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THE HEURISTICS OF MOTOR SKILLS

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Abstract

A promising approach to the implementation of control strategies for dextrous robot manipulators is introduced in this paper. With particular emphasis on the design of dextrous robot manipulators and the performance of grasping tasks, the role of anthropomorphic models is considered, and the integration of observed human heuristics in the overall control program is described. The utility of using concepts and techniques currently in use in the artificial intelligence field of computational heuristics is then discussed. The utilization of these concepts in the design of the control program of the Belgrade/USC mechanical hand is described in some detail.

Introduction

Recent years have seen the introduction of ever more versatile and elaborate robot manipulators dedicated to the performance of a wide variety of challenging tasks. The automatic or semi-automatic control of these mechanisms frequently entails computational requirements too complex to be handled in real-time by conventional computer techniques. This has led to a quest for new approaches to the problem. In the present paper we focus on the control of dextrous manipulators such as the multi-fingered hands which have recently been introduced by a number of investigators. [1,2,3] It is hoped, however, that the concepts presented in this paper will be useful in the development of control strategies for many other robot applications.

We are specifically concerned with the tasks associated with the grasping of objects of arbitrary shapes. One of the basic problems in achieving such a task is that every reaching and grasping effort in an unspecified environment appears to be a new situation. The hand controller must therefore be able to adapt to a very wide variety of initial conditions (relative initial positions of the hand and the object to be grasped), and sizes, shapes, orientations, and compositions of the object. Contemporary manipulators may have as many as 32 degrees of freedom. The objective of the control program is to accept inputs from the various optical and mechanical sensors and to send appropriate command signals to the actuators within the hand.

Most contemporary approaches to the control of dextrous hands are based essentially on the solution of kinematic and kinetic equations of motion. The relative position of the hand and the object to be grasped as well as descriptions of the object are provided as inputs. A computer is then employed to solve the equations of motion and to provide the requisite actuator signals as outputs. Usually this entails the suboptimal solution of a variational problem to satisfy separately-specified criteria such as the minimization of the distance traveled by the hand, the minimization of the energy expended by the hand, etc. Such an approach to hand control is deductive, commencing with the general laws of mechanics and leading to the numerical solution of a specific problem. As the complexity of the grasping task increases, the number of arithmetic operations which must be performed grows exponentially, and the computational load eventually becomes unmanageable even when very powerful special purpose computers are available.

As an alternative to the deductive - numerical approach, the authors have introduced a non-numerical method based largely on inductive, empiric techniques. [4] This method features the development of a knowledge base including a large amount of specific input/output data obtained by observing a large number of successfully completed grasping tasks. The logic program for utilizing this data base includes the implementation of pattern recognition algorithms capable of utilizing the visual clues provided by the optical sensors and providing object classifications in a simplified observation space. If it is desired to employ such an inductive approach to devise control strategies for mechanical hands, two principal questions need be answered: How are the data comprising the knowledge base to be obtained or generated? How are these data to be utilized in determining the required control outputs?

In the research described in this paper, the model upon which the control strategy for the robot hand is based is anthropomorphic. That is, human hands and the strategies employed by humans in performing grasping tasks are used to provide the initial data base and the insights for the logic program. There are a number of advantages in attacking the problem in that way. First of all, human hands are successful in carrying out a wide variety of grasping tasks, tasks that the mechanical hands are also expected to accomplish. A robot hand mimicking human hands is therefore likely to satisfy many industrial as well as prosthetic applications. In fact, in many robot applications it is desirable that the mechanical hand be as similar as possible in its functions as a human hand. Also, the input and output data, required to build the knowledge base, can be generated and gathered relatively easy by observing human hands. Some recently developed instruments can be applied to greatly facilitate that task. On the other hand, an apparent disadvantage of employing the anthropomorphic model is that the grasping strategies of human hands are constrained by the structure and capabilities of the human body. Robot hands are not necessarily subject to the same constraints. For example, the joints in the wrist and the fingers are unable to bend with equal facility in all directions, while the joints of a mechanical hand need not be limited in the same way. It follows, that a mechanical hand could be expected to employ control strategies leading to performance superior to that of the human hand model. For this reason, a data base which is employed by observing human hands can serve as a very useful starting point in developing the strategy for the mechanical hand. However, at some point in the development of the control strategy, the mechanical hand must be permitted to learn from its own experiences.

Parallels with Computer Heuristics

In exploring the conceptual basis for the non-numeric method, it is interesting to observe some striking similarities between the problem of devising a control strategy for grasping tasks using an inductive technique, to the methodology employed in the recently emerging computer science field of heuristics. As described in detail by J. Pearl [5], "Heuristics are criteria, methods or principles for deciding which among several alternative courses of action promises to be the most effective in order to achieve some goal. They represent compromises between two requirements: the need to make such criteria simple and, at the same time, the desire to see them discriminate correctly between good and bad choices". As a problem solving tool, heuristics constitute an alternative to more formal methods for finding optimum solutions for complex problems. Generally regarded as falling within the artificial intelligence area, heuristic problem solving systems generally consist of:

1. A knowledge base

2. Production rules

3. A control strategy

The control strategy is designed to produce relatively rapid though sub-optimal solutions of the problem.

The execution of grasping functions performed by human hands, which constitute the anthropomorphic models for the problem under discussion in the present paper, are generally considered to be carried out completely automatically. That is, they entail no conscious intellectual activity. None-the-less, the acquisition and improvement of human and animal motor skills constitutes an important optimization activity, which depends upon heuristic-like methods, albeit at the reflex level. It is one purpose of the present paper to consider the nature of heuristics pertinent to such skills.

A study of the parallels between heuristic problem solving and robot manipulation, may provide interesting fundamental philosophical insights. More directly pertinent to the problem at hand, however, is the possibility of applying computer techniques developed in the heuristics area to the realization of successful controls strategies for dextrous hands. During the past years there have been many studies aimed at providing the basic tools for heuristic problem solving. These include methods for the representation of the problem space and the organization of the knowledge base, while other studies have concentrated on logic programming to facilitate the processing of the information in the data base; and many other studies have explored alternative control strategies.

Heuristic approaches owe their effectiveness to the fact that they help problem solving without necessarily taking into account the full complexity of the problem domain. Heuristic techniques were initially applied in developing computer programs to solve puzzles and to play games and then extended to more complicated intellectual challenges. It must be kept in mind, however, that heuristic problem solving is not confined to the conscious decision level. The development of motor skills is another important optimization activity in which humans and animals depend upon heuristics. Unlike other forms of problem solving, it involves the reflex level.

An interesting feature of human motor activities is the relatively large number of options or alternatives by which a given functional motion may be carried out. This is due to redundant skeletal degrees of freedom, to the large number of available muscles, and to the adaptability of the nervous system. In spite of the richness of options for the implementation of a given functional motion, the motor act is performed with remarkable speed and uniformity; that is, it is performed in a similar manner by all members of a species. An improved insight into the heuristics of functional motions may therefore throw new light on the functioning of neural networks and on the origins of cognitive capabilities in biological systems. This problem has been considered in detail by Arbib [6], but will not be treated further in this paper.

Optimization of Functional Motions

In this paper, two kinds of goal oriented muscular activities are considered. These include functional motions of the body and extremities which belong to the domain of mechanics and biomechanics. In addition, goal oriented activities of muscle groups which arise in speech and vision processes be discussed. The output of the muscular activity in the first case is a motion, while in the second case the output is information. Evidently, the outputs of the two kinds of muscular activity are basically different in nature; but that does not imply that the optimization criteria are distinct. In fact, experimental observations of both kinds of muscular activities speak in favor of a common performance criterion. It is our contention that this common optimization criterion, termed "the minimum effort principle", can be expressed in the following manner: A goal oriented muscular activity tends to be performed so as to minimize the metabolic energy expended. This usually implies a minimization of the number of muscles involved in a task as well as of the stress experienced by each muscle.

It is not difficult to produce evidence supporting the role of the minimum effort principle in the execution of a variety of functional motions. Swing type movements in locomotion and ballistic joint trajectories are preferred whenever feasible in motor acts, since they take advantage of the available internal system energy. It may be observed that unconstrained target approach trajectories in man and animal never follow zig-zag patterns but rather follow straight lines, whenever possible. Moreover, smooth rather than jerky joint trajectories, which would require large acceleration, are normally practiced in functional motions. The minimum effort principle also applies to muscular activities involved in data acquisition and communication. For example, the effect of minimum effort solutions in spoken languages is remarkable. It appears that the most frequently pronounced vowels are those which require minimum effort [7].

Another principle which has been identified in earlier research efforts deals with hierarchical control systems [8]. In order to cope with the complexity of functional motions, it may be assumed that the control systems in humans and animals is structured in a hierarchical manner. In this connection three levels of control of functional motions can be discerned: motion planning, coordination, and reflex and learned responses. The decomposition of a controlled structure into multiple levels can be implemented in many different ways, and an optimization criterion must be employed to choose from among these options. It has been postulated that in biological systems, the survival goal for organisms assigns the task of environment monitoring and motion planning to the high control level, while the reflex and learning level takes care of implementation. Consequently, the optimization goal affecting the interaction of control levels of functional motions tends to minimize the amount of down-flowing commands. Such a division of tasks in a multilevel control system has been termed the principle of maximum autonomy.

Searching and Clustering

The techniques of searching a domain space and the simplification of the problem domain by organizing various options into "clusters" are widely used heuristic approaches to problem solving. Both methods play an important role in learning - a subject outside the scope of the present paper, since the systems under development attempt to mimic human skills but not how these skills are acquired or learned. Clustering, however, is also directly pertinent to the identification of the optimum control strategy.

When applied to biologic systems, the term clustering refers to the capability of the nervous system to classify a wide variety of sensory patterns (visual, audio, odor, etc.) into a small number equivalence classes. For example in speech, all sounds falling within a class are understood as being functionally equivalent. It has been shown that the sounds associated with all spoken languages are classified into no more than 50 categories [9]. As described below, the clustering of the multitude of target shapes into a number of equivalence classes helps to develop efficient skill-based controllers of manipulators with dextrous hands. The understanding of the heuristics of such mechanical processes is, therefore, of considerable theoretical and practical interest.

The studies of grasping heuristics and clustering from the artificial intelligence point of view, were originally motivated by the need to develop nonnumerical approaches to the control of robots [3,10]. In order to store, in the computer knowledge base, observations of human reflexes controlling the execution of functional motion, it is necessary to identify the invariant features of a given motor act, as well as formal descriptions of relevant sensory inputs and descriptions of sensory motor pattern matching. For example, the observation of human subjects involved in the act of grasping shows that the target approach phase is used to prepare the hand in an approximate way to match the shape of the target. The interesting question therefore arises as to what geometric form or forms serve as a reference for the preshaping of the hand, when only passive tactile sensors are used. Records of the target approach processes of numerous human subjects show that the hand preshaping process displays the following inherent features:

a. References for hand preshaping are smoothed, simplified target contours.

b. For a given object contour, human preshaping habits are practically invariant.

The clustering phenomena in grasping are not determined solely by the vision system. The anatomy of the human hand, including finger articulation and joint coordination, also contributes to the clustering of target shapes into equivalence classes. As is well known, the degree of controllability of finger joints is greatest at the root of the finger and diminishes as one approaches the finger tip; the most distant joint as a rule is hardly controllable for preshaping purposes. A further reduction in the preshaping options of finger configurations in many cases is imposed by the necessity to follow a forced opposition pattern [12]. As yet, no general consensus regarding the minimum number of geometric primitives which serve as reference for human hand preshaping is available. Therefore, the choice of the number and types of geometric primitives for clustering purposes depends upon the problem domain. In the study described below, the objective was the development of industrial robots, and equivalence classes and their representations appropriate to that application were selected.

It is interesting to relate the significance of clustering in this context to the subject of autonomy in multilevel control systems. By reducing the multitude of grasping tasks to a small number of representative situations, the decision processes at the voluntary level are greatly reduced in volume and accelerated, while the system is made more amenable to automatic control at a lower level.

The technique of clustering target shapes is but one mechanism used to simplify the control of a complex multivariable system such as the human arm; that is, preshaping accommodates only the simplified target model. The task of adapting the fingers to the details of a grasping zone has yet to be considered. This adaptation is under the control of reflex mechanisms. The fingers are driven to advance until they exercise a desired pressure against the surface of the object, which effectively impedes their further progress. From the control point of view, the finger adjustment reflex is a part of a positive feed-back loop increasing the tactile inervation. An artificial reflex loop, based on this concept, has been used successfully in the control of a multifingered prosthetic hand [13]. It is also integrated in the control system of the Belgrade/USC robot hand [3]. The hand opening reflex operates in precisely the opposite way from the grasping reflex, relying on negative feedback which reduces the tactile inervation to zero.

Since biomechanical systems have redundant degrees of freedom, they are difficult to control because the motions are mechanically undetermined. In biomechanical systems, the genetically determined and learned synergy copes with the problem of redundancy. For example, in the adaptation of fingers to the actual contour of the target, the closing of the fingers never starts from the most distant joints. The motion of these distant joints is constrained and determined by the state of the finger route. The general role of synergy in the execution of motor acts has been lucidly expressed by Bernstein: The coordination of a movement is the process of mastering redundant degrees of freedoms of the moving organ; i.e. its conversion to a controllable system [14].

Application

The concepts discussed above have proven to be very useful in the design of skill-based controls for industrial manipulators with dextrous hands. Such an installation consists of a three dimensional computer vision model, a skill based expert system, a manipulator and a dextrous hand [15]. A PUMA robot equipped with the Belgrade/USC hand is shown in Fig. 1. The computer vision module serves to cluster target shapes into five equivalent classes, whose primitives are shown in Fig. 2. The hand preshaping controls for these geometric primitives are encoded in the knowledge base. Unlike the grasp control of two-finger grippers, which is relatively simple, the control system for a multifingered hand must deal with all of the following tasks:

Selection of the grasping zone.

Selection of the grasping mode.

Hand preshaping.

Size of the hand opening.

Decision as to the grasping depth.

Choice of the initial finger pressure.

All but the last two of the above tasks are handled by an expert system. Sufficient knowledge regarding the selection of grasping depth and initial finger pressure is as yet unavailable, so that a human operator must take care of these parameters.

The operation of the skill-controlled manipulator. i.e. of the expert system incorporating human experience in the execution of grasping tasks, will be illustrated with the aid of a specific example. The chosen task is to grasp a screwdriver lying on a table. The actual grasping task is only partially defined, so that a number of options are offered by the expert system. If, in addition to the grasping act, the task description is given (for example to use the screwdriver for a screwing operation), the output of the expert system will be more specific.

Fig. 3 shows the format presented as the input to the expert system to describe the shape of the screwdriver after clustering. The reduced geometric primitives describe the screwdriver as a composite object consisting of two cylinders. The computer vision module also provides additional information to the expert system such as "the axis of the geometric primitive is straight", "the cross-section is circular", "the radius is constant", etc., so that the input to the expert system may be identified with one of the five primitives shown in Fig. 1.

The description of the task constitutes another input to the expert system. The expert system is capable of handling a limited set of domain-oriented tasks, which can then be expanded according to the needs of the user. For our robotic system, which is assembly-oriented, a typical set of task descriptions for this purpose is:

Use the wrench to tighten the nut

Tighten the nut

Use the screwdriver to turn the screw

Insert the pin into the piston

Move the cylinder from location 0 to location 1

The formal presentation of the above tasks can be accomplished with the aid of two general patterns:

Pattern 1:Grasp ?object 1 [to] [?action] [?object 2] [?where].

Pattern 2:Grasp ?object and ? action it [?where]

The knowledge base contains the accumulated expertise about the problem domains stored in tabular form. Such a table, called the p (primitive) - g (grasping mode) table, associates with each geometric primitive those grasping modes which are feasible. The mapping is one-to-many, since several grasping modes may be associated with any of the primitives. The p-g table has the following entries:

Object name

Orientation

Size parameters

Approach orientation

The output of the p-g table is:

Grasping modes

Number of fingers involved in the prehension

Size of the opening of the hand (large, medium, small)

In order to derive the p-g table, the characteristics and performance of the robot hand must be known. Such features as the available grasping modes, the controllability of the finger joints, and size parameters of the mechanical hand must be known. Actual tests with the hand and the object are used to determine which grasping modes are feasible for each entry in the p-g table. The p-g table for a cylinder and the Belgrade/USC hand is presented in Fig. 4.

In general, a number of grasping nodes will satisfy a given target description, task requirement and p-g table. Heuristic rules, in conjuntion with target and task description data, serve as criteria for the selection of the prefered grasping mode among the set of feasible solutions offered by the p-g table. The inference process starts with the application of classification rules. The vision module provides data regarding the cross section contour of the geometric primitive, the cross-section function, etc., which are presented in the format shown in Fig. 3 (screwdriver). Pattern matching rules are used to identify the simplified model of the target with one of the five geometric primitives by a sequential search. Task requirements, such as stability, affect the choice of the grasping zone center. If, for instance, the emphasis in task description is on stability of the grasp, then the center of the grasping zone should be close to the center of gravity of the target. The location of the center of gravity is found in the corresponding slot of the input schema of the relevant geometric primitive.

A table relating the task properties (stability, controllability, etc.) and the heuristic rules, which help to implement such a requirement (using the appropriate grasping mode or modes) is stored in the knowledge base. It is consulted in the last phase of the inference procedure when the optimal grasping mode is to be selected. Since several heuristics may correspond to a task property, heuristics associated with each property are stored in the knowledge base with weighting factors assigned by the human operator on the basis of experience and tests.

The following are examples of human heuristics which are stored in the knowledge base and which are consulted by the inference engine when selecting the prefered grasping mode:

Larger contact preference

Close to the center of gravity

Simpler end preference

Longer part preference

Thicker part preference

Smaller contact preference, etc.

The heuristic rules are common sense expressions of physical laws and experience gathered from successful and unsuccessful attempts to grasp objects of different shapes and sizes. In the knowledge base, they are represented as LISP functions. Full details regarding the knowledge base selection of grasping modes are found in the references [16,17].

The output of the expert system is the location of the center of the grasping zone, the target orientation in terms of symmetry axes, and the finger positioning vector. In the case of the Belgrade/USC, hand the finger positioning vector is defined by only three angles, since the coordination of finger joints as well as the automatic shape adaptation mechanism is built-in mechanically [3]. The hand controller acts upon three positioning servo systems which transform the angular data into the desired grasping mode and opening.

The hand is provided with touch sensors, pressure sensors and slip sensors. Sensory information is integrated into two reflex loops which take care of the automatic finger adaptation to the details of the target contour and of automatic slip prevention. The manipulator control system therefore consists of three levels:

Voluntary level (human operator)

Expert system (computer level)

Reflex level

with the shape adaptation synergy used by human subjects being built into the control system of the Belgrade/USC hand. In this way, a high degree of autonomy in the execution of grasping tasks is built into the multilevel control system. A block diagram of the complete control system is shown in Fig. 5.

Conclusion

Classical techniques for the control of robots, including the solution of kinematic equations of motion, become more and more difficult to apply as the mechanical complexity of robot components increases and as more and more complex tasks are to be automated. In this paper we have proposed an alternative approach based upon human heuristics. Human subjects are observed while performing complex grasping tasks, and the observed heuristics employed by human hands are included in the knowledge base which forms part of an expert system for robot hand control. The successful application of these concepts to the Belgrade/USC hand suggests that the use of anthropomorphic models and observed human heuristics constitute a promising avenue for the development of control strategies for a variety of robot devices. The methodology employed in this approach closely parallels the implementation of heuristic programs for solving intellectual problems as is currently practiced in artificial intelligence studies. A collaboration between the fields of robot control and computer heuristics may therefore provide interesting new insights and valuable cross-fertilization.

References

[1] L.C. Jacobsen, E.K. Iversen, D.F. Knutti, R.T. Johnson and K.B. Biggers, "Design of the Utah/MIT Dextrous Hand", *Proc. IEEE Int. Conf. on Robotic and Automation.* pp.1520-1530, San Francisco, CA, 1986.

[2] J.K. Jr. Salisbury and M.T. Mason, *Robot Hands and the Mechanics of Manipulation.* The MIT Press, Cambridge, MA, 1985.

[3] G. Bekey, R. Tomovic and I. Zeljkovic, "Control Architecture for the Belgrade/USC Hand", Workshop on Dextrous Robot Hands, T. Ventakatwaman and T. Iberall (Editors), Philadelphia, PA, April 1988.

[4] R. Tomovic, G. Bekey and W. Karplus, "A Strategy for Grasp Synthesis with Multifingered Robot Hands", *Proc. Int. Conf. on Robotics and Automation.* pp. 87-101, Raleigh, NC, 1987.

[5] J. Pearl, *Heuristics.* Addison-Wesley Publishing Company, Reading, MA, 1984.

[6] M.A. Arbib, T. Iberall and D. Lyons, "Coordinated Control Programs for Movement of the Hand", *Hand Function and the Neocortex.* Goodwin, A. W., and Darian-Smith, I., (Editors), Springer-Verlag, pp. 111-129, Berlin, Germany, 1985.

[7] G. R. Zipf, *Human Behavior and the Principle of Least Effort.* Addison-Wesley Publishing Company, Reading, MA, 1949.

[8] R. Tomovic and R. Bellman, "Systems Approach to Muscle Control", Mathematical Bioscience, Vol. 8, No. 3/4, pp 265-277, 1970.

[9] R.S. Michalski, Y. G. Carbonell and T.M. Mitchell,"Machine Learning", Vol. 2, Morgan Kaufmann Publishers, 1986.

[10] R. Tomovic, *Skill Based Control of Robots, in Intelligent Robotic Systems.* Jzafeshas, M.,(Editor) Marcel Dekker Publisher, New York.

[11] M. Jeannerod, "Intersegmental Coordination During Reaching at Natural Visual Objects", Long, Y.,and Baddeley, A., (Editors), *Attention and Performance.* IX, pp 153-168, Hillsdale, Erlbaum, 1981,

[12] T. Iberall, G. Bingham and M.A. Arbib, "Opposition Space as a Structuring Concept for the Analysis of Skilled Hand Movements." Heuer, H., and Fromm, C. (Editors), *Generation and Modulation of Action Patterns.* pp 158-173, Berlin, Springer Verlag, 1986.

[13] R. Tomovic and G. Boni,"An Adaptive Artificial Hand ", IRE Transaction, Vol. AC-7, pp 3-10, April 1962.

[14] N. Bernstein, *The Coordination of Regulatory Movements.* Pergamon Press, London, 1967.

[15] K. Rao, G. Medioni, H. Liu and G. Bekey, "Robot Hand-Eye Coordination: Shape Description and Grasping", *Proc. IEEE Int. Conf. on Robotics and Automation.* Philadelphia, PA, pp ------------,1988.

[16] H. Liu, "Task Analysis: a Method for Dextrous Robot Hand Grasping Control", AI Manufacturing, SME, October 1987.

[17] R. Tomovic and H. Liu, "Knowledge Based Selection of Grasping Modes for Dextrous Hands", USC Technical Report, Computer Science Dept., 1988.

Captions for Figures

Fig. 1. Skill controlled robot station of the Robotics Lab, USC

Fig. 2 Geometric primitives used for hand preshaping

Fig. 3. Screwdriver after clustering

Fig. 4. The p-g table for the cylinder

Fig. 5. Structural diagram of the skill controlled robotic system

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