ResearchGate

See discussions, stats, and author profiles for this publication at: https://www.researchgate.net/publication/224620228

Grasping unknown objects based on 3d model reconstruction

Conference Paper · August 2005

DOI: 10.1109/AIM.2005.1511025 · Source: IEEE Xplore

CITATIONS
38

READS
345

4 authors, including:

Liuting Jiang
University of Leicester

140 PUBLICATIONS **4,477** CITATIONS

SEE PROFILE

Jiawei Li
University of Nottingham Ningbo China

47 PUBLICATIONS **734** CITATIONS

SEE PROFILE

Some of the authors of this publication are also working on these related projects:

Project EPSRC DAASE project View project

All content following this page was uploaded by Jiawei Li on 29 May 2014.

The user has requested enhancement of the downloaded file.

Proceedings of the 2005 IEEE/ASME
International Conference on Advanced Intelligent Mechatronics
Monterey, California, USA, 24-28 July, 2005

Grasping Unknown Objects Based on 3D Model Reconstruction

B. Wang, L. Jiang, J.W. Li and H.G. Cai
Robot Research Institute
Harbin Institute of Technology (HIT)
Harbin 150001, P.R. China
wbhit@hit.edu.cn

H. Liu
Institute of Robotics and Mechatronics
German Aerospace Center(DLR)
82230 Wessling, Germany
Hong.Liu@dlr.de

***Abstract* - Automatic grasping of unknown objects for multifingered robot hand is a very difficult problem because the location and model of the object are unknown and the possible hand configurations are numerous. In this paper, we propose a new strategy for modeling and grasping prior unknown objects based on powerful 3D model reconstruction. The whole system consists of a laser scanner, simulation environment, a robot arm and the HIT/DLR multifingered robot hand. The object to be grasped is scanned by a 3D laser scanner and reconstructed in simulation scene. After different grasping are evaluated within the simulation scenes, an accurate arm and hand configuration can be calculated to command the robot arm and multifigered hand. The experimental results strongly demonstrate the effectiveness of the proposed strategy.**

***Index Terms* –Grasping, Unknown objects, 3D reconstruction, Multifingered hand.**

I. INTRODUCTION

The grasp planning is a basic but a very complex problem in robotics. Humans can grasp and manipulate an object with great ease, but asking a robot with multifingered hand to perform a simple task is not a trivial work. Because it relates to kinematics, motion planning, force-closure grasp, optimization of grasp forces and finger gaits etc.. Also the number of degrees of freedom (DOF) of a robotic hand creates a large number of hand configurations.

In order to make a robotic mutlifingered hand grasp an unknown object, the following issues will be considered: (a) features of the grasped object; (b) grasping configuration of the hand; (c) contact locations and contact normal vectors between the hand and the object; (d) appropriate finger forces exerted on the grasped object to balance external forced acting on the object, which are subject to friction cone constraints. These are fundamental problems in grasp and manipulation. These problems become more difficult by the fact that friction cone constraints are inherently nonlinear.

Previous work on grasping planning can often be classified into knowledge-based, behavior-based and model-based methods.

Knowledge-based method on grasping is about how a robot would preshape his hand and grasp an object. Accurate knowledge is important for manipulating and grasping. Stansfield [1] presented a general-purpose robotic grasping system based on knowledge. They integrated knowledge into the grasping task to allow the robot to deal with unknown objects. Other examples of knowledge-based grasping techniques include [2], [3]. However, the problem of knowledge-based systems is that the decision process is based on previous experience or expert knowledge. These are limited to the level of accurate knowledge available.

A behavior based approach employs a distributed representation and is often used when the environment cannot be accurately modeled or characterized. Wheeler [4] formulated robotic pick and place operation as prospective behavior, which can be learned by an intelligent agent using experience gained through interaction with the environment. Balch and Arkin [5] also applied primitive behaviors to mobile robotics. However, primitive behaviors have often been used to accomplish higher-level goals. There are few robust behavior methods for grasping objects of unknown geometry [6].

Model-based grasp planning is a general method, which is often used in synthesis and analysis of grasp, Such as force closure problem, force feasibility problem and force optimization problem. Many researchers have done great effort on these problems [7] [8]. During the planning phase, contact locations between a hand and an object should be decided. Mirtich and Canny [9], Tsutomu Hasegawa [10] and Zhu and wang [11] addressed the problem of grasp planning. However, all these methods depended on precise geometric information of objects and assumed that models of object were known. But precise and complete models are hard to be constructed for complex objects. How to acquire the feature, position and orientation of the object to be grasped and plan a stable grasp is a hard nut to crack.

In this paper, we introduce a new strategy for grasping prior unknown objects with a multifingered robot hand, using which the robot hand could autonomously complete a reliable grasp task for unknown objects. The grasp planning is also based on object model. One important distinction between other researcher's work and ours is that we incorporate a laser scanner and simulation environment into our robot grasping system. Using the laser scanner, profile information of grasped objects can be obtained. And 3D object models can be reconstructed in simulation environment, which are used for robotic motion and grasp planning on

*This work was supported by National Natural Science Foundation of China (NSFC) Project 60275032.

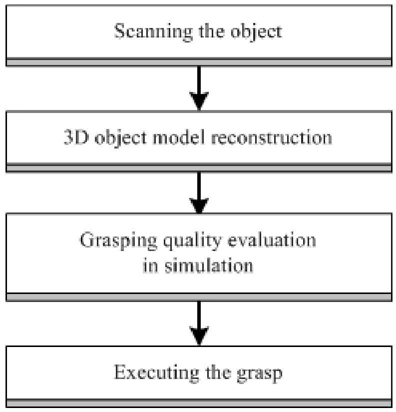


Fig. 1 Scheme of grasping unknown object.

line. Prior information of objects is not required and no learning occurs in this system. Instead of computing the finger forces, the compliance control strategy is used to maintain stable grasp. As illustrated in Fig. 1, before executing the grasp, the strategy consists of three steps: scanning the object, 3D object model reconstruction, and grasping quality evaluation.

In section II, the system setup is introduced. The detail of the above steps is described in section III and IV respectively. Experiments and results are shown in Section V. The discussion and conclusion are in the last section.

II. The System Setup

The system is shown in Fig. 2, which consists of a laser scanner, a six degree-of-freedom (DOF) RX60 robot arm, a four finger HIT/DLR robotic hand, a commercial PC and a Sgi workstation.

The laser scanner is composed of a laser stripe generator and two CCD cameras (TOSHIBA IK-CU50), which is connected to the hand palm by a support. The laser scanner is driven by RX60 robot arm. After a laser beam is swept over an object, precise 3D point cloud information of the object surface can be obtained. After processed in PC, these data is transmitted into Sgi workstation for the object reconstruction in simulation environment.

The multisensory hand used in this system is developed jointly by HIT (Harbin Institute of Technology) and DLR (German Aerospace Center), which is mounted on the sixth joint of RX60 robot arm as an end effector. The hand is a little large than that of an adult's hand and weights about 1.6Kg. It has four same fingers. Each finger consists of four degrees of freedom and has three actuators. The thumb has an extra degree of freedom for fine manipulation and power grasping. All the motors are integrated in the fingers and in the palm, respectively. The distal and middle joints of each finger are coupled, such that the two joint angles are always equal. The working range of the base joint is 90 degree forward and 20 degree sidespin. The Maximum continuous fingertip force is 10N, which is enough for grasping many kinds of object. Information of position and force/torque could be available from the hand. Each joint is equipped with a joint angle sensor and a strain gauge based joint

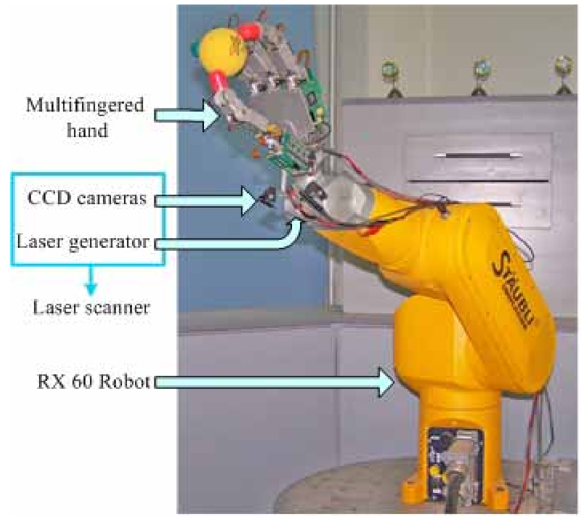


Fig. 2 Grasping system.

torque sensor. Moreover, a miniaturized six dimensional force/torque sensors are mounted on the fingertips of each finger.

A high speed real-time serial communication bus (25 Mbps) has been implemented using FPGAs (Field Programmable Gate Array). Altogether only three cables are needed for the serial communication between the hand and external CPU. From the PC, the hand can be controlled easily. The hand palm is also like that of humans. So it can handle objects with various shapes, such as sphere, cylinder, cup, disk and so on. The dimension range of grasped object is from 10mm to 140mm. In the case of small or thin objects, it can use two or three fingers for pinch and fine manipulation. In case of large and long objects, it can adjust the extra degree of freedom of thumb for power grasp.

III. Scanning The Object

In this section, we introduce the method of scanning the object by using the laser scanner. It consists of two parts: camera calibration and process of scanning.

A. Camera Calibration

The laser scanner system consists of two CCD cameras and a liner laser generator. The laser generator is fixed in the middle of the two cameras. A laser curve will occur on the object surface when a laser stripe beam meets an object. Points on the curve are the measured points, which are also projected to the CCD image plane. Multi-layer neural network has been successfully applied to some nonlinear problems. In order to find the mapping relationship between measured points and image points and to avoid calibrating the intrinsic and extrinsic parameters of the camera, the CCD camera is calibrated by using neural network. It is fixed on the one end of a high-precision coordinate measuring machine (CMM) during calibration. A planar pattern with twenty white marker points and black background is also used, which is placed vertically on the rail of the CMM. The distance between two marker points is 5mm.

The process of the calibration is described as follows. The planar pattern moves along the high precision linear rail of CMM. As it moves in every step, we note down the actual coordinates t_i (x_i, y_i) and the corresponding image coordinates p_i (u_i , v_i) of the marker points. The pattern moves 1mm in each step along the rail. When it moves 50 times evenly, 1000 pairs data set of p_i (u_i , v_i) and t_i (x_i , y_i) are obtained. These data are used as the training data set of the neural network. A multi-layer feed forward back-propagation neural network is used. The network contains four layers, which includes two hidden layers. The numbers of input, hidden and output nodes are chosen as 2, 6, 8, 2 respectively. Two different transfer functions are used in the neural network. The unsymmetrical logsig transfer function is used for computation of hidden layer nodes activities and the Purelin linear transfer function is employed for computation of output activities. In order to increase the learning speed, the neural network is trained by Leveberg-Marquardt algorithm [12, 13].

The input and output data set of the network is denoted as $\{(p_1, t_1), (p_2, t_2), \ldots, (p_Q, t_Q)\}$, The objective function of the network is defined as:

$$V = \frac{1}{2}\sum_{q=1}^{Q}\left[\sum_{i=1}^{S_m}(t_q(i) - a_q^M(i))^2\right] = \frac{1}{2}\sum_{q=1}^{Q} e_q^T e_q \qquad (1)$$

where a_q^M(i) is the output of the ith node corresponding to p_q, $t_q(i)$ is the (target) output of the ith node, and S_m is the number of the output layer node.

The network reaches convergence after taking about 719 iteration steps.

After calibration of the camera, the laser scanner itself can only get 2D information. But when it moves together with robotic arm, 3D profile information of the object can be collected.

B. Process of Scanning

The scanning process is described as follows:

1) The laser scanner moves together with the robotic arm to sweep an object. The laser source emits a plane of light, which forms an illuminated stripe on the object's surface. So the 2D image pixel coordinates of sample points illuminated by laser, can be obtained through the CCD cameras.

2) By given RX60 robot joint angle and the image pixel coordinates, the coordinates (*x, y, z*) of the sample points of the measured object relative to the robot base can be calculated using forward kinematics and trained neural network. So the unorganized point cloud data of the object profile is obtained.

3) Defining the boundary and extracting the profile feature of the object from the point cloud data by using Nearest Neighbor method.

4) Triangulating the scattered data by using Hoppe's algorithm [14].

Then the triangulated points used for object reconstruction are acquired. These data can be saved in the form of Open Inventor file, which can be used for 3D object model reconstruction in simulation environment.

IV. 3D Model Construction and Grasp Evaluation

In order to analyze force-closure grasp and grasping stability, the geometric relationship of the robotic hand and the objects should be known, including contact locations, the shape of the object and fingertips. There are numerous approaches in the area of image processing concerned with recognition and localization of the object. However, most of these methods only analyze planar objects. In this paper, based on Miller's[15] simulator "GraspIt", we also build a virtual environment in Sgi workstation using Open Inventor toolkit, which is used to analyze 3D objects grasp quality. Through the collision detection between the fingers and the object in simulation scene, the contact positions and normal vectors can be calculated. After linearization of the friction cones on the contact points, a grasp wrench space is constructed. The grasping quality can be evaluated on line and the result will be shown by digital values.

A. 3D Model Construction in Simulation Scene

Simulation development is done on the Sgi workstation in UNIX environment using C++ programming language. The 3D models of the hand and robot arm used in simulation can be constructed in Pro/ENGINEER software according to real size and be saved as an Open Inventor format files. After the files are loaded into the simulation scene, each joint of the robot arm and hand as a node is assembled according to kinematics relationship, and it can rotate around its axis. Scattered data of the object to be grasped can be obtained from the laser scanner. The triangulated data of the gasped object can be loaded into the simulation scene and the 3D model of the object can be reconstructed.

In order to detect contacts between the robot hand and the object, and also to prevent the hand from passing through the object as it moves, we incorporate the V-Collide collision detection algorithm [16] into the simulation. So collision can be detected in real time in the simulation environment. If a collision is detected, the motion of the body stops, and the contact regions can be determined through V-Collide algorithm. Depending on the contact regions between the fingers and the object in simulation scene, the contact position and normal direction of contact facets can be calculated.

B. Grasp Quality Evaluation

1) Relative Notions

We assume Coulomb friction in our work. Under Coulomb friction, as shown in Fig. 3, a friction cone at C_1 is bounded by vector n_{11} and n_{12}, the angle between the vector n11 and the normal n1 is half-angle α, whose tangent, tan α, is called the friction coefficient μ. Any contact force f_1 is constrained to lie in a friction cone and is a nonnegative combination of these vectors.

Wrench: A force f and a moment τ can be combined into a wrench $w = (f, \tau)^T \in R^6$ in the case of spatial mechanics.

Force-closure: A grasp achieves force-closure when it can

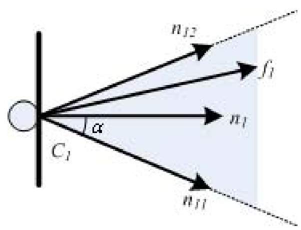


Fig. 3 Coulomb friction.

resist arbitrary forces and torques exerted on the grasped object.

Equilibrium: A set of n wrenches is said to achieve equilibrium when the convex hull of the points contains the origin.

A main character of stable grasp is force-closure. In particular, force closure implies equilibrium.

2) Build Grasp Wrench Space

There are many contact points between the hand and the object. In order to simplify the computation, we assume the contact type is point contact with friction. The finger tip is coated with rubber. So the value of the friction coefficient depends on the grasped object. For example, when the object is plastic, the vale is defined by 0.4 conservatively. Each contact force f is broken into its respective f_x, f_y and $f_\perp$ components. According to coulomb friction, if the contact does not slip, the contact force must lie within its friction cone. When working in 3 dimensions, it can be written as

$$f_x^2 + f_y^2 \le \mu^2 f_\perp^2 \tag{2}$$

If an object is grasped, there must be several forces exerting on the object. According to [17, 18], in order to evaluate grasp quality, grasp wrench space should be built, which is according to contact locations and contact normals between the hand and the object. The building of the grasp wrench space is presented below.

When a force exerts on an object, the contact wrench within the contact frame c can be describe with a wrench basis as

$$F_{c_i} = B_{c_i} f_{c_i} \qquad f_{c_i} \in FC_{c_i}$$

$$FC_{c_i} = \{ f \in R^3 : \sqrt{f_x^2 + f_y^2} \le \mu f_\perp, f_\perp \ge 0 \} \tag{3}$$

where B_{c_i} is wrench basis matrix, f_{c_i} is contact force vector, and FC_{c_i} is the friction cone constraints.

To find the net wrench acting on the object by a grasp through several different contacts, all of the contact wrench should be transformed into the object frame, namely the grasp map. For the ith contact point we have the contact wrench

$$w_i = Ad^T_{g^{-1}_{oc_i}} F_{c_i} = \begin{bmatrix} R_{oc_i} & 0 \\ \hat{p} R_{oc_i} & R_{oc_i} \end{bmatrix} B_{c_i} f_{c_i} \tag{4}$$

where $Ad^T_{g^{-1}_{oc_i}}$ is the transformation matrix.

The friction cones are approximated with polyhedral cones because of the nonlinear friction constraints. Thus any contact force can be represented as a convex sum of m force vectors around the boundary of the cone:

$$f \approx \sum_j^m \alpha_j f_j \tag{5}$$

where $\alpha_j \ge 0$, f_j is a force vector along one edge of a polyhedral cones.

After friction cone is linearized, the ith point contact wrench becomes

$$W_i = \left\{ w_i \mid w_i = \sum_{j=1}^m \alpha_{i,j} w_{i,j}, \alpha_{i,j} \ge 0 \right\} \tag{6}$$

The convex combination of all wrenches W_i is called the grasp wrench space W. The set of wrenches that can be applied to the object is

$$W = \left\{ w \mid w = \sum_{i=1}^n \sum_{j=1}^m \alpha_{i,j} w_{i,j}, \alpha_{i,j} \ge 0 \right\} \tag{7}$$

To analyze the properties of a grasp, the method described by Ferrari and Canny [19] is used to build the total grasp wrench space. It described the sum magnitude of the contact normal forces to 1.0. Under this constraint, equation (7) becomes

$$W_{L_1} = ConvexHull\left(\bigcup_{i=1}^n \{ w_{i,1}, \cdots, w_{i,m} \} \right) \tag{8}$$

We use the Qhull software [20] for this computation. If this convex hull contains the origin of the wrench space then the grasp is Force-Closure [18]. The minimum of the perpendicular distance from each facet of the hull to the origin of the grasp wrench space is used as the grasp quality measure. So the grasp quality can be evaluated in simulation environment on line and the result is shown in digital values. And a suitable grasp configuration can be generated after many times attempts in virtual scene.

V. Experiment

In this section, the method of grasping unknown object automatically by multifingered robot hand has been tested in experiments. All the performed action is decided by the system itself by incorporating the laser scanner and simulation environment. First, we describe the procedure of experiment, and then present an example.

A. *Procedure of Experiment*

The procedure of grasping an unknown object is described as follows:

1) Data Collection: The surface of the grasped object is scanned by the laser scanner, which is moved together with RX60 robot arm. The density of point cloud data is determined by the scanning speed. The scattered data is triangulated by using Hoppe's algorithm [14]. After being triangulated, the data can be written into a file which can be loaded by Open Inventor and transmitted to the Sgi workstation through TCP/IP Protocol.

2) Reconstruct the Object in Simulation Scene: After the data of the grasped object is loaded into simulation environment, the 3D model of the object is reconstructed using Open Inventor.

3) Automatic Grasp Attempt: Let the virtual robotic hand approach to the object from different position and pose together with robotic arm, and grasp the object using different grasping configurations automatically. In default setting this will do 300 times, and a "best" grasp configuration is selected. In this work, we present a simple grasp planner that only contains precision grasp. Eight typical candidate grasps are first tested, which includes four-finger, three-finger, nip, etc.. Let the virtual hand and arm approach to the object and put the palm over geometry center of the object. Adjust position and pose of the palm until all four fingers can touch the object simultaneously. This position is set as an initial site of grasp. Based on this site, rotate and move the palm in a small range to grasp the object. For each grasp, the hand and arm are moved, fingers are closed, and contact locations and contact normal direction are detected.

4) Grasp Evaluation: According to contact information, grasp wrench space is built. It is used for computing force-closure grasp and evaluating grasp quality in simulation at each grasp. Grasp quality of different hand configurations to the same object is compared. One of the "best" hand configurations is selected from the set of feasible force-closure grasp configurations.

5) Executing and Strategy: When a suitable and stable grasp configuration is found, each joint angle of virtual robotic arm and hand in the simulation is written down. In order to prevent the object from being disturbed while arm and hand move from the initial position to the target grip site, the motion trajectory should be planned according to the position of the object and the pose of the arm in grasp site. Also the approaching direction should be considered. We define an approach site and a grasp site. When the appreciate grasp configuration is determined in simulation, we set the position of the sixth joint end of arm as a grasp site. Then open all virtual fingers and move the virtual hand together with the arm back off a little from the object in the simulation environment, we write down the position of the sixth joint end of the arm as an approach site. Then the actual arm and hand are driven respectively to complete the grasping task. The sixth joint end of arm must passes by the approach site and moves straightly to grasp site before close hand fingers.

An excessive contact force can damage the finger. Although the precise 3D model of the grasped object has been obtained from the scanner, there exist vision and position errors. To solve these problems and avoid complex computation of each finger's contact force, impedance control [21] is applied to the thumb. Position control based on PD feedback is applied to the other fingers. And the inertia of the link is ignored for simplifying computation.

The closer the value of grasp quality is 1.0, the better the grasp quality is. In order to decrease the computation cost, a threshold value is also set. By default the value is 0.2.

The grasping attempts in virtual environment will stop once the value of grasp quality is above the threshold value. If there is not a force-closure grasp in simulation, there is no actual grasp. If the object is not grasped successfully and the fingertip slips on the object, it can be felt through force/torque sensors of fingertip according equation (2), coulomb friction law, and the process will be redone.

B. Example

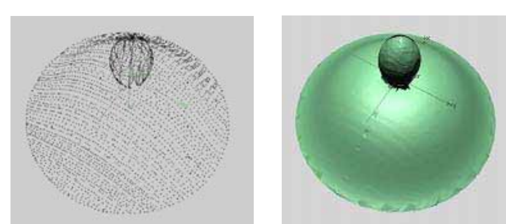
The example of grasping a teacup cover is shown bellow. We assumed the coefficient of friction is 0.4. A teacup cover is scanned and the thumb rotates to one side (see Fig. 6 (a)). The scanning time is about 3 *s*. After the data is collected, it is triangulated in less than 2 *s* of CPU time on a P4 2.8GHz PC. Fig. 4 (a) shows the result of scanning and 5436 points is collected. Fig. 4 (b) shows the reconstruction of the 3D model of teacup cover on a Sgi O_2 workstation. It takes about 7 *s* to perform 33 grasp attempts in virtual environment and the "optimal" hand configuration is selected. In Fig. 5, a stably grasping is shown in simulation environment, the quality is 0.23571. When the fingers contact with the object, friction cones will be shown in the contact regions. Its normal vectors are vertical to the contact facets. Fig. 6 (b - d) shows an actual grasp.

We used this system to grasp cubes, cylinders, computer mice and disks etc.. Nearly 110 actual grasp executions have been performed using this system. The success rate was more than 94%.

There are two kinds of failure observed during the grasping process. The first is that the grasp forces are too small and the object slips from the hand. By adjusting the stiffness of thumb, the problem has been solved. The second is that the object slightly moves by the first arrived finger. When the method of Paul's quartic equation trajectory interpolation [22] is incorporated into the finger control, the phenomenon occurs rarely.

VI. Conclusion and Future Work

In this paper, we present a general framework of automatic grasping unknown objects with multifingered hand. By incorporating a laser scanner and simulation environment, nearly "optimal" grasp could be found on line among a huge number of grasp configurations. Although it now takes much time to compute grasp configuration, the result indicates



(a) Scattered data (b) Reconstruction

Fig. 4 Reconstruction of a teacup cover.

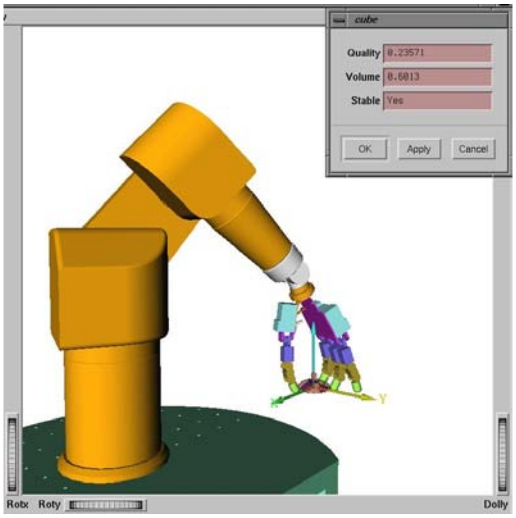
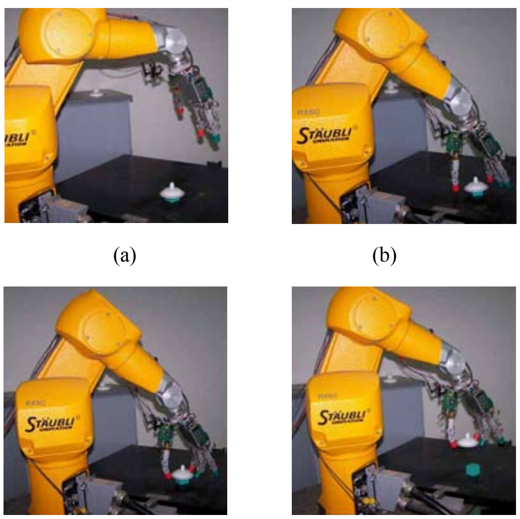


Fig. 5 Grasp quality evaluation in simulation.



(a) (b)

(c) (d)

Fig. 6. (a) Scanning the object, the support of thumb rotates to 0 degree. (b – d) The process of actual grasp. The support of thumb returns back to 90 degree.

this strategy is feasible to complete a grasping task automatically under this framework in uncertain environment.

The system is currently restricted to precision grasp. In future work we will intend to incorporate a complex grasp planner into this system and realize power grasp. Future work will also be concentrated on incorporating smart learning algorithms into this system so that the time cost on computing grasp quality will be decreased.

REFERENCES

[1] S. A. Stansfield, "Robotic grasping of unknown objects: A knowledge-based approach," International Journal of Robotics Research, vol. 10, no. 4, pp. 314-326, August 1991.

[2] Thea Iberall, Joe Jackson, Liz Labbe, and Ralph Zampano, "Knowledge-based prehension: Capturing human dexterity," In Proceedings of the IEEE International Conference on Robotics and Automation, 1988.

[3] Bekey G. A., Liu H., Tomovic R., Karplus W. J., "Knowledge-Based control of grasping in robot hands using heuristics from human motor skills," IEEE Trans. On Rob. And Aut., vol.9, pp. 709-722, 1993.

[4] Wheeler, D.S.; Fagg, A.H.; Grupen, R.A., "Learning prospective pick and place behavior," in Proceedings of the 2nd International Conference on Development and Learning, 2002

[5] Balch, T. and Arkin, "Behavior-based formation control for multi-robot teams," IEEE Transactions on Robotics and Automation, 1998.

[6] R. Platt, AH Fagg, and R. Grupen, "Nullspace Composition of Control Laws for Grasping," In Proc. of the IEEE/RSJ International Conference on Intelligent Robots and Systems, Lausanne, Switzerland, 2002.

[7] A.Bicchi, "On the closure properties of robotic grasping", International Journal of Robotic Research, 14(4):319-334, 1995.

[8] Li Han, Jeff C. Trinkle, and Zexiang X. Li, "Grasp analysis as linear matrix inequality problems," IEEE Transactions on Robotics and Automation, vol. 16, No.6, December 2000.

[9] Mirtich, B., and Canny, "Easily computable optimum grasps in 2D and 3D," In Proceedings of the IEEE International Conference on Robotics and Automation, 1994.

[10] Hasegawa, K. Murakami, T. Matsuoka, "Grasp Planning for Precision Manipulation by Multifingered Robotic Hand," In Proceedings of the IEEE International Conference on Systems Management and Cybernetics, October 1999.

[11] X. Zhu and J. Wang, "Synthesis of force-closure grasps on 3-d objects based on the Q distance," IEEE Trans. Robotics and Automation, vol.19, no.4, pp.669-679, 2003.

[12] M. T. Hagan, M.B. Menhaj, "Training Feedforward Networks with the Marquardt Algorithm", IEEE Transactions on Neural Networks, Vol. 5, No. 6, pp. 989 – 993, 1994.

[13] G. Lera, M. Pinzolas, "A quasi-local Levenberg-Marquardt algorithm for neural network training," In Proceedings of the 1998 IEEE International Joint Conference on Neural Networks, vol.3, pp. 2242-2246, 1998.

[14] H. Hoppe, T. DeRose, T. Duchamp, "Surface Reconstruction from Unorganized Points," Computer Graphics, vol. 7, pp. 71-78, 1992.

[15] Andrew T. Miller and Peter K. Allen, "GraspIt!: A Versatile Simulator for Grasp Analysis," In Proceedings ASME International Mechanical Engineering Congress & Exposition, Orlando, FL, pp. 1251-1258, November 2000.

[16] T. Hudson, M. Lin, J. Cohen, S. Gottschalk and D. Manocha, "V-COLLIDE: Accelerated Collision Detection for VRML," In Proceedings of the Second Symposium on Virtual Reality Modeling Language, Monterey, California, February 1997.

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

[18] R. M. Murray, Z. X. Li and S. S. Sastry, "A Mathematical Introduction to Robotic Manipulation", CRC Press, 1994.

[19] C. Ferrari and J. Canny, "Planning optimal grasps," In Proceedings of the IEEE International Conference on Robotics and Automation, pp. 2290-2295, Nice, France, 1992.

[20] http://www.qhull.org

[21] H. Liu, G. Hirzinger, "Joint Torque Based Cartesian Impedance Control for the DLR Hand," In Proc. of the IEEE/ASME International Conference on Advanced Intelligent Mechatronics, pp. 695 -700, Atlanta, USA, September 1999.

[22] R. P. Paul, "Robot Manipulators Mathematics, Programming, and Control," MIT Press, 1981.

View publication stats