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A Comparative Study on Behavior-based Agent Control for Computer Games

Taehee Kim, Ph.D.
School of Multimedia Engineering
Youngsan University

김태희
영산대학교 멀티미디어공학부
thkim@ysu.ac.kr

Abstract

Computer games could be regarded as simulation of the real world. Control problems of software agents have long been studied in the field of Artificial Intelligence (AI), resulting in giving a birth to the behavior-based approach. Three main approaches might be categorized out of the history of AI study. First, Cognitivists propose that intelligence could be represented and manipulated in terms of symbols. Second, Connectionists claim that symbols could not be isolated but they are embedded in the body structure. Third, the behavior-based approach is an approach to AI which suggests that intelligence is dynamic property that exists nowhere but emerges in the relationship of an agent and the world including observers while the agent performs behavior. This paper explains and compares the three approaches to AI, then discusses the plausibility of the behavior-based approach and problems. Finally, this paper proposes application of behavior-based approach to computer games in terms of agent control.

요약

컴퓨터 게임은 실세계에 대한 시뮬레이션으로 간주되어질 수 있다. 소프트웨어 에이전트의 제어 문제는 인공지능 분야에서 오랫동안 연구되어져 왔으며, 이는 행동기반 접근법이라는 것을 내놓았다. 인공지능 분야에서는 지금까지 크게 세 가지의 접근법을 볼 수 있다. 인지주의는 기호의 형태로 지능이 표현되어질 수 있고 다루어질 수 있다는 것을 제안하였으며, 연결주의에서는 표현이 신체 구조에 내포되어있어서 신체로부터 분리되어질 수 없음이 강조되었다. 행동기반 접근법에서는 인공지능은 동적인 성질을 가져서 어디서든지 존재하지 않는 대신에 에이전트가 환경에서 행동할 때 비로소 우러나오는 성질을 가진 것으로 제시된다. 본 논문에서는 이러한 세 가지의 접근법을 비교하고 행동기반 접근법의 타당성과 문제점에 대하여 논한다. 본 논문은 또한 행동기반 접근법의 컴퓨터 게임의 에이전트 제어에 대한 활용을 제안한다.

1. Introduction

"Complex behavior may simply be the reflection of a complex environment." [1]

AI has been a field of study for over 30 years with two main aims, first producing intelligent machinery in the form of powerful tools using computers (weak AI), such as by simulating biological intelligence. Second, whether and how machines can be given real mental functions (strong

AI) is controversial (See [2] for the categorization of AI into 'weak AI' and 'strong AI'.).

In line with the effort to achieve AI, three major suggestions have been made in the course of its history:

Cognitivism A position in psychology and philosophy that intelligent behavior (only) can be explained by appealing to internal "cognitive processes," that is, rational thought in a very broad sense [3]. Thus, in AI, the central technical problems become a) how to represent knowledge, and b) how to reason about it.

Connectionism An approach to cognitive modeling which focuses on causal processes by which units excite and inhibit each other and does not provide either for stored symbols or rules that govern their manipulations [4].

Behavior-based approach An approach to AI claiming that intelligence emerges while an agent behaviors in the dynamics of the world.

In this paper, the above three approaches to AI are explained. Advantages and some guidelines of the behavior-based approach are suggested in building autonomous agents. The problems of the behavior-based approach are last discussed.

2. Cognitivism

In implementing AI, it may be supposed that intelligence is in the creature, not in the environment, because the creature shows the intelligence. Thus the world is divided into two parts: the creature and the world. The creature is further divided into two parts: body and mind. Mind is believed to be the place where intelligence resides, because intelligence is abstract and seems likely to be a phenomenon of mind, not body. Further, the mind is divided into two aspects: phenomenological mind and computational mind, where the computational mind performs computations, e.g., syntactic transformations of propositionally expressed knowledge, while the phenomenological mind has qualitative subjective experiences, such as consciousness (see Figure 1 [5]). The computational mind can be implemented by symbolic manipulation alone (e.g., symbolic AI). In cognitivism, it is asserted that intelligent behavior is the result of the operation of the computational mind, and the computational mind is the main place where intelligence is implemented, as claimed in Newell and Simon's Physical Symbol System Hypothesis [6] and supported by Brian Smith's Knowledge Representation Hypothesis [7]. Cognitivism is based on this distillation of intelligence, and intelligence is thought of as the result of cognitive processes, which can be implemented by manipulating symbols.

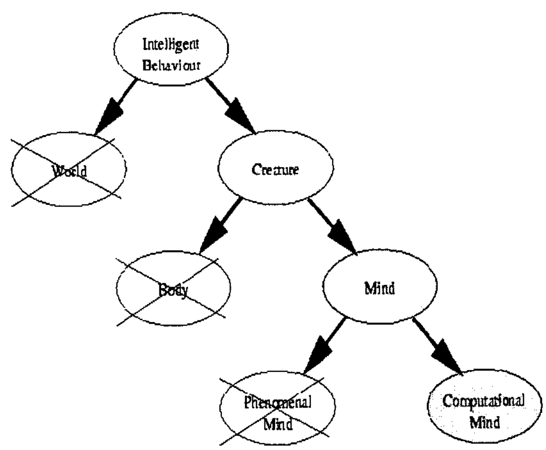

Fig. 1. The Distillation of Intelligence

3. Connectionism

An alternative approach to simulating cognitive phenomena has been suggested, known as Connectionism. Since computation is performed on symbols in Cognitivism, loss of any symbols may cause a serious problem to the system. In Connectionism, the representation is distributed throughout the topological connections between the neurons. Damage to individual neurons slightly degrades the resolution of the system, a more graceful degradation than is caused by loss of symbols. This leads connectionist systems to be robust. They also have adaptive learning potential. Connectionists have shown that intelligent behavior emerges from the network without any explicit centralized symbolic representation having been implemented [8]. The topological structure of an artificial neural network plays an important role in the computation while allowing the representation to be decentralized. This provides an alternative model of the body/mind relationship (compared to the program/computer model of symbolic AI).

Connectionism agrees with symbolic AI that representation is the crucial issue in implementing intelligent behavior, but disagrees about the way in which the knowledge should be represented [9]. Where symbolic AI represents knowledge as propositions that are to be reasoned with, Connectionism represents knowledge as clusters of neuronal weightings whose fundamental operations are association and generalization. In this way, it criticizes the body/mind relationship implied by symbolic AI.

4. The Behavior-based Approach

The behavior-based approach makes a more radical criticism [10]. The behavior-based approach disagrees with Cognitivism, asserting that high-level human mental functions are a phenomenon of complicated sub-systems mostly beyond self-awareness. Our belief in ourselves as rational creatures plays an important role in justifying Cognitivism. Churchland defines folk psychology as:

"Folk psychology is commonsense psychology?the psychological lore in virtue of which we explain behavior as the outcome of beliefs, desires, perceptions, expectations, goals, sensations, and so forth. It is a theory whose generalizations connect mental states to other mental states, to perceptions, and to actions. ⋯ Folk psychology is 'intuitive psychology,' and it shapes our conceptions of ourselves." ([11, p. 299], original emphasis)

In Folk psychology, we deduce our behavior from our beliefs and desires, i.e., our behavior is caused by our beliefs and desires.

In the behavior-based approach, Cognitivism is criticised as the result of Folk Psychology [12, 5], because in Cognitivism, empirical mental functions have been formulated as cognition in symbolic terms. It is claimed that, in traditional AI, there is something missing between the creature and the environment as well as between body and mind. Moravec emphasizes the significance of the underpinning mechanisms for the mental functions of the human being:

"The deliberate process we call reasoning is, I believe, the thinnest veneer of human thought, effective only because it is supported by this much older and much more powerful, though usually unconscious, sensorimotor knowledge. We are all prodigious Olympians in perceptual and motor areas, so good that we make the difficult look easy. Abstract thought, though, is a new trick, perhaps less than 100 thousand years old. We have not yet mastered it. It is not all that intrinsically difficult; it just seems so when we do it." ([13, pp. 15-16])

Dreyfus also notes the importance of the underlying structure:

"Indeed, sensory motor skills underlie perception whose basic figure/ground structure seems to underlie all "higher" rational functions ⋯" ([14], p. 255, original emphasis)

Varela et al. refer to the behavior-based approach as Enactivism, where they explain the enactive approach as 1) perception consists of perceptually guided action and 2) cognitive structures emerge from the recurrent sensorimotor patterns, which develop cognitive structures that enable action to be perceptually guided [9].

In the behavior-based approach, a creature is believed to be a collection of goal-directed behaviors. Every behavior is independent in that it interacts with the environment for its own purpose. Because each interacts with the environment purposefully, combining behaviors implies summing the purposefulness of every behavior, without increasing the complexity of any particular part of the system. The accumulation of behaviors allows the system to grow incrementally, incrementally developing into a more sophisticated structure rather than being redesigned. The potential to exhibit intelligence is included implicitly in each behavior, the relationship between the behaviors, and the purposefulness of every behavior in the environment. Intelligence is exhibited while the creature interacts with the environment. Brooks emphasizes the importance of actual interaction between the creature and the environment, which results in the emergence of intelligence:

"Intelligence is determined by the dynamics of the interaction with the world"; "Intelligence is in the eye of the observer, i.e., although intelligence has not been implemented, it appears while the creature interacts with the environment." [10]

The following features can be seen to be important in the behavior-based approach and could be also regarded as guidelines in building behavior-based systems [10, 15, 16, 17].

[Intelligence Emergent, not Implemented]
Intelligence is not implanted explicitly in the robot, but appears while it interacts with the real world.

[Low-level Amalgamation of Sensing and Action]
Sensing is tied into the action at a low level in order to decrease the complexity and increase the flexibility of the high level.

[Parallelism]
The atomic units (behaviors) are all parallel unless otherwise constrained.

[Distaste for Symbolic Representations]
Knowledge about the world is always incomplete and liable to error, therefore the behaviors wherever possible use the real world as their model (i.e., by intimate interaction with the environment).

[Active Use of the World]
Instead of the delegation of control via the procedural hierarchy and parameter passing typical of modern programming practice, behaviors are preferentially activated and controlled by sensed environmental triggers.

[Minimalism]
Through the previous principles (parallelism, distaste for symbolic representation, and active use of the world), comparatively little computational power is required to achieve the desired level of performance.

[Behavioral not Functional Modularity]
The task is segmented in terms of purposeful task-achieving behaviors.

5. The Practical Viewpoint of the Behavior-Based Approach

5.1. Active Involvement with the Environment

Brooks' assertion that Intelligence is in the observers' eyes implies that the detailed description of intelligence is not necessarily an ingredient in the implementation. This possibly results in an economic implementation, by exploiting the nature of the environment.

This situation is exemplified by one of the vehicles described in [18]. The mobile robot drawn in Figure 2 has two actuators and two photo sensors. They work such that the revolutions of the actuators are proportional to the amount of light that the contralateral photo sensors absorb. Thus a light offset to one side will steer the robot towards it, and only even illumination will steer the robot straight ahead. (If the sensors and the actuators are wired in the opposite way, then the robot will show the behavior of being repulsed by the light.) As the light is turned on, the robot will approach the light. If the light is moving, the robot will follow. There is no explicit representation of behavior, environment, or goal. But an observer may argue that the robot has the purpose or will to follow the light. The apparently unified behavior of the robot is not even produced by a central controller, but by the interaction in the environment of two completely independent controllers for each individual wheel. Exploiting the environment and the physical properties of the world that are related to the task resulted in a simplified implementation since some of the information processing (or computation) is performed implicitly, i.e., non-computationally, by the inherent physics of the entire creature/world system.

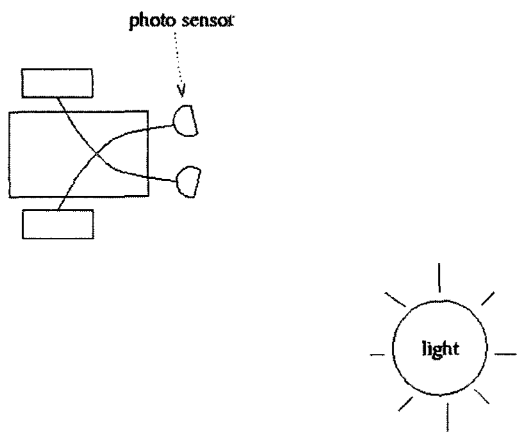

Fig. 2. One of Braitenberg's vehicles

A well-managed relationship between the environment and the agent, e.g., structural coupling [9] reduces the amount of explicit information processing to be performed by the agent. A well-organized structure of the subsystems of the agent also possibly diminishes the amount of computation to be done by a high-level information processing part of the agent. In the behavior-based approach, the implications of the relationship between the environment and the agent, and the importance of the physical and the logical structure of the agent's goal seeking subsystems are emphasized.

Both for biological systems and robots, sensors play an important role as channels through which information about the environment is obtained. According to the characteristics of the task performed, appropriate selection of sensors will contribute to the effectiveness of the system. The purpose of dynamic sensing [19] is to enhance sensing by exploiting robot motions. Robot motions can reduce the complexity of sensory information processing, at the cost of the extra motions.

5.2. Low-level amalgamation of sensing and action

The principle of the low level amalgamation of sensing and action often encourages a system to be built without any central control. Investigation and robotic implementation of the cricket's phonotaxis provides an example of how a high-level-look function can be implemented in a relatively simple way without any central control and symbolic representation [20], hence economic-minimalism. The cricket robot navigates towards the source of a particular sound, while overcoming obstacles. The phototaxis of the Braitenberg's vehicle, explained above, can be also in this category. Structural coupling, i.e., well-managed interaction, is also evident in the cricket auditory system.

5.3. Approaches to Behavioral Modularization

Decomposing a task into manageable and tractable subsystems provides practical benefits. The subsystems are designed to be as independent as possible. A subordinated behavior is a complete system in its own right and is ignorant of the existence of the subordinating module. This feature implies the modules are independent, so that a system can grow incrementally and can be modified flexibly. This helps a system to be more manageable.

However, approaches to the modularization of behaviors in practice can vary depending on the circumstances, although the principle is the same. In the Subsumption Architecture [21] used on mobile robots, AFSM's (Augmented Finite State Machines) represent behaviors. They can be accumulated in a vertically hierarchical manner. For instance, a wandering behavior (AFSM) can be subsumed by a light sensitive behavior (AFSM) by means of the connection, inhibit: the activation of the light sensitive behavior deactivates the wandering behavior when there is light. AFSM's can also run in a physically independent manner.

5.4. Micro Abstraction versus Macro Abstraction

In terms of the context of abstraction in practice, artificial neural networks, which are practical implementations of Connectionism, involve micro abstraction, while the behavior-based approach involves macro abstraction.

In artificial neural networks, functions of real biological neurons and their topological structures are modeled. Individual artificial neurons have very simple information processing capability, such as summing the inputs and thresholding the sum. What makes the real neuronal network powerful is the plastic topological structure of many neurons. However, as a system becomes more sophisticated requiring the coordination of numbers of behaviors, it would demand a large number of artificial neurons, perhaps millions, to be organized. This would give rise to a design and management problems, i.e., 'How to organize them?' and 'How to train them?' That this neuronal level of micro abstraction might be inappropriate for investigating the problems of the organization of behaviors is a frequent criticism.

On the other hand, in the behavior-based approach, behaviors are modularized (abstracted) and the problems of relationships between the behaviors are investigated, as well as the implementational problems of individual behaviors. For a reasonably sophisticated robot which exhibits numbers of behaviors adapting to the changing environment flexibly, what each neuron does is not very important, but the organization of the behaviors is important, since the robot shows its autonomy and purposefulness by means of exhibiting appropriate behaviors under the prevailing circumstances. However, artificial neural networks may well be used to compose a behavior.

6. Problems of the Behavior-Based Approach

Although the behavior-based approach proposes plausible methods to build autonomous agents, it also has some problems that need to be considered and further investigated.

6.1. Defining a Behavior

Behaviors are defined arbitrarily case by case. For instance, a behavior may be defined as a wandering behavior, and another may be an avoiding light behavior. If they are subsumed by a sound reactive behavior in a certain manner, the agent will show a behavior wandering while avoiding light, and reactive to sound where noticed. However, the question naturally arises of what are the defining characteristics of a behavior, i.e., what makes something a behavior (or behavioral module) rather than an element of some other architecture. Unfortunately, there are no definitive rules, although there are guidelines.

However, as long as behaviors are defined in terms of purposes under given circumstances, the agent could be a purposeful system. It relies on the designer's intuition and experience, i.e., expertise with reference to the design specification and the characteristics of the environment.

6.2. Coherence

In the behavior-based approach, behaviors are built to work as independently as possible of other behaviors to achieve a behaviorally distributed constitution. But, this gives rise to the problems of maintaining overall behavioral coherence. For simple insect-like agents, this is not a big problem. But, as the system becomes more complex, especially if using many sensors, coherence will become a major problem. This problem has been recognized and addressed by Brooks [22]. Brooks proposes that coherence can be achieved for complex systems in at least two ways: 1) exploiting natural sources of coherence; 2) exploiting certain mechanisms (design coherence):

Exploiting natural coherence

- The world often integrates things, such as an ant' s trail.
- The structure of the task may impose a natural sequencing of actions.
- Multiple behaviors may actually be additive even if some of them contribute negatively.

Exploiting certain mechanisms

- Using internal parameters: feeling hunger will activate food foraging behavior, but fear will inhibit this, while exciting other behaviors.
- Using the environment for communication: the effect on the environment of one behavior may trigger or inhibit other behaviors.
- Mutual exclusion: a form of lateral inhibition1

Action selection has been proposed for mobile robots, as a method to organize sensing and action modalities in complex dynamic environments, where there are multiple sources of incoming information [24]. By virtue of the purposefulness of behaviors, action selection, where the agent responds to different sensory states, is regarded as attention, because the system looks as if it pays attention to certain aspects [22]. The method, "using internal parameters", as stated above, is equivalent to action selection.

The problem of coherence is a fundamental problem. It is related to the problem of defining behaviors, how to structure sets of behaviors, and how to exploit direct2 and indirect3 communication between them.

1 Lateral inhibition: a set of conditions established when two or more neural cells are interconnected so that excitation of one produces inhibition in the other [23].

2 i.e., explicit physical communications between modules, although it is better kept to its minimal form

3 i.e., making use of the environment

7. Summary and Future Study

This paper introduced the taxonomy of approaches to AI in three terms: cognitivism, connectionism, and behavior-based approach. Three approaches were explained and compared. The behavior-based approach claims that it could overcome the limitations of the former two approaches, by taking into account the dynamics between an agent and the environment. An agent could not even been given a chance to prove its intelligence without the environment. The behavior-based approach claims to be the most plausible understanding of AI and it suggests a number of properties that could be exploited in building actual autonomous agents. Active involvement of the Environment and low-level amalgamation of sensing and action are examples. However, it still suffers from problems in defining a behavior and coherence in managing distributed behaviors. Further research in behavior-based approach might spans from practical application to theoretical studies including subtle philosophical analysis in the property of relational existence.

Computer games simulate the real world. Various AI approaches could be applied to the computer games as models of the real world. Agent control in computer games has been implemented using traditional symbolic system, i.e., behavior controlling expert systems, which are symbolic systems. This kind of systems could suffer from exaggerated complexity like many traditional symbolic systems, as discussed earlier. We argue that this problem could be explained such that the agents have been modeled with reference to the observer, or the central system. In order to exploit the advantage of the behavior-based approach, agent are better be modeled with reference to itself ? internal modality. Agents have their own ability of perception even in the simulated world like computer games. Autonomous behaviors could be described using the modalities characterized out of their perception being associated with available mobility. Future study could span from characterization of the simulated world to building general purpose controller for intelligent agents in the simulated world such as computer games.

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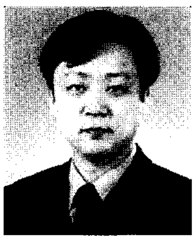

김태희

1990. 2 아주대학교 학사
1992. 9 Edinburgh Univ., AI 석사과정
1996. 12 Edinburgh Univ., AI 박사
1997. 1 ~ 1999. 8 연구개발정보센터 실장
1999.9 ~ 현재 영산대학교 멀티미디어공학부 조교수
관심분야 : 지능에이전트, 지능로봇