DISTRIBUTION OF MULTILEVEL CONTROL IN ARM PROSTHESES AND ORTHOSES

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Summary

Studies conducted by the UCLA Biotechnology Laboratory have revealed that a human operator is unable to provide the information rates required for adequate prosthetic performance. In coping with this problem, a subsystem which contains ancillary control information with the capabilities for controlling the output device is added to the control loop. In such configurations the decision load of the operator is shared between him and the system. The control information load then is distributed to a number of lower level processing subsystems. Ideally, with such aiding subsystems, the operator acts principally in the role of a goal setter, action initiator, and modulator. The approach has partly been realized in such aids as predictor displays, autopilots, tape programmed arm aids and, recently, supervisory control techniques. The approach suggested here presents a concept of adaptive aiding which provides the aiding subsystems with the ability to respond to environmental changes and operator skills. These properties are achieved by the construction of a task decision model which models the operational environment in terms of its states and operator response to it. Having such a model empowers the aiding subsystem to respond to the environment quicker than the operator would respond alone. The approach promises solution to the information problem but at the expense of increased hardware requirements.

Introduction

Human control of a multidimensional manipulative device which mimics and functionally substitutes for the human arm requires an intricate communication and control system. In controlling the system, the operator acts as an information processor, limited by his inherent psycho-physiological characteristics such as bandwidth, fatique limits of the muscular system, and ability to maintain perceptual vigilance. Studies conducted by Freedy [3] indicated that the information load of the operator necessary in control of prostheses and orthoses exceeds his channel capacity. In coping with the problem, a subsystem which contains ancillary control information with the capabilities of controlling the prosthesis can be added to the control loop. Ideally, with such a system the operator acts principally in the role of a goal setter, action initiator, and modulator. This approach has been partly realized in such aids as predictor displays, auto-pilots, tape programmed machines, and the like. A unique example related to remote handling equipment is the Case-Western Reserve University "Arm-Aid" which has certain motions preprogrammed so that a handicapped operator can select a repertory of desired functions with a minimum of input information [11].

A more recent approach is represented in the concept of "Supervisory Control" developed by Sheridan and his associates at M.I.T. [10] for use with remote manipulators. The system employs a computer able to generate patterns of movement upon operator command, via teletype. To date, however, such aiding techniques have emphasized equipment performance independently from operator performance, utilizing rigid task programs independent of operator skill; that is, there has been no intent to design a system that optimizes the decision load sharing between the man and the machine he is controlling.

The approach that is taken here presents a concept of adaptive aiding, that provides the aiding mechanism with the ability to respond to variations in the environment and in the operator skill. The approach is based on the phenomenon that movement patterns of a manipulator simulating a normal arm in bounded space of operation are non-random [17]. There appear to be favored paths of movement which are determined by the optimization criteria of the operator, the physical structure of the output device and the environment so that with manipulator in a given state certain future states are more likely than others. If an aiding subsystem which could acquire and learn these patterns is realized, it could drive the prosthesis along these patterns autonomously unless corrected. The decision load associated with the correction would be less than is normally encountered by the operator [5].

Diagramatical representation of such a system is shown in Figure 1.

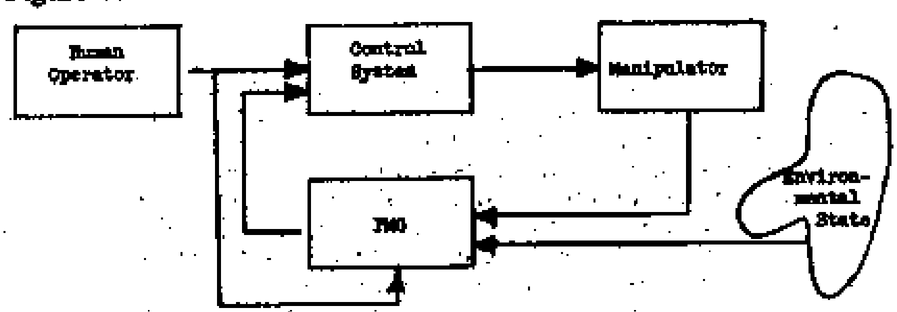

Fig. 1. The aided system

The output device is controlled by a Probabilistic Movement Generator (PMG) as well as by the operator, who acts as a controller-inhibitor. Initially, the output device will be totally controlled by the operator, while the PMG acts as a passive observer. As operation continues and the patterns are acquired by the PMG, it will gradually transform from a passive observer to a controller.

Under this configuration the control will be distributed to three loops: (1) a local reflex loop which will control the manipulation in response to the environment, (2) an operator sub-loop which will respond to operator signal and environmental information, and (3) a major control loop which operates under direct operator control. This arrangement provides three levels of control and distributes the information load between the two sub-loops and the operator.

Realization of the PMG is based on proposed models of learning such as the Perceptron [9], Conditional Probability Computer (Uttley, 1959) and application of established theories of machine learning [8], [6], [2], [1], together with techniques of computer aiding in remote manipulators control [4].

Method of Approach

The Probabilistic Movement Generator is the basic feature which provides adaptive aiding to the operator (See Figure 1). It acts as a subsystem whose output is a vector describing the future state of the manipulative device; mathematically its information processing capability can be described as the process of mapping a set of inputs $[X, Y, E]$ onto an output a_i, $i=1,2,\ldots k\ldots R$. X represents the present state, Y is the operator response and E is a matrix representing the environmental state. The environmental state consists of a map of the work space representing location of objects and obstacles. The output a_i, $i=1,2,\ldots k\ldots R$ which is generated by the PMG, is selected from the total decision space of all possible R outputs. The system decision, a_k is obtained by an algorithmic operation, as shown in Equation (1).

$$a_k = f(X, E, Y, P) \tag{1}$$

where P is a matrix whose elements represent the experience acquired by the subsystem. The basic requirement for an optimal function will be to select the most likely output and minimize machine decision error.

The values of the vectors X and Y represent a set of events occurring jointly and is defined as the input pattern (See Figure 2).

In applying the concepts discussed to adaptive prosthesis control systems, the following limitations were set in order to allow realization of a feasible concept:

1. The space of movement of the output device is divided by a three dimensional grid into n discrete subspaces. Each subspace

constitutes a decision category in the decision space. When the operator directs the device to a certain position the PMG interprets it as a decision outcome classified by the subspace which the arm's end point has reached. When the PMG assumes control over the device it can direct it only to one of n dicrete locations defined by the grid.

2. The input to the system consists of a binary vector of m components. Each component describes a certain event on which the decision outcome is based. The input vector components contain the information concerning the present position of the arm, its most recent past position, environmental information, etc. For example, describing a position in space in a binary vector can be accomplished by a one-to-one mapping of all possible subspaces into the i^{th} component in the vector. Suppose we have a space with three subspaces and the manipulator is located at subspace number three. Then the binary vector representation of the manipulator state will be:

$$\begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \tag{2}$$

Using these limitations provides simplicity in mathematical manipulation, allows fast computation, and minimizes the computer memory size.

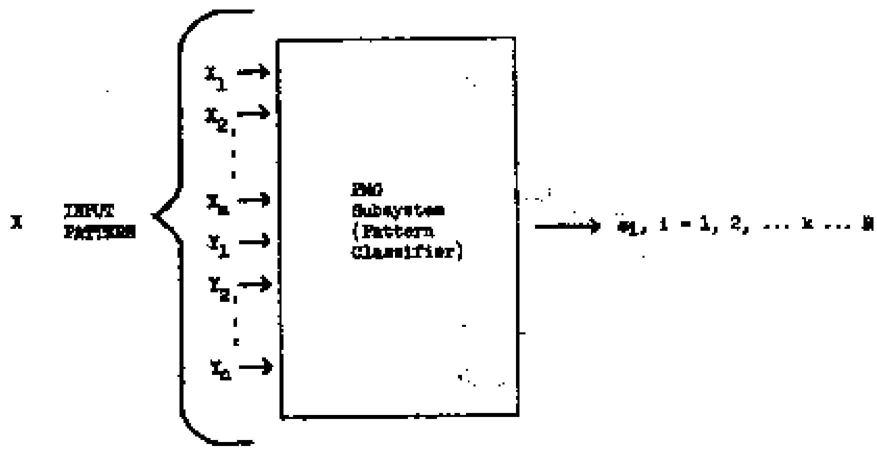

Fig. 2. Pattern classifying system

The selection of the specific output from the decision space involves a process of pattern classification, where a specific input configuration is classified into a_k category out of a populational R choices. The operation of classification adopted here is based on the Maximum Likelihood Decision Principle and is discussed in [8]. Using this principle, the decision depends on the conditional probability function P $(a_i|X_i)$ A decision theoretic rule can be constructed by introducing the concept of loss function. A loss function $\lambda(a_i|a_j)$ represents the loss incurred when the decision system places an input pattern belonging to output category a_j into output category a_i, $i=1, 2, \ldots k \ldots R$ and $j=1, 2, \ldots k \ldots R$. It assigns a cost to an incorrect decision. Suppose that the subsystem continuously generates the wrong output. It will decide that all patterns belong to category a_i. The conditional average loss due to this decision policy will be:

$$L_X(a_i) = \sum_{j=1}^{R} \lambda(a_i \mid a_j)\, P(a_j \mid X) \tag{3}$$

Using the above expression the conditional average loss can be calculated for all possible values of a_i, $i=1, 2, \ldots k, \ldots R$. The loss will be minimized if the subsystem selects a specific a_i for which $L_i(a_i)$ is minimum.

The process of selecting future position by the PMG can be summarized as follows:

1. The pattern of inputs which contain the present position, and the past position of the manipulator, the environmental state and operator response cues is presented to the decision subsystem.

2. The subsystem calculates the average conditional loss for all a_i, $i=1, 2, \ldots k \ldots R$.

3. The subsystem decides whether or not the input pattern **X** belongs to the category a_k for which $L_x(a_k) \leq L_x(a_i)$ for $i=1, 2, \ldots k \ldots R$, where a_k is defined to be the category which yields the minimum loss.

Using a symmetrical loss function (see Appendix A), a decision-theoretic approach leads to a decision algorithm which simply requires the calculation of the product:

$$P(X|a_i)\, P(a_i) \tag{4}$$

for each event, a_i, and selects the a_i^{th} value which maximizes Equation (4). Such a decision strategy will minimize the loss and minimize the probability of an erroneous decision.

Application of Equation (4) toward classification in the decision space of the prosthesis, assuming that all events are independent, yields the following mathematical procedure:

Select Maximum row sum, M_i, of

$$[[\log P] \cdot [X + \log(1-P)] \cdot [1 - X] + [\log P(a_i)]] \tag{5}$$

where log P is a matrix whose elements are the logarithm of the conditional probabilities and log $P(a_i)$ is the logarithm of *a priori* probabilities. The decision subsystem (PMG) calculates the above expression and simply selects the i^{th} component of the output whose value is maximum. A diagramatic presentation of the decision process is shown in Figure 3. The data for this operation is accumulated by the log P matrix which contains a measure of the experience acquired by the PMG in observing the human operator. The P = (log P) matrix can be written as:

$$\log P] = \begin{bmatrix} P_{11} & P_{12} & P_{16} & & \\ P_{21} & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & P_{mn} \end{bmatrix} \quad (6$$

where $P_{ij} = \log P(X_j|a_i)$, or the logarithm of the probability that even X_j occurs given that a_i occurred. The number of rows in the P matrix corresponds to the number of decisions that can be made.

The values of the matrix elements are continuously adjusted and are the adaptive properties of the system.

These probability values are obtained by a process of training in which the decision subsystem (PMG) "observes" the operator and his manipulative device. At this stage a library of log P values can be compiled to provide the decision data. Assuming that the input pattern consists of a set of discrete inputs, determination of the conditional probability can be obtained as follows:

$$P(X_j|a_i) = \frac{\text{Number of times the prosthesis reached position } a_i \text{ when the input } X_j \text{ was presented.}}{\text{Total number of times the position } a_i \text{ was occupied.}} \quad (7)$$

The *a priori* probability of a_i can be obtained as follows:

$$P(a_i) = \frac{\text{Number of times } a_i \text{ previously occurred}}{\text{Total number of trials}} \quad (8)$$

Since finite counters are used for the type of calculation given in (7) and (8), saturation may occur and the value of the probabilities will converge to a fixed level. In order to overcome this, the concept of forgetfulness is introduced. For example: If within a certain number of tasks a certain input pattern, X_1, occured without giving rise to an event (a_i) then the value of the conditional probability $P(X_j|a_i)$ can be reduced by a certain level. Under such a configuration, the decision processor is subjected to repeated parameter adjustment, and is thus able to *change decision strategy* with time and any environmental changes that may occur.

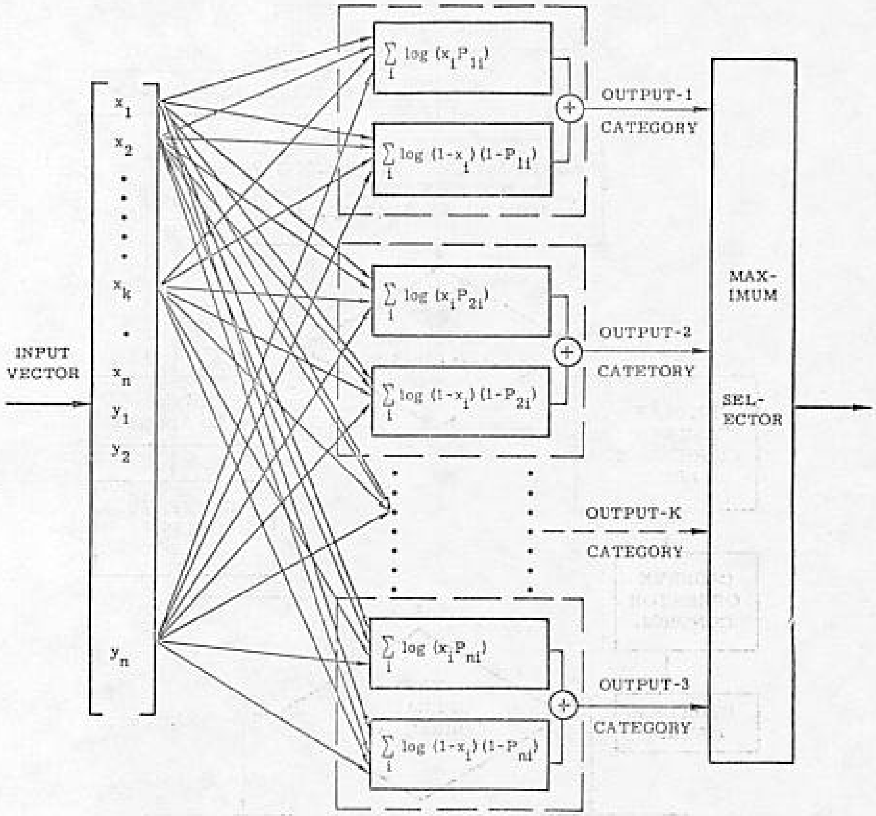

Fig. 3. Maximum likelihood decision mechanism

System Operation and Implementation

The overall organization of the Probabilistic Movement Generator is shown in the flow diagram in Figure 4.

The system reads out the input pattern and decision procedure. It selects the future position. The decision undergoes a level of confidence test where the absolute "quality" of the decision is checked. This process is accomplished by comparing the value of the M_r to the preset threshold level, θ. If the M_r selected is such that:

$$M_r > \theta$$

then the PMG decision is accepted. Following decision acceptance the system checks the environmental state by scanning a stored three dimensional map of the environment. If the selected state is

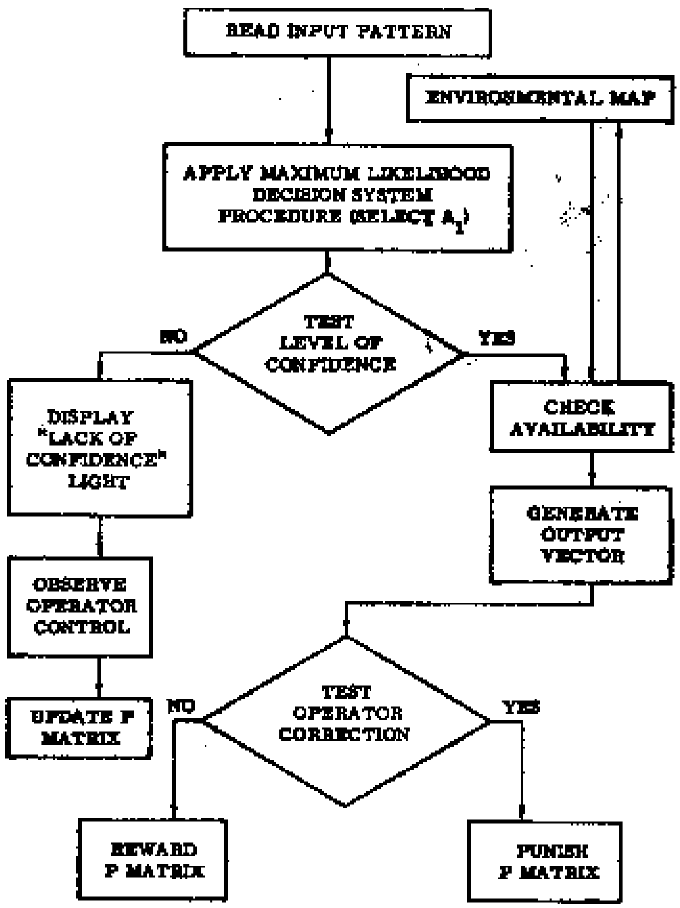

Fig. 4. Flow diagram of the experimental system

unoccupied, i. e., does not contain obstacles, the decision is accepted. If the decision outcome agrees with the operator's wish the PMG will drive the arm to its terminal state. Under such a decision outcome the components of the P matrix associated with this decision are rewarded. It the PMG does not generate the correct decision and the operator has to take over control from the PMG, the P matrix elements associated with this decision will be punished, i. e., their value will be lowered.

If the decision made by the *Maximum-Likelihood* processor does not possess the required level of confidence, the control of the prosthesis is transferred to the operator, by signaling to him through a visual display. The operator-manipulator control system is shown in Figure 5. The communication links between the various subsystems are presented and the data mode, analog or digital, is marked. The present experimental system consists of the IBM 1800 process control computer and a set of analog to digital and digital to analog converters. The manipulator control system consists of a control logic system and three parallel rate and/or position servo loops. The function of the control logic subsystem is to interpret operator responses and to decide whether to give control to the manipulator or to give the operator direct control over the device. The operation of the system can be summarized as follows: Suppose the prosthesis is at point a_1 in space and operator desires to move to a_2. Initially the operator activates his controller as if he has direct rate control over the output device. The control logic will feed a signal into the First Priority Interrupt Unit, which

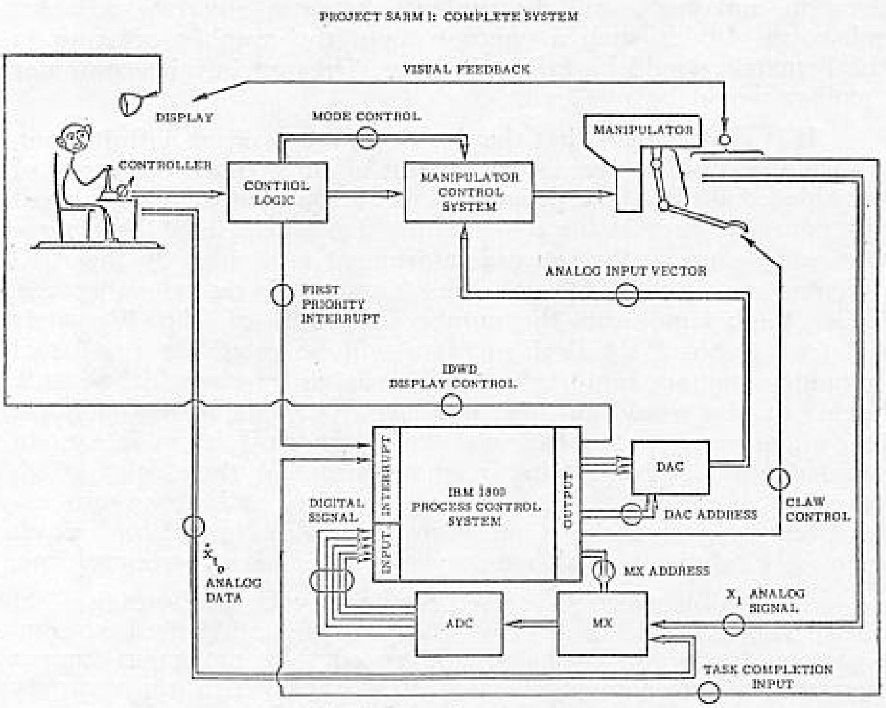

Fig. 5. Complete system

starts the computer control process. The computer will record the position of the arm, operator initial control vector, claw position, etc., and will construct an input pattern for the decision process. The PMG subsystem selects the most probable position and directs the manipulator to that point. An incorrect decision by the system will be corrected by the operator and computer control will be cut off. As soon as the task is completed a task completion signal will call the computer to start the P matrix update process, i. e., reward or punish. In order to permit an adequate man-machine interface the computer decision process must be shorter than the operator's reaction time.

One of the problems associated with the system implementation is imposed by the constraints of the finite speed and memory of a particular process control computer. These constraints affect the capability of the proposed system as an efficient aid to the human operator since they depend on the accuracy and speed of the PMG. The accuracy and speed of the PMG is determined by the size of the available computer memory and its speed of operation. Suppose that the space of movement of the manipulator was divided into infinitesimally small subspaces such that the PMG decision outcome could discriminate between any two adjacent subspaces. Under such a configuration, the number of rows in the P matrix would be infinitely large. Thus an infinite computer memory would be required.

It is also evident that the decision process in an infinite matrix would require an excessive amount of time. Given the range of possible conditions, the prosthesis would be able to reach almost any point in space at the cost of time. Let us consider the reverse approach; suppose the space of movement is divided by the PMG decision system into a very small number of coarse subspaces. Under these conditions the number of rows of the P matrix required to store the decision data will be relatively small and computer memory requirement and decision time would be small. Such a system would not provide much assistance to the operator. It can be seen that there is a direct trade-off between system sophistication and computer memory size and time delay. High precision of output requires a large memory and may require a relatively long response time. Conversely low precision output requires a relatively small memory size and a short response time.

The problem can be solved empirically by performing a set of experiments which will provide data for selecting the best combination of position precision and speed to complement human operator information deficiencies. In such experiments a variety of output precision levels and time delays can be tested in conjunction with variations of control mode. For example, it might be preferable to provide the operator with a fine rate control while the computer or the PMG would operate in end-point position control. The PMG can direct the manipulator for gross movements while the operator controls the arm for fine movements. A set of system evaluation experiments is planned upon the completion of computer programs and system construction.

Practical Implications

The practical aspect of the system for patient rehabilitation is not as remote as one might assume. This is basically due to the provision that a "special purpose" type aiding system can be realized with a much smaller memory requirement than that of the experimental system. Once the significant parameters associated with the movement space of prosthesis operation are defined, the Probabilistic Movement Generator could be micro-programmed for its specific structure. For example, when an arm prosthesis is given to a new amputee, it could be connected initially to a large laboratory computer facility which would act as an aiding system. The laboratory computer could follow the operator training progress and construct a probability space matrix which would relate his responses to the environment. A state would be reached where both the operator and the aiding system would achieve a training criterion. As the PMG system defines the environment its probability parameters will converge to a certain level. As convergence is completed the values of the conditional probability are defined. At that point it becomes a straight forward circuit problem to design and construct a micro-programmed aiding system. If for example an amputee is exposed to a variety of environments, which include ordinary living requirements and specific vocational requirements, a set of micro-programs for the probability matrix can be constructed for all the relevant environments with the aid of the laboratory computer.

From the patient's point of view, the system proposed offers assistance in prosthesis operation but is not tightly controlled to produce stereotyped responses.

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APPENDIX A

The conditional average loss is given by:

$$L_X(a_i) = \sum_{j=1}^{R} \lambda(a_i | a_j)\, P(a_j | X) \tag{1}$$

The loss function selected assigns a zero loss when the correct decision is made and a loss of one unit for an erroneous decision $(i=j)$; it can be written as:

$$\lambda(i\,j) = 1 - \delta\, ij \tag{2}$$

where δ is the Kronecker delta function.[8].

By Bayes rule:

$$P(a_j | X) = \frac{P(X | a_j)\, P(a_j)}{P(X)} \tag{3}$$

Substituting equation (3) into equation (1) yields:

$$L_X(a_i) = \frac{1}{P(X)} \sum_{j=1}^{R} \lambda(a_i | a_j)\, P(X | a_j)\, P(a_j) \tag{4}$$

If the input pattern is random P(X) can be assumed a constant. Substituting equation (2) into equation (1) and deleting P (X), equation (4) can be written as:

$$L_X(a_i) = \sum_{j=1}^{R} P(X|a_j)P(a_j) - P(X|a_i)P(a_i) \tag{5}$$

which can be written as:

$$L_x(a_i = P(X) - P(X|a_i)P(a_i) \tag{6}$$

Since P (X) is constant the loss will be minimized if $P(X|a_i)$ $P(a_i)$ is maximized.

By the assumption that all inputs are independent:

$$P(X|a_i) = P(X_1|a_i)P(X_2|a_i)P(X_3|a_i) \tag{7}$$

Suppose there are three inputs of which two are *one* and one is *zero* or

$$X = \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} \tag{8}$$

then:

$$P(X|a_i) = P(X_1|a_i)P(X_2|a_i)(1 - P(X_3|a_i)) \tag{9}$$

Taking the logarithm of (9) for a general n component vector in matrix form the following expression is obtained:

Select
Maximum
row sum,
M_r, of

$$\{[\log P]\ [X + \log(1-P)]\cdot[I - X] + [\log P(a_i)]\} \tag{10}$$