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KNOWLEDGE-BASE AUTOMATION IN SMART MANUFACTURING SYSTEMS

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Abstract

This paper analyzes the problem of intelligent automation techniques within the framework of smart manufacturing systems. Special attention is given to perspective trends of automation as a technical cybernetic system and its evolutionary development, with focus on evolutionary links between cyber-physical and real-biological systems via information processing ability. This paper also reviews and analyzes the advantages and disadvantages of existing models and algorithms, for example: primarily reactive behavior, lack of expressive possibilities that hinder task completion etc.

INTRODUCTION

Industrial automation theory and application is one of the most critical and rapidly developing fields in the Industrial sector. Promising trends of this subject are based on the effective development of automation as an information processing system. This can be achieved by developing new approaches and mathematical models for information sensing, analysis and cooperation in various distributed technological systems. Special attention in this process must be reserved for the relationship between the general laws of development of technical systems and the fundamental laws of evolutionary development that characterize our world's ongoing evolution. Such a focus, while setting the stage for preliminary research work, also opens up the possibility of understanding promising directions for our next generation of industrial automation systems. The first steps of our work are about searching for similarities between biological and technical cybernetic systems. A complete analysis of these laws allows us to formulate the general mechanisms of construction of information cybernetic systems. In addition we can also get an insight into the functioning of information processing and information exchange with other systems and environments, while acquiring understanding of the basic mechanisms of control and development. Such approach, based on fundamental evolutionary laws and development mechanisms, has formed the basis for the formation and later development of new promising directions in interdisciplinary research of information management systems, known as "Evolutionary Cybernetics" [1 - 2].

The key function of cybernetic intelligence is the ability of the system to extract, accumulate and use knowledge. This ability is one of the basic assets of artificial intelligence, and permits the system to operate under autonomous control. In addition, the system is equipped to perceive the environment and stay in it for a long time, adapting to changes and achieving its assigned goals.

As an example of an area of industrial intelligence, let us look at the problem of situation assessment i.e. cooperative task planning and prediction. In such applications, the primary requirement is to have a flexible means to change the systems behavior at all times. The need for which is dictated by the progress of the system and the current state of the environment in real time. In simple terms this is basically: the ability to use knowledge for reasoning and decision making in pursuit of obtaining optimal solution for dynamically changing conditions.

The capacity to produce new knowledge and reasoning allows intelligent systems to generate sets of effective strategies in the presence of not only, continuously changing external and destructive influences, but also given little or no information. This corresponds to the basic principle of the unity of intelligence and performance in complex systems, using intelligence as a regulator of effective performance in the behavior of complex systems. This feature furthermore has a direct link to knowledge base capability and optimal decision making analysis in standard and various non-standard situations, for e.g. alarms, pre-alarm, etc. It can also mean functionality analysis of cybernetic systems in applying various methods of information processing and usage in its learning and adaptation to constantly changing environmental influences.

Formal decision analysis with knowledge base automation has been increasingly used to address complex technological recourse planning problems. This complexity requires the use of more advanced modeling technique. Initially, the most common methodology used to evaluate decision analysis problems was the standard decision tree. Standard decision trees have serious limitations in their ability to model complex situations, especially when outcomes or events may recur over time. As a result, standard decision trees are now often replaced with Markov process-based methods to model recurrent technical states and future events. However, standard decision trees based on Markov models cannot be used to represent problems that have a large number of embedded decision nodes in the branches of the decision tree. This limitation is often seen to occur in situations that require sequential decision making.

A model of complex hybrid cognitive system is provided to elaborate the general mechanisms of knowledge base automation development [3]. This model elicits the implementation of the basic principles of the synergetic methodology of intelligent systems development. This methodology is used in integrating the beginning of cybernetic information control environment with the physical elements of perception and impact that exist for that environment. This class of systems is most promising for the development of the basic paradigm of adaptive self-learning systems. Systems that are based on integrating control information systems with knowledge accumulation and application capabilities, and are used for the sole purpose of deriving complex objective functions. Control, none the less, remains the key question in such models. This is because the effectiveness of system operation depends on how the chosen behavior corresponds with reality.

One of the algorithms from the field of machine learning that best correlates with the aforementioned concepts is presented in the next chapter.

ALGORITHM FOR KNOWLEDGE-BASED AUTOMATION

Fuzzy Sarsa is one of the best fitted algorithms to the problems considered. Sarsa is an on-policy temporal difference learning algorithm. The main principle of Sarsa is summarized by its name: State, Action, Reward, State and Action. Modification of this Fuzzy Sarsa algorithm is provided in [4]. In the approach provided by the authors, a combination of the Sarsa planning algorithm and the power of Fuzzy logic leads to the finding of an optimal solution. This solution represents actions and statements in human-friendly format- suited for learning. Sarsa (λ)-algorithm, can be considered as one of the most powerful methods in reinforcement learning. Usually this algorithm is used for finding the best path from point A to B utilizing Markov Decision Processes.

The main difference of this algorithm from classical POMDP (Partially Observable Markov Decision Processes) is the updating Q-function method:

$$Q_{t+1}(s,a) = Q_t(s,a) + \propto \delta_t e_t(s,a), \quad (1)$$

where α is the learning gain ($0 \leq \alpha \leq 1$), δ_t is the temporal difference error, $e_t(s,a)$ - eligibility traces.

The model of agent is presented on Fig. 1.

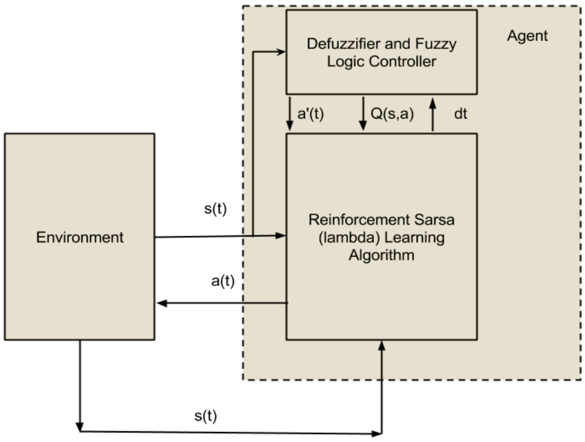

Figure 1. Fuzzy Sarsa (λ) Learning architecture with Fuzzy Logic Controller.

The Agent connects to the environment by acquiring information about the states. In a typical route problem, the state can be described as the position of a robot and its accompanying parameters, for e.g. velocity and direction. After obtaining the states, the algorithm can run the cycle of state-action-reward as per usual practice in reinforcement learning algorithms. The Defuzzifier, given the actual states and δt updates the Q-function and propagates it back to the evaluation algorithm. Given the Q(s,a) values Sarsa(λ) algorithm selects best action from the known set of actions with probability 1-ε (ε-greedy policy). More concrete explanation of Sarsa algorithm is presented in [4].

The work process with the developing system can be listed as follows:

- Expert knowledge as fuzzy-logic rules entered into the system (on robot routing example it can be a set of actions, behavior in different states and etc.)
- Agent uses the initial data for generating the set of optimal actions and then updates the information about the state of environment
- Actions can be executed by some actuator, device, program or even by a human

- System can learn from the history of selected actions the optimal solution for occurring situations.

As a result, a full stack of problems can be solved by the system – search of optimal path, plan or decision, storing of big amount of rules and learning of the system on the fly.

As an engine of learning on fuzzy rules, one of the perspective approaches seems to be to use ANFIS-toolbox, a technique that is widely used in all fields related to the fuzzy-inference learning [5]. ANFIS can be used for the adjustment of the Sarsa-algorithm or as a part of it.

The realization of described algorithms is under development and currently undergoing application testing at the Festo laboratory. This laboratory offers the facility of modeling an assembly plant and of modeling various chemical processes.

A systems approach to the analysis of the evolutionary development of technical cybernetic systems is associated with the development of the principles of network organization and group control of individual intelligent systems. These components together make up the distributed environment for artificial intelligence. The determining factor in this case is the priority of coordination - horizontal interactive links above the vertical "purely competitive" strategies in complex integrated systems. Cybernetic solutions in this direction over all suggest the creation of a fully interactive multi-agent system, one that includes communication between control agents (Vehicle-to-Vehicle, V2V) and between each agent and the outer surrounding infrastructure (Vehicle-to-Infrastructure, V2I).

An important aspect of this system is that it makes use of principles of self-organization and development. Supervised by key principles of complex (after G.Haken and Prigogine) hybrid system functioning- the evolutionary development of this system is based on fundamental processes of interaction among its components and, in particular, their cooperation and coordination. This limits the ability of the systems to adapt; they are not able to extract additional information from the data or to build more flexible optimization algorithms.

The extraction of maximum amount of information from the experimental data has always been one of the key tasks of performing the physical experiment. A significant number of works have been devoted to this problem, including adaptive filtering techniques, experimental design, and other approaches. However, despite the abundance of such works, most of the proposed approaches, since the classical work by Wiener on adaptive filtering, have been based on the error minimizing criteria by the method of least squares. This approach greatly limits the data required for the analysis of statistically significant features, modeling complex dependencies, separating weakly connected components in a priori uncertainty of their characteristics. The basis of such an approach is the creation of an algebraic criterion for neural network training, which maximizes mutual information on the outputs of the neural processor.

SUMMARY

Nowadays, the amount of data in modern production is growing at a phenomenal rate. This growth is directly proportional to the increasing number of information systems around the world and also to the rapidly increasing volume of information on the Internet. This trend leads us to the observation that the modern manufacturer now requires automation of all production processes that are linked to the flow of large data streams. A promising approach in this situation is the approach of intelligent self-learning knowledge base systems that can make decisions on pre-defined rules, as well as, learn from the decisions that are eventually taken. This article proposed the prospective ideas of use in this area, as well as a brief description of a model that can be applied towards the building of a knowledge base. Lastly, the process of implementation of such a system on a model that could be scaled to the real production systems was also reviewed.

REFERENCES

[1] V.F. Turchin. The phenomenon of science. Cybernetic approach to evolution. M,. Science, 1993

[2] V.G. Redko. Evolutionary cybernetics. M., Science, 2001

[3] D.G. Arseniev, V.M. Ivanov, V.P. Shkodyrev. Adaptive control of computational Processes, M., Science, 2001

[4] L. Tokarchuk, J. Bigham, and L. Cuthbert1: “Fuzzy Sarsa: An approach to fuzzifying Sarsa Learning”, International Conference on Computational Intelligence for modelling Control and Automation, 2004.

[5] H. Chaudhary, V. Panwar, N. Sukavanam, and R. Prasad: “ANFIS PD+I Based Hybrid Force/ Position Control of an Industrial Robot Manipulator”, International Journal of Materials, Mechanics and Manufacturing, Vol. 2, No. 2, May 2014.