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Intellectual Management - Cognitive Approach

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Abstract

Control of structurally complex industrial and technological objects belongs to the class of problems of intelligent control, which demands making decisions in states of uncertainty. Further development of this industry will be associated with technologies of intelligent control based on knowledge. Such technologies use methods, models, and algorithms extracting and accumulating knowledge needed to find optimal decisions. Intelligent control theory is based on learning surrounding world and adapting to changes in the process of reaching the defined goal. In this paper we consider a cognitive approach to learning developed following the human cognitive ability and a scientific method of physics. Cognitive approach opens new wide directions towards control of industrial objects and situations that are not well structured and difficult to formalize, especially in real life circumstances with significant uncertainty. A class of cognitive models control agents based on the principles of learning is described in the paper. Cognitive agents are such kind of agents that are learning from their surrounding and modifying their actions to achieve the goals, this type of agents enables solving problems of a wide area of control in presence of uncertainty.

Keywords: Artificial intelligence; Theory of control; Cognitive models; Cognitive agents; Hierarchy of industrial or technical systems; Cyber-physical system

Introduction

Artificial Intelligence (AI) and Intelligent System (IS) are central notions in current theory of control system [1]. Intelligent system is capable to function autonomously, by learning its surrounding, adapting to changes, and reaching defined goals [2]. Other researchers consider key to intelligence ability to accumulate knowledge, define aims, and plan actions [1]. At present a widely used notion of cognitive agent is such kind of agent that is learning the surrounding and modifying its actions to achieve the goals [2,3]. Cognitive agents capable of reaching goals in varying situations are a most perspective class of mathematical models of intelligent control [1-6]. A key principle of intelligent control is control based on knowledge [7]. Existence of knowledge of how to make the best control decisions in presence of uncertainty is the foundation of intelligence. Thus learning, or accumulation of knowledge is the foundation of intelligent control [8-9]. There are two aspects of knowledge that agents use for making good decisions. First, the agent must be in a possession of rules for making good decisions. Second, surrounding circumstances are changing, therefore agents should be able to adapt to these changes. Future intelligent systems will combine learning from data by estimating probability densities with learning from language text. This ideas were previously discussed in the works of the authors [10-14].

It is assumed that the intelligent control agent receives certain information about the current state of the surrounding, defined as situation S_i, as well as actively uses the data to interact with the surrounding. Knowledge of regularities, determining the cause-effect relationship between events in a specific situation and enabling to predict the various situations or controlled objects development, is a base control agent use to elaborate efficient strategies for making the best – optimal control decisions. This information exactly refers to be knowledge or representations of control agent cognitive capacities.

Cognitive control agents' key characteristics are autonomous and purposefulness of actions. It is an autonomous commands execution based on a targeted, problem-oriented reasoning. As the main characteristics of cognitive intelligent agent are also considered autonomous, in which the intelligence is associated with perception and reasoning, but autonomous – with making decisions and actions in the states of uncertainty of surrounding. In this case, critical for cognitive agent becomes its ability to acquire knowledge through learning – that is, the ability to learn. Such ability requires the possibility to extract, accumulate and apply knowledge used for control. Such cognitive agents are able to learn and to be aware of its surrounding and adapt to it and change it on account of knowledge accumulated in the functioning process and acquired skills. Cognitive process is a process by which an autonomous artificial system perceives the surrounding, gains experience through learning, predicts the result of the events, acts and adapts to changes in the surrounding.

Formulation of the Problem

We consider a cyber-physical system that controls a hierarchy of industrial or technical systems [12]. Possible system states are estimated by clustering available data $(x_1,...,x_N)$, where x_n are characteristics of agents and technical systems states. A powerful clustering method is dynamic logic (DL), using Gaussian mixture model [13]. In this model every cluster m is characterized by Gaussian likelihood:

$$l(n\,|\,m) = (1/2\pi)^{d/2} \det C_m^{-1/2} \exp(-(x_n - M_m)^T C_m^{-1}(x_n - M_m)/2).$$

Here M and C are the mean and covariance parameters of Gaussian likelihood. In addition, every cluster is characterized by its rate:

$$r_m = N_m / N,$$

where N_m is the number of data points belonging to the cluster, and N is the total number of data points.

DL algorithm for estimating likelihood parameters starts with arbitrary values of unknown parameters r, M, C. The next step is to compute association variables:

$$f(m\,|\,n) = r_m l(n\,|\,m) / \sum_{m'} r_{m'} l(n\,|\,m'),$$

Using these association variables data points in the cluster and rates are computed:

$$N_m = \sum_n f(m\,|\,n), \;\; r_m = N_m / N,$$

Next, mean value is computed:

$$M_m = 1/N_m / \sum_n f(m\,|\,n) x_n,$$

As well as the covariance:

$$C_m = 1/N_m / \sum_n f(m\,|\,n)(x_n - M_m)^T (x_n - M_m) \Big/ .$$

Having parameters of clusters, it is possible to evaluate the total likelihood of all defined clusters. The total number of clusters will be defined by maximizing the total likelihood.

The clusters make up the system states, they are denoted by

$$S = \langle s_1, ..., s_m \rangle$$

These estimated states represent one aspect of knowledge. Another aspect of knowledge consists in selecting control actions $u(t)$ at every moment t.

Control action $u(t)$ transforms state $s(t)$ into $s(t+1)$. Beginning with the initial state $s(1)$ at the moment $t=1$, system goes to the state $u(1)s(1) = s(2)$

Results of actions $u(t)$ on every state s_i are considered to be known; they are derived from the system model. We also know the system gain $g(i,j)$ derived from transforming any state s_i into s_j. The system goes through the following states

$$s(1), u(1)s(1) = s(2), u(2)s(2) = s(3), ..., u(T)s(T) = s(final),$$

Optimal control therefore consists in maximizing the total gain over time T

$$G(T) = g(t=1, t=2) + g(t=2, t=3) + ... + g(t=T, g=final),$$

This gain is maximized by selecting actions $u(1), u(2), ...u(T)$ at every moment t.

Cognitive Control Agent

Cognition, considered in the context of the agents' ability to make conclusions about things and events in the world around us, as well as the ability to learn its surrounding, are the most important characteristic of intelligent control concept [10]. We suppose that cognitive agents which capable of automatic accumulation and use of knowledge for making better control decisions, represent the next step in the development of distributed control systems. Such agents have adaptive capabilities that provide efficient activity of devices and systems in dynamically changing surrounding.

Agent knowledge represents its awareness of the surrounding and directly itself. We consider the notion of $i-th$ agent as its ability to display the current situation S_t, defining agent's interaction with surrounding or controlled object, as some action A_i:

$$\psi_i = S_i \to A_i,$$

which, in turn, is directed to the agent's (or system of agents) reaching the defined goal – target state S_G:

$$S_G = f(S_t, A_i) \qquad (1)$$

Current situation S_i is perceived by agent through its receptors - sensors as a certain set of measured during the time t_i, $i = 1, 2, ..., m$ values – parameters-signs $z_k(t1)$, $k = 1, ..., K$, which are base for making certain evaluation Qt current state or surrounding or controlled object:

$$\tilde{Q}_t \cong S_i,$$

where estimation of current state $\tilde{Q}_t$ may be evaluated by feature vectors Z_{ti} as:

$$\tilde{Q}_t \equiv Z_{ti} = [z_1(t), ..., z_k(t)]^T, ...$$

In essence, transition to a new state reflects agent achievement of certain formula $\varphi = \{R_i\}$, which defining f-transformation operator of current situation S_i, represented in specific way – characteristic of state "agent-surrounding" or "controlled object" $Q = q_k$, to control command U, triggering controlling rules. In this context, consider knowledge of Ψ agent Ai as multitude of rules $\{R\}$, defining the displays "signs of situation" (controlled object state) – in action (set of control decisions):

$$\{R_i\} \equiv \{z_1^i \,\&\, ... \,\&\, z_k^i \Rightarrow r_i\}, z_1^i, ..., z_k^i, r_i \in L,$$

where $z_1, ..., z_k$ are situation characteristics values, performing as incentives (predicates), triggering control agent response to perception of current situation; r_i is response of agent (predicate), represented (meaning "initiation") of specific control act. Group of control agents, interacting with each other and the surrounding in order to achieve a certain target state, from the functional point of

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view should be considered as a whole, and therefore the dividing line between the surrounding and the agent is sufficient relative. In this sense, each agent $i \in N$, interacting with the surrounding or the controlled object, at each time $t = 1, 2, \ldots, T$ is assigned a time-varying state:

$$S^i_{t+1} = f(s^i_t, u^i_t),$$

which from a formal point of view is determined (may be considered) as the hypergraph (of classes).

Each control agent of network from a mathematical point of view can be defined as cognitive functional module (CFM), which implements the cognitive mapping process of perceived information – In the knowledge of control strategy:

$$F : X \times U \to Q,$$

$q = f(X,U)$ or, more compactly: $\psi_i : S_{i \to} U_i$,

which, in its turn, is directed to the achievement by agent (or system of agents) some preassigned – target state S_G:

$$S_G = f(S_t, U_i).$$

Groups of agents knowledge accumulation and connection in a network - is the realization of cognitive models abilities through the startup of cognitive mechanisms of transformation of received data about the current state of S_i into knowledge of object control strategy, i.e. sequence of actions of change of controlled object current state S_0, control objective specification and strategies to achieve it. Combining of individual network agents' knowledge triggers a cognitive process of forming a qualitatively new properties – network emergence. The group of agents combined knowledge making is considered a cognitive process, explains the new quality emergence – network emergence. Control agents group knowledge ψ_i, combining by unitary target control function (1) into cumulative knowledge ψ_Σ.

Hyper-Network Model of Agent's Hierarchy

Control knowledge making cognitive models' practical implementation effective apparatus is a paradigm of self-learning and self-organizing neural network models that illustrate the mechanisms of machine learning.

Primary network adaptive quantization principle we shall apply to create a neural network model of control strategy knowledge making. Neural network model implementing cognitive function module (CFM) displaying controlled object current status into control strategy knowledge, can be represented as hypernetwork HN [14]: $HN = (V, E, R, P, F, W)$, where: $V = (v_1, v_2, \ldots, v_n)$ – plurality of nodes (vertexes-states) of the primary network $PNet$ graph, $E = (e_1, e_2, \ldots, e)$ – plurality of edges corresponding branches (transitions states) of primary network $PNet$, $R = (r_1, r_2, \ldots, r_n)$ – plurality of edges corresponding branches of secondary network $Wnet; P : E \to 2^x$ – mapping which associates each element – primary network edge $e \in E$ set of vertices $P(e) \subseteq V, F : R \to 2^e{}_{PNet}$ – mapping associating each element – edge $r \in R$, corresponding branches of secondary network $WV = (V, R)$ a plurality of traces $F(r)$, forming a simple route in the graph $PNet = (V, E; P)$. Each control meta-level hypernetwork agent may be regarded as a cognitive function module that implements the cognitive process of displaying information about the perceived information about situation S_i into knowledge of control strategies:

$\psi_i : S_i \to U_i$, or, considering the knowledge of control strategy as a certain control operator F_i

$F : X \times U \to Q, q = f(X,U)$, which, in its turn, is directed to the achievement agent (or system of agents) some preassigned – target state S_G:

$$S_G = f(S_t, U_i).$$

Holonic principle of organization in the coalition interaction: every agent displays the objective function as a strategy for the group of lower-level agents. The strategy of the accumulation of knowledge by learning in this case is constructed as an iterative process of synaptic connections ΔW parameters correction:

$$w_{k+1} = w_k + \Delta w_k,$$

and forms antigradient search direction $-\nabla J(w_k, \pi)$ function (functional) error:

$$J(w_k, \pi) = J(\|S_G - S_k(w_k, \pi)\|)$$

$$\Delta W = -\varepsilon \nabla J(w, \pi)$$

which determines the current discrepancy between the target (desired) S_G and the current state of the control object S_t. This suggests that at each iteration is a correction of synaptic connections W matrix, representing knowledge parameterization. Where in the ant gradient $-\nabla J(w_k, \pi)$ value largely depends on the reference method (parameterization) of title S_G and current $S_k(w_k, \pi)$ state.

Conclusion

Control of the hierarchies of the structurally complex industrial and technological objects belongs to the class of problem of intelligent control, which demands making decisions in states of uncertainty. The future in this area belongs to technology of intelligent control, technology based on the knowledge. This technology uses methods, models, and algorithms extracting and accumulating knowledge needed to find optimal control decisions. Capabilities of Control Systems to extract, accumulate and use knowledge for system control requires cognitive abilities of control agents [15]. Cognitive control agents learn its surrounding, adapt to its changes, and modify it, by using accumulated knowledge. Cognitive approach opens new wide directions towards control of industrial objects and situations that are not well structured and difficult to formalize, especially in real life circumstances with significant uncertainties. Here the authors considered a class of cognitive models control agents based on the principles of learning. These types of control agents enable solving problems of a wide area of control in presence of uncertainty [16-21].

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