Robust Manipulation of Deformable Objects Using Model Based Technique

Takahiro Wada[1], Shinichi Hirai[2], Hiroshige Mori[2], and Sadao Kawamura[2]

[1] Kagawa University, Faculty of Engineering,
2217-20, Hayashi-cho, Takamatsu, 761-0396, Kagawa, Japan
wachan@robot.club.ne.jp
http://www.eng.kagawa-u.ac.jp/~wada/
[2] Ritsumeikan University, Department of Robotics,
1-1-1, Noji-higashi, Kusatsu, 525-8577, Shiga, Japan
{hirai, rm141954, kawamura}@se.ritsumei.ac.jp

Abstract. Manipulation of deformable objects will be discussed. Manipulation of deformable objects is defined as controlling deformation of objects as well as their positions and orientations. The manipulation is a fundamental and important task in many industrial fields. In fact, there exist many operations of deformable objects such as textile fabrics, rubber parts, paper sheets, strings, and foods. In order to realize the manipulation of deformable objects by mechanical systems, an object model is indispensable. It is, however, difficult to build exact model of the deformable objects due to their strong nonlinearity such as friction, hysteresis and parameter variations. Thus, such operations strongly depend on skilled human workers. To overcome this problem, we will propose a robust control strategy using a model based technique. We will build a coarse model of an object for the manipulation and will develop a control method robust to the discrepancy between the object and its model. Experimental results will show the robustness of the proposed method.

1 Introduction

There exist many manipulative tasks that deal with deformable objects such as textile fabrics, rubber parts, paper sheets, and food products. Most these operations strongly depend on skilled human workers. We define manipulation of deformable objects as controlling of deformation of deformable objects as well as their positions and orientations in this paper. For example, a positioning operation called *linking* is involved in the manufacturing of seamless knitted products [1]. In linking of fabrics, knitted loops at the end of a fabric must be matched to those of another fabric so that the two fabrics can be sewed seamlessly. This operation is now done by skillful humans and automatic linking is required in manufacturing of knitted products. In this research, we describe the manipulations of deformable objects including linking by positioning of multiple points on the objects. Then, we regard the manipulations as the operations in which multiple points on a deformable object should be guided to the final locations simultaneously as shown in Fig.1. In many cases these points cannot be, however, manipulated directly. Thus, the guidance of positioned points must be performed by controlling some points except the positioned points. This operation is referred to as *indirect simultaneous positioning* [2]. In this paper, we will focus on indirect simultaneous positioning as an example of manipulation of deformable objects.

Some researches on manipulations of deformable objects have been conducted. For automated manufacturing of textile fabrics, many researches have been done [3]. Ono et al. [4] have derived a strategy for unfolding a fabric piece based on cooperative sensing of touch and vision. In these researches, since their approaches are for a specific task, thus it is difficult to apply the results to other different tasks with a systematic manner. In addition, some researches have tried to deal with on more general deformable object with systematic manners as follows. Hirai et al. [5] have proposed a method for modeling linear objects based on their potential energy and analyzed their static deformation. Wakamatsu et al. [6] have analyzed grasping of deformable objects and introduced bounded force closure. Their approach is static, control of manipulative operations is out of consideration. Howard et al. [7] have proposed a method to model elastic objects by the connections of springs and dampers. A method to estimate the coefficients of the springs and dampers has been developed by recursive learning method for grasping. This study has focused on model building. Thus, control problems for manipulative operations have not been investigated. Sun et al. [8] have studied on the positioning operation of deformable objects using two manipulators. They have focused on the control of the object position while deformation control is not discussed.

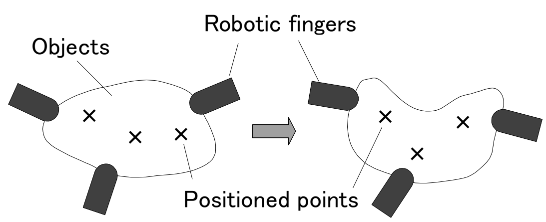


Fig. 1. Indirect positioning of deformable object

In order to realize indirect simultaneous positioning, object model is indispensable. However, it is difficult to build exact model of the deformable objects in general due to nonlinear elasticity, friction, hysteresis, parameter variations, and other uncertainties. These are main difficulties in manipulating deformable objects. To solve this dilemma, we propose to utilize a coarse object model to derive task strategies with a vision sensor. In our approach, we first build a coarse model of a manipulated object. Then, the task is analyzed based on the proposed coarse model. One of the advantages using the coarse object model is that we can analyze the task and may realize its essence relatively easily. Based on the results of the analysis, we can derive a control law robust to discrepancy between the object and its coarse model.

In this article, we will firstly propose a coarse model of deformable objects. Next, indirect positioning will be analyzed based on the coarse model. As the result, we will derive conditions to examine whether the given positioning is feasible or not. Then, we will propose a control method robust to model errors based on the coarse model. Experimental results show the validity of the proposed method and the effects of the parameter errors on the convergence.

2 Formulation of Indirect Positioning

2.1 Modeling of Extensible Deformable Objects

First of all, a model of deformable objects is proposed. On modelling of deformable objects, many researches have been conducted. For example in the area of computer graphics, cloth deformation is animated by Terzopoulos [9] or Louchet, Provot and Crochemore [10] and other many researchers. Our research goal is to realize robust manipulation of deformable objects. Therefore, we employ more simple deformation model. We model the object by connection of simple springs similar with Naster and Ayache [11]. For simplicity, we deal with two dimensional deformable objects such as textile fabrics. We discretize the object by mesh points. Each mesh point is connected by vertical, horizontal, and diagonal springs as shown in Fig.2. In the model, we assume that the object deforms in a two-dimensional plane. In order to formulate the manipulation of deformable objects, object model must have the ability to describe translation, orientation, and deformation of the object simultaneously. Thus, position vector of the mesh points is utilized. Position vector of the (i, j)-th mesh point is defined as $\boldsymbol{p}_{i,j} = [x_{i,j}, y_{i,j}]^{\mathrm{T}}$ $(i = 0, \cdots, M; j = 0, \cdots, N)$. Coefficients k_x, k_y, k_θ are spring constants of horizontal, vertical, and diagonal springs. Assume that no moment exert on each mesh point. Then, the resultant force exerted on mesh point $\boldsymbol{p}_{i,j}$ can be described as eq.(1).

$$\boldsymbol{F}_{i,j} = \sum_{k=1}^{8} \boldsymbol{F}_{i,j}^{k} = -\frac{\partial U}{\partial \boldsymbol{p}_{i,j}} \tag{1}$$

U denotes whole potential energy of the object. Then, function U can be calculated by sum of all energies of springs [2]. Here, we assume that the shape of the object is dominated by eq.(1). Then, we can calculate the deformation of the object by solving eq.(1) under given constraints. Note that the following discussions are valid even if the object has an arbitrary three-dimensional shape by modeling the object similarly. Details have been reported in [2].

2.2 Problem Description

Here, we classify mesh points $\boldsymbol{p}_{i,j}$ into the following three categories(see Fig.4) in order to formulate indirect simultaneous positioning.

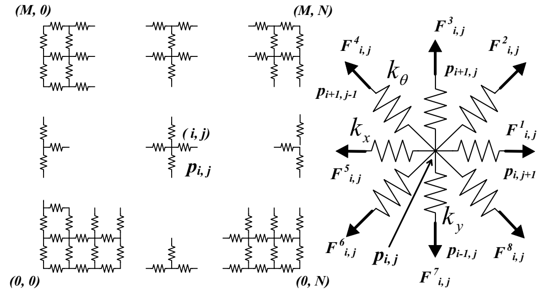


Fig. 2. Spring model of deformable object

manipulated points: are defined as the points that can be manipulated directly by robotic fingers. (Δ)

positioned points: are defined as the points that should be positioned indirectly by controlling manipulated points appropriately. ($\bigcirc$)

non-target points: are defined as the all points except the above two points. (others in Fig.4)

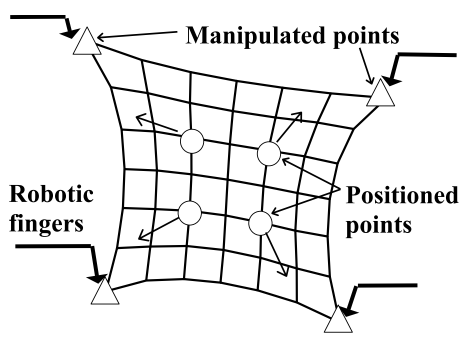


Fig. 3. Classification of mesh point

Let the number of manipulated points and of positioned points be m and p, respectively. The number of non-target points is $n = (M+1) \times (N+1) - m - p$. Then, $\boldsymbol{r}_m$ is defined as a vector that consists of coordinate values of the manipulated points. Vectors $\boldsymbol{r}_p$ and $\boldsymbol{r}_n$ are also defined for positioned and non-target points in the similar way. Eq.(1) can be rewritten as eqs.(2),(3) using $\boldsymbol{r}_m$, $\boldsymbol{r}_p$, and $\boldsymbol{r}_n$.

$$\frac{\partial U(\boldsymbol{r}_m, \boldsymbol{r}_n, \boldsymbol{r}_p)}{\partial \boldsymbol{r}_m} - \boldsymbol{\lambda} = \mathbf{0}, \tag{2}$$

$$\begin{bmatrix} \frac{\partial U(\boldsymbol{r}_m,\boldsymbol{r}_n,\boldsymbol{r}_p)}{\partial \boldsymbol{r}_p} \\ \frac{\partial U(\boldsymbol{r}_m,\boldsymbol{r}_n,\boldsymbol{r}_p)}{\partial \boldsymbol{r}_n} \end{bmatrix} = \mathbf{0} \tag{3}$$

where a vector $\boldsymbol{\lambda}$ denotes a set of forces exerted on the object at the manipulated points $\boldsymbol{r}_m$ by robotic fingers.

Note that the external forces $\boldsymbol{\lambda}$ can appear only in eq.(2), not in eq.(3). This implies that no external forces are exerted on positioned points and non-target points. These equations represent characteristics of indirect simultaneous positioning of deformable objects.

Let us consider the following task:

[Task] *Assume that the configuration of robotic fingers and the positioned points on an object are given in advance. Then, the positioned points $\boldsymbol{r}_p$ are guided to their desired location $\boldsymbol{r}_p^d$ by controlling manipulated points $\boldsymbol{r}_m$ appropriately.*

In order to realize the given task, an object model is indispensable since we have to predict directions of displacements of positioned points during the positioning. Then, the proposed model is useful for this purpose. However, in general, the model errors cannot be ignored in modeling deformable objects due to many uncertainties. Thus, a model inversion approach is not effective. Therefore, it is important to develop a control method that is robust to the error between the object and its model.

3 Analysis of Indirect Positioning

3.1 Infinitesimal Relation among Positioned Points and Manipulated Points

In this section, we analyze indirect simultaneous positioning based on the proposed coarse model. Let us derive infinitesimal relation among positioned points and manipulated points. Now, consider a neighborhood around an equilibrium point $\boldsymbol{r}_0 = [\boldsymbol{r}_{m0}^{\mathrm{T}}, \boldsymbol{r}_{p0}^{\mathrm{T}}, \boldsymbol{r}_{n0}^{\mathrm{T}}]^{\mathrm{T}}$. We can obtain the following equation by linearlizing eq.(3) around the equilibrium point.

$$A\delta\boldsymbol{r}_m + B\delta\boldsymbol{r}_n + C\delta\boldsymbol{r}_p = 0 \tag{4}$$

where

$$A \triangleq \left. \begin{bmatrix} \frac{\partial^2 U}{\partial r_m\, \partial r_p} \\ \frac{\partial^2 U}{\partial r_m\, \partial r_n} \end{bmatrix} \right|_{r0} \in R^{(2p+2n)\times 2m},$$

$$B \triangleq \left. \begin{bmatrix} \frac{\partial^2 U}{\partial r_n\, \partial r_p} \\ \frac{\partial^2 U}{\partial r_n\, \partial r_n} \end{bmatrix} \right|_{r0} \in R^{(2p+2n)\times 2n},$$

$$C \triangleq \left. \begin{bmatrix} \frac{\partial^2 U}{\partial r_p\, \partial r_p} \\ \frac{\partial^2 U}{\partial r_p\, \partial r_n} \end{bmatrix} \right|_{r0} \in R^{(2p+2n)\times 2p}.$$

Vector $\delta \boldsymbol{r}_m$ is defined as an infinitesimal deviation of the manipulated points from their equilibrium points. Vectors $\delta \boldsymbol{r}_n$ and $\delta \boldsymbol{r}_p$ are defined in the similar way. By transforming eq.(4), eq.(5) is obtained.

$$F \begin{bmatrix} \delta \boldsymbol{r}_m \\ \delta \boldsymbol{r}_n \end{bmatrix} = -C \delta \boldsymbol{r}_p \tag{5}$$

where $F = [A \ \ B]$.

3.2 Feasibility of Indirect Positioning

We can obtain the following theorems. The proof of these theorems have been reported in [12].

Theorem 1. There exist infinitesimal displacements of manipulated points $\delta \boldsymbol{r}_m$
corresponding to arbitrary infinitesimal displacements $\delta \boldsymbol{r}_p$, if and only if,
rank$[A \ B] = 2p + 2n$ **is satisfied.**

In addition, Theorem 1 needs the following result.

Result 1 *The number of the manipulated points must be greater than or equal to that of the positioned points in order to realize any arbitrary displacement $\delta \boldsymbol{r}_p$, that is, $m \geq p$.*

In the case that the number of the manipulated points is equal to that of the positioned points, that is, $m = p$ is satisfied, Theorem 1 can be rewritten as follows:

Theorem 2. *In the case of $m = p$, there exist displacements of the manipulated points $\delta \boldsymbol{r}_m$ corresponding to any displacements of positioned points $\delta \boldsymbol{r}_p$ and these are determined uniquely, if and only if,* $\det[A \ \ B] \neq 0$.

4 Iterative Control Law of Indirect Simultaneous Positioning

In this section, we propose a novel control method to achieve an indirect simultaneous positioning. An iterative control law is derived based on a linearlized model of the object eq.(5).

In the control of indirect simultaneous positioning of deformable objects, a vision system is utilized to measure current positions of positioned points. Positions of the manipulated points can be computed from the locations of the robotic fingers because the fingers pinch an object firmly. On the other hand, it is difficult to measure positions of non-target points due to their number.

Now, let us derive an iterative control law for indirect simultaneous positioning based on linearlized equations (5). Fig.4 shows a flow of our proposed control method. Assume that the number of positioned points is equal to the number of manipulated points, that is, $m = p$. In this case, F is a square matrix. This article deals with only the case that the matrix F is non-singular during operations, for simplicity. Then, eq.(5) can be rewritten as the following two equations:

$$\delta \boldsymbol{r}_m = -S_U F^{-1} C \delta \boldsymbol{r}_p \tag{6}$$

$$\delta \boldsymbol{r}_n = -S_L F^{-1} C \delta \boldsymbol{r}_p \tag{7}$$

where $S_U = [I_m \quad 0_{m\times n}] \quad S_L = [0_{n\times m} \quad I_n]$. Let $\boldsymbol{r}_m^k$, $\boldsymbol{r}_n^k$ and $\boldsymbol{r}_p^k$ be positions of manipulated points, those of non-target points, and those of positioned points at k-th iteration, respectively. In eq.(6), replacing deviation $\delta \boldsymbol{r}_m$ with difference ${}^d\boldsymbol{r}_m^{k+1} - \boldsymbol{r}_m^k$ and deviation $\delta \boldsymbol{r}_p$ with error $\boldsymbol{r}_p^d - \boldsymbol{r}_p^k$, we obtain the following equation:

$${}^d\boldsymbol{r}_m^{k+1} = \boldsymbol{r}_m^k - dS_U F_k^{-1} C_k (\boldsymbol{r}_p^d - \boldsymbol{r}_p^k) \tag{8}$$

where F_k and C_k are functions of $\boldsymbol{r}_m^k$, $\boldsymbol{r}_n^k$, and $\boldsymbol{r}_p^k$. Superscript and subscript k on variables denote their values at k-th iteration. A scalar d denotes a scaling factor. The right hand side of this equation can be evaluated at the k-th iteration. Thus, desired locations of manipulated points at the k-th iteration can be updated into those at the $(k+1)$-th iteration by this equation. Note that matrix F_k^{-1} depends not only $\boldsymbol{r}_m$ and $\boldsymbol{r}_p$ but also $\boldsymbol{r}_n$. Thus, non-target points $\boldsymbol{r}_n^k$ is estimated by eq.(9).

$$\boldsymbol{r}_n^k = \boldsymbol{r}_n^{k-1} - dS_L F_{k-1}^{-1} C_{k-1} (\boldsymbol{r}_p^{k-1} - \boldsymbol{r}_p^{k-2}) \tag{9}$$

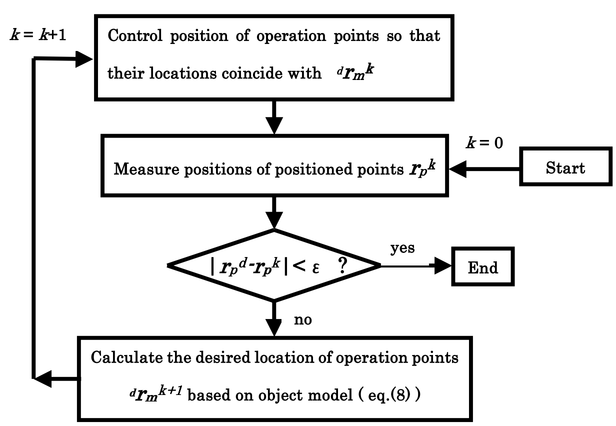


Fig. 4. Flow of proposed control method

As a result, the proposed iterative control method is summarized as follows: First, a vision system senses current positions of positioned points. Second, locations of manipulated points and those of non-target points are updated using eq.(8) and (9), respectively. Then, robot fingers are controlled with respect to task oriented coordinates using ${}^{d}\boldsymbol{r}_m^{k+1}$ as their desired positions in $(k+1)$-th iteration with an appropriate controller. For example, we can utilize linear PID feedback. After robot fingers converged to ${}^{d}\boldsymbol{r}_m^{k+1}$, positions of positioned points $\boldsymbol{r}_p^{k+1}$ are measured again by the image sensor. Then, the same procedure is iterated.

We can show that the positioned points r_p can be converged to the desired ones by control law (8) even if the model includes some errors. The details have been reported in [12].

5 Experiments

5.1 Textile Fabric

In this section, we will show experimental results in order to illustrate the validity of the proposed control method and to investigate the effect of model errors on the convergence quantitatively. Fig.5 illustrates the experimental setup. Three 2DOF robots with stepping motors are utilized as robotic fingers. A CCD camera is utilized as a vision sensor. A deformable object is laid on a table. In the experiments, knitted fabrics of the acrylic 85[%] and wool 15[%] (100[mm]×100[mm]) are utilized. The fabric is descritized into 4×4 meshes. Both of the numbers of the manipulated and positioned points are three. Their initial locations on the object are shown in Fig.6. Markers are put on the positioned points of the fabric. Their positions are measured by the CCD camera. The configurations of the manipulated and positioned points are as follows:

$$\boldsymbol{r}_m = [x_{0,3}, y_{0,3}\ ,\ \ x_{1,0}, y_{1,0}\ ,\ \ x_{3,2}, y_{3,2}]^T,$$

$$\boldsymbol{r}_p = [x_{1,1}, y_{1,1}\ ,\ \ x_{1,2}, y_{1,2}\ ,\ \ x_{2,2}, y_{2,2}]^T.$$

The desired positioned points used in the experiments are

$$\boldsymbol{r}_p^d = [30, 40,\ 65, 50,\ 53.6, 90]^{\mathrm{T}}.$$

We have identified spring constants $(k_x, k_y, k_\theta) = (4.17, 13.2, 3.32)$ [gf/mm] coarsely for the control method, through tensile tests. Note that the ratio of the spring constants is important in our control method. Then, we define $\alpha = k_x/k_\theta$ and $\beta = k_y/k_\theta$. From coarsely identified spring constants, $\alpha = 1.256$ and $\beta = 3.976$ are obtained. In experiments, various values of β including errors were utilized in the control method in order to investigate the effects of model errors. Moreover, values 0.1 and 0.5 of scaling factor d are used in eq.(8) to show the effects of the scaling factors. Fig.7-(a) and (b) illustrate the experimental results of $d = 0.1$ and 0.5, respectively.

In these figures, we can find that the positioned points can converge to the desired positions if the coefficients (α, β) is near their identified values, while they are gradually oscillatory or diverge if spring constant is far from the identified values. Fig.7-(a) shows that the positioned points converge to the desired ones

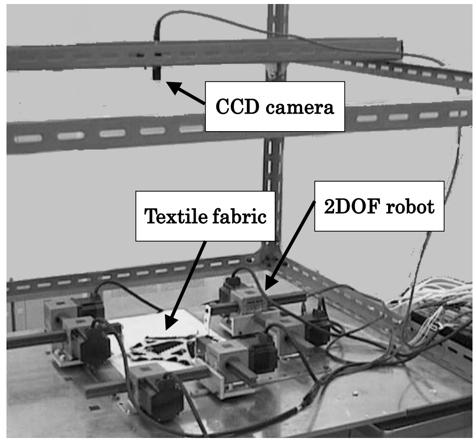


Fig. 5. Experimental setup

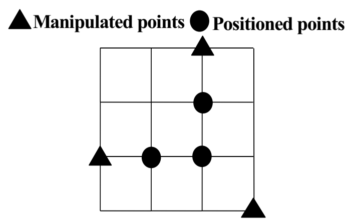


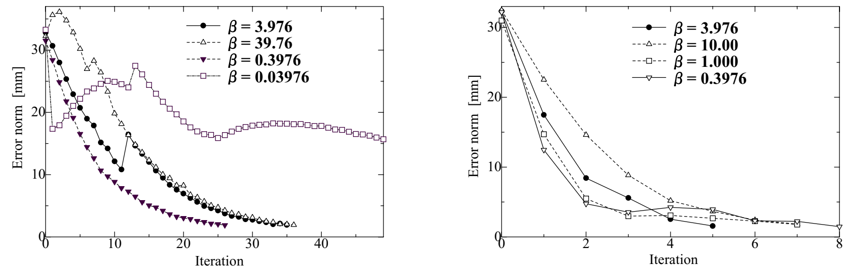
Fig. 6. Configuration of points in experiments

despite of 100 times or 0.01 times of deviations of parameters α and β. Fig.7-(b) shows that the positioned points diverge for 10 times and 0.1 times deviations of the parameters. On the other hand, the speed of convergence is higher with $d = 0.5$. As an example, Fig.8 shows behaviors of manipulated and positioned points with $d = 0.5$, $(\alpha, \beta) = (1.256, 3.976)$. The accuracy of convergence to the desired ones can be reached to a resolution level of the visual sensor (about 1[mm]).

According to the experimental results, we can conclude that very coarsely estimated parameters can be utilized in the proposed control method. Scaling factor d should be chosen carefully.

5.2 Sponge Block

In this section, we apply the proposed control method to compressing deformation of sponge blocks. In these operations, we have to consider the following items:



(a) $d = 0.1$ (b) $d = 0.5$

Fig. 7. Experimental results

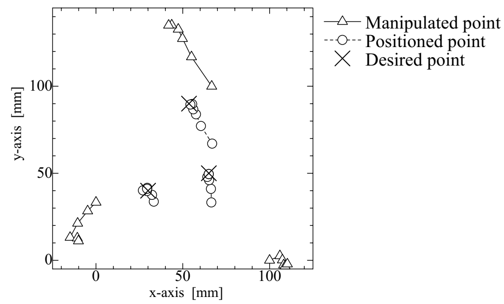


Fig. 8. Behavior of positioned and manipulated points in experiments

1. In section 5.1, the robots pinch the object firmly. In the operation of sponge blocks, we cannot pinch the objects. Thus, we have to realize manipulations with grasping the object stably. In this paper, we do not deal with this matter, and apply the same control law. We will investigate the effect experimentally with various desired locations.
2. The positions of manipulated points on the objects may change by slipping. With the proposed control method, we do not have to consider the effect in detail since our proposed method is also robust to error of the locations of manipulated points on the object. Thus, we can employ the same method.

In this experiments, sponge blocks (90[mm]×90[mm]×30[mm]) are utilized as shown in Fig.9. Suppose that we consider two-dimensional deformation in a plane, then we ignore the deformation along thickness direction. Locations of positioned points and those of manipulated points are illustrated in Fig.10. Coordinates of positioned points and those of manipulated points are given as follows:

$$\boldsymbol{r}_p = [30, 30, \ \ 60, 30, \ \ 60, 60]^T \ , \ \ \boldsymbol{r}_m = [60, 0, \ \ 0, 30, \ \ 90, 60]^T \qquad (10)$$

As shown in Fig.11, experiments performed for 6 patterns of desired positions. Desired location of each pattern is given as follows:

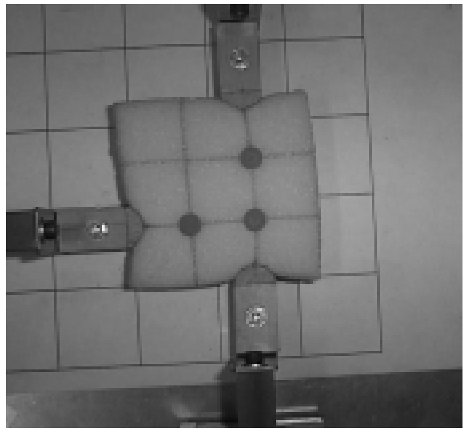


Fig. 9. Manipulation of sponge block

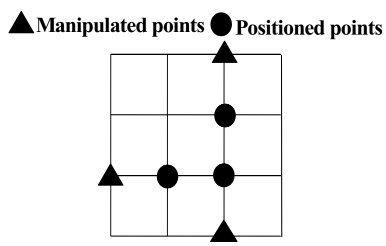


Fig. 10. Location of positioned and manipulated points

Pattern 1: $\boldsymbol{r}_p^d = [35, 30,\ 65, 30,\ 65, 60]^T$ (translation)
Pattern 2: $\boldsymbol{r}_p^d = [35, 30,\ 62, 30,\ 62, 60]^T$ (compression with translation)
Pattern 3: $\boldsymbol{r}_p^d = [32, 30,\ 65, 30,\ 65, 60]^T$ (stretching with translation)
Pattern 4: $\boldsymbol{r}_p^d = [27.6, 32.8,\ 57.2, 27.6,\ 62.4, 57.2]^T$ (rotation)
Pattern 5: $\boldsymbol{r}_p^d = [32, 32,\ 58, 32,\ 58, 58]^T$ (compression)
Pattern 6: $\boldsymbol{r}_p^d = [32.6, 37.8,\ 62.2, 32.6,\ 67.4, 62.2]^T$ (orientation and translation)

Experimental results of sponge manipulations are shown in Table 1. In the first row of each pattern, $\bigcirc$ denotes convergence with $\epsilon = 1$[mm], Δ denotes convergence with $\epsilon = 2$, and $\times$ for no convergence. Second and third rows denote the numbers of iterations that are needed for convergence within $\epsilon = 1$ and 2, respectively. Fig.12 (a) and (b) illustrate the experimental results of pattern 2 and 4, respectively.

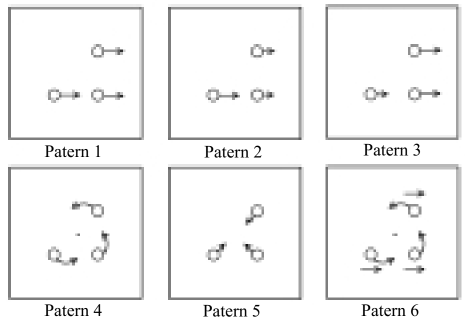


Fig. 11. Motion pattern of positioned points

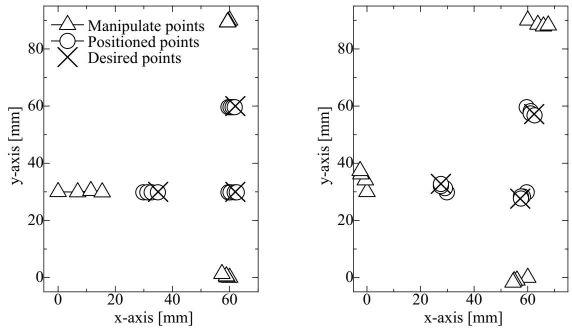
Table 1. Experimental results for sponge block

	1	2	3	4	5	6	7	8	9	10
Pattern 1	○	○	○	○	○	○	○	○	○	○
	5	9	4	10	3	4	4	5	5	4
	3	4		4				4	4	
Pattern 2	○	△	○	△	△	△	△	△	○	△
	4		16						12	
		3	4	4	3	4	3	3	4	4
Pattern 3	×	×	×	×	×	×	×	×	×	×
Pattern 4	○	○	○	○	○	○	○	○	○	○
	4	3	4	9	4	9	4	4	7	4
	3			7	3	3	3	3	3	
Pattern 5	△	△	△	△	△	△	△	○	△	△
								25		
	3	3	3	3	3	3	3	3	4	3
Pattern 6	○	○	○	○	○	○	○	○	○	○
	9	4	7	8	6	14	10	4	8	5
	4		4	4	4	5	5		5	4

According to the results, we can find that the error norm is converged within $\epsilon = 1$ in pattern 1, 4, and 6, manipulations without deformation. In pattern 2, 5 with deformation, the errors are converged in 2. One of the reasons is on accuracy of the vision sensor. In the experiments, the accuracy is 0.72[mm]. In addition, inappropriateness of the locations of manipulated points on the objects is also one of the reasons. Pattern 3 denotes the stretching operations. Thus, the manipulation is failed since the robots do not pinch the object.

6 Conclusions

In this paper, indirect simultaneous positioning of deformable objects were discussed as an example of manipulation of deformable objects. First, we have proposed a coarse model of deformable objects for their positioning operations. Second, indirect simultaneous positioning of deformable objects have been formulated. Based on the formulations, we analyzed the indirect positioning. As the result, we derived the conditions that the given positioning can be achieved. Then, we have proposed a novel iterative control method to realize indirect si-



(a)pattern2 (b)pattern4

Fig. 12. Motion of positioned and manipulated points

multaneous positioning based on the coarse object model. The validity of the method has been shown through experimental results using the textile fabrics, and effects of the model errors on the convergence were investigated. Then, we conclude that very coarse identifications can be utilized for the proposed method. In addition, we apply the proposed control method to compressing operations by grasping. In compressing operations, the error can be converged in a desired region.

In this article, initial locations of operation points on a deformable object were given before executing the manipulation. However, the task may be failed in or excessive forces may be exerted on the object in the case that the configuration of the positioned points is not appropriate. Then, task planning including configuration of operation points is important. Therefore, we need a method to plan configurations of robot fingers on a deformable object [13]. In compressing operation, it is impossible to prove that stable grasp is maintaining during manipulations in all cases since we do not take states of grasping into consideration. Therefore, we have to add information of grasping states to control law. Use of force sensor for this purpose is one of the important future works.

References

1. Wada, T., Hirai, S., Hirano, T., Kawamura, S., "Modeling of Plain Knitted Fabrics for Their Deformation Control", Proc. of IEEE Int. Conf. on Robotics and Automation, pp.1960–1965, 1997
2. Wada, T., Hirai, S., Kawamura, S., "Planning and Control of Indirect Simultaneous Positioning Operation for Deformable Objects", Proc. of IEEE Int. Conf. on Robotics and Automation, pp.2572–2577, 1999
3. Taylor, P.M. et al.(Ed.), "Sensory Robotics for the Handling of Limp Materials", Springer-Verlag, 1990
4. Ono, E., Kita, N., Sakane, S., "Strategy for Unfolding a Fabric Piece by Coorperative Sensing of Touch and Vision", Proc. of Int. Conf. on Intelligent Robots and Systems, pp.441–445, 1995

5. Hirai, S., Wakamatsu, H., and Iwata, K., "Modeling of Deformable Thin Parts for Their Manipulation", Proc. IEEE Int. Conf. on Robotics and Automation, pp.2955–2960, 1994
6. Wakamtatsu, H., Hirai, S., Iwata, K., "Static Analysis of Deformable Object Grasping Based on Bounded Force Closure", Proc. IEEE Int. Conf. on Robotics and Automation, pp.3324-3329, 1996
7. Howard, A.M. and Bekey, G.A., "Recursive Learning for Deformable Object Manipulation", Proc. of Int. Conf. on Advanced Robotics, pp.939–944, 1997.
8. Sun, D., Liu, Y., Mills, J.K., "Cooperative Control of a Two-Manipulator System Handling a General Flexible Object", Proc. of Int. Conf. on Intelligent Robots and Systems, pp.5–10, 1997
9. Terzopoulos, D., Platt, J., Barr, A., Fleischer, K., "Elastically Deformable Models", Proc. of Siggraph 87, Computer Graphics, 1987, Vol.21, No.4, pp.205–214
10. Louchet, J., Provot, X., Crochemore, D., "Evoluntionary Identification of Cloth Animation Models", Computer Animation and Simulation'95: Proc. of the Eurograpics Workshopin Maastricht, pp.44–54, 1995
11. Nastar, C. and Ayache, N., "Frequency-Based Nonrigid Motion Analysis: Application to Four Dimensional Medical Images", IEEE Trans. on Pattern Analysis and Machine Intelligence", Vol.18, No.11, pp.1067–1079, 1996
12. Wada, T., Hirai, S., Kawamura, S., "Indirect Simultaneous Positioning Operations of Extensionally Deformable Objects", Proc. of Int. Conf. on Intelligent Robots and Systems, pp.1333–1338, 1998
13. Wada, T., Hirai, S., Kawamura, S., "Analysis and Planning of Indirect Simultaneous Positioning Operation for Deformable Objects", Proc. of Int. Conf. on Advanced Robotics, pp.141–146 1999