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Analytical Design of Intelligent Machines*

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An analytical formulation for the design of Intelligent Machines which operate in uncertain and unfamiliar environments with minimum human interaction, is based on the principle of Increasing Precision with Decreasing Intelligence and composed of the Organization, Coordination and Execution levels.

Key Words—Intelligent control; intelligent machines; knowledge; entropy; information theory; optimal control; nuclear plant.

Abstract—The problem of designing "intelligent machines" operating in uncertain environments with minimum supervision or interaction with a human operator is examined. The structure of an "intelligent machine" is defined to be the structure of a Hierarchically Intelligent Control System, composed of three levels hierarchically ordered according to the principle of "increasing precision with decreasing intelligence", namely: the organizational level, performing general information processing tasks in association with a long-term memory, the coordination level, dealing with specific information processing tasks with a short-term memory, and the control level, which performs the execution of various tasks through hardware using feedback control methods. The behavior of such a machine may be managed by controls with special considerations and its "intelligence" is directly related to the derivation of a compatible measure that associates the intelligence of the higher levels with the concept of entropy, which is a sufficient analytic measure that unifies the treatment of all the levels of an "intelligent machine" as the mathematical problem of finding the right sequence of internal decisions and controls for a system structured in the order of intelligence and inverse order of precision such that it minimizes its total entropy. A case study on the automatic maintenance of a nuclear plant illustrates the proposed approach.

1. INTRODUCTION

SINCE 1971, when K. S. Fu coined the name Intelligent Controls (Fu, 1971) as the field of interaction of Artificial Intelligence and Automatic Control Systems, many attempts have been made to formalize them into a scientific discipline. In most of them one of the two basic components dominated the other with a result non-conducive to efficient and successful applications.

A different approach was proposed by Saridis (1977), which expanded the field of Intelligent Controls to include three components, Artificial Intelligence, Operations Research, and Automatic Control Systems, as in Fig. 1. Different ideas for the formalization of the definitions and the structure of Intelligent Controls have been debated among various researchers (Albus, 1975, Bejczy, 1986; Meystel, 1986; Stephanou, 1986; Pao, 1986; Vamos, 1986). This paper presents an outline and summary of the most important results of the research to give a concrete idea of this new field of science and engineering.

First of all, a number of definitions are necessary to establish the structure of the discipline of Intelligent Controls. Intelligent Control is the process that drives an Intelligent Machine to attain its goal autonomously. The entity Intelligent Machines encountered in the above definition requires a definition. Intelligent Machines perform anthropomorphic tasks, autonomously or interactively with a human operator in structured or unstructured, familiar or unfamiliar environments.

In common words, Intelligent Machines are machines that may replace human efforts in hazardous, remote, tedious, or high precision jobs, where their higher efficiency proves to be more cost-effective in terms of human and/or humanistic values. Current flexible manufacturing factories are typical examples of interactive intelligent systems while robots are typical examples of autonomous systems. Intelligent Controls Systems are used to drive autonomous intelligent machines to reach their goal without any interaction with a human operator. In doing so, they must be equipped with intelligence, scheduling and execution capabilities. The theoretical foundations of such systems should, therefore, be found at the intersection of

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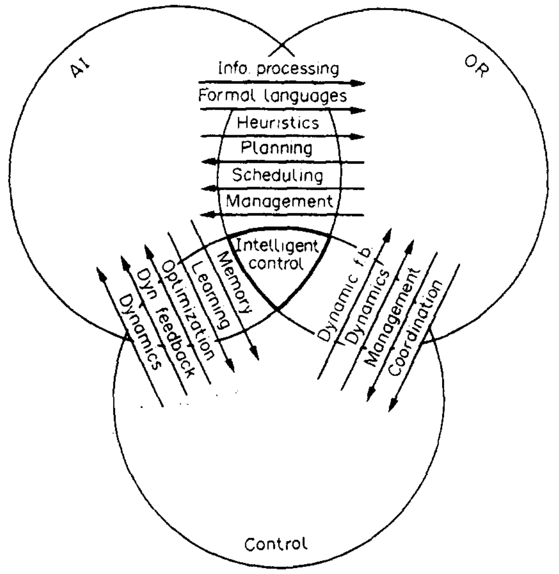

FIG. 1. Intersection of artificial intelligence, operations research and control theory and the resulting intelligent control.

disciplines like Artificial Intelligence, Operations Research and System Theory as depicted in Fig. 1 and should be structured according to a principle very commonly found in most organizational structures: the principle of *Increasing Precision with Decreasing Intelligence* (IPDI). This principle, which establishes a hierarchy in the distribution of intelligence of an Intelligent Control System, very much resembles Heisenberg's Principle of Uncertainty and simply says that where intelligence is high, precision is not required and vice versa.

As a result of such a structural axiomatic definition, Saridis (1977) proposed a Hierarchically Intelligent Control System composed of three main levels of intelligence (or precision) as depicted in Fig. 2. The three levels are:

(1) the *Organization Level* represents the brain of the system with functions dominated by Artificial Intelligence, to reason, plan and make decisions about the organization of a task;
(2) the *Coordination Level* is the interface between high and low levels of intelligence with functions dominated by Artificial Intelligence and Operations Research that coordinate the activities of the hardware; and
(3) the *Execution Level* is the lowest level with high requirement in precision with functions dominated by system theory.

In order to coordinate all those activities under a common mathematical formulation, which has been assumed to be most efficient, some of the concepts of the above disciplines must be adjusted accordingly.

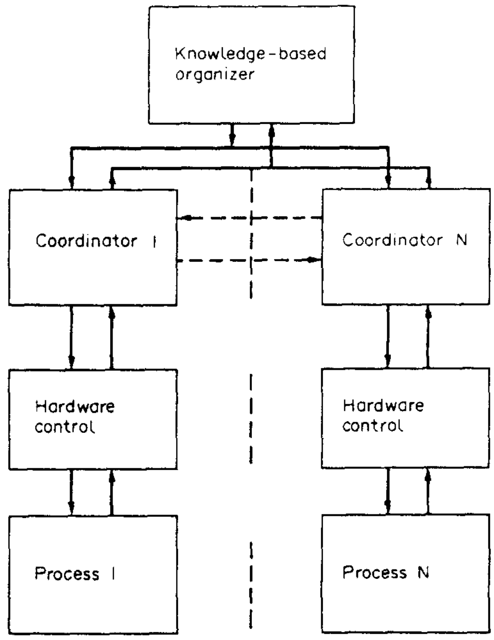

FIG. 2. Hierchical intelligent control system.

Since we are dealing with intelligence pertaining to a machine and not a human being, it is appropriate to talk about Machine Intelligence and not Artificial Intelligence. This may be thought to be an inverse mapping of AI into the space of human activities as shown in Fig. 3. A formal definition of Machine Intelligence is given in the next section where most of the general concepts of Intelligent control Systems are defined.

It is appropriate also to confine operations research to automata theory since Intelligent Control deals with a finite set of execution tasks. Linguistic methods may equivalently be applied since their equivalence to a finite automation has been established.

The execution always involves the selection of an appropriate controller, suitable to the appropriate specification given by the designer. Since in an autonomous system the designer is the machine itself, the problem of design must be recast to accommodate various specifications according to the following definition.

The control design problem may be thought of as the problem of selecting the best controller in a sense of meeting the specifications of the problem, from all the controller distributed over the subspace of admissible controls.

This approach, hierarchically distributed in intelligence and precision from the organization to the execution level, originally suggests a tree structure for top-to-bottom decision making purposes. Each level may have more than one layer of resolution represented by a nested

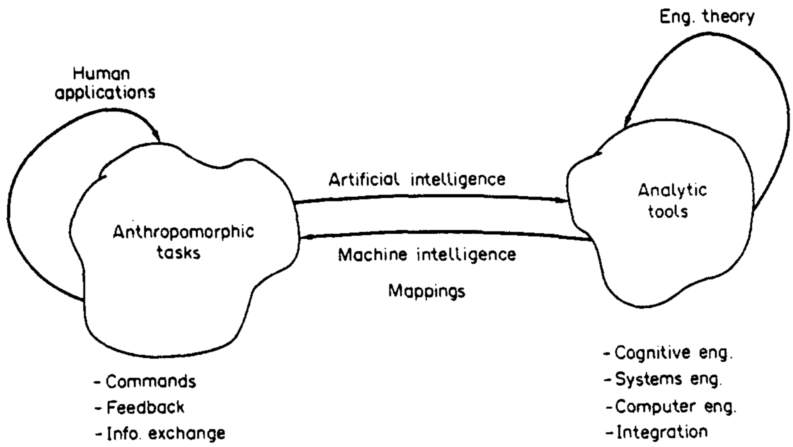

FIG. 3. The problem of designing machines to execute anthropomorphic functions.

network interacting with each other in a graph sense (Meystel, 1985). This is especially true at the coordination level where various activities of the Intelligent Control System act interactively, e.g. vision and custom coordinators.

At this time, the best known applications of Intelligent Controls are the Intelligent Robots (Saridis, 1983). Therefore, after a few conceptual definitions needed in the mathematical (probabilistic) formulation of the Intelligent Control problem we shall proceed in defining the various activities of the process with such an Intelligent Robot in mind, including the implementation of an Intelligent Robotic System for automatic maintenance in a nuclear power plant.

2. SOME DEFINITIONS OF INTELLIGENT CONTROLS

The common element in all the levels of an Intelligent Control System is the uncertainty involved with the various actions of the machine. This suggests the use of probabilistic models to describe those actions with a common measure, their respective *Entropies*.

These entropies have physical meanings at the different levels of the Intelligent Control System.

At the *organization level,* the highest in the hierarchy, it has an information theoretic connotation, in the sense of Shannon and Weaver (1963), for the following reason; this level deals with knowledge representation and processing. The following is assumed.

Definition 1. Knowledge is a form of structured information.

Therefore, it is natural to consider Shannon's Entropy as the measure of lack of knowledge.

At the *coordination level,* represented by several nested automata in the form of probabilistically described decision schemata, their entropy is used as the measure of uncertainty of coordination (Meystel, 1986; Saridis and Graham, 1984).

Finally, at the *execution level* the cost of execution is equivalent to the expended energy of the system which is expressed by an entropy in the sense of Boltzmann (Boltzmann, 1872; Saridis, 1985b).

All these entropies may be added together for every alternate complete action of the Intelligent Control System to represent its own cost. The activities of an Intelligent Machine may be formulated mathematicaly as follows.

Definition 2. The theory of Intelligent Machines may be postulated as the mathematical (probabilistic) problem of finding the right sequence of decisions and controls of a system structured according to the Principle of Increasing Precision and Decreasing Intelligence such that it minimizes its total entropy.

The concept of entropy may be generalized if one introduces theory of evidence for the cases that Intelligent Machines are endowed with judgment, a very human property. Thus, according to Stephanou (1986) the probabilities may be replaced by possibilities and the entropies are possibilistic measures.

What remains to be investigated about the general concepts of Intelligent Control Systems are the fundamental notions of Machine Intelligence, Machine Knowledge, its Rate and Precision.

Definition 3. Machine Knowledge is defined to be the structured information acquired and applied to remove ignorance on uncertainty about a specific task pertaining to the Intelligent Machine.

Knowledge is a quantity accrued by the machine and cannot be used as a variable to execute a task. Instead, the Rate of Machine Knowledge is a suitable variable.

Definition 4. Rate of Machine Knowledge is the flow of knowledge through an Intelligent Machine.

Intelligence is defined by the American Heritage Dictionary of the English Language (1969) as: *Intelligence* is the capacity to acquire and apply knowledge.

In terms of Machine Intelligence, this definition may be modified to yield the following.

Definition 5. Machine Intelligence (MI) is the variable (source) which operates on a database (DB) of events to produce flow of knowledge (RK).

It is straightforward then to apply the Law of Partition of Information Rates of Conant (1976) to analyze the functions of intelligence within the activities of an Intelligent Control System.

The Law of Partition of Information Rates of Conant (1976) is applied to analyze the functions of intelligence within the activities of an Intelligent Control System. More details are given in the following.

On the other hand, one may define Precision as follows.

Definition 6. Imprecision is the uncertainty of execution of the various tasks of the Intelligent Machine

and

Definition 7. Precision is the complement of Imprecision, and represents the complexity of a process.

Analytically, the above relations may be summarized as follows.

Knowledge (KN), representing structured information, may be defined analytically in a way similar to the definition of information of Shannon and Weaver (1963):

$$(KN) = -\ln p(KN) = (\text{Energy}) \tag{1}$$

where $p(KN)$ is the probability density of knowledge, distributed over the various states S of the system of events. In view of the relatively small database, the density $p(KN)$ may be elected to satisfy Jaynes' Principle of Maximum entropy:

$$p(KN) = e^{-\lambda-\mu(KN)}; \quad \lambda = \ln \int_S e^{-\mu(KN)}\, \mathrm{d}s. \tag{2}$$

The Principle of Maximum Entropy defines a density function which maximizes the entropy associated with uncertainty of selection of an event, given a known constraint of the event (Jaynes, 1957). Such a density has a sharp form even when a small database is available.

The Rate of Knowledge (RK), which is the main variable of an intelligent machine, is given as:

$$(RK) = \frac{\mathrm{d}(KN)}{\mathrm{d}t} = (\text{Power})$$

and satisfies the following relation which manifests the principle of *Increasing Precision with Decreasing Intelligence*

$$(MI):(DB) \rightarrow (RK). \tag{3}$$

If RK is fixed, machine intelligence is largest for a smaller database, e.g. complexity of the process. This is in agreement with Vamos' theory of Metalanguages (1986).

It is interesting to notice the resemblance of this entropy formulation of the Intelligent Control Problem with the ϵ-entropy formulation of the metric theory of complexity originated by Kolmogrov (1956) and applied to system theory by Zames (1979). Both methods imply that an increase in Knowledge (feedback) reduces the amount of entropy (ϵ-entropy) which measures the uncertainty involved with the system.

If imprecision is measured by the cost of executing a certain task, an energy function, and Jaynes' Maximum Entropy Principle (1957) is used to define its distributions, imprecision is expressed as the entropy associated with such a density.

It remains to find a "Heisenberg Uncertainty Principle" relation between Precision and Intelligence to give the Principle of IPDI a physical interpretation.

A specific investigation of the functions of the various levels and their entropies follows this section.

3. THE ORGANIZATION LEVEL AND KNOWLEDGE BASED SYSTEM

The function of the organizer, the highest level of the hierarchy of Intellegent Controls, is based on several AI (knowledge based) concepts forming the foundations of Machine Intelligence. These concepts, translated into probabilistic models, form the functions of representation and reasoning, planning, decision making, long-term memory exchange and learning through feedback to set up a task in response to some outside command. The probabilistic model generated provides the mechanism to select the appropriate task for the appropriate command. The principle followed here is that instead of task decomposition a collection of tasks is generated from a list of primitives stored in the memory and matched against the input command applied.

To specify the functions of the organizer, it is essential to derive the domain of the operation of the machine for a particular class of problems (Valavanis, 1986). Assuming that the environment is known, one may define the following sets.

The set of *commands* $C = \{c_1, c_2, \ldots, c_m\}$ in natural language, received by the machine as inputs. Each command is compiled to yield an equivalent machine code explained in the next section.

The *task domain* of the machine which contains a number n of independent events.

The *events* $E = \{e_1, e_2, \ldots, e_n\}$ are *individual primitive rules or activities* e_i stored in the long-term memory and representing tasks to be executed. The task domain indicates the capabilities of the machine.

Activities A, are groups of events concatenated to define a complex task; e.g. $A_{234} = \{e_2, e_3, e_4\}$. If the events are ordered, then we have an *ordered activity.*

A *random variable* $x_i \in [0, 1]$ is associated with each individual event e_i. If the random variable x_i is binary (either 0 or 1), it indicates whether an event e_i is *inactive* or *active,* in a particular activity and for a particular command. If the random variables x_i are continuous (or discrete but not binary) over $[0, 1]$, they reflect a membership function in a fuzzy decision making problem. At this point, we consider the x_is to be binary.

Functions, F, are internal operations on the activities A. As such, they are defined in their right order within the organization level.

(a) *Machine Representation and Reasoning, R,* is the association of the compiled command to a number of activities and/or rules. A probability function is assigned to each activity and/or rule and the Entropy associated with it is calculated. When rules are included one has active reasoning (inference engine).
(b) *Machine Planning, P,* is the ordering of the activities. The ordering is obtained through a sparse matrix M of 0s and 1s, which indicate the proper order of the primitive events.
(c) *Decision Making, DM,* is the function of selecting the sequence with the largest probability of success.
(d) *Feedback, FB,* is the evaluation of cost functions and updating of the probabilities associated with each primitive event and activity.
(e) *Memory Exchange, ME,* is the retrieval and storage of information from the long-term memory based on selected feedback data from the lower levels after the completion of the complex task.

An algorithm of the functions of the organizer is given below. The received command is related to a random word through reasoning that associates the various strings of events in binary code with appropriate probabilities. Planning and decision making follow, while feedback provides an off-line upgrading of the probabilities through learning algorithms. Long-term memory exchange updates the stored information and related probabilities, and provides the actual job for the coordinators.

The organization level algorithm must perform the following functions.

- Receive a command and reason about it. Reasoning and representation associates different primitive activities and rules with the received command and evaluates probabilistically each activity.
- Planning which involves operations on the activities. The ordering of the activities and insertion of repetitive primitive events to complete a plan is accompished according to the selected rules. Transition-matrices (masks) and transition probabilities are used to order the activities and calculate their total probability.
- Decision Making which selects the most probable plan.
- Feedback which updates the probabilities through learning algorithms after the completion of the job, after the completion and evaluation of each task.
- Memory exchanges which updates the stored information in the long-term memory.

The algorithm which performs a number of sequential functions is outlined by the following specifications.

(1) The set of commands $C = \{c_1, c_2, \ldots, c_M;$ M fixed and finite$\}$ with associated probability distribution functions (pdfs) $p(c_n)$, $n = 1, 2, \ldots, M$, sent to the Intelligent Machine via any remote or not channel.
(2) The set of classified compiled input commands $U = \{u_1, u_2, \ldots, u_M;$ M fixed and finite$\}$ with associated pdfs $p(u_j/c_n)$, $j = 1, 2, \ldots, M$, which are the inputs to the organization level of Intelligent Machines.
(3) The task domain of the Intelligent Machine with the set of independent but not

mutually exclusive disjoint sub-sets of non-repetitive and repetitive primitive events $E = \{e_{nr}, E_r\} = \{e_1, e_2, \ldots, e_{N-L}, e_{N-L+1}, \ldots, e_N; N \text{ fixed and finite}\}$.

(4) The binary valued random variable x_i associated with each e_i indicating if e_i is active ($x_i = 1$) or inactive ($x_i = 0$) given a u_j, with corresponding pdfs $p(x_i = 1/u_j)$ and $p(x_0 = 0/u_j)$, respectively.

(5) The set of the $(2^N - 1)$ activities which are groups of primitive events concatenated together to define a complex task. They are represented by a string of binary random variables $X_{jm} = (x_1, x_2, \ldots, x_n)_m$, $m = 1, 2, \ldots, (2^N - 1)$, which indicates which e_is are active or inactive within an activity with a pdf $P(X_{jm}/u_j)$.

(6) The set of compatible ordered activities obtained by ordering the primitive events within each activity and represented by a string of compatible ordered binary random variables Y_{jmr}, where r denotes the rth ordered activity obtained from X_{jm}, with a pdf $P(Y_{jmr}/u_j)$.

(7) The set of compatible augmented ordered activities obtained by inserting repetitive primitive events within appropriate positions of each Y_{jmr} and represented by $Y_{jmr}(a_s)$, where a_s denotes the sth augmented activity obtained from Y_{jmr} with a pdf $P(Y_{jmr}(a_s)/Y_{jmr})$.

(8) The set of mask matrices M_{jmr} with associated pdfs $p(M_{jmr}/u_j)$ used to obtain the compatible ordered activities (Y_{jmr}) from the activities (X_{jm}).

(9) The set of augmented mask matrices $M_{jmr}(a_s)$ with associated pdfs $p(M_{jmr}(a_s)/Y_{jmr})$ used to obtain the compatible augmented ordered activities from each Y_{jmr}.

(10) The set of rules for the compatibility and completeness test.

(11) The learning mechanism for decision making where the Entropies corresponding to the total probabilities are compared for minimum value.

(12) The Feedback mechanism which updates the probabilities by learning, through an evaluation of the task execution from the lower levels.

When a user command c_n with a pdf $p(c_n)$ is sent to the Intelligent Machine, it is received and classified by the classifier to yield the (classified) compiled input command u_j with a pdf $p(u_j/c_n)$, which is the input to the organization level.

The organization level formulates complete and compatible plans and decides about the best possible plan to execute the user requested job. This is done by associating u_j with a set of pertinent activities X_{jm} with corresponding probabilities $P(X_{jm}/u_j)$ (reasoning), and by organizing the activities in such a way (planning) to yield complete and compatible plans: the compatible ordered activities Y_{jmr} are obtained via the mask matrices M_{jmr} and their associated pdfs are: $P(Y_{jmr}/u_j) = p(M_{jmr}/u_j)P(X_{jm}/u_j)$. The compatible augmented ordered activities $Y_{jmr}(a_s)$ are obtained by inserting repetitive primitive events in appropriate positions within each Y_{jmr} and their corresponding pdfs are:

$$P(Y_{jmr}(a_s)/Y_{jmr}) = p(M_{jmr}(a_s)/Y_{jmr}) \cdot P(Y_{jmr}/u_j).$$

Every incompatible activity and incomplete plan is rejected. The most probable complete and compatible plan Y^F is the final plan that is transferred to the coordination level (see Fig. 4).

Each function has been described in a set theoretic manner and probabilities are assigned as measures. Entropies $H(F(X))$ are associated with each function in a straightforward way. Transmissions of information $T(X_i : X_j)$ measure the interdependence between different functions.

The Entropy function is used to calculate the uncertainty of the activities and ordered activities.

Assume that there are S different states of the organizer and that the inputs to the organizer belong to C. It has been shown that the functions of the organization level obey a generalized law of partition of information rates

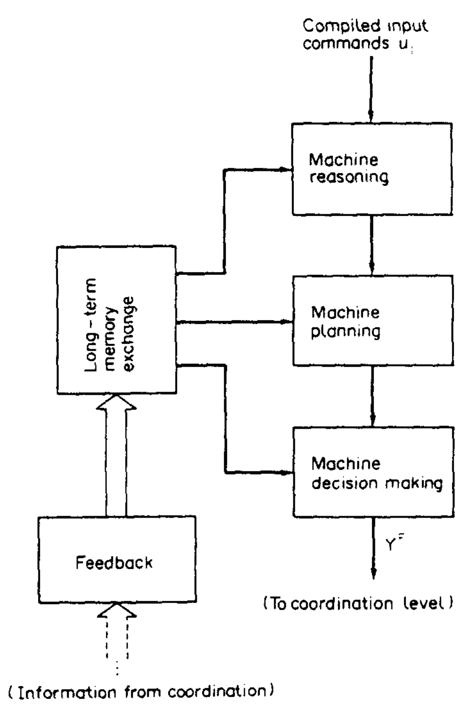

FIG. 4. Block diagram of the organization level.

(Conant, 1976). According to this law the total activity rate of the organizer is decomposed into the Throughput Rate (flow of Knowledge), the Blockage Rate (Decision Making), Coordination Rate (Planning), Internal Decision Rate (Reasoning) and Noise Rate:

$$F = F_T(C:S) + F_B(C:S) + F_C(C:S) + F_D(C:S) + F_N(C:S) \quad (4)$$

where:

F = the total activity rate

F_T = the throughout rate corresponding to information transfer within the organizer

F_B = the blockage rate corresponding to Decision Making

F_C = the coordination rate corresponding to Planning

F_D = the internal decision making rate corresponding to Reasoning

F_N = the noise rate corresponding to information when the command C has been already received.

Learning in the organizer, as well as the entire Intelligent Machine, is obtained through selective feedback from the lower levels. Feedback in the organization level is applied after the completion of a whole task, in contrast to real-time feedback provided to the lower levels. The task is evaluated by cost functions J_c and all the probabilities associated with the organizer are upgraded by the stochastic approximation algorithm:

$$p(t+1) = p(t) + \gamma_{t+1}[\xi - p(t)];$$
$$\gamma_{t+1} = \frac{1}{t+1}; \quad \xi = \begin{cases} 1; & J = \min J_c \\ 0; & \text{otherwise.} \end{cases} \quad (5)$$

Convergence of this algorithm has been proven elsewhere (Saridis and Graham, 1984), establishing the learning property of the organizer.

A total Entropy is calculated for each final complete plan. This Entropy includes both the reasoning and planning uncertainty. The complete ordered activity with the minimum total Entropy is considered the most likely to execute the job, and is communicated to the coordination level.

Explicit mathematical expressions for each of the rates in (4) have been derived in Valavanis (1986). Stability and controllability aspects associated with the overall operation of the organizer have also been considered.

4. THE COORDINATION LEVEL AND THE NESTED TREES

The coordination level is an intermediate structure serving as an interface between the organization and the execution level. It is essential for dispatching organizational information to the execution level.

Its objective is the actual formulation of the control problem associated with the most probably complete and compatible plan formulated by the organization level that will execute in real-time the requested job.

This includes selection of one among alternative plan scripts that accomplish the same job in different ways according to the constraints imposed by the workspace model and timing requirements.

The coordination level is composed of a specified number of coordinators. Specific hardware (execution devices), from the execution level, is associated with each coordinator. These execution devices execute well-defined tasks when a command is issued to them by their corresponding coordinator (Valavanis, 1986).

The major advantage which results from this association is that the individual functions of each coordinator may be defined *a priori* (during the design phase of the Intelligent Machines) because they are considered to be unmodifiable with time. Thus, they are assumed to be deterministic functions because the number of parameters involved in each one of them is also pre-specified.

This structure implies that the coordination level does not have any reasoning capabilities like the organizer. *Its intelligence is related to its ability on how to execute the organizer plan in the best possible way.* The coordination level involves decision making associated with specific knowledge (information) processing based on the already formulated plan, utilizing decision schemata proposed by Saridis and Graham (1984).

The functions of the coordination level are defined in terms of the individual functions of the different coordinators of an Intelligent Machine, i.e. for an Intelligent Robotic System:

(1) the Vision System Coordinator (VSC),
(2) the Sensor System Coordinator (SSC),
(3) the Motion Coordinator(s) (MSC), and
(4) the Gripper(s) Coordinator(s) (GSC).

It is important to clarify at this point that we consider the VSC as a separate coordinator and not as a part of the SSC. The main reasons for this distinction are: first, Robotic Vision has become a very important component in modern robotic systems and robotic vision systems are studied and treated separately from all other types of external (and internal) sensors, second, the hardware associated with the VSC is different from that associated with the SSC, and, third, this paper is mainly concerned with the VSC and ignores the details of operation of the other sensory systems.

Each coordinator when accessed performs a pre-specified number of different functions. A cost is assigned to each individual function. An accrued cost is associated with the operation of each coordinator. An overall accrued cost is calculated in terms of the weighted sum of the accrued costs of the coordinators after the execution of the requested job. This cost is communicated to the organizer *after the completion of the requested job* and is used to upgrade the information stored in the long-term memory of the organization level. This feedback information (which is sent from the coordination to the organization level after the completion of the requested job) will be called *off-line* feedback information learning. On the other hand, feedback information is communicated to the coordination level from the execution level *during the execution of the requested job.* Each coordinator when accessed issues a number of commands to its associated execution devices (at the execution level). Upon completion of the issued commands feedback information is received by the coordinator and is stored in the short-term memory of the coordination level. This information is used by other coordinators if necessary, and also to calculate the individual, accrued and overall accrued costs related to the coordination level. Therefore, the feedback information from the execution to the coordination level will be called *on-line, real-time* feedback information. More details about the feedback mechanism are given in the corresponding sections where the functions of each coordinator are explained.

A block diagram of the coordination level is shown in Fig. 5. This diagram suggests the

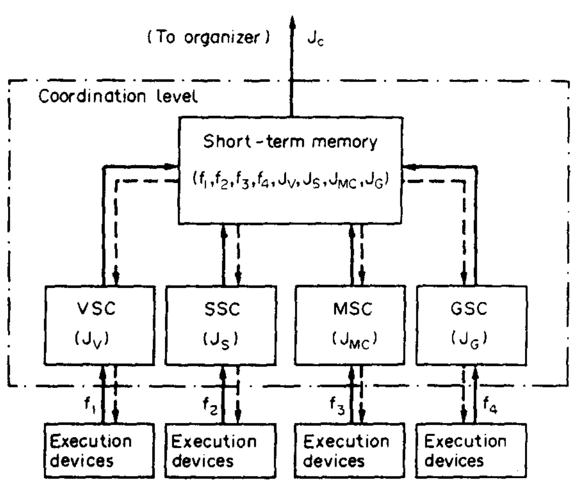

FIG. 5. The architectural model for the coordination and execution levels.

n-tuple nesting structure of the coordinator as well as its multi-layer organization. Even though its operation is based on a tree mode the different coordinators may communicate with each other directly by changing the diagram to a graph mode.

5. THE EXECUTION LEVEL WITH ENTROPY FORMULATION

The cost of the control problem at the hardware level can be expressed as an entropy which measures the uncertainty of selecting an appropriate control to execute a task. By selecting an optimal control, one minimizes the entropy, e.g. the uncertainty of execution. The entropy may be viewed in this respect as an energy in the original sense of Boltzmann, as in Saridis (1985b).

Optimal control theory utilizes a non-negative functional of the states of the system $x(t) \in \Omega_x$, the state space, and a specific control $u(x, t) \in \Omega_u \times \Pi$, $\Omega_u \subset \Omega_x$, the set of all admissible feedback controls, to define the performance measure for some initial conditions $(x_0(t_0))$, representing a generalized energy function of the form

$$V(x_0, t_0) = \int_{t_0}^{t_f} L(x, t, u(x, t))\, dt \qquad (6)$$

where $L(x, t, u(x, t)) > 0$, subject to differential constraints dictated by the underlying process

$$\dot{x} = f(x, u(x, t)), t; \quad x(t_0) = x_0; \quad x(t_f) \in M_f \quad (7)$$

with M_f a manifold in Ω_x. The trajectories of the system (7) are defined for a fixed but arbitrarily selected control $u(x, t)$ from the set of admissible feedback controls Ω_u.

In order to express the control problem in terms of an entropy function one may assume that the performance measure $V(x_0, t_0, u(x, t))$ is distributed in Ω_u according to the probability density $p(u(x, t))$ of the controls $u(x, t) \in \Omega_u$. The entropy $H(u)$ corresponding to this density is defined as

$$H(u) = -\int_{\Omega_u} p(u(x, t)) \ln p(u(x, t))\, dx$$

and represents the uncertainty of selecting a control $u(x, t)$ from all the possible admissible feedback controls from Ω_u. The optimal performance should correspond to the maximum value of the associated density $p(u(x, t))$. Equivalently, the optimal control $u^*(x, t)$ should minimize the entropy function $H(u)$.

This is satisfied if the density function is selected to satisfy James' Principle of Maximum Entropy (1957), e.g.

$$p(u(x, t)) = c \exp\{-V(x_0, t_0, u(x, t))\}. \quad (8)$$

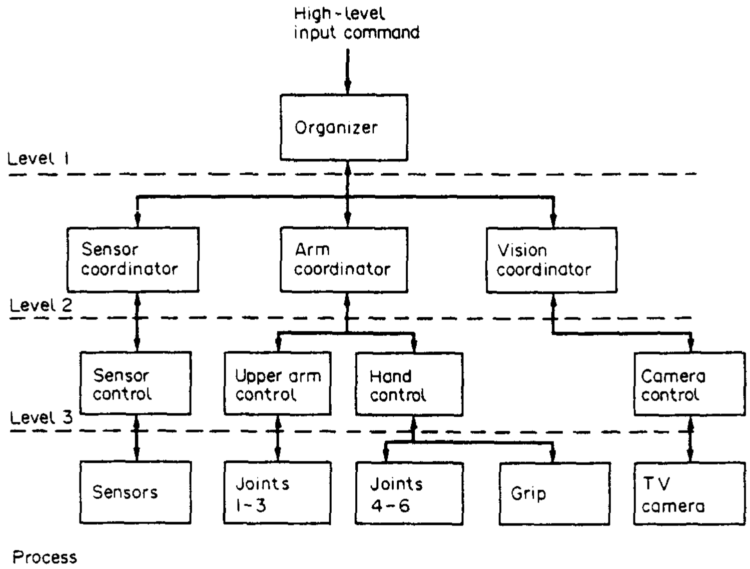

FIG. 6. Hierarchically intelligent control system for the Unimation's PUMA-600.

It was shown by Saridis (1985b) that the expression $H(u)$ representing the entropy for a particular control action $u(x, t)$ is given by

$$H(u) = \int_{\Omega_u} p(x, u(x, t))V(x, t, u(x, t))\,dx$$
$$= E_x\{V(x_0, t_0, u(x, t))\}. \tag{9}$$

This implies that the average performance measure of a feedback control problem corresponding to a specifically selected control, is an entropy function. The optimal control $u^*(x, t)$ that minimizes $V(x, t, u(x, t))$, maximizes $p(x, u(x, t))$, and consequently minimizes the entropy $H(u)$:

$$u^*: E_x\{V(x, t, u^*(x, t))\}$$
$$= \min_u \int_{\Omega_x} V(x, t, u(x, t))p(u(x, t))\,dx. \tag{10}$$

This statement establishes equivalent measures between information theoretic and optimal control problems and provides the information and feedback control theories with a common measure of performance. A block diagram for an Intelligent Robot is given in Fig. 6 which demonstrates the flow of information at the various levels.

6. A CASE STUDY

The above mathematical formulation has been implemented in the Nuclear Power Plant with a Pressurized Water Reactor shown in Fig. 7. An Intelligent Robotic System with a mobile robot is used to overcome and control emergency situations within the plant. Three types of emergency operations are considered: valve-related (relief, safety, isolation valves), flange-related and pipe-related operations in ascending order of complexity. Valve-related operations are the simplest. Flange-related operations include operations on the valve(s) associated with the particular flange(s), while pipe-related operations include both. Three types of user commands are also considered related to valves, flanges and pipes. Given a user command the intelligent robotic system formulates complete plans and specific strategies to execute the requested job.

The overall strategy formulation for the above operations includes: (a) location and identification of the proper valve(s), flange(s), pipe(s); (b) approach techniques via possible paths based on the model of the environment and present obstacles, (c) evaluation of the operability of the faulty part(s) by inspection, etc.

The mathematical model used in this case study considers: 29 user commands, 18 different primitive events (two repetitive and 16 non-repetitive), three relief valves, three safety valves, nine isolation valves, seven flanges and six pipes as labeled in Fig. 7. Furthermore, two possible paths within the reactor have been assumed, one dynamic model (since we use a mobile robot) and three penalty functions, one for each type of operation, associated with the accuracy of execution of the requested jobs.

For sequential testing of a faulty valve and a faulty flange, the results are shown in Figs 8 and 9.

Figure 8 shows the reduction of the uncertainties associated with the organization and execution of the best (minimum organization entropy) plan related to valve and flange operations and the reduction of the uncertainties related to irrelevant knowledge (blockage) and relevant knowledge (throughput) throughout the

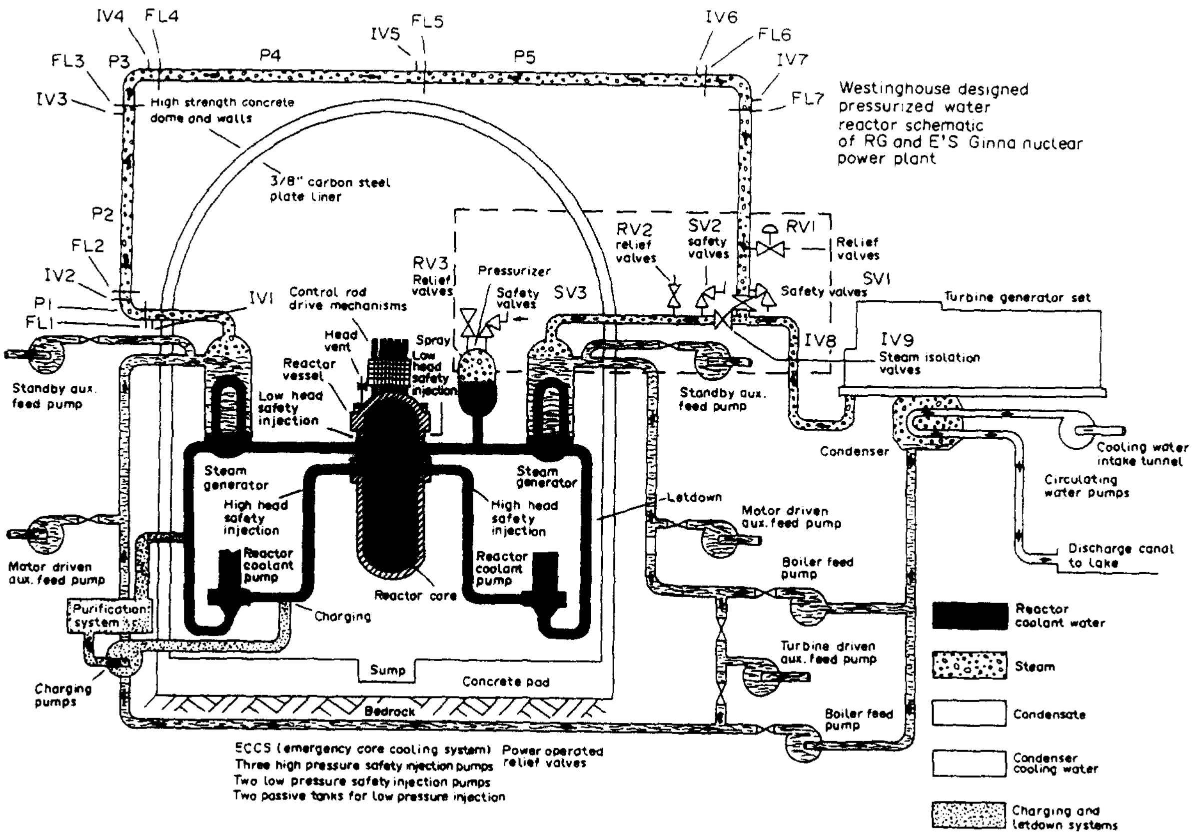

FIG. 7. The modified PWR schematic.

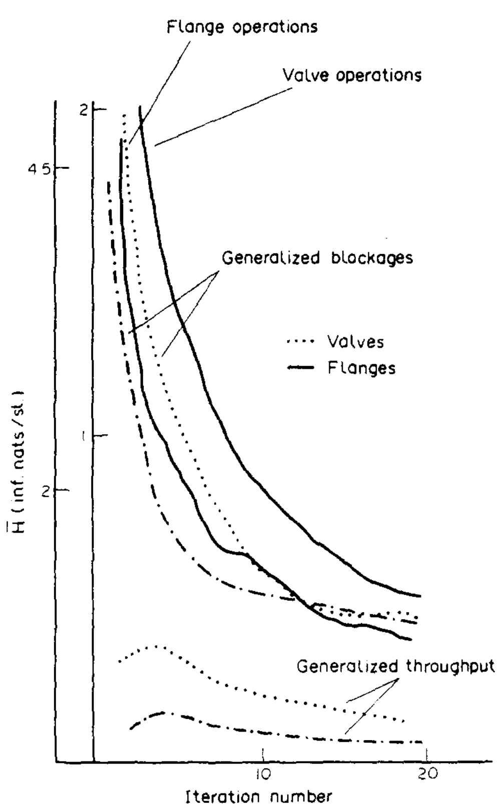

FIG. 8. Evaluation of entropy rates.

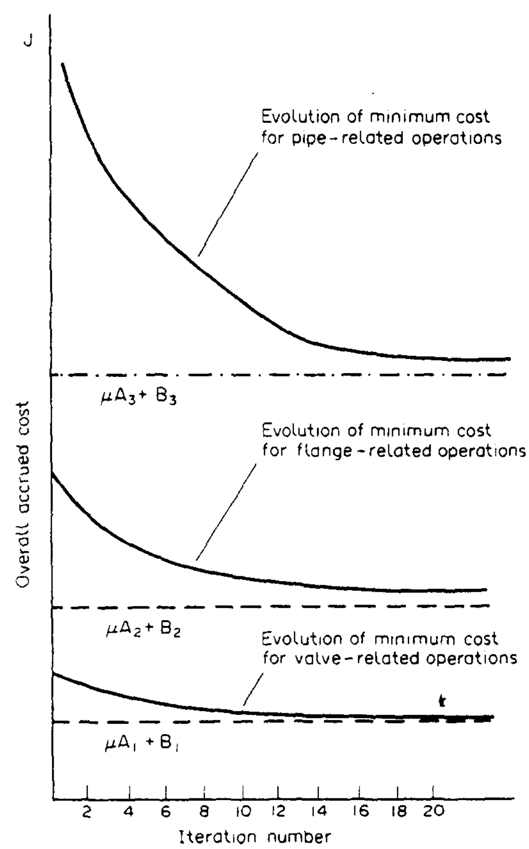

FIG. 9. Evolution of minimum accrued cost, J_C.

system. The effect of learning feedback to improve the performance, e.g. reduce entropy, is obvious through plan iterations.

Figure 9 shows the reduction of the accrued cost for coordinating and executing the best plan. The minimization procedure obtained through learning by feedback is demonstrated. The accrued cost for either type of operation asymptotically reaches the line $\mu A_i + B_i$, $i = 1, 2, 3$. This cost represents the minimum cost function necessary to complete the requested job if the system has complete knowledge of the environment.

A complete analysis of the case study, including details of the structures of the organizer coordinator and execution level of the intelligent machine, along with the derivation of the individual and accrued costs are found in Valavanis (1986).

This case study establishes the validity of our approach since by minimization of the Entropy we have obtained improved performance of the system.

7. CONCLUSIONS

Intelligent Controls have been formulated as a multi-level hierarchical structure obeying the Principle of Increasing Precision with Decreasing Intelligence. Probabilistic models to express the uncertainty of reasoning, planning decision making at the organization level, the assignment of tasks at the coordination level, and the control activities at the execution level Entropies are used as measures of the execution of various commands by the Intelligent Machine and they serve for the optimal decision making.

This method provides an efficient approach to implement autonomous Intelligent Control Systems suitable for the demanding needs of modern industry, space exploration, nuclear handling and medicine.

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