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Probabilistic Estimation of Whole Body Contacts for Multi-Contact Robot Control

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***Abstract*— Today most robots interact with the surroundings only with their end-effectors. However there are many benefits to utilizing contact along the entire length of robot body and links especially for human-like robots. Existing control strategies for link contact require knowledge of the contact point. In an uncertain environment, locating link contact point is difficult for most robots as they do not possess skin capable of sensing. We propose a probabilistic approach to link contact estimation based on geometric considerations and compliant motions. Since for many robots, link geometry is also uncertain, we broaden our approach to simultaneously estimate link shape and environment contact. Our experimental results demonstrate that efficiency of control is significantly improved by link contact estimation.**

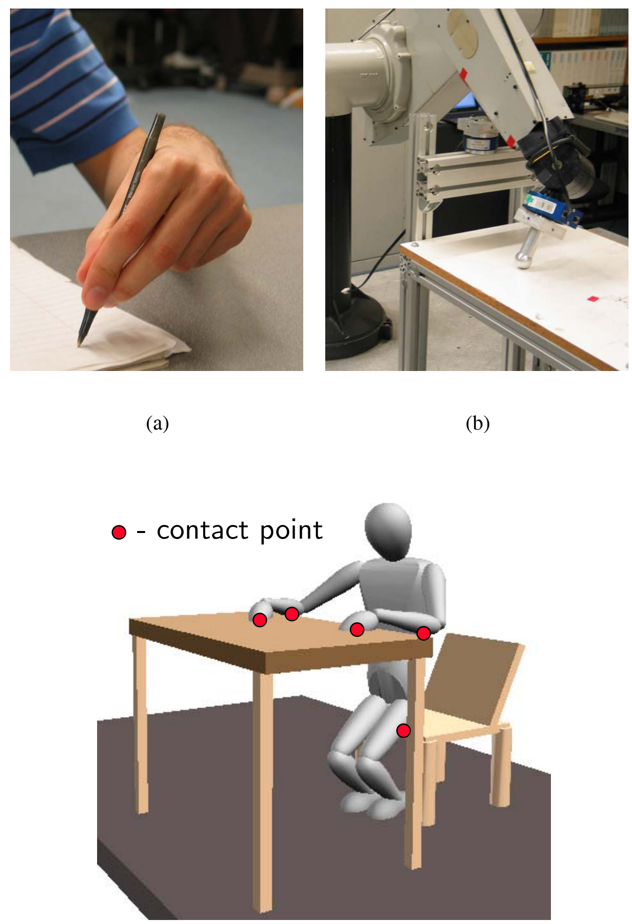
***Index Terms*— contact estimation, probabilistic estimation, link contact, multiple contact, force control**

I. Introduction

Today robots prefer to avoid contact with the environment along body or links. They strive to interact with the surroundings only by their end effectors. In contrast humans are able to do a great deal by using contact along their limbs and torso. For example, we brace against a desk while handwriting. When stumbling in the dark, we stretch our arms forward to feel the environment. We support ourselves with our knees and forearms while climbing into a tight space.

By learning to utilize contact along manipulator links, robots gain the same advantages as humans (see Figure 1 for illustration). For example, it has been shown in [1] that bracing increases manipulator precision, and thus it is desirable to brace for fine manipulation tasks. During exploration it is much easier to bump into objects if we utilize the entire robot surface as opposed to just the end effector tip. Just like humans, human-like robots also need to be able to support themselves with arms and knees when climbing.

Recently approaches to control for whole body contact have been proposed in the literature [2]–[4] (see Section II-B for a brief overview). However absence of contact perception is a major obstacle holding robots back from using link contacts. To our knowledge, there has been no work on estimating contact points along manipulator



(a) (b) (c)

Fig. 1. Applications of link contact: (a) Humans use bracing to increase precision during fine manipulation tasks such as handwriting. (b) PUMA manipulator in a similar bracing configuration. It has been shown that bracing improves manipulator precision as well. (c) Human-like robots utilize multiple link contacts for bracing and support.

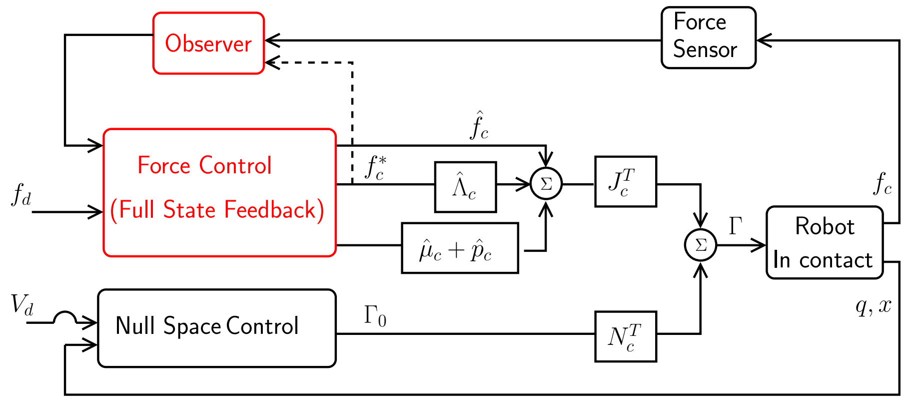


Fig. 2. A block diagram of the contact control framework for a manipulator, where the Active Observer (AOB) design is implemented for force control. The observer in the AOB design includes a state for input disturbance and the estimate of this state will be directly compensated for in addition to the full state feedback.

links, yet this information is clearly required for control algorithms.

Estimation of link contact points is more difficult for robots than for humans, because most robots today do not possess skin capable of sensing. Human skin is a complex sensor and creation of comparable robotic skin is currently an area of active research (see for example [5]). Even once robotic skin is widely available, its complexity and cost may be prohibitive for many applications. In this paper we propose an active sensing strategy that robots can use to estimate link contacts even without skin.

Since probabilistic techniques have been hugely successful in other areas of robotics (e.g. see a recent book on mobile robotics [6]), we focus on a probabilistic approach to contact point estimation. Our approach results in an efficient online technique that we utilize during our experiments. As exact robot geometry is often unknown, we also provide an offline algorithm for estimating geometric parameters of robot links simultaneously with contact point estimation. Our experimental results demonstrate that estimation of contact point is crucial for control performance.

II. Background

A. Related work in perception

To be able to operate in environments built for humans, robots need to estimate environment parameters from sensory information. One popular sensor used for manipulation perception tasks is vision (see [7] for a recent survey). However, due to high precision of manipulators, perception via contact offers very high precision that is difficult to attain with other sensors. High precision is often required for fine manipulation tasks and for balance control tasks. Traditionally manipulation approaches do not have probabilistic basis, e.g. [8], [9]. Recently, several groups explored probabilistic techniques. For example, in [10] a variant of Kalman filter has been used to estimate environment parameters for cube-in-corner assembly tasks. In [11], a particle filter variant was used to localize objects by probing them with end-effector.

B. Related work in control

Research in motion and force control strategy has begun with contact at the end-effector of the manipulator [12]–[14] by using compliant frame selection matrices [15] [16] to describe the decomposition of the end-effector space in the contact frame. Later more general kinematic contact models are presented by [17]–[21] for non-orthogonal decomposition of motion and force directions.

Control strategies for multiple contact over multiple links are presented by [2]–[4]. Liu et al. [2] present an adaptive control approach for multiple geometric constraints using joint-space orthogonalization and Schutter et al. [4] propose a constraint-based approach dealing with multiple contact.

C. Overview of control approach

The control framework in this paper uses the approach in [3], [22], which is to define the operational space coordinates using contact force space, which spans all contacts over the links. The dynamics of the contact forces are then composed by projecting the robot dynamics into the operational space and using an environment model. Control torques are chosen to compensate for the dynamics, resulting in linearized second order systems for each contact force [16], [23]. This framework allows for the use of any linear controller at the decoupled level of control. The Active Observer (AOB) method [24] is then used to deal with unknown disturbances, unmodeled friction, and parameter errors in the environment model. Motion control is then composed in the null-space using task consistent dynamics [25], resulting in dynamically decoupled motion and force control structure (Figure 2).

III. Contact Estimation

A. Active sensing strategy for data collection

To collect data for link contact estimation, we perform compliant motions of the link (see Fig. 3 for an illustration).

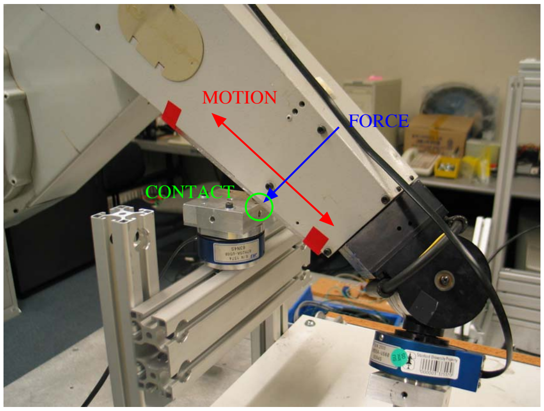


Fig. 3. Active sensing strategy used to collect data for link contact estimation. Force control is applied towards the environment object to maintain contact. Motion control is applied in perpendicular direction.

The goal is to maintain contact with the environment throughout the sensing procedure. This way geometric shape of the robot allows us to estimate the environment. To ensure that contact is always maintained, we pick an arbitrary point on the link and initiate force control towards the environment object. We then perform motion control in direction perpendicular to the force control direction.

B. Model and notation

Our measurements consist of joint angles q of the manipulator. We will denote by q^t the set of all measurements collected from time 1 to time t, i.e. $q^t = \{q_1, q_2, ..., q_t\}$. Since we want to estimate contact along surface of manipulator links, we need a representation of robot's geometric shape. 3D shapes are usually represented by either polygonal meshes or parametric surfaces (e.g. super-quadrics). Since our PUMA manipulator has polygonal shape, we chose the mesh representation. We denote the set of parameters encoding robot's shape by r. We denote by s the set of parameters encoding shape of the environment object and its relative position in robot's coordinate system.

C. Probabilistic inference with known robot geometry

Let us first consider the simpler problem of estimating environment parameters s when robot geometric parameters r are known. In probabilistic terms it means finding values of environment parameters s that maximize the following probability:

$$Bel = p(s|q^t, r) \tag{1}$$

Using Bayes rule, we can re-write the above equation as

$$Bel = p(s|q^t, r) = p(q^t|r, s)\frac{p(s|r)}{p(q^t|r)} \tag{2}$$

Here $p(s|r)$ and $p(q^t|r)$ are prior beliefs about object shape and robot configuration given robot shape. Since s does not appear in $p(q^t|r)$, this prior is constant with respect to s. The object shape prior, $p(s|r)$, encodes many factors, for example that it is not possible for the object to overlap with non-movable parts of the robot or that symmetric objects are more likely than asymmetric in human-made environments. Since it is difficult to obtain an exact representation of this prior, it is convenient to let the robot be unaware of these effects and assume the prior to be uniform. Under this assumption, Bel becomes proportionate to $p(q^t|r, s)$. It is also common to assume separate measurements to be independent of each other, which allows us to factor the belief as follows:

$$Bel \propto p(q^t|r, s) = \prod_{i=1}^{t} p(q_i|r, s) \tag{3}$$

Here $p(q_i|r, s)$ is the probability of i^{th} measurement given state parameters, which is also called measurement likelihood. We model this probability as a Gaussian distribution of the distance $dist(r, s, q)$ between the robot and the environment with variance σ^2. We define the distance as follows. If the robot and the environment object do not overlap, it is the minimum Euclidean distance between the surface of the robot in configuration q and the surface of the object. If the robot and the object overlap, then it is the minimum distance the object has to be moved in order to not overlap with the robot. Then the measurement likelihood can be written as:

$$p(q_i|r, s) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\{-\frac{dist(r, s, q_i)^2}{2\sigma^2}\} \tag{4}$$

Intuitively this makes sense because our active sensing strategy specifically collects data when the robot is in contact with the object. Thus configurations in which the distance between the robot and the object is very small are likely, while configurations for which the distance is large are very unlikely.

Using this distribution for measurement likelihood allows us to transform the belief estimation into a least squares problem. By taking log of the belief we obtain:

$$\begin{aligned}
\log Bel &= \log \prod_{i=1}^{t} p(q_i|r, s) + c_1 \\
&= \sum_{i=1}^{t} \log p(q_i|r, s) + c_1 \\
&= \sum_{i=1}^{t} \log(\frac{1}{\sqrt{2\pi\sigma^2}} \exp\{-\frac{dist(r, s, q_i)^2}{2\sigma^2}\}) + c_1 \\
&= -\frac{1}{2\sigma^2} \sum_{i=1}^{t} dist(r, s, q_i)^2 + c_2
\end{aligned} \tag{5}$$

Here c_1 is a constant resulting from taking log of the proportionality relationship in 3. In the last line we collect all constant terms (including c_1) into a new constant c_2. Thus maximizing Bel with respect to s is equivalent to minimizing $\sum_{i=1}^{t} dist(r, s, q_i)^2$, which is a least squares

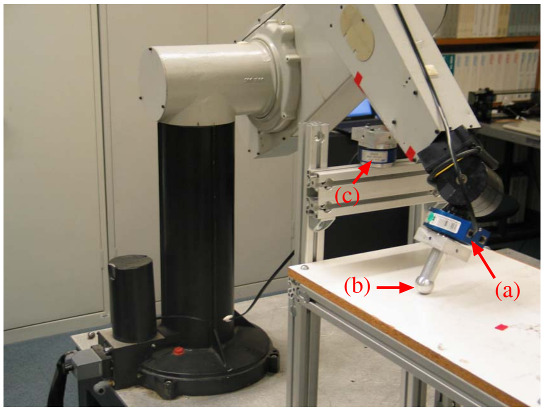


Fig. 4. We used this 6 DOF PUMA robotic manipulator in our link contact estimation experiments. The manipulator is equipped with (a) 6D JR3 force/torque sensor at the wrist, and (b) a robotic finger with a spherical end. For evaluation purposes only, we placed a force/torque sensor in the environment (c). This sensor is not required for operation of our method. We use it solely to evaluate performance.

problem. In general this problem is non-linear in the unknowns. Non-linear optimization search techniques can be applied to obtain a solution.

D. Simultaneous estimation of robot geometry and contact

In the most general case both robot's shape parameters and object parameters can be uncertain. Thus we need to estimate both r and s (collectively state parameters) based on the collected data q^t. In probabilistic terms it means finding values of state parameters that maximize the following probability:

$$Bel_{geom} = p(r, s|q^t) \tag{6}$$

Repeating similar derivations for Bel_{geom} we again reduce it to least squares form:

$$\log Bel_{geom} = -\frac{1}{2\sigma^2}\sum_{i=1}^{t} dist(r, s, q_i)^2 + c \tag{7}$$

The only difference from Bel is that here the robot's shape r is unknown. Greater number of unknown parameters requires longer computation times. Luckily, robot shape parameters only need to be estimated once, as the robot's geometry does not change from one experiment to another.

IV. Experimental results

A. Experimental setup

For our experiments we used a PUMA robotic manipulator equipped with a JR3 force and torque sensor at the wrist (Fig. 4). No additional sensors were placed at the manipulator joints or links. To evaluate performance of control strategies, we placed a second JR3 sensor in the environment. It is important to note that this sensor is not required for operation of our method. Its readings are not used within control or estimation algorithms.

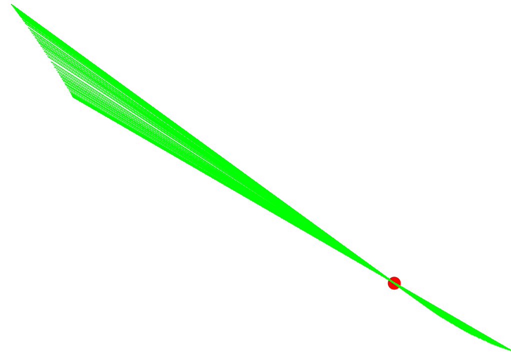


Fig. 5. Plot of all positions of PUMA's third link edge during active sensing step. The estimated contact point is shown as a red circle.

B. Experiments on contact estimation

In our experiments the third link of PUMA robot comes in contact with an edge of an arm rest (Fig. 3). Due to shape of the robot, this creates a single point contact against one of the edges of the third link.

Once the robot comes in contact with the environment, active sensing strategy described in section III-A is initiated. The manipulator motion during this strategy is constrained within one plane. Therefore, the contact point in the environment remains the same throughout the procedure while the contact point on the link moves.

Since the contact is a single stationary point within the environment, we can reduce our environment representation s to single point coordinates in the global frame. Thus for our experimental setup, the distance between the robot and the environment is simply the distance between a point and a line. Moreover, when robot geometry is known, the squared distance is a second degree polynomial in the unknown parameters. Thus the least squares problem (derived in 5) is linear in this case and can be solved in constant time using the eigenvalue method. Figure 5 plots motion of the third link during active sensing and the resulting estimated contact point.

Our initial estimates of the robot's geometry came from measuring the robot with a ruler. However, it turned out that the shape of the link is unobviously asymmetric and thus our initial estimates were several centimeters off. For comparison, we measured the environment contact point with the end-effector of the PUMA manipulator. The error resulting from our estimation algorithm was 3.4cm. This is in part due to incorrect geometry of the link and in part to imprecise measurement of the contact point with the spherical end of the end-effector.

To obtain better estimates, we solve the full estimation problem that simultaneously considers the robot's shape r and the environment contact point s. In this case the distance between the robot and the environment is non-linear in the unknown parameters. This problem can be solved using a variety of non-linear optimization techniques. We made use of Matlab's implementation based on the method described in [26].

As it is widely known, optimization search for non-linear least squares is prone to getting stuck in local minima. To overcome this problem we first obtain initial estimate of the contact point with the ruler-measured geometry of the robot using linear least squares as described above (known robot geometry case). Then we use the obtained contact point estimate together with the ruler-measured robot geometry as a starting point for non-linear optimization search to estimate r and s. Obtaining robot geometric parameters in this fashion improved contact point estimation precision from 3.4cm to 0.4cm.

C. Control using estimated parameters

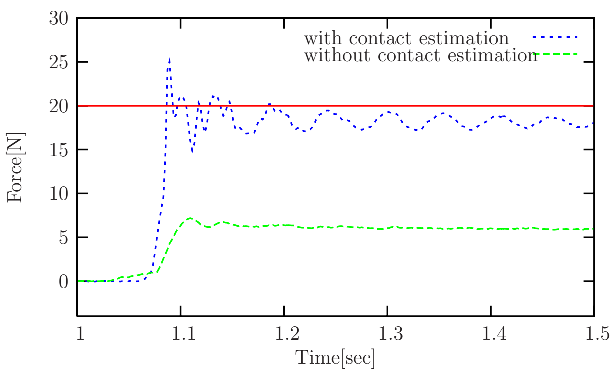


Fig. 6. Comparison of response to step force command with and without link contact estimation. For the experiments without estimation the assumed contact point was offset from actual position by 20 cm. In the experiment shown a 20N step command was commanded to the robot. The target response is denoted by the solid red line.

Intuitively, accurately estimated contact parameters should be important for control performance. To verify the significance in practice, we performed a series of comparison experiments. In these experiments we performed open loop force control with and without link contact estimation. As before, the robot maintained a point contact between the third link and the arm rest. For the experiments without estimation, the assumed contact point was displaced 20 cm along the link edge from the actual contact point. We performed a series of experiments with force step commands ranging from 20 to 50 N. Figure 6 shows comparison plot of force response in one of the step command experiments with and without link contact estimation. To measure these results we placed a JR3 force sensor under the arm rest. This sensor is not needed for the estimation and control algorithms, only for evaluation of the results. Overall, in our experiments with contact estimation the error was less than 20% and without contact estimation it was over 50%.

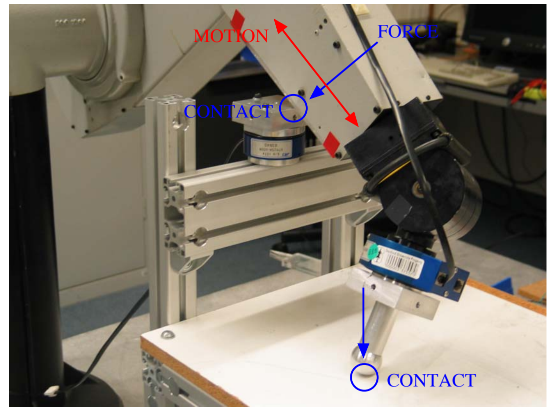


Fig. 7. Performance of multi-contact control using the estimated environment contact point. Two point contacts are maintained during these experiments: third link contact with the arm rest and end-effector contact with the desk. The robot maintains both contact forces and moves at the same time.

D. Multi-contact with estimated link contact

We also conducted multi-contact environment interaction experiments to demonstrate capabilities similar to human handwriting behavior. These experiments are illustrated in Figure 7. During these experiments the robot moves and makes contact with the third link against the arm rest. It then initiates active sensing procedure to estimate the contact point. Once the point is estimated it moves to make contact with its end-effector against the desk, while still maintaining contact of the third link with the arm rest. In this multi-contact configuration it performs the task of force control and motion control simultaneously. For force control, we command the normal direction forces at the third link contact and the end-effector contact. The normal contact force at the end-effector is feedback controlled using the measured force information from wrist mounted force sensor. However, the contact force on the third link is controlled in an open loop and there is no feedback from a force sensor.

Using the remaining degrees of freedom of the robot, the third link was controlled to move in a tangential direction, which created a motion toward and away from the robot in a sinusoidal form. Note that even though we chose to estimate link contact point prior to making a second contact with the end-effector, the motion of the robot after the second contact is made could be used to estimate link contact. Thus the experiment demonstrates the possibility of estimating link contacts using this procedure while maintaining a multi-contact configuration.

Videos of our experiments are available at the website

http://cs.stanford.edu/∼anya/manips.html

V. Discussion and Conclusions

Perception of link contact enables a wide range of applications including bracing to improve manipulation precision, exploration of environment and support during climbing. For robots that do not have skin, we proposed a probabilistic approach to approximating link contact based on an active sensing strategy. Since robot shape is often known only approximately, we have also proposed an approach for simultaneously estimating robot shape and contact point. Our experiments clearly demonstrate the impact of contact estimation on control accuracy.

It is worth noting that estimation of link contact is only possible when the robot has sufficient degrees of freedom to carry out motion around the contact point. For example, estimation via motion is theoretically not possible for second link of the PUMA manipulator. In these cases, artificial skin or other type of sensor is necessary to estimate the contact. However, when degrees of freedom are sufficient, the proposed active sensing strategy provides estimates with good accuracy.

Although the described approach considers one contact at a time, it applies even if the robot maintains multiple contacts with the environment. Moreover the approach can be easily extended to estimation of multiple contacts simultaneously, provided the robot has the freedom to carry out simultaneous exploratory motions around all of the contacts. On the other hand estimation of multiple contact points on the same link is unlikely to be possible using this method, because the link will be unable to move around each contact point independently.

There is ample room for future work on link contact estimation. In our experiments we considered relatively simple robot and environment geometries. For more complex geometries (including complex polymesh and curved representations), more sophisticated active exploration strategies will likely be needed. While the derivations of this algorithm apply to arbitrarily complex geometries, in practice these geometries will entail significantly higher numbers of parameters and lead to non-linear estimation problems. Hence better search algorithms will be required. In addition distance computation is more difficult for complex objects and in fact the notion of distance may need to be redefined depending on the representation.

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REFERENCES

[1] Jae Young Lew and Wayne J. Book. Bracing micro/macro manipulators control. In *ICRA*, pages 2362–2368, 1994.

[2] Y. Liu, K. Kitagaki, T. Ogasawara, and S. Arimoto. Model-based adaptive hybrid control for manipulators under multiple geometric constraints. *IEEE Trans. on Control Systems Technology*, 7(1):97–109, January 1999.

[3] J. Park and O. Khatib. Mult-link multi-contact force control for manipulators. In *Proc. of the Int. Conf. on Robotics and Automation*, pages 3613–3618, Barcelona, Spain, 2005.

[4] J. De Schutter, J. Rutgeerts, E. Aertbeliën, F. De Groote, T. De Laet, T. Lefebvre, W. Verdonck, and H. Bruyninckx. Unified constraint-based task specification for complex sensor-based robot systems. In *Proc. of the Int. Conf. on Robotics and Automation*, pages 3607–3612, Barcelona, Spain, 2005.

[5] T. Someya, T. Sekitani, S. Iba, Y. Kato, H. Kawaguchi, and T. Sakurai. A large-area, flexible pressure sensor matrix with organic field-effect transistors for artificial skin applications. In *National Academy of Sciences*, July 2004.

[6] S. Thrun, W. Burgard, and D. Fox. *Probabilistic Robotics*. MIT Press, 2005.

[7] D. Kragic and H. I. Christensen. Survey on visual servoing for manipulation. Technical Report ISRN KTH/NA/P–02/01–SE, Royal Institute of Technology (KTH), 2002.

[8] S. Shekhar, O. Khatib, and M. Shimojo. Sensor fusion and object localization. In *Proc. of ICRA*, 1986.

[9] M. Moll and M. A. Erdmann. *Reconstructing the Shape and Motion of Unknown Objects with Active Tactile Sensors*, pages 293–310. Springer Verlag, 2003.

[10] P. Slaets, J. Rutgeerts, K. Gadeyne, T. Lefebvre, H. Bruyninckx, and J. De Schutter. Construction of a geometric 3-D model from sensor measurements collected during compliant motion. In *Proc. of ISER*, 2004.

[11] A. Petrovskaya, O. Khatib, S. Thrun, and A. Y. Ng. Bayesian estimation for autonomous object manipulation based on tactile sensors. In *Proc. of ICRA*, 2006.

[12] B. Siciliano and L. Villani. *Robot Force Control*. The Kluwer International Series In Engineering and Computer Science. Kluwer Academic Publishers, 1999.

[13] S. Chiaverini, B. Siciliano, and L. Villani. A survey of robot interaction control schemes with experimental comparison. *ASME Transactions on Mechatronics*, 4(3):273–285, September 1999.

[14] T. Yoshikawa. Force control of robot manipulators. In *Proc. of ICRA*, 2000.

[15] M. H. Raibert and J. J. Craig. Hybrid position/force control of manipulators. *ASME Journal of Dynamic Systems, Measurement and Control*, 103(2):126–133, June 1981.

[16] O. Khatib. A unified approach for motion and force control of robot manipulators: The operational space formulation. *Int. J. on Robotics and Automation*, 3(1):43–53, February 1987.

[17] R. Featherstone, S. S. Thiebaut, and O. Khatib. A general contact model for dynamically-decoupled force/motion control. In *Proc. of the Int. Conf. on Robots and Automation*, pages 3281–3286, 1999.

[18] H. Bruynincks, S. Demey, S. Dutré, and J. De Schutter. Kinematic models for model-based compliant motion in the presence of uncertainty. *Int. J. of Robotics Research*, 14(5):465–482, Oct 1995.

[19] H. Lipkin and J. Duffy. Hybrid twist and wrench control for a robotic manipulator. *ASME Journal of Mechanisms, Transmissions and Automation in Design*, 110(2):138–144, Jun 1988.

[20] H. West and H. Asada. A method for the design of hybrid position/force controllers for manipulators contrained by contact with the environment. In *Proc. of the Int. Conf. on Robotics and Automation*, pages 251–259, 1985.

[21] J. Park, R. Cortesão, and O. Khatib. Multi-contact compliant motion control for robotic manipulators. In *Proc. of the Int. Conf. on Robotics and Automation*, pages 4789–4794, New Orleans, U.S.A., 2004.

[22] Jaeheung Park. *Control Strategies for Robots in Contact.* PhD thesis, Stanford University, 2006.

[23] E. Freund. The structure of decoupled nonlinear systems. *Int. J. Contr.*, 21(3):443–450, 1975.

[24] R. Cortesão. *Kalman Techniques for Intelligent Control Systems: Theory and Robotic Experiments*. PhD thesis, University of Coimbra, 2002.

[25] O. Khatib, L. Sentis, J. Park, and J. Warren. Whole-body dynamic behavior and control of human-like robots. *Int. J. of Humanoid Robotics*, 1(1):29–43, 2004.

[26] T. F. Coleman and Y. Li. An interior, trust region approach for nonlinear minimization subject to bounds. *SIAM Journal on Optimization*, 1996.