Paper

# Trends and Differences of Applying Intelligence to an Agent

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**Abstract—The agent technology has recently become one of the most vibrant and fastest growing areas in information technology. On of the most promising characteristics of agent is its intelligence. Intelligent agent is the agent that percepts its environment, collects all information about its environment that it needs, processes these information and then generate proper actions according to these information. This paper discusses trends and differences between two main types of intelligence that can be applied to agent: accumulative intelligence and dynamic intelligence. Accumulative intelligence is discussed with its two perspectives: moment perspective and historical perspective. Auto-vehicle driver is also discussed as an application example of accumulative intelligence. Also, MOSAIC, Mimesis, and MINDY models are reviewed as the pioneering works of dynamic intelligence.**

***Keywords—accumulative intelligence, dynamic intelligence, intelligent agent.***

## 1. Introduction

Agent technology has received a great deal of attention in last few years and, as a result, wide variety of applications is beginning to get interested in using this technology to develop its own goals. Agent is a software entity that carries out some operations on behalf of a user or another program with some degree of independence and autonomy [1].
New research activities have been proposed to make agent possesses human intelligence characteristics. The concept of intelligence has been addressed by different new research approaches. These approaches have been independently developed in brain science [2], cognitive science [3], psychology [4], and conventional artificial intelligence [5]. They have pointed out that it is necessary for *intelligence* to have a body interacting with an environment which is called *embodiment* approach [6]. This approach insists that the cognitive process should be described with in interaction between both body system and the environment. In contrast, artificial intelligence usually insists that the cognitive process resides only in brain of body.
When agent (like human body) perceives its environment, collects required data knowledge through its sensor, represents this knowledge into predefined patterns (agent experience), analyzes and processes these knowledge patterns to take better decisions, and use these decisions to improve how it carries out its tasks in that environment, this agent is called *intelligent agent* (IA). As a result, applying concept of intelligence to agent [7] gives it the ability to recognize situations it has been in before and improve its performance based on priori experience (i.e., accumulative intelligence). Also, it enables agent to recognize new situations (i.e., situations with no priori experience) to decide what actions to take in this case, and evaluate these actions by predictions algorithms if they reach agent close nearly to its final target (i.e., dynamic intelligence).
The rest of paper is organized as follows. In Section 2, we introduce description of accumulative intelligence. Dynamic intelligence is described in Section 3. Finally, we conclude this paper in Section 4.

## 2. Accumulative Intelligence

Many research studies [7] applied the concept of accumulative intelligence on their agent technology applications. Simply, accumulative intelligence emphasizes the fact that agent (human) must collect a good deal of observed information about its environment before making decisions about the proper actions to transact with a specific situation. This paper introduces the terminology of accumulative intelligence for the first time.

### *2.1. Generic Model for Accumulative Intelligence*

Figure 1 shows generic model and basic phases of accumulative intelligence. The model verifies that agent can be intelligent when it has the ability to interact with its environment. Interface phase makes automatic gathering of information about status of environment components and give to the agent through short-term storage phase. *Short-term storage* is a data storage technique that used to store collected information as attractors. Interface consists of a group of sensors. *Processing and decision rule* phase analyzes and processes momentarily information collected and deliverables gathered from interface phase (attractors). By using decision making rule phase, it generates output signals and transmits to effectors to do the required action into the environment.
Accumulative intelligence can be deliberated from two different perspectives: moment perspective and historical perspective. Moment perspective emphasizes that process of

information collection, processing, and generating proper actions is done momentarily from beginning of agent task to its final or sub-final target (i.e., action-sequence) without using any prediction or anticipating techniques. *Action-sequence* is reached to that target by memorized into long-term storage phase in Fig. 1. In the wake of this, *long-term storage* memorizes different action-sequences to different targets.

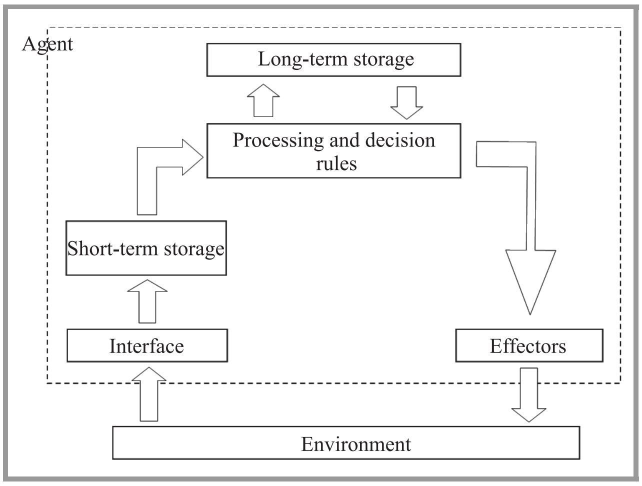


***Fig. 1.*** Generic model of accumulative intelligence.

There are some situations in which agent target is repeated, so agent do not need to find the action-sequence of that target because it is memorized previously in long-term storage. Agent just needs to recall the action-sequence of repeated target from long-term storage. The previous description refers to historical perspective of accumulative intelligence. Some agent applications as anti-money laundering systems [8] applied another view of historical perspective. These applications perform the process of information collection over consecutive fixed time intervals and memorize them into long-term storage directly as information slices in a database. All information slices in that database is processed over random or regular time instants. Processing phase tries to find a predefined information pattern in database by a comparison function. An expert or application designers define previously this pattern. As soon as this pattern was found in database, the proper action is generated. Type and effect of action is related to its application or environment. The salient property of previous historical perspective view is that process of information collection, processing, and generating actions is not performed momentarily.

Variety of agent technology application is ranged between consummating only the concept of *moment accumulative intelligence* (MAI), only the concept of *historical accumulative intelligence* (HAI), or both two concepts which is called *full accumulative intelligence* (FAI). The following section will shed some light on an example of agent technology applications that apply the concept of accumulative intelligence.

### *2.2. Auto-Vehicle Driver (AVD)*

Auto-vehicle driver emphasizes creation of full software and hardware system to be able of driving vehicles automatically without interference of human driver. It is similar to auto-pilot system used in aircrafts. AVD may be composed of only one intelligent agent or a group of more than one (i.e., multi-agent system (MAS)). Regardless of agent number in AVD, each one should perform its tasks of collecting its related information via its sensor. They include, but not certainly limited to the following parameter, road status (e.g., GPS information of road, road width, and etc.…), vehicle status (e.g., speed, fuel amount, vehicle components, position, and etc.…), obstacle status (e.g., is another vehicle (human, animal) in front, at backward, at right, at left of that vehicle), and climate status (e.g., is it rains, windy, sunny, and etc.…). According to processing quality of this information, the proper moving action-sequence will be generated. There is no full AVD system up till now due to huge information amount that must be collected and processed but there are some researches that applied agent technology with accumulative intelligence concept to assist vehicle driver by using algorithms of machine leaning.

In [9] the author addresses the problem of autonomous navigation of a car-like robot evolving in an urban environment. Such an environment exhibits a heterogeneous geometry and is cluttered with moving obstacles. The approach to the problem lies in the design of an intelligent agent able to percept and plan actions that consider explicitly the dynamic nature of the vehicle and the environment while enforcing the safety constraint.

Kolski *et al.* 2006 [10] present a hybrid navigation system that combines the benefits of existing approaches for driving in structured environments (e.g., roads) and unstructured environments (e.g., parking lots). The system uses visual lane detection and laser range data to generate a local map, which is processed by a local planner to guide the vehicle down the lane while avoiding obstacles. When driving in unstructured environments, the system employs a global map and planner to generate an efficient trajectory to a desired goal. The combined system is capable of navigating a passenger car to a given goal position without relying on road structures, yet it makes use of such structure when it is available.

Bertolazzi *et al.* 2008 [11] designed a reduced size autonomous vehicle and focuses on the control strategy which is based on a Nonlinear Receding Horizon Control (NRHC) algorithm. The NRH planner is called by a high level manager, in the outer control loop, to solve a sequence of optimal control problems. The planned motion provides a sequence of reference set points for the faster inner control loop until a new plan is available. The lateral motion is controlled through the steering command by tracking the yaw rate reference. The longitudinal motion is controlled by means of the throttle/braking coupled command by tracking the planned forward speed profiles.

Borges *et al.* 2009 [12] presented an intelligent agent that controls the vehicle speed using knowledge learned from databases. The main effort of this paper was the induction of conduct rules from data of previous trips and collected data from sensors. Sensors capture parameters such as: current kilometer (position), speed, latitude, longitude, and adherence. Algorithms of JRip, Bagging, and Boosting have been used, employing data from past trips to extract patterns of safe and economical conduct.

Several studies have used machine learning techniques for the development of intelligent railway vehicles [13], whose goal is to improve the maintenance and operation of vehicles predicting failures in equipments.

# 3. Dynamic Intelligence

Dynamic intelligence emphasizes relations among observed, predicted, and recalled time sequences in sensory-motor space. Sensory-motor space applications as robots are a luminous examples of interactions between body and its environment. In the literature of dynamic intelligence references, many researchers pursue a range of different characteristics that agent should possess such as: behavior emergence, imitation learning, and spontaneous learning. Agent should be implemented to fulfill part or all of these characteristics.

Behavior emergence is defined as how agent (body) can decide what appropriate actions that can take to overcome unpredictable and complex new situations [14]. Another important factor in dynamic intelligence is imitation based on embodiment. The importance of imitation is also emphasized in brain science with *mirror neurons* [15]. The existence of mirror neurons implies that a human interprets another human's actions as actions by himself, providing an understanding of their meaning. Based on the interpretation of the mirror neurons, embodiment plays an important role in understanding the meaning behaviors. Spontaneous learning is another factor in dynamic intelligence. It can be illuminated by flow theory [16] which insists that a human is highly motivated when he/she tries to learn a task of suitable difficulty for his/her capabilities and skills. It is important to make balance between human (agent) skills and a task difficulty. This balance can be evaluated by progress of agent ability of self-spontaneous learning. For example, if the task is too easy, the agent can predict states correctly and achieve a goal easily. On the other hand, if the task is too difficult, the agent can not predict states correctly neither can it achieve the goal even it tries many times. However, if the task is a suitably difficult, at the beginning of learning, the agent can not predict states correctly and consequently goals can not achieved. But after some attempts, the agent can achieve goals eventually due to predicted states.

## 3.1. Generic Model for Dynamic Intelligence

Figure 2 shows the generic model of dynamic intelligence [17] which is nearly similar to general model of accumulative intelligence. Dynamic intelligence model has a new two phases. The first is *predictor/controller* phase and the second is *reduce dimension* phase.

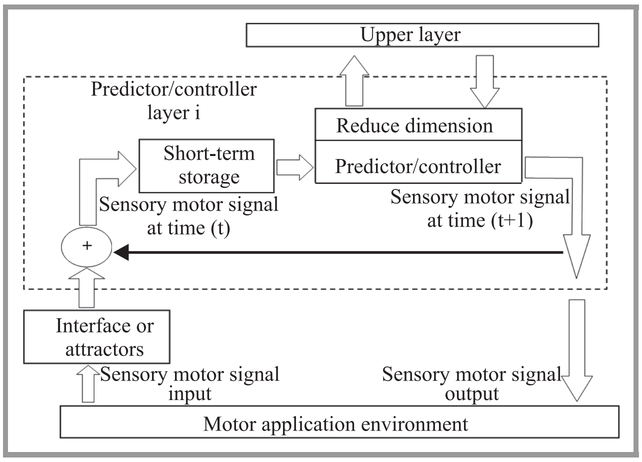


***Fig. 2.*** Generic model of dynamic intelligence.

Predictor/controller phase is responsible of reaching sensory-motor system to its target state through exploration function. Exploration function is used to determine intermediate action-sequence to final target state and use it as training data for the predictor/controller to form the dynamic attractors. This can be done by trying some actions and deciding which action will allow it to reach to its final target.

The main key way to do the exploration is to explore in the real world which can be done using a planning and a rehearsing function. The planning function explores the proper actions to get close to final target state by using the predictor (anticipator), which can predict the state in the next time step. The rehearsing function simulates the sensory-motor signal sequence to get close to the target by using the predictor and the controller. Once the sensory-motor system found action-sequence to reach to final target state, it can be used as teaching signal pairs for the controller. Also, it is important to memorize it in long-term storage for reuse in the future if this final target is repeated.

Chess game is a good example to understand the previous description. Main target of chess player is to reach to "King Dead" state. To do that, chess player is trying to build a theoretical plan in his mind before moving any one of its chess pieces. For example, consider the following steps as a beginning for a plan: firstly, he will move the "Queen" to a specific position, and then he will attack the "Queen" of the other player by his "Bishop" to get it away from its king, and so on. This player will try to predict all possible defense movements that the other player will do against this player movement. He will use each predicted defense movement as a new start step for another subplan from his original plan. So, original plan is divided to subplans which their counts equal to all possible defense movements. Each subplan will be divided into smaller subplans and so on until one of these subplans reach closely to its final target. In the wake of this, predicted whole plan (action-sequence) is determined by using layers of prediction steps (planner function). After that the player simulates in his mind this action-sequence (rehearsing function). Finally, he will begin to move his pieces (signals to controller).

When dealing with dynamic intelligence, it is important to use reduce dimension phase. To understand operation of it, chess example will be reused. At the beginning of chess game plan, player thinks of moving one of 16 pieces, so information about all these 16 pieces must be known (large information space). After player predict first step, number of pieces that will participate for next prediction step will be reduced causing lower information space for next prediction layer. The process of lowering information space will be continued through prediction layers until reaching to target. Reduce dimension phase is responsible of straitening dimensions of information space through predictor/controller layers.

### *3.2. Related Researches of Dynamic Intelligence*

There are some pioneering works that deal with dynamic intelligence. Let us consider the following three works and identify their essential functions and properties: MOSAIC, Mimesis model, and MINDY model.

#### 3.2.1. MOSAIC Model

MOSAIC [2] consists of many prediction and control pairs for sensory-motor signals such as the Locally Weighted Projection Regression (LWPR) [17] as a prediction function. Using MOSAIC the authors succeed to develop the humanoid named DB, which learns performances of juggling, devil stick handling, and so on. The important difficulty of MOSAIC is how to select a controller that properly works in each situation. It selects a controller based on the goodness of the corresponding prediction function. In a more advanced version of MOSAIC [18], the control signal is generated by adding the controllers' output weighted by the goodness of the corresponding predictors. The weighted values based on the predictors' *goodness function* are used as inputs to the next layer, which is again composed of many prediction and control pairs for the weighted values. In summary the prediction function and a layered architecture are the important points of MOSAIC.

#### 3.2.2. Mimesis Model

The Mimesis Model consists of many Hidden Markov Models (HMMs), which are trained with motion data of human actions such as walking, kicking, jumping and so on [19]. Then, distance metrics are introduced among the HMMs. Based on the metrics; the HMMs are set in a low dimensional space named *proto-symbol* space with Multi-Dimensional Scaling (MDS) algorithm. Then, a point in proto-symbol space represents a motion sequence. When a new motion sequence is input, a Mimesis system can recognize the sequence as a point in proto-symbol space. Multiple motion sequences such as walking and then kicking can be recognized as a sequence in proto-symbol space. If we can consider that the sequence in proto-symbol space is input to the upper layer, then the Mimesis system can be considered as the layered architecture.

#### 3.2.3. MINDY Model

MINDY model [20] employs the concept of flow theory [16]. In order to achieve various task, MINDY has a network consisted of various modules. Each of the modules, called basic module, has an identical structure and was designed to achieve a goal for a subtask. The module differs in its location in network layers, in what kind of inputs and outputs are assigned, and in what it has learned. Each module contains a pair of predictor and controller. There is a planner and rehearsing function on top of the network of basic modules. The role of predictor/controller is to observe its inputs and outputs of the module and predicts the inputs of the next time step, which can be directly learned from history of observation and output actions. Accurate Online Support Vector Regression (AOSVR) [21] is used for the predictors and controllers. The planner and rehearsing function is used to generate and search action-sequence to come close to final target value with in each predictor target variable. A planner is used with in MINDY model. MINDY evaluates the progress of spontaneous learning by appraising predictor error, controller error, and goal error.

## 4. Conclusion

This paper introduces and discusses the possibility of applying human intelligence to agent. Claiming, that any human or machine has intelligence, requires that it should have a body and his body should interact with its surrounded environment. Agent can be considered as human body. This paper introduces two kinds of intelligence that many agent technology applications apply. The first is accumulative intelligence which emphasizes that agent must collect momentarily a good deal of its environment information before taking actions. Accumulative intelligence can be applied from two different perspectives: moment perspective and historical perspective. The luminous application of applying accumulative intelligence is auto-vehicle driver. The paper introduces research activities in this field.

The second type of intelligence is dynamic intelligence. Dynamic intelligence emphasizes relations of observed, predicted, and recalled time sequences in sensory-motor applications. In dynamic intelligence, agent can observe initial information of its environment and determine its final target by itself or by assistance of application designers or end users. Agent can predict the action-sequence that will reach it to its final target by using initial information of its environment. Agent should possess characteristics of behavior emergence, imitation learning, and spontaneous learning to be dynamic intelligent. MOSAIC, Mimesis, and MINDY models of dynamic intelligence are also discussed.

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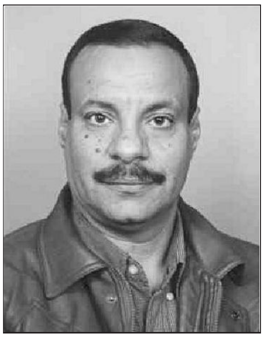


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