

Intelligent control system of autonomous objects

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Abstract. This paper presents an intelligent control system of autonomous objects as framework. The intelligent control framework includes two different layers: a reflexive layer and a reactive layer. The proposed multiagent adaptive fuzzy neuronet combines low-level reaction with high-level reasoning in an intelligent control framework. The formed as the multiagent adaptive fuzzy neuronet the intelligent control system on the base of autonomous object's state, creates the effective control signal under random perturbations.

1. Introduction

Autonomous objects elaborate many practical tasks which are too dangerous or difficult for human to reach (e. g., military assignments, interstellar exploration, searching for victims after earthquake, and nuclear/biological accidents). Such autonomous objects are commonly suffering from restrictions due to the uncertainty of the environment and therefore unstable dynamics when designing control systems to provide stability, disturbance attenuation, and reference signal tracking. Within the research literature, a whole array of differing control strategies is proposed to deal with the control of the linearized system problem [1-6]. One of the most common control strategies is Proportional-Integral-Derivative (PID) controller due to its simplicity and applicability [7]. But the PID controllers for autonomous objects are often designed by hand, requiring extensive analysis of the system and dynamics. This process is generally difficult because it is hard to anticipate all operating conditions. The control algorithm must coordinate the autonomous objects properly, generating robust behavior to negotiate different terrains effectively while maintaining stability. Moreover, the autonomous objects should be robust to different environmental conditions, wear and tear, and even failure to reliably complete its mission. Therefore, automatic design algorithms base on intelligent techniques such as fuzzy neuronet and multi-agent system are a promising alternative [5-7]. In modern world, intelligent control has emerged as one of the most active and fruitful areas of research and development.

Monitoring and fault detection play an urgent role for autonomous objects due to the increasing demands on fault tolerant real-time tasks. This fault tolerant behavior of autonomous objects relates to the opportunity to automatically identify faults early before they result in disastrous failures as well as to the capability to continue operating after a fault has happened by switching to a safe state. However, fault detection for autonomous object is a complex problem because of the large space of possible faults (e.g. autonomous object's sensors, actuators, the uncertainty of the environment). Therefore autonomous objects are best modeled as intelligent systems because their behaviors result from the interaction between continuous and discrete dynamics. Several algorithms have been developed to effectively control of autonomous objects. The general approaches integrate the basic model, which are differential equations, with the intelligent models, which are fuzzy neuronet and multi-agent system. We are using intelligent agent as a generic modeling or abstraction mechanism. This research formalizes problem of autonomous object's control solving by multi-agent system. This paper presents



an intelligent control system of autonomous objects as framework.

2. The proposed architecture of the intelligent control system

The proposed architecture of the intelligent control system of autonomous objects includes two different layers: a reflexive layer and a reactive layer divided according to their complexity, speed and range of effect.

The reactive layer is faster and has a closer range of effects; it is still hierarchical in structure and requires some time for generating a control signal of the autonomous object. The reflexive layer has the closest range, the fastest effect and, most importantly, the highest priority. In cases where the higher level does not directly control the lower level it may train them to perform certain control actions. For example, a deliberative layer may cause a reactive layer to develop new condition-action behavior sequences, which may afterwards run without supervision. Usually, intelligent control system architecture involves several kinds of learning mechanisms in different parts of the system, e.g., neural nets, extendable knowledge bases, etc. The name intelligent is derived from this composite structure, in addition to the capabilities inherited from both the Hierarchical and the Layered Architectures. The components of the two above mentioned layers are described below.

3. Roadmap towards intelligent control system of autonomous objects

In this paper we are using intelligent agent as a generic modeling or abstraction mechanism, independently of whether autonomous object is implemented as object (using object-oriented programming techniques). This research formalizes problem of autonomous object’s control solving by multi-agent system (MAS) with neuroevolution and student-teacher of-line learning. Unlike existing single-agent and team-search problems in proposed algorithm the agents collaborate through knowledge of other agents during the dynamic changes in the autonomous objects. The some main issues of the implementation intelligent multi-agent systems are shown in Figure 1.

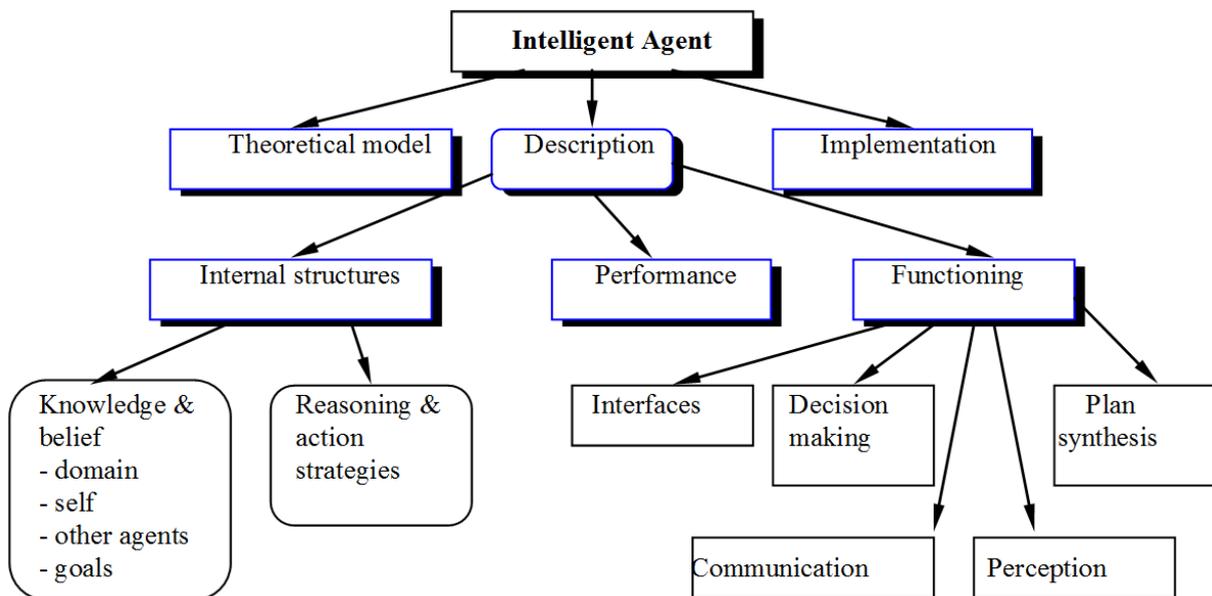


Fig. 1. Levels of specification and design of agents in intelligent control system of autonomous objects
Figure 2 represents a scheme of the basic aspects that correspond to intelligent interactions in cognitive MAS.

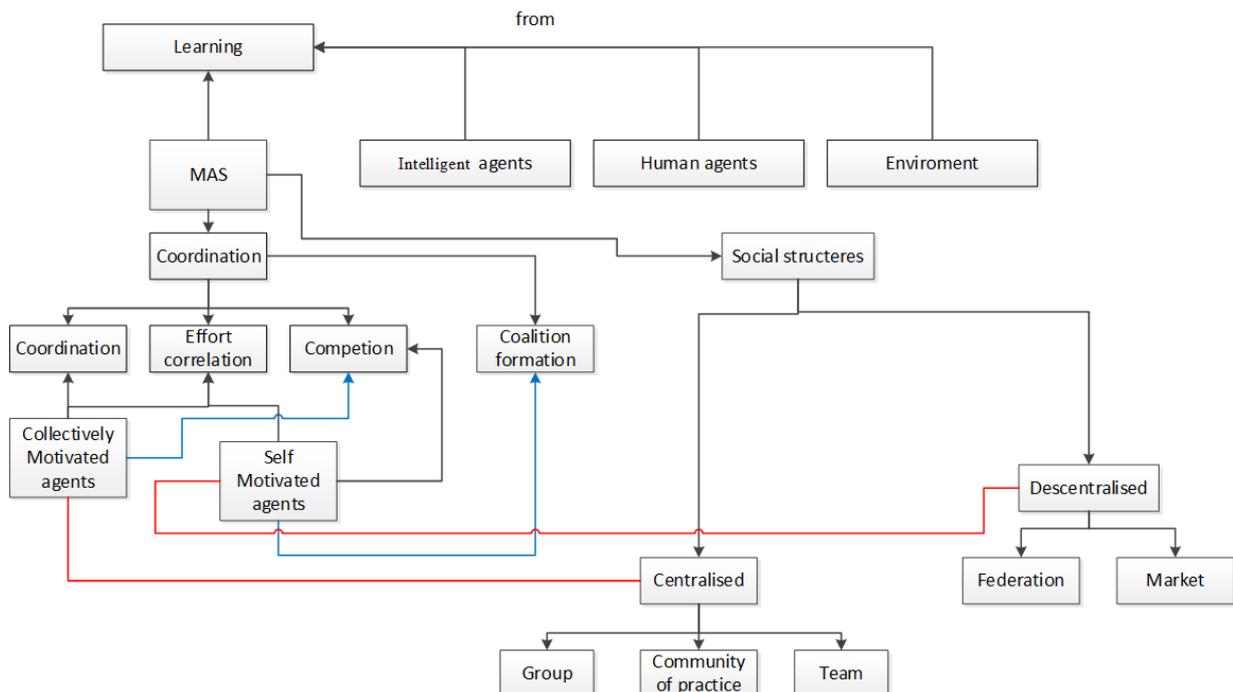


Fig. 2. Intelligent interactions in a MAS

The first two bundles of intelligent control system as MAS are Agent Interoperability and Agent Communication. First one covers agent identity, agent transport, agent registration and discovery. Second one covers agent communication language, ontology, and content language. The first bundle is in several ways orthogonal to the second. Also, within these bundles, the services should be separately specified as they are separable but they must work closely together so they are included in the same bundle.

In this paper a mobile robot prototype with four DC motor actuators was considered as an example of autonomous object. The drive and steering subsystem is included two independent wheels and motor [5].

The behavior of the motor speed for a given voltage is derived from physics law described in Laplace domain by the open-loop transfer function

$$\frac{\dot{\theta}(s)}{V(s)} = \frac{\frac{K_t}{JL}}{s^2 + \frac{(JR + bL)}{JL}s + \frac{bR + k_e K_t}{JL}} \tag{1}$$

where voltage $V(s)$ is input and shaft speed $\omega = \dot{\theta}(s)$ is output [5]. The relation between the reference speed $\dot{\theta}_{ref}$ and the output speed $\dot{\theta}_{out}$ is given by the closed loop transfer function

$$\frac{\dot{\theta}_{out}}{\dot{\theta}_{ref}} = \frac{K \cdot \frac{K_t}{JL}}{s^2 + \frac{(JR + bL)}{JL}s + \frac{K \cdot K_t + bR + k_e K_t}{JL}}$$

where K is a constant gain.

The state space representation of the robot's dynamic as follows

$$\begin{bmatrix} \frac{di}{dt} \\ \ddot{\theta} \end{bmatrix} = \begin{bmatrix} -\frac{R}{L} & -\frac{K_e}{L} \\ \frac{K_t}{J} & -\frac{b}{J} \end{bmatrix} \begin{bmatrix} i \\ \dot{\theta} \end{bmatrix} + \begin{bmatrix} \frac{1}{L} \\ 0 \end{bmatrix} V(t) \text{ and } \dot{\theta} = [0 \ 1] \begin{bmatrix} i \\ \dot{\theta} \end{bmatrix} \quad (2)$$

was used to confirm that the system is stable, controllable and observable.

4. PID controller design

The general transfer function for a PID controller in Laplace domain can be written as follows

$$PID(s) = K_p + \frac{K_I}{s} + K_D s = \frac{K_D s^2 + K_p s + K_I}{s} \quad (3)$$

where K_p is the proportional gain, K_D is the derivative gain and K_I is the integrator gain. The PID gains is choose by hand and are then tune by simulation.

This PID controller is designed by hand. Therefore, automatic design methods utilizing intelligent techniques such as fuzzy neuronet and multi-agent system are a promising alternative.

5. Intelligent control

An intelligent approach is proposed to address the weaknesses of the PID approach. The intelligent controller is carefully designed to correctly tackle the control of autonomous object task under uncertainty of the environment.

5.1. Fuzzy logic control system design.

A typical structure of a fuzzy logic control system is shown in Fig. 3.

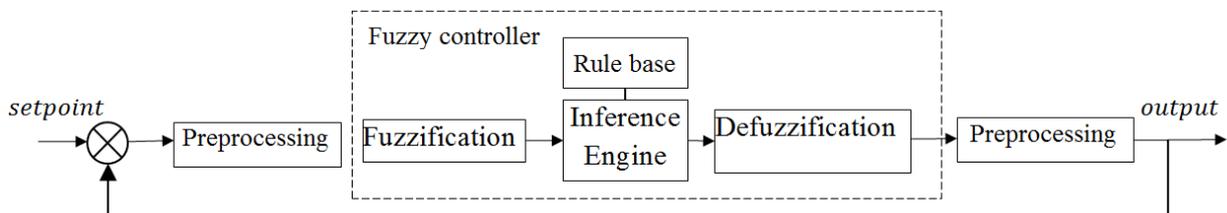


Fig. 3. Fuzzy logic control system

In our work, knowledge was borrowed from proportional integral control error and change of error to define fuzzy membership functions. The inputs that were in the form of crisp values generated from feedback error $-e$ and change of error $-de$ were conditioned in terms of multiplying by constant gains before entering into the main control block. The fuzzification block converts input signals into appropriate way to membership functions, invokes appropriate rules, generates a result for each rule, and combines the results of those rules. The Mamdani-type inference engine combined the output state and assigned a membership value at the truth level of the premise. The truth values are then defuzzified using a discrete centroid computation. The post processing block then transforms these crisp values into control signals. The fuzzy logic controller’s rules had triangular membership function and were implemented in the simulation.

These rules provide control signals based on several if-then statements about (e) and (de) , i.e., if the error is equal Negative Big (NB) and change of error is equal to negative medium (NM), then the change in control (c) is positive big (PB). The numbers of fuzzy logic controller’s rules is determining based on experiment and tuning of the system.

With onboard resources often limited, this paper considers the development of an effective control algorithm that remains easy to implement.

6. The intelligent control system on the base of the multi-agent adaptive fuzzy neuronet

A large body of literature on neuro-control exists on nonlinear systems of the form $\dot{x}=f(x)+g(x)u$,

where the neural nets are used to approximate $f(x)$ and $g(x)$ [5]. Linearization methods have been shown to be very effective for the control of a broad class of systems [5]. In contrast, in this paper, the function approximation capabilities of multi-agent adaptive fuzzy neuronet are exploited to approximate a nonlinear control law. The intelligent control system is capable of handling uncertainties in both the system parameters and the environment. The multi-agent adaptive fuzzy neuronet trained based on data

$$Z^i = (s_1^i, s_2^i, \dots, s_r^i, u_1^i, u_2^i, \dots, u_b^i, \Omega_1^i, \Omega_2^i, \dots, \Omega_q^i, Y), \quad (4)$$

where $i \in \{1, \dots, m\}$ – time, Y – response of the autonomous objects; s – input signal of the autonomous objects; u – control signal; Ω – influences of environment.

The multiagentny adaptive fuzzy neuronet implemented of-line learning. The algorithms of the multi-agent search and interaction employing the neuroevolution (Fig. 4-5).

```

Input: generations; maxTimesteps
population ← InitializePopulation()
g ← 0
t ← 0
loop
  while g < generations do
    subcultures ← FormSubcultures(population)
    while t < maxTimesteps do
      for each subculture in subcultures do
        for each agent in subculture do
          x ← ReceiveAgentInputs()
          f(x) ← GetResponse(agent; x)
          r ← TakeAction(f(x))
          agent.memory ← UpdateMemory({x; f(x); r})
        end for
        for each agent in subculture do
          if Acceptable(agent.memory) then
            for all observer in subculture do
              Train(observer, agent.memory)
            end for
          end if
        end for
      end for
      t ← t + 1
    end while
    population ← SelectAndReproduce(population)
    g ← g + 1
  end while
end loop

```

Fig. 4. Algorithm of the multi-agent search

```

for each agent in subculture  $S_k$  do
     $x \leftarrow \text{ReceiveAgentInputs}()$ 
     $f(x) \leftarrow \text{GetResponse}(agent; x)$ 
     $r \leftarrow \text{TakeAction}(f(x))$ 
     $agent.memory \leftarrow \text{UpdateMemory}(\{x; f(x); r\})$ 
end for
for each agent in subculture  $S_k$  do
    if  $\text{Acceptable}(agent.memory)$  then
        for all observer in subculture do
             $\text{Train}(observer, agent.memory)$ 
        end for
    end for

```

Fig. 5. Algorithm of the multi-agent interaction

Fulfilling of the multiagentny adaptive fuzzy neuronet as intelligent control system of the autonomous objects briefly can be described as follows (Fig 6).

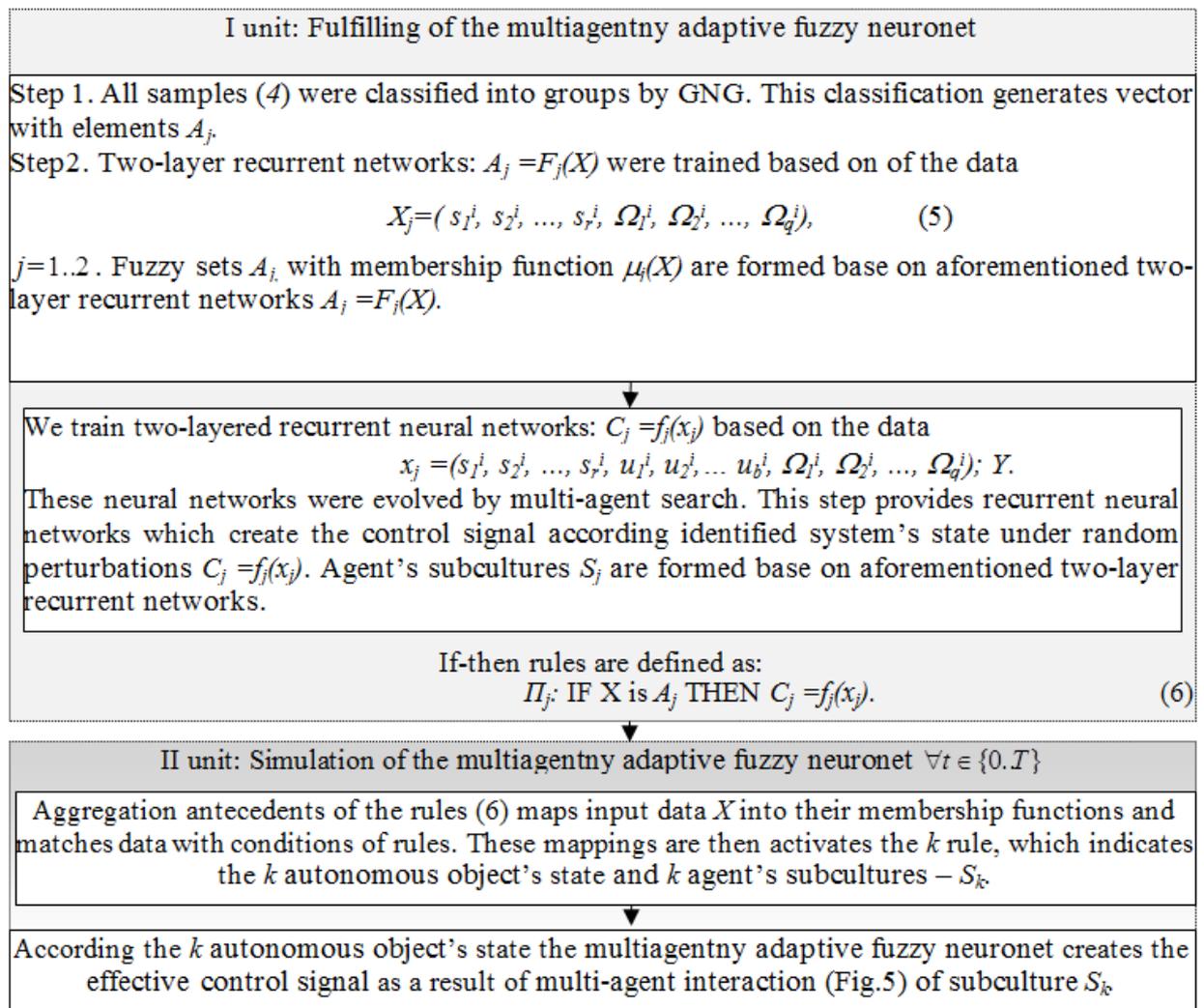


Fig. 6 The multi-agent adaptive fuzzy neuronet.

The formed as the adaptive fuzzy neuronet the intelligent control system creates the effective control signal according identified system's state under random perturbations (Fig. 6).

7. Conclusions

This paper presents an intelligent control system of autonomous objects as framework. The intelligent control framework includes two different layers: a reflexive layer and a reactive layer. The proposed multi-agent adaptive fuzzy neuronet combines low-level reaction with high-level reasoning in an intelligent control framework. The formed as the multi-agent adaptive fuzzy neuronet the intelligent control system on the base of autonomous object's state, creates the effective control signal under random perturbations. Unlike popular approaches to adaptive control, the multi-agent adaptive fuzzy neuronet is used to approximate the control law, and not the system nonlinearities, which makes it suitable to handle a wide range of nonlinearities. This shows the potential of the multi-agent adaptive fuzzy neuronet to control autonomous objects.

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“The reported study was funded by Russian Foundation for Basic Research, Government of Krasnoyarsk Territory, Krasnoyarsk Region Science and Technology Support Fund to the research project № 16-47-242143”