An Informationally-Open, Organizationally-Closed Control Structure for Navigating a Robot in an Unknown, Stationary Environment

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ABSTRACT

This paper examines the roots of purposive behavior in an agent surrounded by a stationary unknown environment. The investigation focuses on deriving a structure for a behavior generation mechanism (BGM) that would semantically embed an agent in the context of its environment. The BGM is made to adhere to the situated, embodied, intelligent, and emergent requirements that were suggested by Brooks [14] for the construction of intelligent control architectures. Concepts from epistemology, artificial life, hybrid systems, and the potential field approach to planning are used. The suggested BGM utilizes both experience and synergy as drivers of action selection. The BGM is intended for use in the specific case of motion planning for a multidimensional agent of arbitrary shape operating in a multidimensional, unknown environment.

1. INTRODUCTION

The demand is increasing for the construction of agents able to tackle environments that deny an operator both informational and physical access. Two examples of the above are: underwater sea exploration where due to the severe attenuation high frequency electromagnetic waves experience by water no communication link between the exploring agent and the operator may be possible. The other involves planetary exploration where long delays in information transmission severely hampers the communication process. Obviously, an agent operating under such conditions cannot rely on guidance from the operator to avoid hazard or to proceed towards its goal. To complicate things more, the agent may not have the benefit of utilizing experience in steering its actions. In such situations failure to properly act the first time may lead to damaging the agent (a swim or sink situation). These restrictions do not only rule out active-guidance where the operator online steers the actions of the agent, it also include indirect guidance that assume the form of algorithms implanted into the agent to steer its actions in a manner that meets the acceptance of the operator who designed these algorithms (not, necessarily, the demands of the environment.) For an agent to be fully autonomous it must be able to meaningfully embed its actions in the context of its environment. Some of the concerns which this gives rise to are:

1. The compatibility of the environment representation with the manner by which the agent makes decisions and actuate motion,
2. The informational adequacy of the representation (i.e. does the representation encode enough information to generate a successful action,
3. If needed, the ability to augment the available information to, at least, the minimum level that is needed to execute the task,
4. The ability to convert the acquired information into successful actions.

The agent may be operating in a known or an unknown environment. To understand the difference between the two cases, it must first be noticed that a form which an agent uses to represent its environment is an instrument for encoding the information (I1) that is available about that environment. On the other hand, a representation that assigns an action to every point in the space of possible events is constructed by encoding the same information contained in the input representation using a format that suits the agent's actuators of motion. In a known environment the amount of information that is needed to construct a successful action-representation (I2) is bounded by the amount of information in the input representation (I1>I2). For this case, the controller plays the role of a format changer that converts part or all of the information contained in the representation to a form that is compatible with the task of motion actuation. As for the unknown, or partially-known environment case, the information encoded in the environment representation is less than that which is needed to execute the task (11<12). Therefore, format changing alone is not enough to generate a successful action representation to guide the motion actuators of the agent. Here, the agent is required, along with format changing, to perform the paradoxical task of learning (i.e. getting to know what it does not know). An area of research that falls under the above is motion planning for an agent in an unknown stationary environment. Here, an agent is required to lay a safe path to a stationary target relying only on the local information that is sequentially being acquired by its finite range sensors. It must be able to coherently tie the stream of fragments of sensory data in a manner that permits the generation of a continuous stream of instructions to the actuators of motion. The structure of such a stream is required to successfully embed the agent in its environment. One approach that has significantly influenced the above area is traditional AI [1-3]. Methods utilizing this approach must have a discrete abstract model of the environment followed by a search for a feasible action plan. Unfortunately, model-based approaches can provide, at best, a costly, precarious performance. The reactive approach to motion planning [4] bypasses the above difficulties by coupling the sensors directly to the motion actuators. While this approach is fast, robust, and easy to implement, it is only able to tackle simple tasks. Attempts to increase the complexity of the tasks tackled by the reactive approach focused on utilizing it within the context of high-level, model-based symbolic reasoning [5]. Petrov and Sirota were, probably, the first to suggest a provably-correct, sensor-based motion planner that can guide a robot of arbitrary shape in an unknown environment using highly localized sensory data. In [6] the planner was developed for the 2-D environment. Later in [7], the planner was generalized for the 3-D case. Lumelsky suggested a similar approach that uses local sensory data for guiding the motion of a point robot in a 2-D space [8]. Unfortunately, extending the approach to the 3-D case [9] was not successful.

To adapt to structural changes in the environment, learning techniques are suggested. Despite their diversity [10-12] the present learning techniques are unified in their reliance on experience as the driver of action selection. As was discussed earlier, the type of environments which an agent is required to operate in rules out experience as the only mechanism for action selection. Despite the popularity of the traditional AI approach, its fitness to synthesize autonomous and intelligent behavior is being seriously questioned [13]. Brooks believe that for a successful grounding in physical reality, the agent must be situated, embodied, intelligent, and emergent [14]. An architecture for mobile agents that satisfies these requirements, the subsumbtion architecture, was suggested in [15].

This paper examines the construction of a BGM that would allows an agent of arbitrary shape to move to a stationary target in a workspace that is populated by unknown, stationary forbidden regions. The BGM is required to adhere to the situated, embodied, intelligent, and emergent requirements that were suggested by brooks.

It is also required to satisfy the four conditions that are stated at the beginning of this section. Ideas from several areas are used in the development, namely: hybrid systems [16,17] which combine both continuous and discrete phenomena in behavior generation., artificial Life [18] which emphasizes that information can be generated from the interaction of a large number of elementary processes, and potential field method for motion synthesis [19], in particular, ones that utilize a potential field in the context of a Partial Differential Equation, Ordinary Differential Equation (PDE-ODE) systems . Finally, ideas from self, and self-monitoring in an agent are used [20]. These areas are used to develop three concepts that are of central importance to constructing the BGM. These concepts are: parallel-distributed representations which are used instead of discrete symbolic ones, a potential field expressed in the context of a PDE-ODE system is a Self-referential, Intelligent, Massive, Parallel, Distributed (SIMPD) machine, and the concepts of autonomy, self, and self-monitoring. This paper is organized as follows: section 2 contains problem formulation, the concept of distributed representations, SIMPD machines, self and autonomy followed by the structure of the BGM are discussed in section 3. Conclusions are placed in section 4.

2. PROBLEM FORMULATION

The BGM assumes the form: $\dot{x} = u$ (1)

where u is the control input ($u \in R^N$), and x and $\dot{x}$ are an N-dimensional position and velocity vectors ($X \in R^N$). O is a set of *a priori* unknown regions in R^N which the agent is required to avoid, Γ is the boundary of O ($\Gamma=\partial O$), and Ω is the workspace which the, agent is permitted to operate in ($\Omega=R^N$ - O). Let Γ ` be a subset of $\Gamma$ that is *a priori* known to the agent ($\phi \subseteq \Gamma` \subseteq \Gamma$). Let Q be the state of a Discrete Event System (DES) [21]. At any time Q must assume a value from the binary set {0,l}. Such a value depends on the event the local sensors register regarding the possible future position of the state X+(t+dt), There are two events, either X+ is in Ω ($X+ \notin O$) which for this case Q assumes the value 0, or X+ is in a forbidden region ($X+ \in O$) where Q is 1. The value of Q is driven from 0 to 1 at time t_i by a combination of the current belief which the agent is using to direct its actions, the remaining unknown part of Γ (Γ-Γ `), and the location of the target. The, opposite transition in Q from 1 to 0 occurs at $t_i$`and is caused by the modified belief which the agent uses for directing its future actions (u). Although Q experience discrete jumps, the cause of these jumps is continuous. Therefore, the planner must have a hybrid, continuous-in-time, discrete-in-time nature. Here action selection is carried out by a continuous process. The discrete phenomenon is manifested as a pattern drawn on the continuous process. The agent react to the $X+ \in O$ event at t_i by modifying its belief so that a transition of Q from 1 to 0 occur at t_i`. The belief is denoted by the vector field $fi(x,T,Q,f_{i-1})$ ($fi \in R^N$). fi maps the hybrid situation space ($x \times T \times Q \times f_{i-1}$) into the N-dimensional, continuous, action space (u), where the index i represents ti, and T is the target set. For successful action, the agent is required to synthesize a finite set of successively dependent fi's ({fi :i=l,..,L<∞}) so that:

$$\dot{x} = f_i(x, T, Q, f_{i-1})$$

$$x(0) = x_0 \in \Omega,\ f_0 = f(x, \Gamma`, T),\ i \in [1,..,L]$$

where $t \in [t_0, ...\infty)$ $\lim_{\substack{i \to L \\ t \to \infty}} x(t) \to T$,

and $x(t) \cap O \equiv \phi \quad \forall\ t.$ (2)

3. ESSENTIAL CONCEPTS

3.1: Parallel-distributed Models

Implicit in the ability of an agent to plan is its ability to test the outcome of an intended action prior to executing it. A representation or a model may be looked upon as the crystal ball which the agent uses to view the possible future from the present. One approach to constructing a representation is the discrete symbolic approach. To construct a discrete symbolic model of an environment, first, similarity grouping is used to partition the environment into homogeneous components that are perceived as unities. Each part is then modeled and assigned an icon or a symbol. These icons are in turn related to each other using a hierarchical set of rules so that the behavior of the resulting discrete automaton satisfactorily mimics that of the environment. One difficulty facing this approach is its inherent subjectivity which stems from the ambiguous notion of similarity. Similarity is heavily reliant on the psychology of the agent that is doing the partitioning, the task which the representation is constructed for, and the amount of information that is *a priori* available. This is a serious obstacle in attaining universality which allows a wide range of agents to use a representation for a wide class of tasks. Another difficulty is encountered in inducing the relations among the symbols from an observed behavioral segment of the environment. Even if the selected segment of behavior is "rich enough" to encode all the latent relations governing behavior, the decoding process can never guarantee that the encoded relations are properly extracted. While surface relations may be accurately modeled, the accuracy deteriorates as in-depth relations are sought after. Since discrete symbolic representations are hierarchical in nature, they face the additional difficulty of determining the depth of such behavioral hierarchy. Also in partitioning an environment into similar components and assigning each component a symbol there is the implicit assumption that the environment is stable enough to allow no changes in the structure of the symbols. Any change of such a sort requires the elaborate relation extraction process to be performed all over again. Unfortunately, realistic environments are unlikely to support this requirement. Representing an environment as a group of discrete heterogeneous entities that are glued together via a hierarchical set of relations is a long standing tradition in philosophy and science. There is, however, an opposing, but less popular, camp to the above point of view stressing that representations should be indivisible, and homogeneous. Such an argument can be traced back to the early Greek philosopher Parmenides [22] whose ideas were vehemently rejected by Plato (a strong supporter hierarchical symbolic reasoning). Later Zeno (a student of Parmenides) paused his famous paradoxes [23] to show the logical contradictions that arise as a result of dividing a physical process into parts. Distributed representations has already found supporters among modern mathematicians, system theorists, and philosophers. Norbert Wiener said "The identity of a body is more like the identity of a flame than that of a stone; it is the identity of a structure, not of a piece of matter" [24,25]. In [26] Lefebvre viewed an entity or a process as a wave that glides on a substrate of parts where the relation between the two is that of a system drawn on a system. And in [27] Campbell argues against the hypothesis that geometrical symbols are used by creatures, to model the environment that they want to navigate. He postulate the existence of a more subtle and distributed representation of the environment inside the agent. Also experiments by psychologists in the manner by which animal and children navigate their environment seems to support the distributed representation hypothesis [28]. It is obvious that there is a strong reason to consider the separation between the identity of an entity or a process and that of its parts (carrier), and to seriously question the belief that a representation of a process may be deconstructed into parts and relations then reconstructed back without distorting the identity of that process. With this in mind, the following guidelines are used for constructing a representation:

1- A representation is a pattern that is imprinted on a substrate of some kind.

2- The substrate is chosen as a set of homogeneous, simple, automata that densely covers the agent's domain of awareness. This domain describes the state of the environment and is referred to as state space (X).

3- The representation is self-referential. A self-referential representation may be constructed using a dense substrate of automata that depicts the manner in which an agent act at every point in state space. Self-referential representations are completely at odd with objective representations. They are a product of the controversial stream of philosophy (originated by Socrates), and theory of knowledge (epistemology) [29-32] which stresses that ontological (absolute or objective) reality does not exist, and any knowledge that is acquired by the agent is subjective (self-referential.)

4- In conformity with the view that objective reality is unattainable, a representation is looked upon as merely a belief. Its value to an agent is in how useful it is, not how well it represents its outside reality. Therefore, a pattern that evolve as a result of a self-regulating construction is at all phases of its evolution a legitimate representation.

3.2: A Potential Field Expressed in the context of' a PDE-ODE System is an SIMPD machine.

A machine is a two-port device that consist of an operator port, an environment port, and a construction that would allow a goal set by the operator, defined relative to the environment to be reached. Despite the significant advances that technology underwent since the first industrial revolution, machines, mainly, remained reliant on the operator's intellectual labor for instructions on how to deploy the actuators of motion so that the goal is reached. In essence a machine is reduced to mere "muscles" of the operator, predictable, and obedient. It seems that the attempts of CYBERNETICS to attach a "true brain" to these muscles were forgotten [33]. CYBERNETICS [24,25], or as Wiener defined it: "communication and control in the animal and the machine," contradicted the belief that intelligence and purposive behavior is a monopoly of the human race. CYBERNETICS is based on the controversial conjectures that a machine can learn, can produce other machines in its own image, and can evolve to a degree where it exceeds the capabilities of its own creator. It is no longer necessary for the operator to generate a detailed and precise plan to convert the goal into a successful motor action. The operator has to only provide a general outline of a plan and the machine will fill in the "gaps"; hence confining the operator's intervention to the high-level functions of the undergoing process. Such functions dictate goals and constrain behavior. The machine is supposed to transform the high-level commands into successful actions. CYBERNETICS unifies the nature of communication and control. It gives actions the soft nature of information. To a cybernist a machine that is interacting with its environment is an agent that is engaging in information exchange with other agents in its environment. In turn, a machine consists of interacting subagents, and is an interactive subagent in a larger machine. A controller which forces an agent to comply with the will of the operator is seen as an encoder that translates the requests of the operator to a language the agent can understand. Therefore, an action is a message, and a message is an information-bearing signal or simply information. Accepting the above paves the way for a qualitative understanding of the ability of a machine to complement the plan of the operator. Let an information theoretic approach [34,35] be used to examine two agents that are interacting or, equivalently, exchanging messages. Assume that the activities of the first organism has Ix equivalence of information, and that the second has Iy. Although what is being contributed by the interacting agents is equal to Ix+Iy (self-information), the actual information content of the process is Ix+Ixy+Iy, where Ixy is called mutual information. While the measure of self information is always positive definite (Ix=-log(Px) ,Iy=-log(Py)), the measure of mutual information (Ixy= log(Px,y/(Px.Py)) is indefinite (Px and Py are the probability of x and y respectively, and Px,y is their joint probability). In an environment where carefully designed modes of interaction are instituted among the constituting agents, the net outcome from the interaction will far exceed the sum of the individual contributions

$$\mathrm{Ix} + \mathrm{Ixy} + \mathrm{Iy} \gg \mathrm{Ix} + \mathrm{Iy}. \qquad (3)$$

On the other hand, in "screwed up" environments the total information maybe much less than the self-information (an interaction that paralyzes the members makes $Px,y \equiv 0$, and $Ixy \rightarrow -\infty$). It has been shown experimentally and by simulation that sophisticated goal-oriented behavior can emerge from the local interaction of a large number of participants which exhibit a much more simplistic behavior. This has motivated a new look at the synthesis of behavior that is fundamentally different from the top-bottom approach. Artificial Life (AL) [18] approaches behavior as a bottom-up process that is generated from elementary, distributed, local actions of individual organisms interacting in an environment. The manner in which an individual interact with others in its loca1 environment is called the Geno-type. On the other hand, the overall behavior of the group (Phenotype, or P-type) evolves in space and time as a result of the interpretation of the Geno-type in the context of the environment. The process by which the P-type develop under the direction of the G-type is called Morphogenesis [36].

To alter its state in some environment an agent (from now on is referred to as the operator) needs to construct a machine that would interface its goal to its actions. The machine (or interface) function to convert the goal into a sequence of actions that are imbedded into the environment(u_0, u_1,..,u_L). These actions are designed to yield a corresponding sequence of states (x_0,x_1,..,x_L) so that the final state x_L is the goal state of the operator. The action sequence is called a plan and it is a member of a field of plans (Action field) that densely covers state space so that regardless of the starting point (x_0), a plan always exist to propel the agent to its goal. To construct a machine of the above kind the operator must begin by reproducing itself (this is explained later in this section) by densely spreading operator-like micro-agents at every point in state space (Figure-1). The only difference between the operator-agent and an operator-like micro-agent is that the state of the Operator evolves in time and space while the state of the micro-agent is stagnant and immobilized to one a priori known point in state space. The second part of machine construction is to induce the proper action structure over the micro-agent group. It is obvious that a hierarchical, holistic, centralized approach for inducing structure over the group entails the existence of a central planning agent/s that is/are not operator-like. Including such an agent in the machine violates organizational closure, i.e. the restrictions on intelligent machines receiving no influx of external intelligence to help them realize their goals. In other words, the agent is must be able to lift itself from its own bootstraps. By restricting the forms of the agents constituting the machine to that of the operator, an AL approach does not require the intervention of any external intelligence to help in the construction of the machine. An AL approach, which is decentralized by definition (i.e. no supervisor is needed), requires a microagent to locally constrain its behavior (Genotype, or G-type behavior) using the information derived from the states of the neighboring microagents (Figure-2). Unlike centralized approaches where each micro-agent has to exert the "correct" action in order to generate a group structure that unifies the micro-agents in one goal-oriented unit, an AL approach only requires the microagents not to exert the "wrong" action that would prevent the operator from proceeding to its goal. Obviously, not selecting the wrong action is not enough, on its own, for each micro-agent to restrict itself to one and only one admissible action that would constitute a proper building block of the global structure that is required to turn the group into a functional unit. In an AL approach, the additional effort (besides that of the G-type behavior) needed to induce the global structure on the micro-agents is a result of evolution in space and time under the guidance of the environment. This interpretation or guidance is what eventually limits each micro-agent to one and only one action that is also the proper component in a functioning group structure.

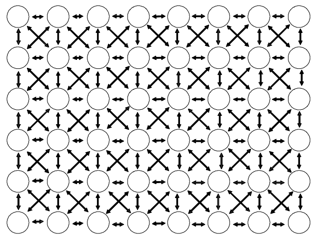

Figure-1: An interacting collective of micro-agents.

To construct a machine that operates in an AL mode, the operator must have the means to:

1- Reproduce itself at every point in state space.

2- Clone the geno-type behavior in each member of the micro-aqent group.

3- Factor the environment in the behavior generation process.

Self-reproduction is accomplished by densely covering state space with micro-agents described by the dynamical system

$$\dot{x} = f(x_i, u) \tag{4}$$

where x_i. is the *a priori* known location of the i'th micro-agent in state space $x \in R^N$ (i.e. x_i. is a constant), u is the action (control input) under the disposal of the micro-agent ($u \in R^M$, $M \le N$), and x is the change that micro-agent i (located at $x_{i.)}$can induce in the state of the operator so that it is driven to X_j, where

$$x_j = x_i + dt \cdot \dot{x}(x_i) \tag{5}$$

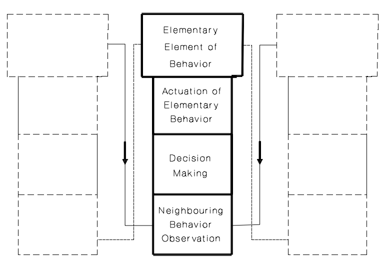

Figure-2: Layers of functions in an interactive micro-agent.

and dt is an infinitesimal time unit. The fact that the state of a micro-agent is immobilized makes x totally dependent on the characteristics of the system and the selected action u at point x_i. Therefore a micro-agent can be exactly represented by its action at each point in state space. Here, creating an action group begins by covering the state space with a potential field that has locally (point wise) extractable vector features homogeneously covering the domain of the field. The selected vector features are determined by the vector partial differential operator which operate on the potential field to induce the vector describing the action of the micro-agent. While there are no constraints on the dimensionality of the potential field the dimensionality of the vector operator must be equal to the dimensionality of the action (control) space so that an onto, one-to-one correspondence between the induced vector and the operator's action may be established. By applying the vector differential operator to the potential field everywhere in state space, a collective of micro agents is constructed. The second step in machine construction is to provide each microagent with the ability to generate a proper G-type behavior. G-type behavior is a self-behavior where a micro-agent does not attempt to influence the actions of any of the micro-agents it is interacting with. Instead it forms a soft informational coupling with them where it only observes their behavior then uses it to derive a self-action that governs its and only its behavior in state space. The above may be achieved by constraining the vector partial differential operator (P) that describes the actions of a micro-agent using a partial differential operator that is defined in state space (L). Unlike P, there are no restrictions on the dimensionality of L. As for the last requirement, the effect of the environment may be factored into the behavior generation process as state boundary conditions in which a micro-agent synthesizes the action that would constrain the behavior of the operator to an *a priori* known one that is released upon encountering a certain situation in the environment. The above three steps for building an intelligent machine describe a Hybrid PDE-ODE system (Figure-3). Therefore, a potential field expressed in the context of a PDE-ODE system is a Self-referential, Intelligent, Massive, Parallel, Distributed (SIMPD) machine. For more details about the structure in Figure-3 see [19]. Figure-4 demonstrates the ability of an SIMPD machine to generate, without any external assistance, the necessary in-formation which the agent needs to reach its goal. It also demonstrates the counter intuitive fact that order can emerge from disorder, where the random, senseless actions that are initially assigned to the group evolve into coherent goal-oriented ones.

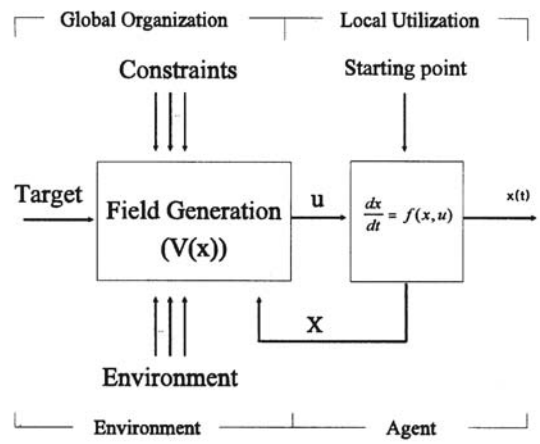

Figure-4: structure of a potential-based path-planning technique.

3.3 AUTONOMY

To achieve autonomy an agent must be:

1- Aware of its environment,

2- Aware of itself as a distinct entity in the environment,

3- Have the ability to formulate goals,

4- Have the Ability to bridge the gap between the mental world, where the above three take place, and the physical world where actions take place,

5- Have the ability to construct a plan.

The above requirements are the basis for constructing cohesive modules that are capable of self-motivation, self-monitoring, self-organizing, and self-steering etc. It is obvious that the concept of the self is of central importance to constructing such modules and a precise technical definition of the self is needed in order to build an autonomous agent. Unfortunately, this important concept is plagued with problems. To begin with, the self is not a uniquely defined concept. It may refer to two different phenomena [20]:

1 "Self as an organization of the entity where the self is a denotation of the synthetic individuality and autonomy of an organized system", 2- "Self as a subject that reflects upon its "self". The self in this sense is conceived as a kind of separate sub-entity that observes ones self."

The first is called the "self" and the second is called the "I" or the "ego" where the I is the self observer". Some of the I's known functions are to recognize the self by making the distinction between the agent and the environment. It also keep a conscious self-monitoring where it emerges if a dissonance occur and dissipate if a mastered, coherent plan is active. While the self may be defined as the body of the agent and any physically measurable processes in it, the problem of what the I is and "the emergence of its activities in which the ego not only distinguishes its "self" as the object among other objects but sees and speaks about its "self" as the originator of an action is still unresolved" [20]. To complicate things more, the coupling between the two (i.e. how apprehension turns into reality) which is known as the mind-body or mind-brain problem is still at a very undeveloped stage [37,38].

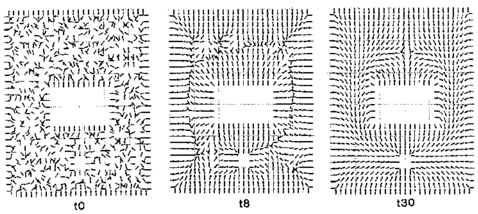

Figure-4: Evolution of structure in an SIMPD machine.

While achieving autonomy seems to be faced with serious challenges, a useful mild form of autonomy which is called here Pseudo-autonomy is achievable. Pseudo-autonomy bypasses the problematic concept of the ego by permitting the initial intervention of an external agent to set the dimensions of the self (i.e. define what separates the agent from its environment; it also tells it what means under its disposal to affect its environment). Despite the lack of a precise definition of the I, the little available information characterizing its behavior combined with the concepts of an SIMPD machine and Parallel-Distributed representations are enough for building a useful pseudo-autonomous BGM. One of the fundamental assumptions the BGM is based on regards the physical environment as the inducer of a subjective (self-referential) form that appears in the mental environment of the operator. This form is used as a descriptor of the environment. The environment remains as an unattainable reality that cannot be objectively characterized. On the other hand, the agent is assumed to have a dual nature (i.e. it has two interconnected parts: one that belongs to the objective environment, and the other belongs to the subjective, mental, environment). Inside and only inside the subjective environment of the agent the activities pertaining to behavior generation can take place. The proposed BGM uses an SIMPD machine to substitute for the mental environment of the agent. The SIMPD machine transforms the goal, constraints on motion, and the initial knowledge the agent has about its environment into a continuous sequence of instructions that the agent uses to direct its actions so that the reaction of the environment can cause the desired change in its state. On the other hand, the SIMPD machine receives two feedbacks from the operator: a continuous one, and a discrete one. The continuous feedback provides the SIMPD machine with the current location of the agent in state space. This location is measured with respect to the goal using a subjectively constructed coordinate system. As for the discrete-feedback, it is supplied at random instants in time. Its presence is indicative of a dissonance situation. Dissonance is a generic term that indicates an irregularity in the agent's internal functioning, a mismatch between outcomes and expectations, or the presence of hazard in the vicinity of the agent. Once dissonance arise, the agent immediately stops using the action instructions that are based on the current belief that was already falsified by the rise of dissonance. At the same time, the dissonance signal sets the SIMPD machine in a self- organizing mode to generate a dissonance-free action plan that is based on the new modified belief. Figure-5 shows the structure of a BGM that behave in the above manner.

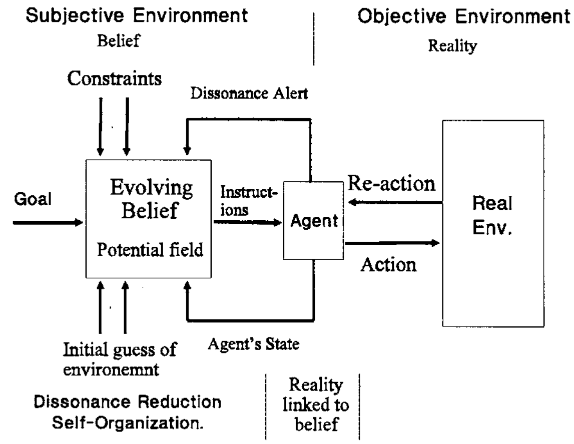

Figure-5: The suggested BGM

4. CONCLUSIONS:

In this paper an epistimologically-correct structure for behavior generation is suggested for the purposive integration of an agent in a stationary environment. Unlike existing structures where centralized modules separately handle representation, control, communication, reasoning, and information processing, the suggested structure distribute these faculties on a massive number of elementary agents where each locally and simultaneously perform the acts of communication, reasoning, and motion actuation. The global function-patterns that are needed to semantically embed the agent in its environment emerge as a result of the constructive interaction among the elementary agents under the guidance of the environment. Such a manner for generating action provides high robustness, high flexibility, and true intelligence. The suggested structure was used as a basis for developing a variety of intelligent controllers capable of planning motion for single or multiple agents under different assumptions and in a variety of situations [39-46].

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REFERENCES

[1] Rimon E., Canny J., "Construction of C-space Roadmaps From Local Sensory Data, What Should The Sensors Look For?", 1994 IEEE Int. Conf. on Rob. and Aut., San Diego May 8-13, pp. 117-123.

[2] Choset H., Burdick J.,"Sensor Based Planning and Nonsmooth Analysis", 1994 IEEE Int. Conf. on Rob. and Aut., San Diego, California, May 8-13, pp. 1-6.

[3] Meystel A.,"Nested Hierarchical Controller For Intelligent Mobile Autonomous Systems", Intelligent Autonomous Systems, Eds. Hertzberger L., Goren F., pp. 416-448, North-Holland Amesterdam, New York, Oxford, Tokyo, 1987.

[4] Arkin r.,"Motor Schema-Based Mobile Robot Navigation", Int.: Jour. Rob. Res., Vol. 8, No.4, 1989, pp. 92-112.

[5] Firby R.,"Building Symbolic Primitives with Continuous Control Routines", Int. Conf on AI Planning Systems, College Park, MD,

June 1992 pp.62-69.
[6] A. A. Petrov, I. M. Sirota, “Control of a Robot-Manipulator with Obstacle Avoidance Under Little Information About the Environment”, the 8th IFAC Congress, Kyoto, Japan, Vol. 14, August 1981, pp. 54-59.
[7]A. Petrov, I. Sirota, “Obstacle Avoidance by a Robot Manipulator Under Limited Information About the Environment”, Automation and Remote Control, Volume 44, Number 4, Part 1, April 1983, pp. 431-440.
[8] Lumelsky V., "A Comparative Study on the Path Length Performance of Maze-Searching and Robot Motion Planning Algorithms",IEEE Trans. on Rob. & Aut. Vol.7, No.1, Feb. 1991, pp. 57-66
[9] Kutulakos K., Lumelsky V., "Vision-Guided Exploration: A step Toward General Motion Planning in Three Dimension", Computer Science Department, univ. of Wisconsin Madison, Tech. Rep. # 1111, September 1992.
[10] Tham C., Prager R., "Reinforcement Learning Methods for Multi-Linked Manipulator Obstacle Avoidance and Control", IEEE Asia-Pacific Workshop on Advances in Motion Control, Singapore, July 16-16,1993.
[11] Humphrys M.,"W-Learning: Competition Among Selfish Q-learners", Univ. of Cambridge Comp. Lab. Tech. Rep. no. 362, April 1995.
[12] Ram A., Arkin R., Boone G., Pearce M.,"Using Genetic Algorithms to Learn Receive Control Parameters for Autonomous Robotic Navigation" Adaptive Behavior, Vol. 2, issue 3, 1994, pp. 277-304.
[13] Brooks R.,"Elephants Don't Play Chess", Designing Autonomous Agents: Theory and Practice from Biology to Engineering, Ed. Pattie Maes, 1990, pp. 3-15, Elsevier Science Publishers.
[14] Brooks R.,"Intelligence Without Reason", MIT AI Lab., A.I. Memo No. 1293, April 1991.
[15] Brooks R.,"A Robust Layered Control System for A Mobile Robot", IEEE Jour. on Rob. and' Aut., Vol. RA-2, No.1, March 1986, pp. 14-23
[16] Nerode A., Kohn W.,"Models for Hybrid Systems Automata, Topologies, Controllability, Observability", pp. 317-356, Vol. 736 of Lectures Notes in Computer Science, Springer-Verlag.
[17] Labinaz G., "Modeling and Control of Hybrid Systems: A Survey", 1996 Triennial World Congress IFAC, San Franscisco, USA, June-3D to July 5, 1996.
[18] Langton C., "Artificial Life", Artificial Life SFI Studies in the Sciences of Complexity, Ed C. Langton, Addison-Wesley, 1988, pp. 1-47.
[19] Masoud A.,"Techniques in Potenital-Based Path Planning", Ph.D. Thesis, Elec. & Comp. Eng., Queen's Univ., Kingston, Ont. Canada, 1995.
[20] Rosseel E., Linden G.,"Self-monitoring and Self-steering in Social Interaction: Theoretical Comments and an Empirical Investigation" Kybernetes, Vol. 19, No.1, 1989, pp. 18-33.
[21] Ramage P., wonham M.,"The Control of Discrete Event' Systems", Proceedings of the IEEE, Vol. 77, No.1, Jan. 1989, pp. 81-97.
[22] Austin S., "Parmenides Being, Bounds, and Logic Yale University Press, New Haven,London,1986.
[23] Salmon W., "Space, Time, and Motion: A Philosophical Introduction", Dickenson Pub. Co. inc., Encino Calif., Belmont Calif., 1975.
[24] Wiener N., "The Human Use of Human Beings: Cybernetics and Society", Houghton Mifflin Company, Boston, 1950.
[25] Wiener N., "Cybernetics, or Control and Communication in the Animal and the Machine", The MIT press, Cambridge, Massachusetts, 1961.
[26]Lefebvre V., "The structure of Awareness", Sage Publications, Beverly Hills,London, 1977.
[27] Campbell J., "Objects and Objectivity", Proceedings of the British Academy, Vol. 83, Ed. Peacock C., Oxford Univ. Press, pp. 3-45.
[28] Hull C.,"The GoaI-Gradient Hypothesis Applied to Some "Field-Force" Problems in the Behavior of Young Children",The Psychological Review, Vol. 45, No. 4,July 1938, pp.271-299.
[29] Glasserfeld, "Steps in the Construction of "Others" and "Reality; A Study in Self-regulation" ,Power, Autonomy, Utopia: New Approaches Toward Complex Systems, Ed. Trappl R., Plenum Press, N.Y.,London, pp. 107-116. 1986.
[30] Lewis C.,"Mind and the World Order: outline of a theory of knowledge", Dover Publications, Inc. New York, 1929.
[31] Nagel E., Brandt R.,"Meaning and Knowledge: Systematic Readings in Epistemology", Harcourt, Brace & World, Inc, 1965.
[32] Masani P.,"The Objectivity Axioms and Their foundation in Faith", Kybernetes, Vol. 23,No. 4,1994, pp.13-18.
[33] The Editor, "What Has Become of Cybernetics", IRE Trans. on Automatic Control, Vol. 7, April, 1962, pp.1-1.
[34] Shannon C.,"A Mathematical Theory of Communication", Bell System Technical Journal, Vol.27, 1949, pp. 379-423.
[35] Gallager R., "Information Theory and Reliable Communication", John Wiely and Sons, N. Y., London, Sydney, Toronto, 1968.
[36] Thorn R.,"Structural Stability and Morphogenesis", W.A. Benjamin Inc., 1975.
[37] Hirst R.,"The Problems of Perception", London George Allen and Unwin Ltd, N.Y., The MacMillan Company, 1959.
[38] Ornstein J., "The Mind and The Martinus Nijhoff/The Hague/, 1972.
[39] Samer A. Masoud, Ahmad A. Masoud, " Motion Planning in the Presence of Directional and Obstacle Avoidance Constraints Using Nonlinear Anisotropic, Harmonic Potential Fields: A Physical Metaphor", accepted for publication at the IEEE Transactions on Systems, Man, & Cybernetics, Part A: systems and humans.
[40]Samer A. Masoud Ahmad A. Masoud, "Constrained Motion Control Using Vector Potential Fields", The IEEE Transactions on Systems, Man, and Cybernetics, Part A: Systems and Humans. May 2000, Vol. 30, No.3, pp.251-272.
[41] Ahmad A. Masoud, "Evasion of Multiple, Intelligent Pursuers in a Stationary, Cluttered Environment: A Harmonic Potential Field Approach", 2002 IEEE International Symposium on Intelligent Control (ISIC), 27-30 October 2002, Vancouver, British Columbia, Canada.
[42] Ahmad A. Masoud, Samer A. Masoud, "A Self-Organizing, Hybrid, PDE-ODE Structure for Motion Control in Informationally-deprived Situations", The 37th IEEE Conference on Decision and Control, Tampa Florida, Dec. 16-18, 1998, pp. 2535-2540.
[43] Ahmad A. Masoud, Samer A. Masoud, "Evolutionary Action Maps for Navigating a Robot in an Unknown, Multidimensional, Stationary Environment, Part II: Implementation and Results", the 1997 IEEE International Conference on Robotics and Automation, April 21-27, Albuquerque, New Mexico, USA, pp. 2090-2096.
[44] Ahmad A. Masoud, "Using Hybrid Vector-Harmonic Potential Fields for Multi-robot, Multi-target Navigation in a Stationary Environment", 1996 IEEE International Conference on Robotics and Automation, April 22-28, 1996, Minneapolis, Minnesota, pp.3564-3571.
[45] Ahmad A. Masoud, "A Boundary Value Problem Formulation of Pursuit-Evasion in a Stationary Environment: A Potential Field Approach", the 1995 IEEE International Conference on Robotics and Automation, May 21-27, Nagoya, Japan, pp. 2734-2739.
[46]Ahmad A. Masoud, Samer A. Masoud, "Robot Navigation Using a Pressure Generated Mechanical Stress Field, The Biharmonic Potential Approach", The 1994 IEEE Int. Conference on Robotics and Automation, May 8-13, 1994 San Diego, California, pp. 124-129.