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Figure 6: Hand Grammar

from the robot, thereby closing the (now open) loop.

The second device is a positional sensor for the hand. This could be one similar to that employed by the VPL DataGlove, a Polhemus sensor. While this paper only addresses the movement of the robot fingers, real functionality of the hand would require that the UMDH be mounted on another robot to allow it to be moved from place to place. The current positioning of the hand in a static position limits most tasks. With the use of a position sensor, the human hand could be moved to a desired position and then the fingers could be moved.

While the current system is still under development, it has demonstrated that a functional, non-analytic approach to teleoperation is realizable. Treating the data obtained from the DHM as streams into a lexical analyzer proved to work quite well and further modifications can make it more robust.

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Figure 5: Fist, Pinch and Flat Poses

in performing gross gestures, loading only gross grasps may be sufficient.

Once the DHM motion has been broken up into a series of tokens representing movement over time, the next step would be to analyze the tokens using a parser to determine what types of tasks are being performed. A type of "hand grammar" could be defined to describe the motion of the hand. In figure 6, the relationship of the lexical analyzer and the position parser is shown. The position parser would be used to recognize the type of task being performed. The use of such a parser would allow grasp parameters such as stiffness of joints to be adjusted. In addition, the understanding of the task being performed could allow the system to predict the next actions of the hand. The system could also be used in "reverse" to request a task and have the task broken down to known positions at certain time intervals.

Two additional devices that would vastly improve this system are a force-feedback master and a hand positional sensor. The current teleoperator system allows the user to control the position of the UMDH, but the force information that is acquired by the robot hand can only be understood by the user by viewing the raw data from the UMDH, either numerically or graphically. A force-feedback master would obtain tendon force information

Figure 4: Two Functional Positions of a 3-dof Manipulator

primarily in a recognition/playback mode. The current system consists of simple set of poses, which are recognized by Jiffe in real-time and which allow for teleoperator control of the UMDH.

5 Conclusion

[Arbib et al. 83], [Iberall and Lyons 84], [Iberall 86], [Iberall 87] have studied human hand grasping and have classified these functional grasps as they apply to dextrous robot hands. In a similar fashion, we would like our system to recognize a set of hand positions that is rich enough to describe necessary tasks. These primitives could then be passed on to the parser. A rich set of known hand positions would allow the system to move smoothly from one defined position to the next. In th current implementation, only a few poses are defined (Figure 5). If the human hand is in an undefined position, the UMDH does not change configuration. Without a rich enough set of defined poses, the movement of the UMDH tends not to be smooth.

Deciding on the set of grasps to incorporate into the system is not a trivial tasks. As surveyed in [Mishra and Silver 89], many researchers have developed grasping taxonomies. Although, we would like to have a rich set of functional grasps, the tables that are created by LEX are large, so a minimal subset of grasps is desirable. Choosing a minimal subset grasps may depend on the tasks that have to be performed. In performing tasks that require precision, only precision grasps load can be loaded; whereas,

positions. LEX takes a description of the tokens and outputs a table driven C-function lexical analyzer. The description of a token used in this system, was a set of sixteen ranges of values. These represented the acceptable range for each joint for the token being described. Each token had associated with it a numerical value. This value is returned by the lexical analyzer when a sequence matching a defined pattern is recognized in the input stream.

Using LEX allows for an easily extended table-driven system. Once the descriptions for the tokens are developed, additional token descriptions can be appended and re-compiled into the system. The definitions of the individual tokens are independent of one another, so the system can be built incrementally. Although the tables produced by LEX are very large, the table driven system allows for fast lookups. Using Jiffe, lexical analysis was performed at rates of 100 Hz or greater, which is sufficient for real-time teleoperation. Once the human hand position is recognized, the numerical value associated with it is sent to the UMDH. The UMDH will then conform to the corresponding functional hand position.

A tool was developed that would automate the training phase for the definition of human hand poses. The tool monitors and identifies the range of motion for each of the human hand joints. During the training phase, the user names the pose to be defined and moves his hand to through the range of motion that will correspond that the named pose. The range for each joint is recorded and written to a LEX definition file in the appropriate form.

The following (from [Speeter 89]) is an example of the form of the pose definition. For the arbitrary 3-dof manipulators in Figure 4, pose **A** is defined by $joint_1 = \delta_1$, $joint_2 = \gamma_1$ and $joint_3$ anywhere in the range φ_1 to φ_2. Pose **B** is define by $joint_1 = \delta_2$, $joint_2 = \gamma_2$ and $joint_3 = \varphi_3$, where δ_i, γ_i and φ_i are integers in the range 0-255. These poses would be defined as follows:

$$\begin{array}{ll} \delta_1\gamma_1\{\varphi_1 - \varphi_2\} & return(A) \\ \delta_2\gamma_2\varphi_3 & return(B) \end{array}$$

where A and B are integers identifying the tokens. After a series of poses is defined, LEX is run and a lexical analyzer capable of recognizing the defined poses is created. The corresponding functional positions for the UMDH are described and stored in a file.

Once the training phase is completed, it would only have to be repeated when new poses are added to the system and the system would be used

Figure 3: System Overview

to-D converter on a VME bus. The Utah/MIT hand has its own controller to drive the pneumatic pistons to the tendons, sending and receiving analog sensory and control signals. In addition, a SUN 3/260 workstation acting as a file server and communication interface, a pair of 68020 realtime processors, and a bus repeater to an additional Jiffe processor [Andersson 89] are on the shared VME bus. The Jiffe processor is capable of 20 Mflops as compared to 200 flops for the 68020. Jiffe's speed allows for real-time interpretation of the hand positions.

The data stream that we obtain from the DHM is a set of sixteen analog values representing the hand joint angles: $< h_1, h_2, \ldots, h_{16} >$. Although the values obtained from the DHM are 12-bit values, in order to limit the number of input symbols that were analyzed and to map these directly onto the ASCII character set, the least significant 5 bits of each h_i were truncated. Although this represents a loss of 5 bits of information per joint, dividing the range of motion for a joint into 128 partitions yields a loss of, at most, 0.8°.

These values can be thought of as words in a sentence and the syntax of the 16-tuple input stream can be analyzed. Using the UNIX LEX tool we were able to parse the input stream and obtain values representing hand

Figure 2: Exos Dextrous Hand Master

Glove is a glove that is worn on the hand with optical cables that run on the outside of the glove on the back of the hand. The bending in the fibers and the change in light transmittance is used to measure joint angles. Each joint is not measured independently, so accurate data for individual joint angles is not obtainable. The VPL DataGlove is ideal for rough measurements of human hand joint position, but does not serve our purpose as a master device.

The Exos Dextrous Hand Master (DHM) [Figure 2] is a device that accurately measures joint angles of the human hand. The metallic device is secured to the back of the human hand via velcro straps. The straps are wrapped around the midpoint of each joint in three fingers, excluding the pinky, and the thumb. There are Hall effect sensors that measure extension/flexion for three joints in each fingers, as well as lateral measurement for the joint at the base of the finger. By using the DHM, sixteen analog values representing the sixteen joint angles are obtained in parallel. Unlike the DataGlove, the values that are obtained for each joint are independent of the motion of the other joints. The sixteen joint values that are obtained parallel the values that are needed by the Utah/MIT Dextrous Hand and are highly accurate. Because of these advantages over the DataGlove, the DHM was the device chosen to measure the human hand master joint values.

The system used for this research is diagrammed in Figure 3. Using the DHM, analog signals from the Dextrous Hand Master, representing the joint angles of the hand, are read in parallel and sent to a multichannel A-

Figure 1: Utah/MIT Dextrous Hand

4 Implementation

In order to demonstrate the feasibility of lexical analysis of master hand positions to control a robot hand slave, a simple real-time hand compiler was developed. Two multifingered robot hands have been made commercially available [Jacobsen et al. 84], [Mason and Jr. 85] and several others have been designed [Bekey et al. 88], (See also [Grupen et al. 89]). The dextrous manipulator that was used in this research is the Utah/MIT Dextrous Hand [Figure 1].

Although the Utah/MIT hand is anthropomorphic, there are several important differences between it and the human hand. Firstly, the thumb in the Utah/MIT hand is mounted from the center of the palm. Because of this arrangement, the range of motion of the thumb does not properly correspond to the human hand's range of motion. In addition, this prevents the hand from being configured in a flat pose. Secondly, the palm of the Utah/MIT hand has no mobility, which limits certain types of grasp. Since this approach does not rely on a mathematically mapping of the human hand work space to that of the robot hand, the robot hand does not have to be chosen because of kinematic similarity, but should be chosen so because of functional similarity. However, these differences will prevent total functional mapping from human hand positions to robot hand positions.

There are currently two devices that are commercially available for measuring human hand joint positions. These are the VPL DataGlove [Foley 87] and the Exos Dextrous Hand Master [DHM 88]. The VPL Data-

- New hand pose definitions can be incrementally added to the system.
- Fast, real-time recognition of hand poses.
- Ability to parse defined hand positions to determine hand actions.

3 Formal Grammar and Language Theory

The goal of this functional transformation is to interpret the human hand master positions and pass this information to the robot hand slave. Given information about the functional position of the master device, the robot hand could respond appropriately with a corresponding functional position. Using this type of system, the kinematic differences between master and slave become less significant as long as functional similarity exists. We are concerned with understanding the hand position as a functional unit and not as individual joint positions.

Using formal grammar and language theory, the sequence of positions from the master is taken as the input stream. Lexical analysis determines the syntax of the master device and using a grammar for hand functions, a parse tree describing activity of the hand can be determined. A lexical analyzer with the ability to interpret hand positions was developed. The hand grammar requires a rich set of production rules to represent the hand's functional activity. This system will produce commands to control the robotic hand in a manner functionally equivalent to that of the master. In order to be used effectively as a teleoperator system, the lexical analyzer must be able to interpret the hand positions and produce a token representing the functional position in real-time.

The robot hand slave can be controlled by using only the position tokens obtained from the lexical analyzer. In addition to positional information, motion information could also be interpreted. The motion could be obtained as a time averaged function over the previous sample. Using two modes of lexical analysis, interpretation of the current hand position and velocity could be performed. With the addition of production rules, parsing of the position and velocity tokens could produce a high level description of the master hand task.

2.2 Nonlinear Transformation

Directly applying forward and inverse kinematics is potentially the most powerful transformation between the hand master and slave. For each finger, forward kinematics defining Cartesian position and orientation of the fingertip as functions of measured joint angles are required. As reported by [Hong and Tan 89], using a VPL DataGlove, the calibration of the master device to measure these angles can be quite complicated. The inverse kinematics are then required for defining the joint angles on the robot hand as functions of Cartesian positions and orientation.

The inverse kinematics does not require extensive computation and is relatively straight forward. Deriving the forward kinematics for the human hand is, however, more complicated. Although there is extensive biomedical research on the mechanics of the human hand [Buford and Thompson 87], [An et al. 79], the performance of the forward kinematic transformation is dependent on the accuracy of the measured parameters and the accuracy and simplifications made in the human hand model. In addition, the lack of correspondence between the robotic hand workspace and the human hand workspace causes problems. Due to these problems, this method is not adequate for telemanipulation.

2.3 Functional Transformation

In using analytic transformations an attempt is made to establish a mathematical relationship between the work space of the human hand master and that of the robot hand slave. Rather than being concerned with the mathematical correspondence between the two different types of hands, a functional approach is concerned with conveying the functionality, or intent, of the human hand master to the slave device.

Interpreting the intent of human hand motion and transferring this information to the slave device requires a system that can take into account both the syntax and semantics of the motions. A formal grammar and language theory approach to this problem is presented. Advantages of this system include:

- Kinematic dissimilarities between the master and slave do not pose a problem, as long as the slave device can functionally perform the same tasks.

2 Motivation

In order to control the Utah/MIT hand using teleoperation, a mapping between the human hand master's motions and the corresponding robot slave's motions is needed. Various methods have been proposed for the control of telemanipulators [Venkataraman and Djaferis 87], [Hong and Tan 89], [Pao and Speeter 89], [Hirzinger et al. 89], [Narasimhan 88]. By studying human hand movement and grasping, kinematic transformations for the human hand and grasp classifications have been developed [Elliott and Connolly 84]. Transformation of human hand motions can be performed analytically using linear or non-linear techniques, or they can be performed functionally. Each of these three approaches has been discussed in [Speeter 89].

2.1 Linear Transformation

A linear joint-to-joint mapping between hand master and slave involves mapping each joint of the master to the corresponding joint of the slave using a linear correspondence function:

$$r_i = h_i(\underbrace{\frac{r_{irange}}{h_{irange}}}_{a}) + \underbrace{(r_{imin} - h_{imin}\frac{r_{irange}}{h_{irange}})}_{b}$$

r_i = position of the i^{th} robotic joint;
h_i = position of the i^{th} human hand joint;
r_{irange} = range of motion of the i^{th} robotic joint;
h_{irange} = range of motion of the i^{th} human hand joint

Using a 68020-based system described later, this method was simple to use and fast. Hand samples (sixteen joints) can be read, this transformation applied and control commands written at rates of up to 500 Hz. The major drawback to this system is the underlying assumption that the master and slave hands are kinematically similar. In this implementation, the master and slave both have the same degrees of freedom, but are not kinematically equivalent. While there is a lack of kinematic correspondence, the user can learn to compensate for the kinematic dissimilarity.

1 Introduction

The future of automation increasingly requires that robot end effectors be able to perform complicated tasks that rely on dexterity, versatility and adaptability. The areas into which automation will be introduced are typically unstructured and unpredictable. These settings include cleaning up nuclear "hot" spots and maintenance tasks in hostile environments such as space, underwater and nuclear and chemically contaminated areas. Multifingered, anthropomorphic dextrous hands are potentially an ideal end effector for these tasks.

Many researchers are currently involved in designing methods for controlling articulated robot hands [Allen and Roberts 89], [Allen et al. 89], [Liu et al. 89], [Kobayashi 85]. Ideally, one would like to be able to endow the manipulator with enough intelligence for performing the desired task by simple instruction. The manipulator, along with a vision and tactile sensing system will be able to "look" at and recognize the objects in the environment. It will then make a decision as to how to go about performing the assigned task given its own limitations and the changing environmental information.

This type of autonomous control of robot hands is computationally very expensive and algorithmically complex. However, manipulation by teleoperation (telemanipulation) provides a less expensive method of control. Utilizing the human's knowledge and learned dexterity, it allows the user to be the eyes and mind of the system and, in real-time, react to changes in the environment. In this manner, error recovery and task planning are performed by the human operator. By exploiting the user's capabilities, particularly his abilities to view the scene, process the information and make decisions as the task progresses, the manipulator can perform the desired task without endangering the user.

While telemanipulation is computationally less expensive and allows the user to be in the control loop, the problem of transforming human hand motions to that of the slave device has to be addressed. A fast, efficient functional transformation of human hand motions to motions of the Utah/MIT Dextrous Hand (UMDH) is presented.

Teleoperator Control of the Utah/MIT Dextrous Hand – A Functional Approach

*Amy Morishima**
Department of Computer Science
Columbia University
New York, NY 10027

Thomas H. Speeter
Machine Perception Research Department
AT&T Bell Laboratories
Holmdel, NJ 07733

November 28, 1989

Abstract

Manipulation in unstructured environments requires versatility and adaptability. Multifingered dextrous robotic hands can provide the necessary kinematic dexterity. By controlling these devices using teleoperation, a system can take advantage of the human's functional dexterity and knowledge. However, mapping the human hand joint positions and motions to that of the robot hand is a complex problem. A simple, non-analytic method, using functional transformations, to control such manipulators via teleoperation is described.

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