A LEARNING SYSTEM FOR TRAJECTORY CONTROL IN ARTIFICIAL ARMS

A. Freedy, F. Hull and J. Lyman

Summary

An adaptive aiding technique for performance improvement in artificial limbs control has been developed and demonstrated. The technique incorporates a learning subsystem that is able to supplement the patients control function. The approach was first presented as a concept at the Third International Symposium on External Control in Dubrovnik and was also applied to remote manipulation in earlier work (Freedy et al.,1971).

This paper deals with the expansion of the learning subsystem toward complete motion trajectory control.

Preliminary results of experiments with the trajectory control system in operation with simulated two dimentional tasks are provided. The learning system is implemented on an Interdate Model-70 mini-computor which is directly connected to the simulated prostheses control system. The computer is capable of observing the control actions of the operator, learning a task at hand and taking over part of the trajectory control responsibility.

A description of on going work for applying the technique to the UCLA/VA assembled prosthesis is given.

Introduction

This paper presents further development and improvements of a learning system for patient aiding in artificial limb control. The mathematical developments of the technique and results of preliminary work have been given in previous publications /1,2,3/. The control concept incorporates the sharing of control responsibility between the operator and a separate automaton able to observe the patient responses, learn part or all of a given task, and take appropriate control actions. Its purpose is to relieve the patient of routine or exacting control requirements and reduce his information handling load. A system diagram of the technique is given in Figure 1.

A computer is incorporated into the control loop. The computer

This work is being supported by the Veterans Administration Conctract No. Vi005P-9779 and NSF Grant Nos. GK28896 and P2K0437.

program contains a learning program which is capable of controlling the prosthesis autonomously. Initially all control actions are generated by the patient. As learning occurs the computer begins to participate in the control process and take over control responsibility. As shown in Figure 1, control is then transferred from loop (A) to lopp (B). The result is to provide a relief on patient control load. Since the control actions of the computer are based on a maximum likelihood decision principle, probability of an error always exists. When an erroneous control action is generated the operator overrides computer control. Overall, from the point of view of the operator, the task appears to become easier to do as successive trials occur.

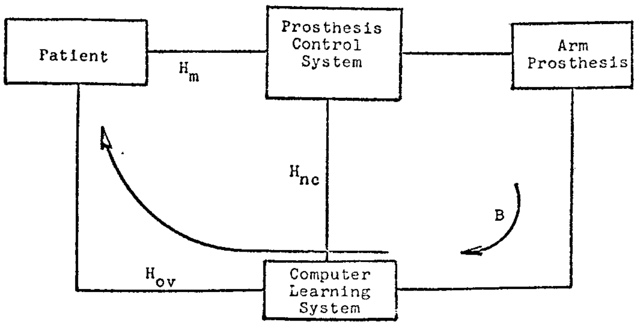


Fig. 1. System diagram

Definition of the Aiding Process

It is possible to define the aiding process quantitatively. Such a definition provides a model for predicting the proportion of control load which is assumed by the learning system. To illustrate, let us assume that in performing a specific set of manipulative tasks T the patient must supply H_m bits of information to the control system. If the computer supplies H_{ac} bits then the net reduction in operator information output is

$$H_r = H_m - (H_{ac} + H_{ov}) \quad (1)$$

where H_{ov} is the information associated with the operator override. This channel is used to override erroneous computer decisions. Equation /1/ can be expressed in terms of the parameters of the learning system. There are two such parameters: (1) P_c -- the probability of correct response and (2) θ -- the level of confidence. The first parameter is a probability measure that the decision of the learning system is correct. The second parameter determines the lowest value of P_c for which control decisions are sutonomously generated by the learning system. That is each decision which is made with a probability of success which is lower than θ is not generated. Having these parameters it is possible to define the information which is generated by the learning system as:

$$H_g = P_r(\theta)\cdot P_c\cdot H_m - P_r\cdot(\theta)\cdot(1 - P_c)\cdot H_{ov} \qquad (2)$$

where H_g is net information gain and $P_r(\theta)$ is the probability that the level of confidence is above θ. The first term defines the proportion of control information that is provided by correct decisions of the learning system. The second term defines the extra patient information load associated with the correction of erroneous decision.

The overall information that must be provided by the patient can be written as:

$$H_p=[1-P_r(\theta)]\cdot H_m+P_r(\theta)\cdot(1-P_c)\cdot H_{ov}+P_r(\theta)\cdot(1-P_c)\cdot H_m \qquad (3)$$

where the first term is the information associated with direct patient control when the decision is made below confidence. The second term is the information associated with overriding erroneous decisions and the third term is the information associated with redoing erroneous trails. Patient aiding will be provided if:

$$H_p < H_m \qquad (4)$$

It is possible to determine the minimum required level of P_c for which patient aiding is assured by the learning system.
This can be accomplished by substituting Equation /3/ in /4/ and solving for P_c

$$P_c > \frac{H_{ov}}{H_m + H_{ov}} \qquad (5)$$

In contrast to the information model the performance time model can be verified by direct time measures. A time measure equation for the patient learning-system control process can be developed based on the performance time interpretation of the aiding function. In this equation, the aiding function is measured in terms of the active control time which is assumed by the computer. This time is defined as Time Gain, T_g, and can be written as:

$$T_g = [P_r(\theta) \cdot P_c \cdot \sum_{n=1}^{N} t_{aci}] + [P_r(\theta) \cdot (1-P_c) \sum_{n=1}^{N} t_{ovi}] \qquad (6)$$

where: Ni = i number of trails

t_{aci} = the time required by the learning system to complete the ith trial, and

t_{ovi} = the time required to override the ith erroneous trial.

The first term is the total active control time contributed by the learning system and the second term is the time lost in overriding wrong learning system responses.

The learning system will reduce patient active control time only if

$$T_g > 0$$

Setting T_g=0 it is possible to solve for the minimum value of P_c which will reduce operator active control time.

$$P_{c\ \min} > \frac{\sum_{i=1}^{N} t_{ovi}}{\sum_{i=1}^{N=1} t_{aci} + t_{ovi}} \qquad (8)$$

The time required to complete a task by the man/learning system control team can be written as follows:

$$T_c = [\sum_{i=1}^{N} P_r(\theta) \cdot P_c \cdot t_{ac}] + [P_r(\theta) \cdot (1-P_c) \cdot (t_{mi} + t_{ovi})] + [(1-P_r(\theta)) \cdot t_{mi}] \quad (9)$$

where t_{mi} is the manual control time of the ith trial.

The first term defines the control time associated with correct computer decision (above P_c), the second term defines the time associated with override and manual correction of erroneous decisions, and the third term describes the manual control time associated with direct manual control (under P_c).

It is worthwhile to examine the level of Pc_{min} as expressed in Equation 5 in terms of the present system. For a typical override time which is equal to .25 t_{ac} the value of Pc_{min} is .2. Thus if only 20% of the decisions are correct, operator aiding is assured.

Learning a Complete Trajectory of Motion

A technique for increasing the capability of the system to learn to generate a complete trajectory of motion has been developed. The computer specifies a unique set of points in space through which the hand must pass in translation between two points in space. This is in contrast to our earlier system that included only point to point control commands (Freedy and al. 1969.). This capability is advantageous for manipulative tasks, where the environment of operation contains obstacles.

The technique is applicable to prosthesis control and has the following properties:

1. Trajectories can be learned from a human operator while he controls the arm in actual tasks. Psychologically the operator can feel he is personally in control whenever the system takes over.
2. Trajectories can be changed as the environment of operation and tasks are changed.
3. The number of trajectories that the system can learn to generate is not constrained by the available computer memory.
4. The learning system can be implemented with the present state of the technology of mini and micro computers to give significant functional gain.

The approach utilizes the learning properties of the computer system to learn typical trajectories generated by the operator. Under this configuration the trajectory of movement of the arm in moving between two points is broken into a set of movement segments. These segments consist of a set of elementary directions which translate the hand between neighboring points. In directing hand to an end point a sequence of decisions are performed to determine the instantaneous direction of the movement trajectory. For each submovement segment that is selected (between two consecutive points) a decision will be required. This occurs in the following way:

- The space of work in which the arm moves is divided into a set of discrete small cells. Each cell is cosidered as a unique position of the hand. The total number of positions that the arm can occupy can be definied by a set X_I, $i = (1, 2, \ldots, K)$ consisting of K specific positions.
- A trajectory is determined by a sequential decision process that select the direction of motion which the hand takes when it passes between point X_{I_1} and X_{I_2} in space.

- The movement trajectory between X_{I1} and X_{I2} is defined by set, T, as

$$T = X^q_{I_1},\ X^1_i,\ X^2_i,\ \dots ,\ X_{I2}$$

where X^q_I, q = 1, 2, ... , K, defines the order at which each of the cells X_I are occupied.

- The elementary decision at an arbitary point of the trajectory consists of the selection of a specific direction for single descrete move to a neighboring cell

The decision space is illustrated in Figure 2. The three dimensional space of motion is shown at each arbitary point in space, P_i. The hand can move in any of 26 directions. These directions include the basic six degrees of freedom along each of the Eucledean axes (x, y and z) and along a direction which falls symmetrically between each of the axes.

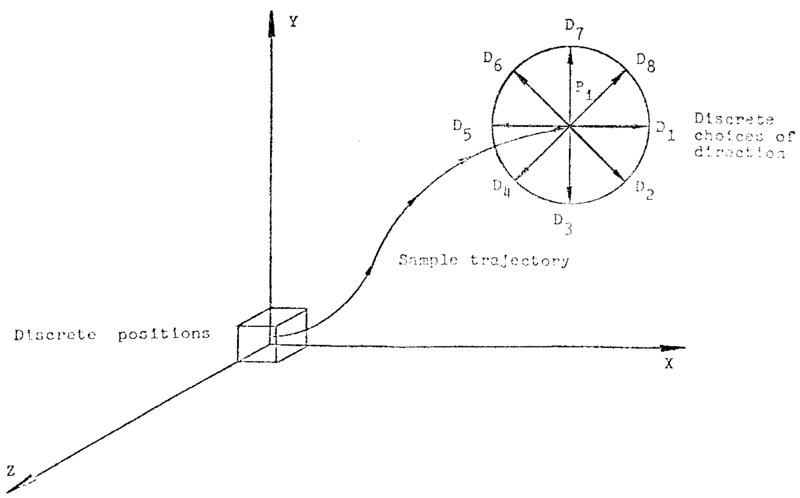


Fig. 2. Directional decision space

By setting the elementary decision to be a specific direction of motion rather than an absolute location the memory requirements are significantly reduced while the capabilities of the system increase. Since the decision space is constrained to 26 choices the elementary decision computation time is fixed and independent of the size of the allowed space of motion.

Refinement of motion accuracy increases the requirement of computer memory in additive fashion rather than multiplicative.

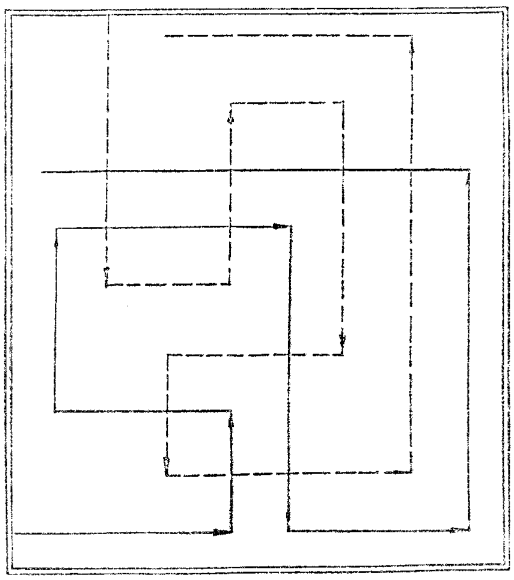
This provides the capability for increasing motion accuracy at minimum cost of memory.

Two Dimensional Simulation Experiment

A prototype trajectory learning system has been developed and implemented on an Interdata Model 70 computer. The system was tested in a simulated 2-dimension environment using a 25 x 25 cm oscilloscope screen. A 2 degree of freedom, second order system was to simulate motor motions in two degrees of freedom. The operator trained the learning system by a joy stick controller, moving the cursor along a trajectory of motion while the computer observed and learned. As the probability of correct response reached the level of confidence, the computer took over control automatically.

The memory requirements of the prototype program included 4K of 16 bit words of memory. 2K were used for storage of the program and 2K were used to store the conditional probability parameters.

Figure 3 illustrates the complete trajectories of motion which



—— Trajectory 1
--- Trajectory 2

Test Trajectories

Fig. 3. Test trajectories of motion

the system was trained to perform. As can be seen the trajectories intersect each other at 10 points. The trajectories were performed in a random order. Figure 4 describes the performance of the learning system in terms of percent of correct control decisions at each complete trail of the trajectory. The figure illustrates system performance over 40 trails of operation. The ordinate describes the percent of correct decisions while the abscissa represent the trails of operation. As shown, after 10 trails the computer took over more then 80% of the control.

As illustrated by the first trajectory, performance monotonically increases to a level of about 80 percent and then fluctuations occur. These fluctations are due to the intersections between the trajectories. Each time the trajectories intersect each other relearning occurs, since the decision regarding a

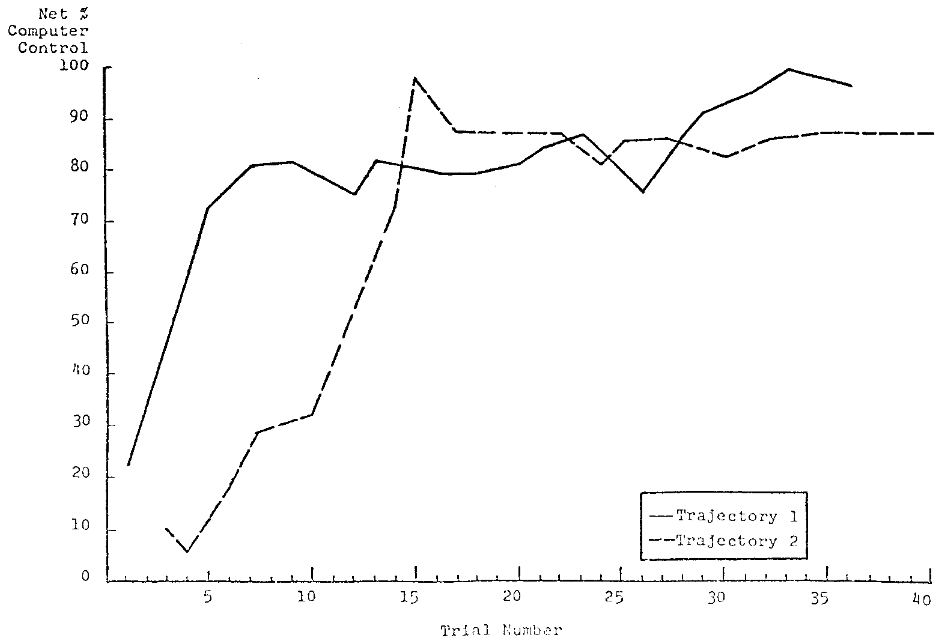


Fig. 4. System learning for two trajectories interacting at single points

a direction of travel is partially based on the location. As two trajectorijes intersect they have a common decision data point with different decision outcomes.

The variation of the learning curves as a function of θ, the the level of confidence, was also investigated. As was shown by Equation 3 the information gain, Hg, that is provided by the learning system is a function of the value of the level of confidence. Figure 5 illustrates experimental observation of the information gain from two different levels of confidence. Hg is represented in terms of percent of total correct moves of the learning system. The data was taken over 9 blocks of three trials each covering as set of three intersecting trajectories. With the higher level of confidence (305), the system learns relatively slowly, but the number of errors it makes remains low throughout. In contrast, with LOC=255 the learning system functions in a "fast and loose" manner. Information gain increases more rapidly, but the number of errors made initially is also much higher. The information gain from both modes initially is also much higher. The information gain from both modes converge as learning progresses, so that

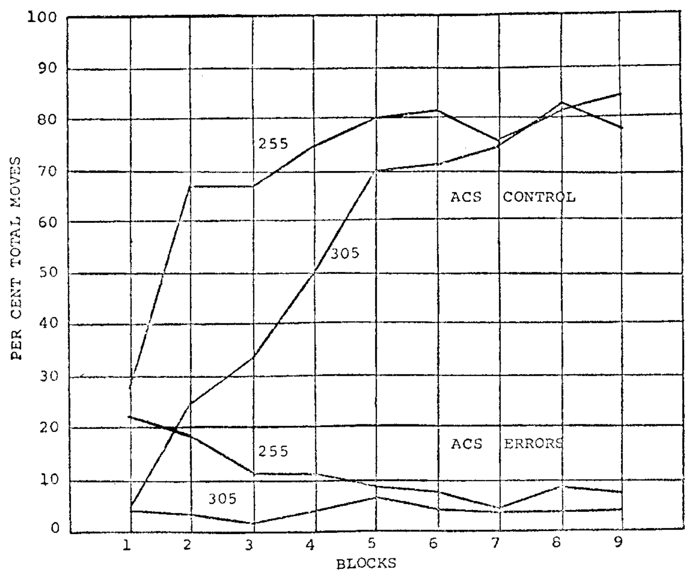


Fig. 5. ACS baseline learning curves

by the seventh block of runs performance is virtually the same for the two conditions. Net information gain is related to percent of moves along the path correctly supplied by the learning system. This reaches about 75% for the test trajectories.

Operator estimation of the capability of the learning system to aid in the control task is of paticular significance with respect to the ability of the patient to use the learning machine effectively. If he can predict the probability that the learning machine is correct than it is possible for the patient to decide whether to take over control and eliminate machine error. Figure 6 illustrates the mean estimates against mean aiding. These estimates are based on experimental runs with a group of technically and non-technically oriented subjects. As shown the estimates are close to reality, however substantial individual differences umong subjects were evident. These differences were attributed to personality and attitude.

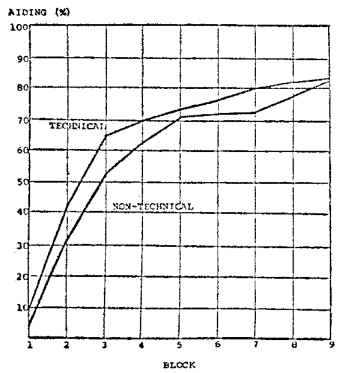


Fig. 6. Mean ACS aiding received on first trial by two subject groups

Experiments in Progress

Our next step was to install a trajectory learning program for controlling an arm prosthesis in three dimensional movement using the system illustrated in Figure 7. To do this the same basic program is used with an increased decision space.

The illustrated system consists of three major subsystems: the arm, the control subsystem and the computer and its associated process control interface equipment.

The basic arm has three degrees of freedom: hand prehension, wrist rotation and elbow flexion extension. The powered components are the Otto Bock hand, the Northwestern University powered elbow and the Army Medical and Biological Research Laboratory wrist rotator. For identification purposes the arm has been called the University of California at Los Angeles Veterans Administration Prosthesis (UVP).

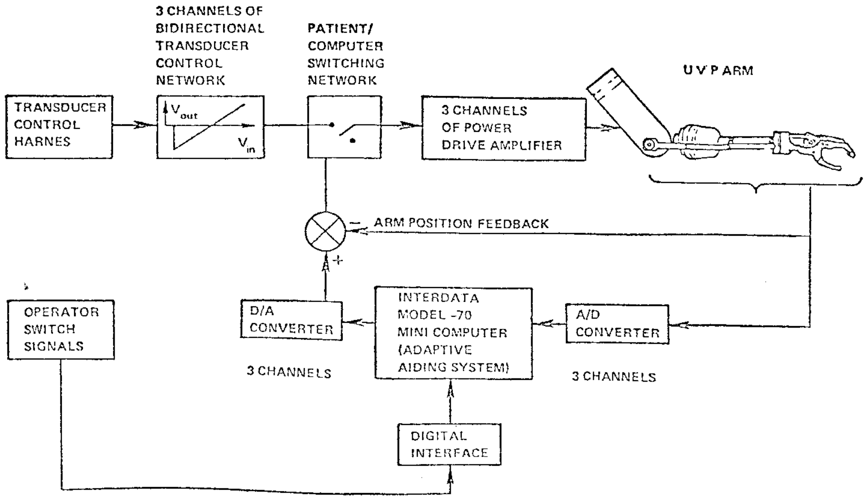


Fig. 7. The integrated operational system

To provide a range of experimental conditions two additional degrees of freedom have been added; these are shoulder lateral rotation and shoulder elevation. The additional two degrees of freedom are powered by two DC motors which are mounted on the test frame. By adding this capability it is possible to test the control of the arm in a motion that could include high AE and SD amputees.

The Interdata Model 70 computer is interfaced to the UVP arm control system. In addition to its use as an adaptive aiding device the computer provides a means for on-line performance data collection.

One version of the transducer control system has been described earlier (Freedy et al., 1970.). On his right shoulder the subject wears a plastic shell which simulates a prosthesis. The shell is held on by a figure eight harness in a configuration similar to a prosthesis harness. He also wears a strap across his chest and a belt around his abdomen; a strap connects his right shoulder to the belt in the center of his back.

The transducers are strain gages attached to the harness straps. A low-force pull on the strap is interpreted by the control logic as a positive control signal, while a larger force is interpreted as a negative control signal. Thus each transducer can control the arm's actuators in two directions. Chest expansion operates the shoulder flexion-extension and shoulder elevation corresponds to lateral rotation.

The transducer control sites provide a total of three parallel bi-directional rate control channels. Control of the five degrees of freedom requires an additional two channels. However, since it is difficult to load the patient with two additional control sities a "shared channel" control scheme was configured. This arrangement is shown in Figure 8.

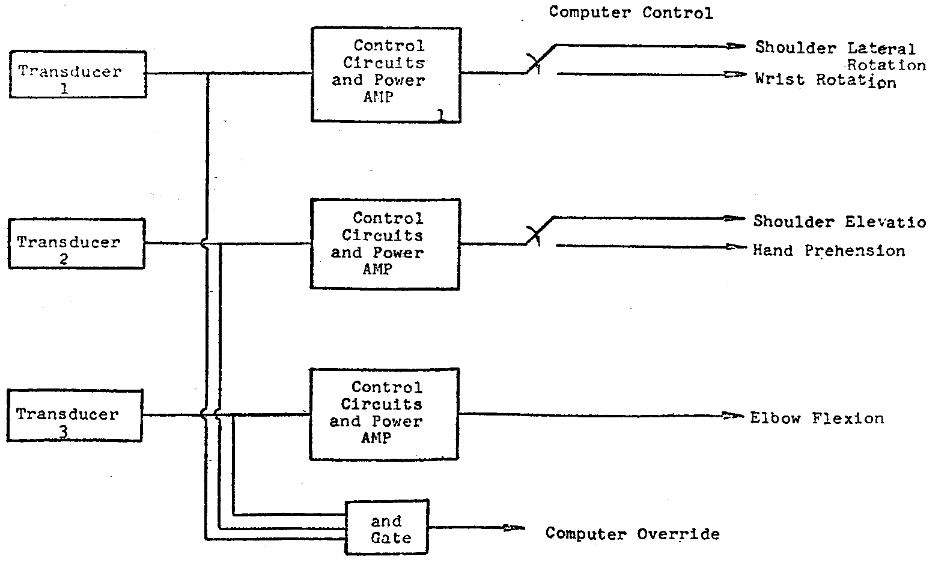


Fig. 8. Transducer control scheme

There are two basic modes of control; one positioning mode and two grasp orientation modes. The transducers are normally connected to the positioning mode. At this mode the transducer controls elbow flexion/extension, shoulder elevation and shoulder rotation. This mode provides the operator with the capability to position the hand at any point in space. In the grasp orientation mode two of the transducers functions are changed to control hand grasp and wrist rotation. The third transducer reamains in control of elbow flexion/extension.

The switching between the position and grasp orientation mode is performed by the computer or by an added micro switch type transducer located on the left shoulder. When the computer takes over control it simultaneously switches over the patient transducer to grasp control. When the patient overrides computer control grasp control is switched to the position mode. When the computer is not used the extra microswitch is used to switch between the grasp control and position control. A summary of the control scheme is given in Table I.

Control System Modes

Mode	Event	1 Transducer	2 Transducer	3 Transducer
Position Control	Computer in Control	Elbow Flexion Extension	Shoulder Elevation	Shoulder Rotation
Grasp Control	Patient in Control	Elbow Flexion Extension	Wrist Rotation	Hand Prehension Support

Table 1

Computer override is performed by simultaneous operation of all three transducers. If the computer decision is below the critical confidence level, control is transferred automatically to the patient. By using this approach the need for special computer control switches is eliminated.

A set of experiments are in progess in order to provide operational data about the learning system. In these experiments the prosthesis is used to perform a set of typical manual tasks. The following aspects of system performance are being studied:

(1) Determination of the type of aiding and the measurement of the absolute level of aiding that can be expected from the learning system.

(2) Evaluation of the specific patient-computer interface technique used and the exploration of required improvements with the goal of introducing a clinically feasible prosthetc system.

References

/1/ Freedy, A., Hull, F., Lucaccini, L. and Lyman, J., "A Computer-Based Learning System for Remote Manipulator Control", *IEEE Transaction on Systems, Man and Cybernetics*, pp. 356-363, Oct., 1971.

/2/ Freedy, A., Hull, F., Lucaccini, L. and Lyman, J., "Adaptive Aiding in Artificial Arm Control", *Proceedings of Human Locomotion Engineering Conference*, University of Sussex, Falmer, England, Sept., 1971.

/3/ Freedy, A., Hull, F. and Lyman, J., "Adaptive Aiding for Artificial Limb Control", *Bulletin of Prosthetic Research*, Vol. BPR 10-16, pp. 3-15, Fall 1971. issue.