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Agent architecture for intelligent manufacturing systems

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Analysis and modelling

ABSTRACT

Purpose: Analysis is made of requirements posed by tasks of agents operating in the intelligent manufacturing systems and their resulting architecture is presented.

Design/methodology/approach: Architecture of agent systems for industrial environment is presented, making it possible to generate the particular agents customised for the specific tasks, based on the automatic analysis of its required features.

Findings: Extension of cellular automata approach underlying the conventional agent behaviour specification using the Fuzzy Cognitive Maps is presented in conjunction with the neural networks providing learning capability of the agents designed for the various levels of the manufacturing supervisory and execution systems. Adding reaction time specification to FCM makes it possible to analyse and design systems with the required behaviour.

Research limitations/implications: Specific features of the designed agent architecture have been tested as separate mechanisms which can be merged into the final comprehensive at a later stage.

Originality/value: Agent architecture is proposed for the industrial applications of single agents and their groups that can collaborate to achieve the individual and joint goals specified in reaction to changing environment conditions and into their agendas in XML format. Automatic generation of custom agent reactions models can be carried out based on a set of requirements that may be specified in the if-then rules form.

Keywords: Fuzzy cognitive maps; Distributed artificial intelligence; Artificial intelligence methods; Autonomous agents

1. Introduction

The term intelligent agent has been always related to the issue of the intelligence itself. For instance according to Wooldridge and Jennings in [12] the strive to define it was in essence an attempt to answer a question what is intelligence?

Some approaches were so broad that they would pertain to nearly any software and others would only include a small number of some specific systems. Development of the artificial agents to be used in the industrial environment will be based here on approaches originally presented in [7], where an agent was described as:

"... *a hardware or (more usually) software-based computer system that enjoys the following properties:*

- ***autonomy:*** *agents operate without the direct intervention of humans or others, and have some kind of control over their actions and internal state,*
- ***social ability:*** *agents interact with other agents (and possibly humans) via some kind of agent-communication language,*
- ***reactivity:*** *agents perceive their environment, (which may be the physical world, a user via a graphical user interface, a collection of other agents, the INTERNET, or perhaps all of these combined), and respond in a timely fashion to changes that occur in it,*
- ***pro-activeness:*** *agents do not simply act in response to their environment, they are able to exhibit goal-directed behaviour by taking the initiative*"'.

Moreover, an agent which should be able to act effectively in the industrial environment should also fulfill Franklin and Grasser requirement [6] stating that *"An autonomous agent is a system situated within and a part of an environment that senses that environment and acts on it, over time, in pursuit of its own agenda and so as to effect what it senses in the future".*

2. Requirements for intelligent agents in industrial environment

Research carried out so far resulted in three different agent architectures – Fig.1.

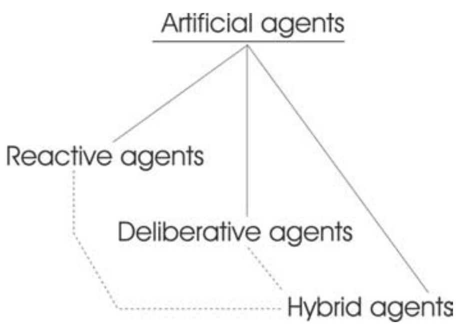

Fig. 1. Agent architectures

For the reactive agents certain sensor information always results in a particular action being taken, which can be implemented as a rule-based system, or using finite state machines [8].

Current World State → Action

They can be implemented efficiently and such architecture is entirely deterministic which makes their thorough debugging and testing easy [10]. However, one has to encode rules for every possible situation in which such agent might have to operate. Therefore, for complex environment this may be a very tedious task, and maintenance of such agent would be very difficult in case of any modifications. Moreover they are unable to carry out any planning and cannot reason about the world in which they exist [13].

On the other hand the deliberative agents can use models of their world to develop long term plans striving to achieve their goal states. The idea of this Belief, Desire, Intention (BDI) architecture was formulated by Rao and Georgeff [Rao & Georgeff, 1991; Rao & Georgeff, 1992].

Current World State + Goal State → Plan

The deliberative agents require constant maintenance of their knowledge base, as it has to represent their dynamic environments, which often involves updating the inferences based on such new knowledge.

Hybrid agents' architecture features a combination of both the reactive and deliberative models. However, this merge introduces a new problem of splitting the tasks between two subsystems. Therefore, usually the reactive subsystem should be used to cope with all issues when reaction time is crucial and the long term planning can be carried out by the deliberative subsystem.

The issue presented in the work is how to model the hybrid agents for the industrial environments. Agents that can react in real time and yet be capable of long term planning.

Analysis of the routine tasks to be carried out in the industrial environment [4] leads to the conclusion that the agents should be capable of the following:

- performing in real-time,
- acting reliably in a wide range of situations,
- displaying behaviour understandable to humans with whom they may have to collaborate,
- demonstrating capability of complex social behaviours
- there should be the possibility to generate their models following a certain procedure and to store the resulting model in a format easy to interpret and process

This work is dedicated to development of the *proactive persistent agent* (PPA) architecture meeting all requirements hereinabove. Such agents are proactive in the sense that they act according to their own will, as specified in their model enabling the agents to schedule their activity, pass their roles and to engage in social interactions, including negotiations. They can do it using the knowledge base where facts are stored describing their world.

3. Fuzzy cognitive maps for modelling agents' behaviour

The idea of the Fuzzy Congitive Maps comes from psychology where the technique of *cognitive maps* was first described by Tolman in the 1940s who used them to describe memorising behaviours in rats. This work was later continued by Axelrod who put them to use in decision theory in the politico-economic domain. FCMs were created finally in 1986 by Kosko who introduced the notions of fuzzy logic to Axelrod's cognitive maps.

A Fuzzy Cognitive Map is a fuzzy, signed digraph with feedback, whose nodes represent labelled causal concepts represented by fuzzy sets with an activation in the interval [0, 1] at all times. These concept nodes can be events, processes, or values. The arcs of such map represent fuzzy rules, or the causal flow between concepts and are weighted. Their weight values are in the interval [-1, 1] representing the degree of the causal flow. One of the advantages of using fuzzy links is that one can use the everyday descriptive terms (such as always or usually) to describe the degree of causal effect between nodes. which can later be converted into the arc weight values in the range [-1, 1]. The FCM networks are generalisation of the Cellular Automata idea, whose functioning is crisp instead of the FCM's fuzzy behaviour – which could, however, be also represented by them as their specific variant.

Moreover, the link weights can also be acquired by learning employing techniques similar to those used in training the artificial neural networks. This is the way in which the new agent's features may be predicted using its world requirements based on its status logs. This is the only known, to date, fuzzy technique revealing the hidden pattern of some situation []. FCMs may therefore be used to model the robotics like plant control [3].

The FCMs allow feedback, so activation of their nodes is not a single step process, but an iterative one. The activation proceeds through the network until it finally either reaches the equilibrium or enters into a chaotic attractor. Reaching an equilibrium means that the FCM either settles at some fixed point within its fuzzy set membership space, or enters a limit cycle. The equilibrium consisting in a fixed point provides a particular set of node activations; whereas, a limit cycle occurs when the system cycles unceasingly between a certain number of node activation sets. In an unlikely case of reaching the chaotic attractor the set of concept activations moves chaotically within a small portion of the potential fuzzy set membership space – Fig. 2 [6-11].

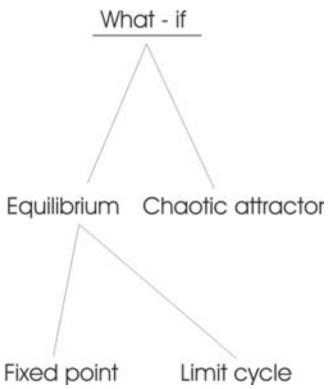

Fig. 2. Possible what-if resolution results

The purpose of FCMs is to answer "what-if" questions when they are given a set of initial activations and further observed reaching the equilibrium. Development, modeling, of an FCM is similar to asking the experts' advices what should the system's reaction be in a given situation, and what is the effect of various concepts. A more complex procedure may take into account varying credibility of various approaches to solve the particular problems which yields the augmented FCM matrix []. In this case the different weights may result in different equilibrium limit cycles or fixed points as hidden network patterns.

3.1. Reaction time

The FCM can model the system whose behaviour has been specified in the form of the what-if rules stored in the agent's knowledge base. However, this traditional approach does not support any time flow representation mechanism. This evident drawback calls for supplementing the base FCM models with some timing provisions. They should be based on the iterative FCM simulation process nature in which nodes states can change at each iteration only; therefore each iteration should bring the state changes to their next states as if the minimum time increment has elapsed. In this way time has a discrete nature in such models. No state change can be modeled that would take place within a time period shorter than such minimum time increment. Therefore, such increment features an important FCM design requirement, which can be equal to a second, minute, hour or any value required by the particular agent application. The same applies to modeling delays in taking an action.

3.2. Automatic rule generation

An important issue is automatic generation of agents that would be needed for particular applications. This procedure cannot be reduced to simple cloning of the predefined agent types, as the agent world requirements may change over time and be unpredictable to agent designer. Therefore, the what-if rules sets that will govern its behaviour should be generated dynamically as the new needs appear [12-14].

Agents intended for industrial applications will not replace the existing controllers, supplementing them rather with the functions needed at the particular moment. Such approach will required designing rule sets that will make it possible to solve problems like decision making, planning, and failure detection [4].

Efficient generation of such rule sets have to deal with actions to be taken when the system irregular operation occurs, which should offer solutions based on for failure mode and cause, effects and severity. Such rules can be derived from the human operators knowledge only. Such knowledge is usually heuristic and can take into account his experience with dealing with alarm signals, common process faults, frequency, and causes.

History of actions taken in similar environments, along with their results, feature the space from which the rules can be extracted when needed. Once the custom what-if rule set is constructed, the relevant FCM may be generated, which will take actions that proved successful when taken by humans, thus being the base for agent design [7-11].

```
<schedule>
   <scheduleEntry>
      <startTime>06:00</startTime>
      <endTime>14:00</endTime>
   <location>Utrecht</location>
   <role>
   <name>at work> … <
!-Role details omitted to conserve space-> </role>
<startTime>14:01 </startTime>
<endTime>22:30</endTime>
<location>workshop</location>
<role>
<name>overhauled</name>
    </Route details omitted to conserve space -> </role>
    </scheduleEntry> <scheduleEntry>
<startTime>23:01</startTime>
<endTime>02:00</endTime>
<location>store</location>
<role>
<name>hot reserve</name> …
</—Rote details omitted to conserve space -> </role>
    </scheduleEntry> </schedule>
```

Fig. 3. Fragment of the simplified agent model

4. Agent's plans

The agents carry out their tasks not only in reaction to their environment conditions but also have their schedules. The agents' behaviour modelled as mentioned above should be realised according to agent's plan, which should be specified in XML. Such schedule which splits the time provided for agent operation into a set of time periods specifies where the agents should be and how they should act at the moment in given conditions. All agents are split among many groups that have different assignments and scope of responsibility (Fig. 3).

Such plan will be carried out by the robot and may come true in eventual cooperation with other robots., to complete a certain task and can decide if it needs to act in cooperation with other agents controlling its internal state and actions [3, 6, 8].

FCMs are used to make a compound system capable of separating the models and to accomplishing kind of maintenance of the system by integrating alternative modeling techniques. The FCM can accomplish identification of the process models and cope with limited uncertainty situations. It may comprise of different FCMs to aggregate the separate models and to perform a kind of maintenance of the system by integrating alternative modeling techniques. An augmented FCM can accomplish identification of the process models and cope with limited uncertainty situations. It may comprise different models, identification and estimation algorithms [13].

5. Conclusions

The fundamentals of industrial agents are presented being capable to carry out the specific tasks – including the possibility to multiplicate, should their tasks call for that. The agents can be modeled according to specific needs. The main features of such robot will be affected and will represent the requirements specified by the prevailing amount of the railway zone setup. The need to take into account timing of operations and the gaps in activity requires a mechanism to supplement the "regular" agent model. Such agent performs its tasks, as they are handed over to him, and with the access to the database.

The robot tasks are specified using the XML language, which represents its roles, as needed in the workshop Generation of such function descriptions may be carried out based on the database containing previous solutions made by human operators. The resulting file features description of its behaviour in the form of the FCM network, while its general operation plan is represented by its schedule written in XML.

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