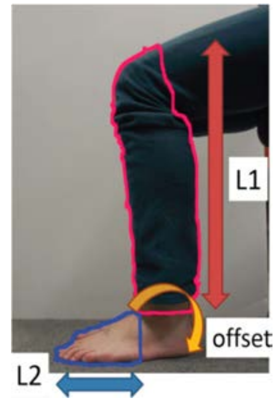

Fig. 4. Three parameters to estimate a shape of a leg

In the region growing algorithm, pixels are connected if they satisfy the following rule:

$$\begin{array}{ll} |d(i,j) - d(i+n, j+m)| & < d_{threshold}, \\ cos^{-1}(\mathbf{n}(i,j) \cdot \mathbf{n}(i+n, j+m)) & > \theta_{threshold}, \end{array} \quad (2)$$

where (i,j) denotes a coordinate on the present depth image and $(i+n, j+m)$ are the coordinates of its neighbors. $(\cdot)$ denotes the inner product.

An example of legs detection by this procedure is shown in the lower left panel of Fig. 3. Each colored region indicates one cluster, and the legs are revealed as two long regions of contiguous clusters.

2) Estimating the joint positions: The two leg regions extracted by the region growing algorithm are obtained as a three-dimensional point cloud. The next step is to estimate two characteristic parts, i.e., knee joint and ankle. Both parts provide essential information for modifying the end-effector trajectory. First, a point cloud corresponding to a leg is divided into two sections by the kneecap, which is characterized by a large bend when the subject sits on a chair or bedside. The region growing algorithm is repeated on this point cloud for a smaller $\theta_{threshold}$ in Eq. (2). This step separates the thigh part from other lower parts.

Note that further division between the knee and toe is unstable because these parts are joined by a gradual curve. In addition, the angle made by the ankle joint depends on situation and individual posture; thus, these regions will not be well modeled by the result of a region growing algorithm with a static threshold.

To overcome this problem, we use statistical human body data [23]. The point cloud of a leg is divided into two parts by second region growing as described above. The lower point cloud comprises the shin and the toe. The length proportion between the two parts, from the kneecap to the ankle and from the ankle to the toe, is assumed as a human anatomical attribute and is retained constant. Similarly, the distance between the ankle joint and heel follows anatomical proportions. Consequently, we represent the leg model by three variables, as shown in Fig. 4. Based on the leg dimensions of average men and women, we set $L_1 = 430.5mm$ and $L_2 = 141.3mm$. The position of

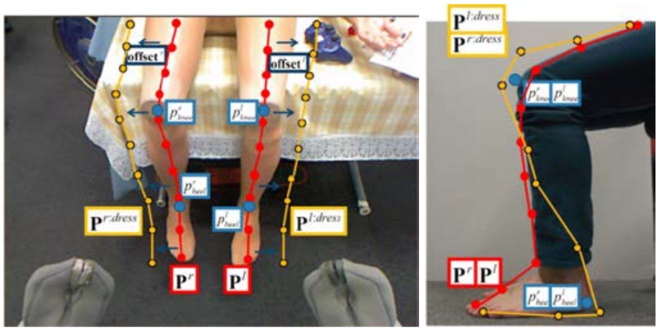

Fig. 5. Waypoint generation. First, two point lists $\mathbf{P}^r$ and $\mathbf{P}^l$ are defined on leg point clouds resulted by region growing. p^r_{knee} and p^l_{knee} are also detected on the point clouds, and p^r_{heel} and p^l_{heel} are decided using statistical human body data. From them, end-effector trajectory represented by two sets of waypoints $\mathbf{P}^{r:dress}$ and $\mathbf{P}^{l:dress}$ are created.

Fig. 6. Three types of bottom used for experiments of dressing clothing.

the ankle joint, which divides the point cloud beneath the kneecap into two sections, is calculated from the ratio of L_1 to L_2. In addition, the ankle joint position determines the heel position. In Fig. 4, the $Offset$ was set to $100.0mm$ based on statistical data.

B. End-effector trajectory generation

To dress a bottom item of clothing, we must avoid failures such as snagging the legs on the cloth. Our approach defines the basic trajectory in advance, and modifies it to fit the point cloud representing the kneecap-to-toe region of the lower legs. In the modification step, ten regularly spaced anchoring points are first extracted from the point cloud. The interval between the points is $50mm$ to $100mm$, sufficient to prevent injury to the subject while correcting a snagging failure.

Let $\mathbf{P}^r$ and $\mathbf{P}^l$ be the sets of anchoring points extracted from the left and right leg, respectively. These points constitute a part of the input point cloud, and are thus unavailable for computing the end-effector trajectory. Therefore, we create new point sets $\mathbf{P}^{r:dress}$ and $\mathbf{P}^{l:dress}$ that are moved outward from $\mathbf{P}^r$ and $\mathbf{P}^l$, respectively. The relationship between the two point sets is illustrated in the left panel of Fig. 5. The yellow points indicate the waypoints of the end-effectors.

To prevent the leg parts becoming entangled with the clothes, we must consider the positions of the kneecap and heel. Let $p^{\{r,l\}}_{knee}$ and $p^{\{r,l\}}_{heel}$ be the kneecap and heel positions, respectively, where $\{r, l\}$ indicates "right, left." If a waypoint $p^{\{r,l\}:dress}$ is close to the $p^{\{r,l\}}_{knee}$ or the $p^{\{r,l\}}_{heel}$, it is shifted away from the subject body, as shown in the right panel of Fig. 5.

C. Dressing failure detection and recovery

In practical dressing actions, the end-effectors track waypoints $\mathbf{P}^{r:dress}$ and $\mathbf{P}^{l:dress}$ in sequence. During dressing, we can detect failures and recover proper actions by combining clothing state estimation with waypoint-based trajectory generation, To detect failure, force sensors also play a role the trigger of the processing of failure type identification. If inadequate force value is acquired from the sensor, a vision function explained in Section IV takes over to identify a "failure" mode in the learning database. Based on the result, the end-effector trajectory is modified for failure recovery. The modification is achieved by inserting one waypoint before the remaining waypoints. The inserted waypoint is a waypoint that was already used just before failure detection, but slightly translated left or right. The translation direction depends on the failure type. For example, if the left toe becomes caught in the crotch of the clothing item, the given end-effector trajectory is biased toward the right side. The magnitude and the direction of translation are manually defined for each failure type. Because a failed action also means that clothing must be disentwined, the failure can be resolved by repeating a past dressing action. This recovery process was validated in experiments using a real robot.

VI. Experimental results of dressing assistance

A. Settings

Three trouser pairs shown in Fig. 6 were prepared for experiments. Item (A) is constructed from stretchable fabric, which exerts high inward friction during dressing. Item (B) is composed of inelastic fabric with high inward friction, and item (C) is constructed from stretchable fabric with low inward friction.

A subject was sat on a horizontal board of height 700 mm. Dressing was performed by a life-sized humanoid robot named HRP2-JSK [16], equipped with 7 degrees of freedom (DoFs) in both arms, 2 DoFs in the torso, and 7 DoFs in both legs. The clothing state was measured by a three-dimensional range camera, Xtion Pro Live, mounted on the head of the robot. Color images and VGA sized (640 pixels $\times$ 480 pixels) depth images were captured at 30 fps. Under this setup, the robot dressed the subject in a pair of trousers.

The dressing procedure was divided into four phases: (i) insert both toes into a target bottom, (ii) pull the item up to cover the knees, (iii) put the dangling hem on one side, (iv) repeat (iii) for the other side. The robot proceeded dressing action by confirming the transition of the phases.

For dressing action, dual arm manipulation is imposed on the robot. Because the proposed method described in Section V provides only two end-effector trajectories, angles of the whole joints should be decided by inverse kinematics calculation. To achieve the calculation, foot position is first specified. Next, a waist joint of the robot was set as a

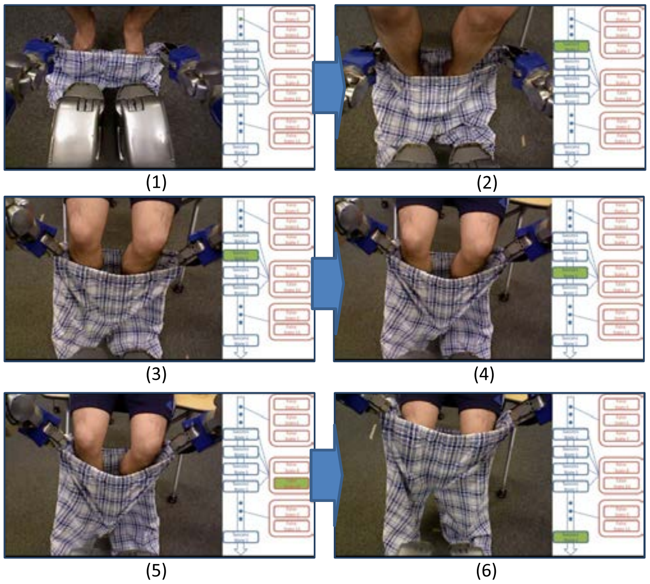

Fig. 7. Online experiment

root link, and then joint angles of two arms and two legs are calculated simultaneously. In this calculation, we must consider about several items such as joint limit avoidance, SR-inverse [15] was used for the purpose.

B. Results of bottom dressing by a life-sized robot

Fig. 7 and 8 shows the images of one dressing experiment using the life-sized humanoid robot. The images in Fig. 7, which illustrate these phases in sequence, are a part of the images captured by the Xtion sensor and the state estimation results. To the right of each image are the dressing phases ordered by temporal sequence. The green-filled blue rectangles indicate successful present phases.

Throughout the experiment, the dressing procedure was temporarily classified into failure because the trouser leg became entangled with the left toe (Fig. 7, (5)). However, the dressing motion was retried based on the estimation result. The dressing behavior continued until the trousers were pulled up over the knees.

Dozens of similar experiments were performed with three bottom clothing items. The results are summarized in Table I. Although the legs frequently became snagged in parts of the cloth, our implement function detected the failure in almost all cases. After detection, the failure states were resolved by the recovery action . In these experiments, "success" was achieved when the robot pulled the bottom item over the subject's knees. The success rate of 30 trials was 83%.

As shown in Table I, the number of successes was rather low for item (A), constructed from highly stretchable fabric exerting high friction during the dressing procedure. Recovery action was impeded by the combination of elasticity and high inward friction. Despite the high number of recovery motions, the robot could not proceed with the dressing procedure.

TABLE I
THE SUCCESS RATE OF DRESSING A BOTTOM

Clothing type	Subject type	No. of hanging up	No. of success
A	Mannequin	5	3
	Human	3	4
B	Mannequin	2	4
	Human	2	5
C	Mannequin	5	4
	Human	1	5

VII. CONCLUSIONS

In this paper, we reported about dressing assistance by a life-sized humanoid robot. We focused on the actions by which the robot can pull a bottom clothing item along the subject's legs. To avoid injuring the subject's legs during dressing, we decided that dressing failures were best detected by vision sensing, and could be predicted from the behavior of optical flows extracted from image streams.

To demonstrate the applicability of the method, we implemented the dressing procedure in a life-sized humanoid robot. Estimating the shape of the legs from images captured by a three-dimensional range camera, we proposed a method of modifying the trajectory from the basic trajectory estimated from statistical human body data. Programmed with the proposed methods, the robot performed trouser dressing of human-like subjects with a success rate of 83 %.

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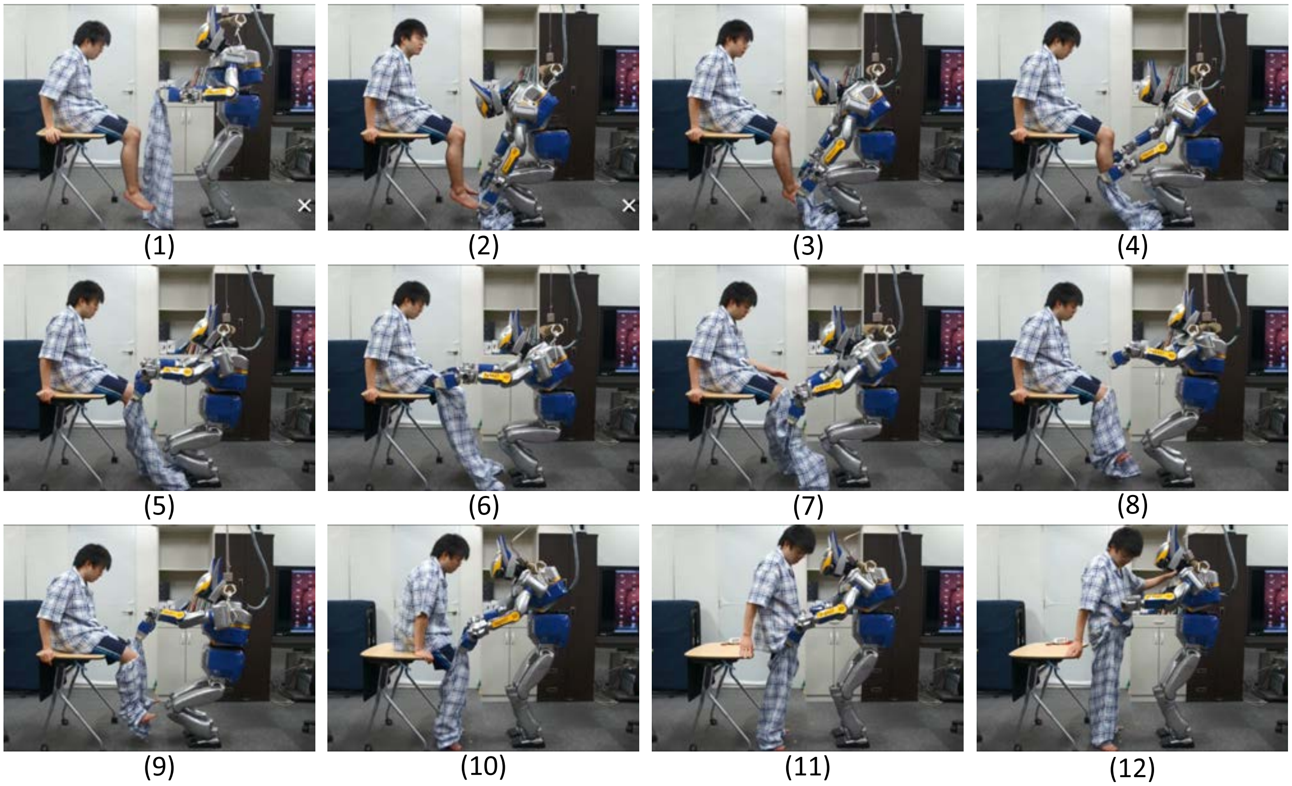

Fig. 8. A dressing experiment by a life-sized humanoid robot. The procedure was: (i) pass both toes into a bottom (figures (1) to (4)), (ii) pull up the bottom until over knees (figures (4) to (6)), (iii) pull up a hanging down hem of the bottom on one side (figures (7) and (8)), (iv) pull up another side of hem (figures (9) and (10)), (v) pull up the bottom over a hip (figures (10) to (12)).

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