Agent Populations as Computational Intelligence

Marek Kisiel-Dorohinicki, Grzegorz Dobrowolski, and Edward Nawarecki

Department of Computer Science
University of Mining and Metallurgy, Kraków, Poland
e-mail: {doroh,grzela,nawar}@agh.edu.pl

Abstract. The paper deals with agent-based architectures of hybrid soft-computing systems, which should exhibit intelligent behaviour at a population level. Three levels of complexity of such systems are distinguished together with their potential advantages. The considerations are illustrated by prototypical realisations of *evolutionary multi-agent systems* dedicated to multiobjective optimisation, data classification, and time-series prediction.

1 Introduction

More and more results in the field of soft computing are reported recently that in their core are based on combining different ideas and methods. Hybrid systems that put together elements of fuzzy logic, neural networks, evolutionary computation and other approaches by the effect of synergy exhibit some kind of intelligent behaviour [1], which is sometimes called *computational intelligence* (CI) as opposed to rather symbolic artificial intelligence.

The idea of building such systems can be essentially ordered and enriched using the notion of an intelligent agent. Conceptual relation between particular soft computing techniques and agents or their populations forms a base for distinguishing various levels of architectural design. It can be foreseen that the proposed approach can not only give a universal platform for cooperation of different known methods but also magnify their solving abilities up to gaining *computational intelligence* at a level of agent populations.

2 Agent-based architectures of CI systems

Let us start from enumeration of the most important features of *multi-agent systems* (MAS) that are currently adopted by community of researchers [4] and can be even regarded as defining ones for the term:

- a set of agents and a sub-system called environment constitute a multi-agent system;
- agents perform (characteristic of them) actions that result in changes of themselves or the environment;

L. Rutkowski et al. (eds.), *Neural Networks and Soft Computing*

- some of agents' actions (elementary) form mechanisms regarded as specific to multi-agent systems in general, i.e. communication, negotiation, exchange of resources etc.;
- if there is a structure embedded in the environment (a graph) reflecting spatial phenomena of a system, it forms a base for migration of agents;
- an agent treated as a *black box* (observed from outside) may have some human features attributed, like autonomy, intelligence, etc.

With two additional assumptions:

- a number of agents in a system is relatively large,
- there are some mechanisms incorporated in a system for *generation and removal of agents* that cause the number of agents changes dynamically

we obtain a very interesting type of considered systems, which may be called a *mass multi-agent system* [3]. Such systems may be used for simulation of problems that are distinguished due to their granularity in the sense of existence of a large number of similar objects that manifest some kind of autonomy, but also as a platform facilitating realisation of problem-solving techniques – these may be called *multi-agent computational systems* (MACS) and will constitute a base for further considerations.

From a multi-agent perspective, three types of architectures of computationally intelligent systems may be distinguished. They show consecutive levels of increasing complication that nevertheless may be organised and utilised thanks to incorporation of soft computing methods into well-cooperating capsules — agents.

Figure 1a presents an example of a traditional approach – an evolutionary decision system that uses a fuzzy rule base and inference machine. Each individual represents here a rule (or a group of them), the evolving population – a knowledge base that refines itself to give the sought-after result of inference. Everything may be encapsulated in a single agent utilising this hybrid mechanism to better adapt to the environment it lives in.

An evolutionary multi-agent system (EMAS) depicted in figure 1b can be regarded as a next step of complication. Here evolutionary processes work at a population level – agents are able to reproduce (generate new agents) and may die (be eliminated from the system) on the base of adequately combined evolutionary operators. Evaluation of agents behaviour and selection mechanisms lead to arising the best fitted population with respect to the goal of the system. The result is formed as a simple composition of results obtained by particular agents. The architecture of EMAS is homogeneous, which means that agents are identical in the sense of an algorithm and built-in actions.

So described EMAS may be considered a new soft computing technique for problems that are being solved by searching some space for elements of the given features. Population of agents is assigned as a means for the search there. Let us investigate what opportunities are hidden behind the proposed approach:

- local selection allows for intensive exploration of the search space, like in parallel evolutionary algorithms,
- the way phenotype (behaviour of an agent) is developed from genotype (inherited information) depends on its interaction with the environment,
- the behaviour of agents can be dictated by their various internal mechanisms uniform or not across the population,
- self-management of the population (with respect to the size or other indexes) is applicable if appropriate selection mechanisms are used,
- the appropriately defined environment should facilitate effective implementation of EMAS based on a distributed computer architecture.

The highest level of complication is exemplified in figure 1c. Agents are heterogeneous in this case. Some of them may use a neural network, others – evolutionary algorithm etc. The global goal is attained as a consequence of negotiation among the agents. Variety of techniques and protocols can be applied for that purpose. It can be said that this kind of systems closely approaches typical multi-agent ones operating in the network environment.

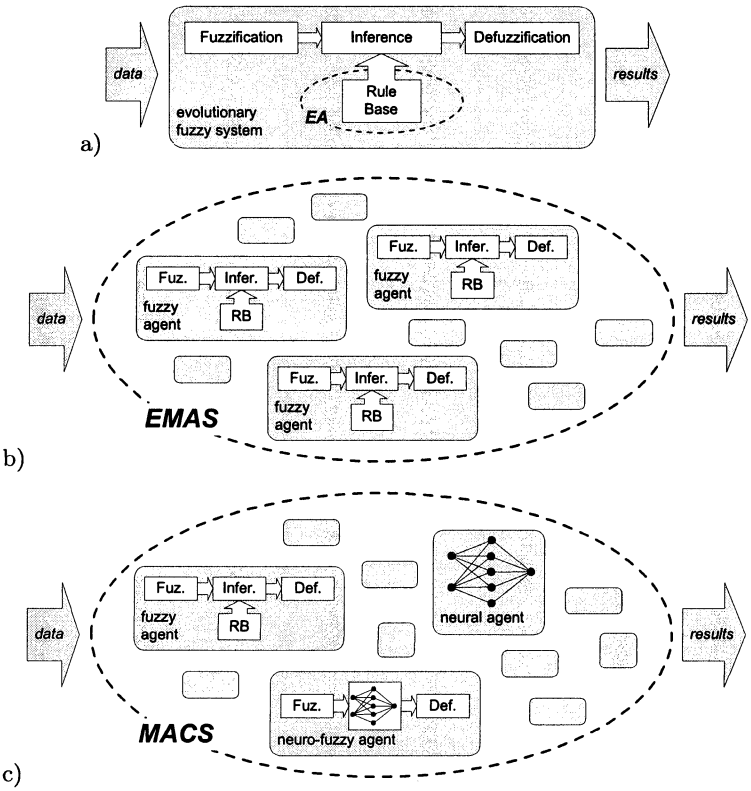

Fig. 1. Architectures of CI systems: a hybrid system in a single agent (a), a population of homogenous agents (b), a population of heterogeneous agents (c)

The terse description of the idea of computational intelligence using as a warp the multi-agent paradigm is attempted to be clarified in the next sections. They include descriptions of three systems developed that can be located somehow in the considered sequence of architectures.

3 EMAS for multiobjective optimisation

The particular EMAS should search for a set of points which constitute the approximation of the Pareto frontier for a given multicriteria optimisation problem [5]. The population of agents represents feasible solutions to the problem defined by a system of objective functions. Energetic reward/punishment mechanism prefers non-dominated agents via *domination principle* forcing dominated agents to give a fixed amount of their energy to the encountered dominants. This may happen when two agents communicate with each other and this way obtain the information about their quality. The flow of energy connected with the *domination principle* causes that dominating agents are more likely to reproduce whereas dominated ones are more likely to die.

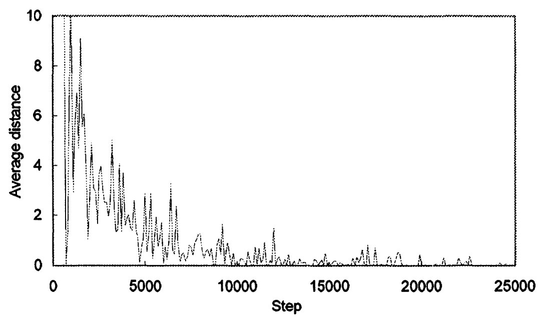

Fig. 2. Dynamics of successive approximations of the Pareto frontier

Dynamics of successive approximations of the Pareto frontier $\mathcal{P}(t)$ in time intervals Δt for a selected test problem [5] is presented in fig. 2. The dynamics is characterised in terms of convergence rate defined as an average distance of new non-dominated solutions $x \in \mathcal{P}(t + \Delta t)$ from previous approximation $\mathcal{P}(t)$.

4 Fuzzy EMAS for data classification

The goal of this particular system is data classification, which means that it should assign membership classes to supplied data sets – vectors of attributes, possibly describing some domain-specific objects, events or phenomena. Of course before the system is able to give correct answers it should be given a

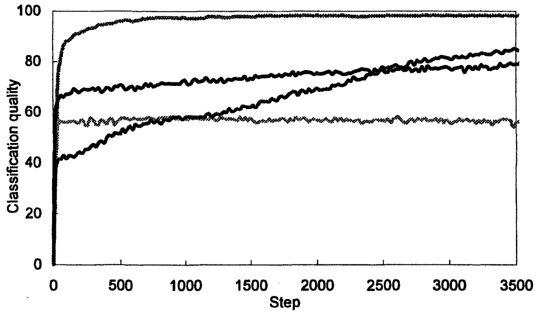

Fig. 3. Classification quality during learning phase for four data sets

representative set of examples: selected vectors of attributes with appropriate class membership assigned. The system consists of two kinds of agents, namely *classifier* and *supervisor* agents [7]. Classifier agents consist of one or more fuzzy classifiers and carry out the classification of incoming data. Supervisor agents are responsible for distributing the data, collecting answers of classifier agents, and generating the whole system's response.

Data sets used in the tests [7] are available from *UCI Machine Learning Repository*. Figure 3 shows the system's classification quality during learning phase. One may notice that for most data sets the systems learns quite quickly, but for some of them a longer learning phase is needed.

5 Neural EMAS for time-series prediction

In this case the goal of the system is *prediction* (or *forecasting*), i.e. generation of information about possible future development of some process from data about its past and present behaviour. Subsequent elements of the sequence(s) to be predicted are supplied to the system, where they become available for all agents. Agents perform analysis of incoming data and give predictions of the next-to-come elements of input. To model the characteristics of a signal agents use artificial neural networks [6] – in the particular case multi-layer perceptrons, which are supervisory trained using the comparison between values predicted and received as an error measure. The networks are also a subject of generational evolutionary optimisation [2].

Figure 4 shows the results of experiments [2] with weather data from the Biological Station Mountain Lake (University of Virginia), namely the temperature measured at about 2.5 m above the ground every 30 minutes during 7 years. In the first plot the prediction error in consecutive steps of the system activity is presented – one may notice that it is mostly below 10%, which is not a bad result considering complexity of the time-series. In the second plot the number of hidden neurons in all networks in the system (mean and standard deviation) is also presented.

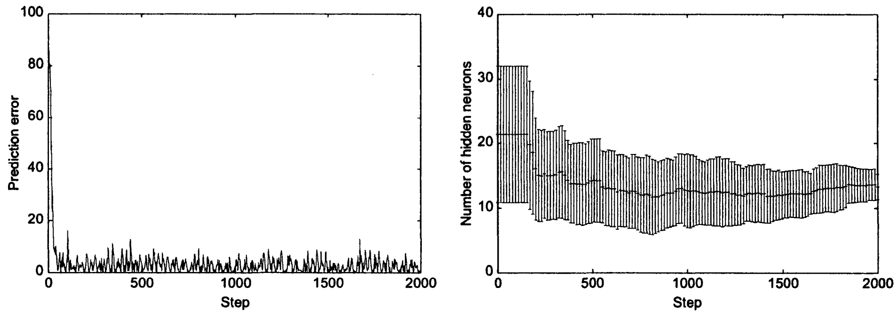

Fig. 4. Weather time-series prediction error and average number of hidden neurons

6 Concluding remarks

The idea of building computational intelligence using the framework of multi-agent systems together with strong suggestion of awaited benefit is presented in the paper. It is justified by two facts:

- results of agent technology (theoretical foundation, methods of design and specification, even some programming tools) can be utilised,
- some systems of the discussed type has been already built and tested and seem to be promising.

The most complicated (heterogeneous) architectures are now the subject of the studies. The main question is whether similar results can be obtained on the basis of simpler architectures — this requires extended simulation experiments for a representative set of test cases.

References

1. P. Bonissone. Soft computing: the convergence of emerging reasoning technologies. *Soft Computing*, 1(1):6–18, 1997.
2. A. Byrski, M. Kisiel-Dorohinicki, and E. Nawarecki. Agent-based evolution of neural network architecture. In M. Hamza, editor, *Proc. of the IASTED Int. Symp.: Applied Informatics*. IASTED/ACTA Press, 2002.
3. G. Dobrowolski, M. Kisiel-Dorohinicki, and E. Nawarecki. Some approach to design and realisation of mass multi-agent systems. In R. Schaefer and S. Sędziwy, editors, *Advances in Multi-Agent Systems*. Jagiellonian University, 2001.
4. J. Ferber. *Multi-Agent Systems. An Introduction to Distributed Artificial Intelligence*. Addison-Wesley, 1999.
5. M. Kisiel-Dorohinicki, G. Dobrowolski, and E. Nawarecki. Evolutionary multi-agent system in multiobjective optimisation. In M. Hamza, editor, *Proc. of the IASTED Int. Symp.: Applied Informatics*. IASTED/ACTA Press, 2001.
6. T. Masters. *Neural, Novel and Hybrid Algorithms for Time Series Prediction*. John Wiley and Sons, 1995.
7. A. Niemiec, R. Pajak, and M. Kisiel-Dorohinicki. Agent-based fuzzy classifier system. Accepted for publication in *Intelligent Information Systems XI – Proc. of IIS 2002 Conference*.