Dexterous manipulation of objects with unknown parameters by robot hands

R.A. Hilhorst
Consyscon
Kennedylaan 47, 2324 ES Leiden
The Netherlands

K. Tanie
Mechanical Engineering Laboratory
Namiki 1-2, Tsukuba, Ibaraki 305
Japan

Abstract

Human hands can perform dexterous manipulation of objects after a small learning phase. In this learning phase we receive knowledge about the objects shape and mass/inertia by use of our visual, tactile and force sensors. Using this knowledge we can determine how to move the object accurately around a prescribed trajectory such that the object is not lost during manipulation. In this paper we will consider the problem of manipulating an object with unknown mass and inertia by a robotic hand. It will be shown by experiments that by use of knowledge about the robot hand dynamics and by incorporating an adaptive control scheme, dexterous manipulation of an object with unknown parameters can be obtained.

Keywords. Grasping, robotic hands, adaptive control.

1 Introduction

In the last decade a number of robotic hands which can perform dexterous operations like our human hand have been designed and developed. Among those designs are the 3-fingered Stanford/JPL hand [1], four fingered Utah/MIT hand [2], University of Bologna hand [3], two-fingered MEL hand [4] and three-fingered MEL hand [5]. Due to the possibility of fast and fine motion these robot hands allow us to perform various dexterous manipulation with objects, rather than be restricted to only pick and place as is nowadays performed by most industrial robots. Also in order to perform dexterous manipulation, no use has to be made of a large set of different end-effectors, each designed for a specific task.

In comparison with an object rigidly attached to the end of a robot, grasping and manipulation by a robot hand is more complicated for two reasons [6]. The kinematic relations between the finger joint motion and object motion are complicated. For instance, the type of contact can be various, friction, sliding and rolling. Furthermore, in order to manipulate the object it should be grasped firmly such that the object is not lost during manipulation but also without squeezing it.

In order to accomplish this both the kinematic design as the control of the robot hand are important. The majority of literature has dealt with kinematic design of hands and automatic generation of stable grasping configurations [7]. The control problem for the coordination of multi-robots (e.g. multi-fingered hand) also received attention for two decades. Literature shows a development towards more advanced control algorithms. Pioneering from *master/slave* approaches [8], to *coordinated motion* approaches [9] [5], we end up with *object motion* [10] [11] approaches. The first and the second approach take robot fingers as starting point of reasoning, in opposite with the object motion approach. The latter approach allows us to specify objectives directly related to the object and transform it to tasks for the fingers in a rather straightforward way. Also, dynamics of manipulator and object can be taken in account easily compared to the former two approaches. Furthermore, practical experiments performed by Schneider and Cannon [10] and Murray and Sastry [11] show that the object motion approach results in a better manipulation performance. However, it requires that knowledge of the robot hand and object is available. High performance manipulation requires knowledge about the dynamical parameters of both robot and object and about the contact point such as the friction cone. In this paper we will consider the manipulation of objects when knowledge about the *object mass* and *inertia* is lacking.

In this paper we present a scheme, which enables a robot hand to perform dexterous manipulation with unknown mass. This scheme consists of two steps. In the first step the mass of the object is estimated by using adaptive non-linear control techniques. In the second step the mass estimate is used to optimize the trajectory speed and the internal force such that the object is not lost during manipulation. In this paper the first step of this scheme has been tested on an experimental set-up of a two-finger robotic hand. The obtained results show that with the adaptation to unknown mass/inertia a better performance can be achieved than without.

This paper is organized as follows. In section 2 the equations of dynamics of robot hand and object developed by Murray and Sastry [11] are summarized. In section 3 we will describe the control objectives. In section 4 adaptive control of an unknown object is described. In section 5 the experimental results obtained with the two-fingered MEL hand are presented. Finally, in section 6 conclusions are drawn.

2 Grasp dynamics

This section provides a brief introduction to grasping and the notations used in this paper. For a more complete discussion of the kinematics of grasping see [12]. The dynamics outlined and formulation used here were developed in [11]. If the generalized position of the object center is given by X_{o} then the dynamics of a robot hand manipulating an object can be written as

$$(M_{\mathrm{h}}+M_{\mathrm{o}})\ddot{X}_{\mathrm{o}}+(C_{\mathrm{h}}+C_{\mathrm{o}})\dot{X}_{\mathrm{o}}+N_{\mathrm{h}}+N_{\mathrm{o}}+R_{\mathrm{h}}=f_{\mathrm{h}}, \quad (1)$$

where M_{h} is the inertia matrix of the robot hand, M_{o} is the object inertia matrix, C_{h} is a vector of coriolis and centrifugal forces acting on the robot hand, C_{o} is a vector of coriolis and centrifugal forces acting on the object, N_{h} is a vector of gravity terms on the robot hand, N_{o} is a vector of gravity terms on the object, R_{h} is a vector of friction terms on the robot hand, and f_{h} is a vector of applied forces applied on the center of the object. The mass matrix M_{h} and vectors C_{h}, N_{h}, R_{h} and f_{h} of the robot hand are given by

$$\begin{aligned}
M_{\mathrm{h}} &= GJ_{\mathrm{h}}^{-\mathrm{T}}M(\theta)J_{\mathrm{h}}^{-1}G^{\mathrm{T}} && (2)\\
C_{\mathrm{h}} &= GJ_{\mathrm{h}}^{-\mathrm{T}}(C(\theta,\dot{\theta})J_{\mathrm{h}}^{-1}G^{\mathrm{T}}+M(\theta)\frac{d}{dt}J_{\mathrm{h}}^{-1}G^{\mathrm{T}}) && (3)\\
N_{\mathrm{h}} &= GJ_{\mathrm{h}}^{-\mathrm{T}}N(\theta) && (4)\\
R_{\mathrm{h}} &= GJ_{\mathrm{h}}^{-\mathrm{T}}R(\theta,\dot{\theta}) && (5)\\
f_{\mathrm{h}} &= GJ_{\mathrm{h}}^{-\mathrm{T}}\tau && (6)
\end{aligned}$$

where G is the grasp matrix [1] , $J_{\mathrm{h}}^{-\mathrm{T}}$ is the inverse transpose of the hand jacobian J_{h}. The hand jacobian J_{h} is derived by stacking the jacobian matrices for each finger. In a same way the matrix M and vectors C, N, R, and τ (in joint space) are derived by stacking the corresponding terms for each finger. We assume a point contact model, i.e. that the finger coordinates, θ, are derivable from the object position, X_{o}.

In this paper we will restrict ourselves first to manipulation of the object in two-dimensional space. This implies that if we represent the position as (x,y) and orientation of the object as φ the generalized coordinate is given by $X_{\mathrm{o}}=(x,y,\varphi)$. Also the object dynamics are simplified since the object is only allowed to rotate about the axis perpendicular to the plane of motion. If the mass and inertia of the object are given as m_{o} and i_{o}, the object mass matrix M_{o} and C_{o} are given by

$$\begin{aligned}
M_{\mathrm{o}} &= \begin{bmatrix} m_{\mathrm{o}} & 0 & 0\\ 0 & m_{\mathrm{o}} & 0\\ 0 & 0 & i_{\mathrm{o}}\end{bmatrix} && (7)\\
C_{\mathrm{o}} &= 0 && (8)
\end{aligned}$$

Since there is only one axis of rotation in the planar case, the representation of the orientation of the object is particulary simple. This is the description of the hand dynamics in object coordinates.

For our purposes we have assumed that all bodies are rigid and the contacts are never broken. In this case the fingertips are constrained to move at the same speed as the contact points on the object, i.e.

$$J_{\mathrm{h}}\dot{\theta}=G^{\mathrm{T}}\dot{X}_{\mathrm{o}}, \quad (9)$$

where $J_{\mathrm{h}}\dot{\theta}$ is the vector of fingertip velocities $\dot{x}_{\mathrm{c}}^{\mathrm{h}}$ and $G^{\mathrm{T}}\dot{X}_{\mathrm{o}}$ is the velocity $\dot{x}_{\mathrm{c}}^{\mathrm{o}}$ of the contact points on the object.

3 Control objectives

Accurate manipulation of an object implies requirements on both *holding* and *tracking*. In case of holding it requires that the finger forces should be within the friction cone for each finger from the moment of grasping till the end of the manipulation. In case of tracking, it requires that the center of the object should follow a specified trajectory. Accurate tracking can be performed when a good model of the robot hand and object is available. Here, we assume that a good model of the robot hand is available before manipulation. In the following we will consider adaptive controllers which can adapt to changes in object mass/inertia based on the ideas of Slotine and Li [13] .

4 Adaptive control of object

The dynamics of an object in planar space can be written as

$$M_{\mathrm{o}}\ddot{X}_{\mathrm{o}}=f_{\mathrm{o}} \quad (10)$$

where M_{o} is given by (7) and f_{o} is equal to $[f_x,f_y,\tau_\varphi]^{\mathrm{T}}$ and X_{o} is equal to $[x,y,\varphi]^{\mathrm{T}}$. If the mass m_{o} and/or inertia i_{o} are unknown use can be of an adaptive controller, which estimates these unknowns. In literature several adaptive controllers have been reported. Slotine and Li [13] among the first proposed a non-linear controller, which results in an asymptotic tracking of a desired reference trajectory. However, this controller is not robust against noise. As robustness is important for practical application we adopt an approach as taken in [14] to obtain a robust adaptive controller.

4.1 Robust adaptive control

One way to adapt to changes in the mass/inertia of an object is to make use of the adaptive controller proposed by Berghuis et al. [14] for robotic manipulators. This controller which is robust to noise can be derived as follows. Let the control force f_{o} be given as

$$f_{\mathrm{o}}=\hat{M}_{\mathrm{o}}\ddot{X}_{\mathrm{d}}-K_{\mathrm{d}}\dot{e}-K_{\mathrm{p}}e \quad (11)$$

where $\hat{M}_O$ is an estimate of (7), K_P and K_d are symmetric positive definite matrices, and $e = X_O - X_d$. We can prove that this controller will result in an asymptotic tracking of a desired reference trajectory by taking the positive definite Lyapunov function candidate

$$V(t) = \frac{1}{2}s^{T}M_{O}s + \frac{1}{2}e^{T}(K_{P} + \lambda K_{d} - \lambda^{2}M_{O})e + \frac{1}{2}\tilde{a}^{T}\Gamma\tilde{a} \tag{12}$$

where a is a 2-dimensional vector containing the unknown mass m_O and inertia i_O of the object, $\tilde{a} = \hat{a}$ - a, and Γ is a symmetric positive definite matrix, and where s is defined as

$$s = \dot{e} + \lambda e \tag{13}$$

with λ a positive constant.

Differentiating V yields

$$\begin{aligned} \dot{V} = & \quad s^{T}M_{O}\dot{s} + e^{T}(K_{P} + \lambda K_{d} - \lambda^{2}M_{O})\dot{e} + \tilde{a}^{T}\Gamma\dot{\tilde{a}} & (14) \\ = & \quad -e^{T}(K_{d} - \lambda M_{O})\dot{e} - \lambda e^{T}K_{P}e + \tilde{a}^{T}(\Gamma\dot{\tilde{a}} + Y^{T}s) & (15) \end{aligned}$$

where we have made use of (13) and of the linearity in parameters, i.e.

$$M_{O}\ddot{e} \quad = \quad Y\tilde{a} - K_{d}\dot{e} - K_{P}e \tag{16}$$

where Y is equal to

$$\begin{bmatrix} \ddot{x}_{d} & 0 \\ \ddot{y}_{d} & 0 \\ 0 & \ddot{\varphi}_{d} \end{bmatrix} \tag{17}$$

If the gain K_d satisfies the following bound

$$K_{d} > \lambda M_{O} \tag{18}$$

and if we choose the adaptation law such that

$$\Gamma\dot{\tilde{a}} + Y^{T}s = 0 \tag{19}$$

that is

$$\dot{a} = -\Gamma^{-1}Y^{T}s \tag{20}$$

then $\dot{V} < 0$. This implies that the tracking error and velocity error between desired trajectory and real trajectory is zero. Furthermore, in case of measurement noise with zero mean no drift will occur in the estimates. Comparing the derived bound (18) with the bounds derived by Berghuis et al. [14] shows that this bound is particulary simple in the case of an object. Comparing the derived result with the adaptive controller based on the ideas of Slotine and Li, shows that the robustness property goes at the expense of a bound on the controller gain K_d.

4.2 Transformation from object to finger and vice versa

Once the manipulation force f_O has been calculated it has to be transformed to finger tip forces f_{c_i}. Furthermore, in order to compute the manipulation force f_O the object position X_O and velocity $\dot{X}_O$ have to be determined.

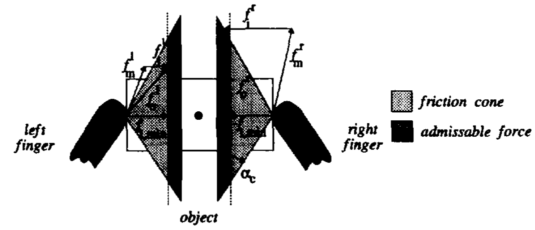

Figure 1: Determination of the internal force satisfying friction and minimum constraints.

Assuming that no direct measurement is available, the position and velocity can be derived from the measurement of joint positions and velocities. These derivations can be made by use of the generalized inverse of the grasp matrix $G^{+} = G^{T}(GG^{T})^{-1}$, i.e.

$$\begin{aligned} \dot{X}_{O} &= (G^{+})^{T}J_{h}\dot{\theta}, & (21) \\ f_{c} &= G^{+}f_{O}, & (22) \end{aligned}$$

The use of the generalized inverse of the grasp matrix G^{+} results in a solution for $\dot{X}_O$, which minimizes the least mean square error between the velocities of the contact point on the object $\dot{x}_c^{O}$ and on the fingertips $\dot{x}_c^{h}$. In case of force the use of the generalized inverse of the grasp matrix G^{+} results in a solution for f_c, which has smallest Euclidean norm [15]. Implying that there is no internal force. Hence, in order to hold the object an additional internal force f_i has to be added.

4.3 Internal force

Once the force f_O for manipulation has been calculated one has to determine an internal force f_i such that the force implied by each fingertip on the object is inside of the friction cone. One method to accomplish this is to take the internal force sufficiently large. However, this has the disadvantage that it reduces the stability of prehension, because even a small position error may cause a large disturbing force at the mass center of the object. Also large internal forces are not appropriate for holding fragile objects. Furthermore, it results in an unnecessary energy loss. Nakamura and coworkers [16] defined therefore *optimal* internal forces as the internal forces that give the minimal forces under frictional constraints. The optimal internal forces can be found by solving a non-linear programming problem. Here we will restrict ourselves to the case of a two-fingered robot hand. In order to prevent that the optimal internal force becomes too small, such that e.g. gravitational forces cause slippage in vertical direction, a constraint on the minimum force $f_{i,min}$ on both left and right finger has been added.

1. Determine for the left and right finger the force f_i^l and $f_i^r \in \mathcal{N}$ such that the finger forces on the object f_O^l and f_O^r are

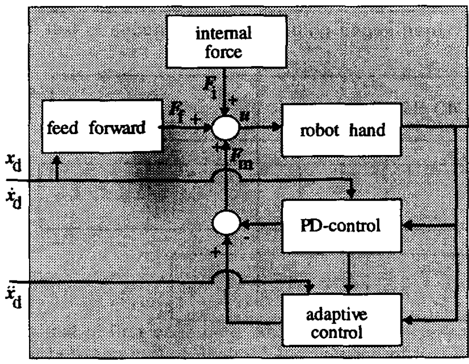

Figure 2: Overall object motion control system with feedforwarding of robothand dynamics and with adaptation to object mass/inertia parameters.

- inside of the friction cone specified by the friction cone angle f_{c_1}
- $f^l_o, -f^r_o \in \mathcal{N}$ is larger than a minimum internal force $f_{i,min}$.

2. If the internal forces generated by each finger are not equal in magnitude, then
   - determine the finger which generates the largest internal force,
   - adjust the internal force of the other finger such that it generates an internal force with same magnitude.

The procedure to find the optimal internal force is clarified by Fig. 1. In order to satisfy the constraints defined by the friction cone and minimum internal force, a force f^l_i has to be selected for the left finger and a force f^r_i for the right finger. As the right finger will generate the largest internal force the internal force generated by the left finger must be changed. This is accomplished by adjusting the force f^l_i, which will result in a changed force f^l_o on the object.

4.4 Adaptive PD-control with feedforward

In order to compensate for the dynamics of the hand, the dynamics of the hand are feedforwarded. This is performed by applying the feedforward force f_f

$$f_f = M_h \ddot{X}_d + C_h \dot{X}_d + N_h + R_h, \qquad (23)$$

where M_h, C_h, N_h and R_h are computed by use of equations (3) - (6) along the desired trajectory.

The total control system is shown in Fig. 2.

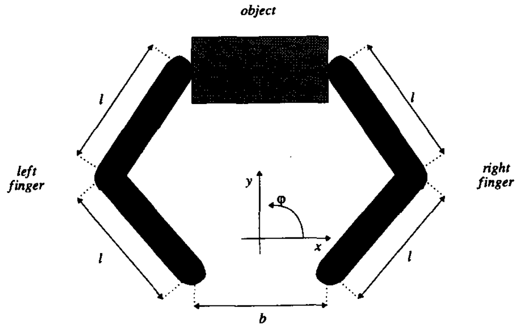

Figure 3: Schematic overview of the two-fingered MEL hand.

variable	*symbol*	*value*
Link lenghts	l	0.04m
Base separation	b	0.04m
Link mass	m	0.04kg
Joint friction	r	0.04Nms/rad

Table 1: Parameters for the two-fingered MEL hand.

5 Experiments

5.1 Experimental setup

In order to test the adaptive controller it was applied to an experimental set-up of the two-fingered Mechanical Engineering Laboratory (MEL) robot hand [4]. In Fig. 3 a schematic picture of this hand is shown. Each robot finger consists of three joints. For reasons of simplicity during the experiments only the last two joints were used. Each joint is driven by a DC-motor. The power is transmitted by use of a tendon-pulley system. The motors are capable of delivering a torque of 0.15 Nm on each joint. Furthermore, in order to compensate for losses in torque in the tendon-pulley transmission system torque sensors were located near each joint axis. By use of these torque sensors [17] a primary high gain torque control loop is closed. The position of each joint was measured by potentiometers. Each motor is equipped with a position sensor and tacho generator. As the bandwidth of the tendon transmission is high, the motor velocity measurements can be used for the determination of the joint velocity.

As a first step only viscous friction in the joints was considered. The parameter values for the two-fingered MEL hand are given in Table 1. The two-fingered MEL hand is controlled by use of a NEC-386 PC. A transputer board with 5 T800's was installed in the PC. The algorithms were written in parallel C. By use of only one transputer the execution of the full algorithm including adaptive PD control, feedforward and internal force computation could be done in a sampling period of 3ms.

variable	*symbol*	*value*
Prop. gain x	k_p^x	400N/m
Prop. gain y	k_p^y	2500N/m
Prop. gain φ	k_p^φ	4N/rad
Deriv. gain x	k_d^x	2Ns/m
Deriv. gain y	k_d^y	5Ns/m
Deriv. gain φ	k_d^φ	0.004Ns/rad
Friction cone	α_c	60^o
Internal force	$f_{i,min}$	1N
Adapt. gain mass	γ_m	10
Adapt. gain inertia	γ_i	0.0025
Adapt. gain	λ	25

Table 2: Control parameters for the two-fingered MEL hand.

5.2 Control parameters

In order to show the result of applying an adaptive controller a number of experiments was carried out. In these experiments the object center had to follow an ellipsoidal trajectory:

$$x_d = A_x sin(\omega_d t) \quad (24)$$

$$y_d = 0.06 + A_y cos(\omega_d t) \quad (25)$$

$$\varphi_d = 0 \quad (26)$$

where $A_x = 0.02$m, $A_y = 0.005$m, $\omega_d = 2\pi$rad and $0 \le t \le 10$s. This trajectory is just contained in the workspace of the robot. The range of object masses was selected between [0,0.6] kg.

Suitable control parameters were selected experimentally and are listed in Table 2. The controller gains K_p and K_d were taken diagonal, i.e. diag(k_p^x,k_p^y,k_p^φ) and diag(k_d^x,k_d^y,k_d^φ) respectively. The control gains in the planar direction were selected different. Experiments revealed that in the y-direction a higher gain could be used, probably due to the fact that the trajectory in this direction is smaller. The velocity gains used were taken small as the amount of noise on the velocity signal was relative high compared to the position signals. Due to the presence of high contact friction material at the finger tips an absolute friction cone angle α_c of 60^o could be established. In order to firmly grasp the object for the range of masses considered a minimal internal force $f_{i,min}$ of 1.0 N was sufficient. For smaller masses a smaller minimal internal force proved to be sufficient. The adaptation gain Γ=diag(γ_m,γ_i) was selected such that a fast adaptation could be obtained. Although selection of $\lambda = 25.0$ in combination with the control gains provides no stability guarantee (i.e. violation of equation (18)) it was stable in the experiments. Also, this choice was stable in simulations of the two-fingered MEL hand [18].

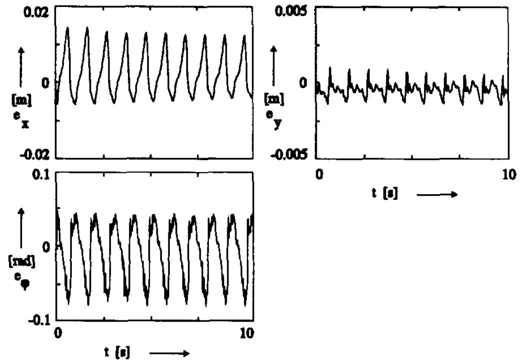

Figure 4: Experimental results obtained with PD control only.

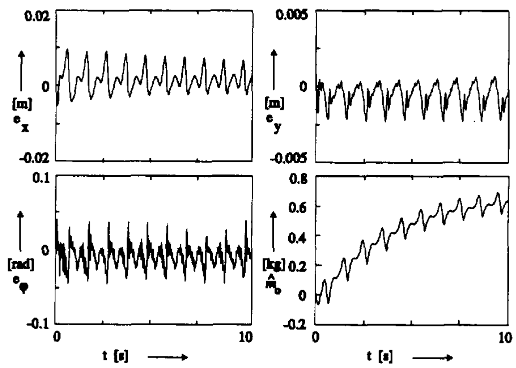

Figure 5: Experimental results obtained with *adaptation* and *feedforward* added to the PD-controller.

5.3 Experimental results

In the experiments the object to be manipulated has a mass of 0.6 kg and a length of 0.04 m. The initial value of both mass and inertia estimate were take equal to 0. In order to show the influence of adaptation and feedforward two experiments were carried out. In the first experiment a PD-controller was used. The controller parameters were taken according to Table 2. The recorded errors e_x, e_y and e_φ between desired trajectory and measured trajectory are shown in Fig. 4. In the second experiment the same PD-controller but now with it adaptation and it feedforward was used. The recorded errors and the recorded estimated object mass $\hat{m}_O$ are shown in Fig. 5.

Comparing Fig. 4 and 5 shows that with feedforward and adaptation a significant improvement in the tracking is obtained. The tracking error in x-direction and in orientation are significantly decreased at the expense of a slight increase in the error in y-direction (note the difference in the scales of the x and y-axis). The estimated mass converges to a value around the real mass value of 0.6 kg. Figure 5 shows that convergence of the mass takes about 6-8 seconds to reach its final value. Longer experiments than 10 seconds showed that the mass estimate did not diverge. The figure also shows that a vibration both in the error signals as well as in the estimated mass $\hat{m}_O$ is present. One possible reason for this is the flexibility of the tendons. In simulations where the flexibility was not taken into account, the vibration in the errors and estimated mass was not present. Increasing the adaptive gain resulted in a more dominant behaviour of the flexibility of the tendons. Hence, increasing the adaptive gain λ to obtain a faster adaptation is not possible with regard to stability.

6 Conclusions and suggestions

In this paper the dexterous manipulation of an object with unknown parameters by a robot hand was studied. It is shown that in order to obtain dexterous manipulation the dynamical parameters of both robotic hand and object are necessary. For instance, experiments showed that without proper feedforwarding of the robot hand dynamics no good control was possible. It is also shown that by use of a robust PD adaptive controller a good estimate of the mass parameter could be obtained. Hence, this makes it possible to use it in the second step of the scheme for obtaining dexterous manipulation, i.e. optimization of the trajectory speed and/or internal force.

The results show that estimation of the mass takes about 6-8 seconds. In order to obtain a faster estimation of the mass it could be considered to adopt a supervisory control approach as described in Hilhorst [19].

References

[1] J. Salisbury, *Kinematic and Force Analysis of Articulated Hands.* PhD thesis, Department of Mechanical Engineering, Stanford University, 1982.

[2] S. Jacobsen, E. Iversen, D. Knutti, R. Johnson, and K. Biggers, "Design of the utah/m.i.t. dextrous hand," in *Proceedings of the 1986 IEEE Int'l. Conf. Robotics and Automation*, pp. 1520–1532, 1986.

[3] C. Melchiorri and G. Vasurra, "Whole-hand robotic manipulation: considerations on results and open problems," in *IMACS/SICE Int'l Symp. on Robotics, Mechatronics and Manufacturing Systems*, pp. 653–660, 1992.

[4] N. Imamura, M. Kaneko, K. Yokoi, and K. Tanie, "Development of a two-fingered robot hand with compliance adjustment capability," in *USA Symposium on Flexible Automation - A Pacific Rim Conference - ISCIE, Kyoto*, pp. 997–1004, 1990.

[5] H. Maekawa, K. Yokoi, K. Tanie, M. Kaneko, N. Kimura, and N. Imamura, "Development of a three-fingered robot hand with stiffness control capability," *Mechatronics*, vol. 2, pp. 483–494, 1992.

[6] Z. Li and S. Sastry, "Issues in dexterous robot hands," in *Dexterous Robot Hands*, (S. Venkataraman and T. Iberall, eds.), ch. 8, New York, N.Y.: Springer Verlag, 1990.

[7] M. R. Cutkosky, "On grasp choice, grasp models, and the design of hands for manufacturing tasks," *IEEE Transactions on Robotics and Automation*, vol. 5, pp. 269–279, June 1989.

[8] S. Fujii and S. Kurono, "Coordinated computer control of a pair of manipulators," *Industrial Robot*, vol. , pp. 155–161, August 1975.

[9] M. T. Mason and J. K. Salisbury, *Robot Hands and the Mechanics of Manipulation.* Cambridge, Mass.: The MIT Press, 1985.

[10] S. Schneider and R. H. Cannon, "Object impedance control for cooperative manipulation: theory and experimental results," *IEEE Journal of Robotics and Automation*, vol. 8, pp. 383–394, June 1992.

[11] R. Murray and S. Sastry, "Control experiments in planar manipulation and grasping," in *Proceedings of the 1989 IEEE Int'l. Conf. Robotics and Automation*, pp. 624–629, 1989.

[12] S. Venkataraman and T. Iberall, *Dexterous Robot Hands.* New York, N.Y.: Springer Verlag, 1990.

[13] J. Slotine and W. Li, "On the adaptive control of robot manipulators," *International Journal of Robotics Research*, vol. 6, pp. 49–59, Fall 1987.

[14] H. Berghuis, R. Ortega, and H. Nijmeijer, "A robust adaptive controller for robot manipulators," in *Proceedings of the 1992 IEEE Int'l. Conf. Robotics and Automation*, pp. 1876–1881, 1992.

[15] V. Kumar and K. Waldron, "Suboptimal algorithms for force distribution in multifingered grippers," *IEEE Journal of Robotics and Automation*, vol. 5, pp. 491–498, August 1989.

[16] Y. Nakamura, K. Nagai, and T. Yoshikawa, "Mechanics of coordinate manipulation by multiple robotic mechanisms," in *Proceedings of the 1987 IEEE Int'l. Conf. Robotics and Automation*, pp. 991–998, 1987.

[17] M. Kaneko, K. Yokoi, and K. Tanie, "On a new torque sensor for tendon drive fingers," *IEEE Journal of Robotics and Automation*, vol. 6, pp. 501–507, June 1990.

[18] R. Hilhorst and K. Tanie, "Dextrous manipulation of objects with unknown parameters by robot hands - simulation and experimental results," Tech. Rep., Mechanical Engineering Laboratory, 1993.

[19] R. Hilhorst, *Supervisory Control of Mode-switch Processes.* PhD thesis, University of Twente, Enschede, Netherlands, 1992.