Object Manipulation by Learning Stereo Vision-Based Robots

Minh-Chinh Nguyen
University of Technology Munich
Dept. Computer Science
81667 Munich-Germany
Nguyen@in.tum.de

Volker Graefe
Bundeswehr University Munich
Inst. of Measurement Science
85577 Neubiberg - Germany
Graefe@UniBw-muenchen.de

Abstract

An approach to realize learning calibration-free stereo vision-based robot for manipulating objects is introduced. It allows a robot gather experiences through interaction with the world and continuously improve its performance based on the collected experiences. It uses a direct transition from image coordinates to motor control commands, but no world coordinates and no inverse perspective or kinematic transformations.

The approach has been tested in real-world experiences on an uncalibrated vision-guided manipulator with five degrees of freedom to grasp a variety of differently shaped objects.

Keywords: *Calibration-Free Robots, Knowledge-Based Object Grasping, Learning Robots, Robot Vision, Uncalibrated Robot Control.*

1 Introduction

Object manipulation by calibration-free robots, i.e., robots depend neither on inbuilt quantitative models nor on pre-defined numerical values of any parameter [3], has long occupied the attention of researchers in vision-based robot control. Recently a variety of methods has been developed for this challenging and difficult task. For instance, [1, 5] do not need to use an exact kinematic model of the manipulator or knowledge of the camera parameters by performing a self-calibration at four known points combined with the use of visual feedback. Other researchers, e.g., [9, 13] have addressed similar problems. They have proposed try-and-iterate approaches to robust and adaptive robot control. These approaches allow the manipulation of a variety of differently shaped objects in any chosen orientation in a horizontal plane. They treat each degree of freedom (DOF) individually and use qualitative, but *not quantitative*, knowledge of the robot's kinematics and the camera arrangement. [4] have built on those approaches and introduced the Sensor-Control Jacobian matrix to allow a unified control of all DOF of a robot without using any knowledge of its kinematics. In their demonstrations this method was limited to the control of robots with three DOF only and, therefore, to the grasping of flat cylindrical objects.

In addition, all the robots mentioned above can "learn" (in the sense that they are independent on the accuracy of the models and their parameters) whatever knowledge they need in the course of their normal operation. But, they forget this knowledge immediately after the end of each experiment, and thus, no experience is accumulated. The reason is that these systems lack a long-term memory. This makes the systems insensitive to changes of parameters between experiments. But, more importantly, it also prevents the robots from collecting experiences and improving its skills and operating speed in repeated experiments.

To overcome these shortcomings, an approach to realized learning calibration-free vision-guided robots is presented in this paper. A key point of the approach is a direct transition from image coordinates to motion control commands of a robot. The parameters controlling this transition are learned automatically and remembered in the robot's knowledge base.

2 Uncalibrated Grasping

2.1 The Problem

A control system for a vision-based robot is to be designed that does not depend on any quantitative knowledge of the robot's characteristic parameters and, therefore, does not require any calibration. Specially, in contrast to classical approaches to robot control, no knowledge should be required regarding:

Figure 1: The gripper of the robot and objects that were used in our experiments, as seen by one of the robot's cameras

- the exact locations of the cameras
- the exact viewing directions and the internal parameters of the cameras
  (except that both cameras should have the actual work space of the robot in their fields of view)
- the dimension, kinematics and joint angles of the robot
  (except that, for practical reason, we presently assume that the robot is of the articulated arm type, and that the general type of the system are known)
- the quantitative relationships between the control words sent to the motor controllers and the resulting motions
  (except that these relationships are assumed to be "smooth")

2.2 A solution for Special Cases

Of the manipulated objects used in our experiments (Fig. 1) some have a vertical axis of rotational symmetry and can be accessible from above. They may be grasped with the gripper hanging down vertically (joint J_4, Fig. 2), while the orientation of the gripper around its axis (joint J_5) is irrelevant. It is sufficient for a successful grasp, therefore, to make two points, the center point of the open gripper and the reference point of the object (cf. [10]), coincide. Therefore, only three DOF (J_1, J_2 and J_3) of the robot have to be controlled. An effective control strategy is then to make the apparent center point of the gripper coincide in the images of both cameras with suitable chosen reference point on the images of the object to be grasped.

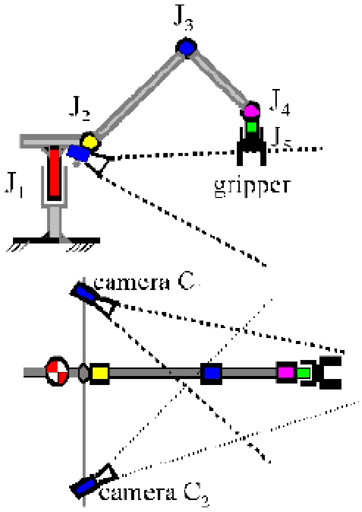

Figure 2: The robot arm used for our experiments in uncalibrated manipulation, its joints J_1 to J_5, the unsymmetric arrangement of the cameras, and their fields of view (cf. Figure 4).

Motion of the robot's joints are effected by sending control commands to the motors. The direction and magnitude of the resulting motion depends (in our case, in an unknown way) on a numerical parameter contained in each command. The robot determines the correct values of those parameters automatically and without any previous knowledge by first sending arbitrary control commands to the motors and observing the resulting motions of the gripper in the camera images. For details see [4, 9].

2.3 A More General Case

To grasp objects that lack rotational symmetry, but have such a shape and orientation that they may be grasped from above, a fourth DOF, the one associated with joint J5, must be activated. To grasped objects shown in Fig. 1 in all possible orientations, an arm with 6 DOF is necessary. If, as it is the case with our robot, only 5 DOF are available, the objects can be grasped in many, but not all orientations.

The method we have developed for this is an extension of the previous one. First, by controlling joints J_1,

J_2 and J_3 (Fig. 2), the gripper is brought to a location (in both images) where the image of its center point is near the image of the object reference point. Then the gripper is aligned with the main axis of the object in both images by controlling joints J_4 and J_5. Generally, when two lines in an image, such as the edges of the gripper and the main axis of the object, are parallel to each other, it does not imply that the corresponding lines in the world are parallel too. However, when in the the final phases of the grasping process the gripper is close to the object, this error is small enough to be neglected. For details see [9, 13].

Due to the kinematics of the articulated arm, the orientation and location of the gripper cannot be controlled independently of each other. Therefore, the process must be iterated until both the orientation and the location of the gripper are simultaneously approximately correct.

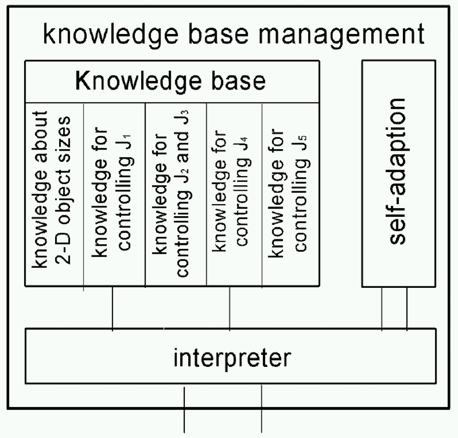

Figure 3: The knowledge module is structured into a set of independent sub-modules.

3 learning, Remembering, Forgetting

Ideally, a uncalibrated robot should be able to start working immediately after it has been switched on, without requiring a training phase. Since it does not yet know its own characteristics its movements will not be optimal. The robot should then learn from experience while it is performing its task and improve its skills over time. For this purpose it must have some kind of long-term memory(knowledge base) that the robot described above is lacking. However, the characteristics of the robot or of the environment may change, for instance due to the aging of parts or to some maintenance that is performed on the robot. In such a case the robot should be flexible enough to replace or modify the contents of its long-term memory, either gradually or in large steps, depending on the nature of the changes, in order to adapt to the new situation.

An example of a robot with some of those characteristics was introduced by [15] for grasping cylindrical disks. With it, the acquired knowledge is stored in multi-dimensional tables, where the dimensionality of the tables depends on the dimensionality of the sensor data space which is at least equal to the number of DOF that need to be controlled. Consequently, the number of data that the robot must collect before a learning effect becomes apparent increases exponentially with the number of DOF to be controlled. Although that method has work well for a robot with 3 DOF, the learning would soon become unacceptably slow as the number of DOF were increased. To overcome these shortcomings, the knowledge base for our robot to grasp a variety of differently shaped objects (Fig. 1) is built in such a way that its dimensionality is not depending on the number of DOF that must be controlled, and that the acquired knowledge can be used flexibly and efficiently. Its characteristics are:

- The required knowledge for the manipulator control is not saved centrally in a single knowledge base, but distributed in the complete system. Thus, the respective knowledge is represented optimally for carrying out the respective task. It is acknowledged that in this way under some circumstances the same knowledge may be saved several times in different places in the system.

- The knowledge module is organized as a set of fairly independent submodules each performing a limited task. While the knowledge bases is built as a set of 1-D and 2-D tables each containing limited knowledge.

- The content of the knowledge base is characterized as static, i.e., new entries in the knowledge base do not lead in our case to a change, or an overwriting of available knowledge base contents.

Figure 3 illustrates the knowledge module structure for our robot. It contains not only the knowledge base itself, but also other separate submodules which manage the initiation of the knowledge base, and the use, expansion and adaptation of the acquired knowledge. Therefore, this module is generally called the knowledge base management. Where the module for the knowledge base is further subdivided into the five following subknowledge bases each containing limited knowledge:

- The first contains knowledge about the 2-D gripper model and position-dependent 2-D object sizes for recognizing the gripper and objects,
- The second is 1-D table that contains knowledge for controlling the joint J_1,
- The third is 2-D tables that contains knowledge for controlling the joint J_2 and joint J_3,
- The fourth is 1-D tables that contains knowledge for controlling the joint J_4, and
- The last is 1-D tables that contains knowledge for controlling the joint J_5.

The required capacity of each table was introduced in [7].

The advantage of such a modular structure is that the size of the knowledge base increases only linearly with the number of DOF to be controlled. Moreover, knowledge for each DOF can in some cases be acquired and used independently since, depending on the task, it is not always necessary to use all available DOF of the robot for a given task. For instance, as long as a submodule of knowledge is still empty, the robot merely needs to learn to control the joint(s) corresponding to this submodule, while the control of other joints can be totally based on the available knowledge. Additionally, we also separate the inference engine and knowledge base. This is realized by the complete separation of the interpreter submodule from the knowledge base submodule (Fig. 3). This makes the knowledge easily accessible and explicit as possible.

The interpreter submodule is responsible for the management of the whole knowledge module. This comprises the initiation of the knowledge base, the choice and application of the available knowledge, and the expansion of the knowledge base. The working mechanism of this submodule was presented by [8].

The self-adaption submodule is responsible for adapting the available knowledge to changes of the robot's parameters or of the environment. Depending on the changing conditions the acquired knowledge may be also forgotten (cf. [8]).

As long as no knowledge is available in a subknowledge base, the corresponding joint(s) of the robot is controlled with the try-and-iterate method introduced in sections 2.2 and 2.3 above without memory function. Otherwise, the robot control is to be based on the stored knowledge and current data about completing tasks from the vision system. How the robot acquires necessary knowledge and uses the acquired knowledge were presented in [8].

4 Image Interpretation

The task of the image interpretation is to locate and track the gripper and object to be grasped in both camera images, and to report the image coordinate and orientation of the gripper and the object to the higher-level processes. This task includes the following sub-tasks:

- Object detection, i.e., separating the gripper and other objects from the background and other irrelevant image information and locating an object that may be grasped
- Classification of differently shaped objects according to the way how they should be grasped: cylindrical, non-cylindrical, convex, concave etc.
- Determination of the object's reference point and its orientation in the camera images
- Determination of the gripper center point and the orientation of the gripper in the camera images
- Determination of the priority of grasping multiple objects, i.e., the selection of the object to be grasped first when there is more than one object that is to be grasped.

The software of the image interpretation was realized as a set of subtasks that may run sequentially or in parallel. It is described in more detail in [10, 12].

5 Experiments and Results

To test and demonstrate the presented approach, a robot comprising a 5-DOF manipulator Mitsubishi Movemaster RV-M2 (Fig. 4), a vision system and a controller was used. The robot is completely uncalibrated, i.e., no quantitative model of its kinematic, sensor and control characteristics exists. The sensors of the robot are two video cameras which are mounted on the arm and participate in the rotation of the arm around its vertical axis, but are fixed relative to the work plane of the robot (the plane containing the axes of the joints J_1 and J_5, Fig. 2).

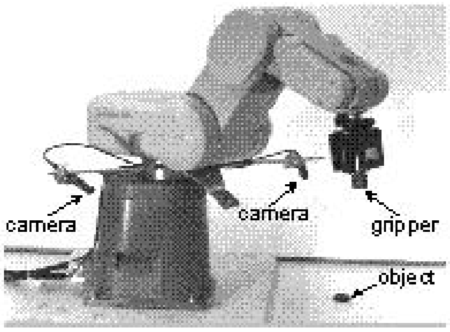

Figure 4: Mitsubishi Movemaster RV-M2 with two cameras C_1 and C_2 of adjustable arrangement.

The image from the two cameras are processed by a vision system, implemented on two Digital Signal Processors TMS320C40 (Texas Instruments), one processor for each camera. During the grasping process the vision system delivered continuously and in real time the image coordinates of the reference points of the object and of the gripper, as well as their orientations, in the image of both cameras.

The grasped objects were placed on supports of unknown height (0 to 20 cm) in various almost arbitrary orientations somewhere in the robot's 3-D work space. Due to the lack of a sixth DOF and to certain limitations of the vision system, e.g., slim long objects should not point into one of the cameras, some objects orientations had to be avoided.

As expected, in the experiments the objects were searched, detected, located, classified and grasped reliably, regardless of their initial locations and orientations in the robot's work space. To verify the robustness of the robot against unexpected parameter changes two experiments were performed. In the first one the orientations of the cameras were arbitrary modified by large angles, limited only to the requirement that the gripper and object to be grasped had to remain in the fields of view of both cameras. In the second experiment the cameras that are normally mounted at equal heights above the table were misadjusted in such a way that one of them was about twice as high above the table as the other one. In both experiments the changes were in no way modeled or communicated to the robot. Nevertheless, the robot continued to function and to grasp objects as before.

By skillfully choosing the initial position and orientation of the object to be grasped the robot can already acquire the sufficient knowledge about the control of the joints in larger working area after only one full learning phase. Then, the robot is able to move its gripper to any position in the images that is physically reachable with the use of the acquired knowledge. The more knowledge acquired, the faster and smoother the robot moves.

6 Summary and Conclusion

We have realized a learning uncalibrated robot for manipulating objects. It does not use any quantitative model of itself and, therefore, never needs any calibration. Due to the lack of a quantitative model and the resulting independence of any calibration the robot is extremely robust against even major changes in its characteristic parameters. During the actual use of a robot such changes might be caused, e.g., by maintenance operations or the replacement of parts. In Experiments it was shown that even arbitrary disturbances of the camera orientations could be tolerated whilst the robot was operating. This robustness has the potential for substantial cost saving in the operation of robots in the real world.

In contrast to earlier systems [4, 9, 13], the robot now has a permanent memory and is, thus, able to remember what has learned and to build up experience. No dedicated training phase is necessary. The robot acquires and updates the required knowledge and improves its skill during its normal operation. After having executed a few grasps, the robot can work much faster and smoother than before. The key point of the presented approach is a direct transition from image coordinates to motor control commands. The parameters controlling this transition are learned automatically and remembered in the robot's permanent memory. The memory is organized as a set of tables containing motor control words as functions of the image coordinates of the gripper and the object to be manipulated.

Other researchers, e.g., [2] have addressed similar problems. They have used neural networks to represent the functions necessary for controlling a manipulator that is mounted on a movable platform. An advantage of neural networks is that they are, generally speaking, well suited for representing arbitrary nonlinear functions, which is exactly what is needed here. However, disadvantages are that neural networks require an - often lengthy - training phase before they can begin to do useful work. In addition, it is difficult to design neural networks that can continue to learn and relearn while they perform their duty after the initial training phase. Such an ability is, however, needed if the system is to adapt to continuous changes. As [6] states that the major limitation of neural networks and genetic algorithms is the difficulty of introducing large amounts of domain specific knowledge to them and explicitly exploiting that knowledge or any feedback information in the learning process.

Compared to the methods using neural networks, our method has obviously the advantages: the robot not only learns autonomously how to perform the task of grasping an object, but also remembers what it has learned. Additionally, it can adapt the acquired knowledge to new situations. Specially, it does not need a training phase and can start working immediately, even with an empty knowledge base.

7 Outlook

Learning uncalibrated vision-based robot control will show its full potential when it is used for mobile robots that are to operate in complex and varying environments.

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