Applications of Artificial Intelligence

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The paper will introduce methods of artificial intelligence, mainly softcomputing tools for optimization like evolutionary techniques and symbolic regression or neural networks for classification problems. Also difference between evolution and metaevolution is mentioned. The paper will then present applications and their results from all these fields, which have been developed at our department.

Introduction

Artificial intelligence is not only about “clever” machines, humanoids or robots communicating with us in a common language. Artificial intelligence has also a field which is called softcomputing. This is the field where huge computations are done every day in different domains of human activities. Main part of softcomputing is focused on optimization tasks but there are also applications like classification or pattern recognition.

Optimization is one of these words, which are used every day in almost all fields of human activities. Everybody wants to maximize profit and minimize cost. This means optimizing in every task of industry, transportation, medicine, everywhere. For these purposes, we need to have suitable tools, which are able to solve very difficult and complicated problems. As previous years proved, use of artificial intelligence and soft computing contribute to improvements in a lot of activities. One of such tools of soft computing are evolutionary algorithms [1].

Evolutionary algorithms are a group of algorithms, which use their special operators as mutation, crossover and others to find an ideal solution. Possible candidates are defined by a cost function which arguments are values of each solution. The best one is in the global extreme – maximum or minimum [1].

These evolutionary algorithms have been known for decades and live through the advancement from the weaker ones to more robust ones, which are used

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with success in a lot of tasks nowadays. Since their first appearance there is quite long queue of representatives: Genetic Algorithms [2], Differential Evolution [3], Self-Organizing Migrating Algorithm [4], Particle Swarm Intelligence [], Ant Colony Optimization [], Artificial Immune system [7]. In optimization, algorithms belong also to some stochastic and deterministic ones: Hill Climbing [8], Simulated Annealing [9], Monte Carlo and a lot of others or their mutations [1].

These techniques promise fast optimization compared to classical mathematical approach. On the other hand, also between these optimization techniques is possible to find better and worse. Their behaviour was described in a lot of references. And the research in this area is still full of white places. There is wide field of possible applications as tuning of parameters, making of comparisons, trying to find new ones somehow.

There exist special tools, which are connected with evolutionary algorithms and are able to work with symbolic regression. Nowadays, mainly three are known for that – Genetic Programming [10] - [12], Grammatical Evolution [13] - [15] and superstructure of evolutionary algorithms – Analytic Programming [16] - [24]. These techniques can produce a complex formula from basic functions according to required behaviour of function in the case of mathematical data set, of an electronic circuit, trajectory of robots, etc.

Also, some other approaches to the field of symbolic regression can be found – either based only on evolutionary techniques or hybrid ones. Interesting investigations using symbolic regression were showed by Johnson [25] working on Artificial Immune Systems and Salustowicz in Probabilistic Incremental Program Evolution (PIPE) [26] which generates programs from an adaptive probability distribution over all possible programs. To Grammatical Evolution foreruns GADS, which solves the approach to grammar [27], [28]. Also from evolutionary algorithm artificial immune systems evolved the artificial immune system programming for symbolic regression [29]. Approaches which differ in representation and grammar are described in gene expression programming [30], multiexpression programming [31], meta-modelling by symbolic regression and pareto Simulated Annealing [32]. To the group of hybrid approaches, it belongs mainly numerical methods connected with evolutionary systems, e.g. [33].

To softcomputing also neural networks belong. These techniques are suitable for pattern recognition, classification, recovering of noisy data however in optimization tasks too [34] - [36].

Applications and their results

Data Approximation

Simulations with regression were carried out on four selected problems – Quintic, Sextic, ThreeSine and FourSine problems [37]. These problems were selected from Koza's Genetic Programming [10] to compare these two methods. The aim was to find a suitable mathematical formula which fits measured data (generated from the defined functions) as well as possible.

The following equations and figures show the four problems mentioned above in a practical way. Equations (1) - (4) are for Quintic, Sextic, Three Sine and Four Sine problems. The corresponding figures are given in Figure 1.

$$x^5 - 2x^3 + x \tag{1}$$

$$x^6 - 2x^4 + x^2 \tag{2}$$

$$\mathrm{Sin}(x) + \mathrm{Sin}(2x) + \mathrm{Sin}(3x) \tag{3}$$

$$\mathrm{Sin}(x) + \mathrm{Sin}(2x) + \mathrm{Sin}(3x) + \mathrm{Sin}(4x) \tag{4}$$

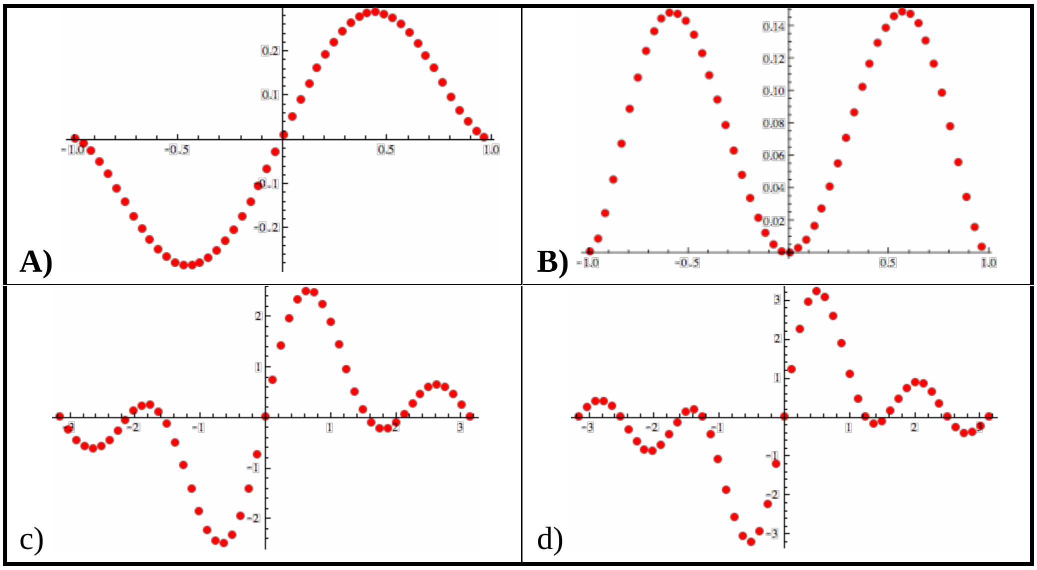

Figure 1: Four problems – a) Quintic, b) Sextic polynomial in the interval [-1.0, +1.0],
c) Three Sine, d) Four Sine problem in the interval [-π, +π]

Figure 2 shows examples of all 50 simulations in one picture for SOMA algorithm simulations. The nonlinearities in figures c) and d) are caused by measurement in some points not in the interval continuously. As can be seen such tool is suitable for this kind of problems very effectively.

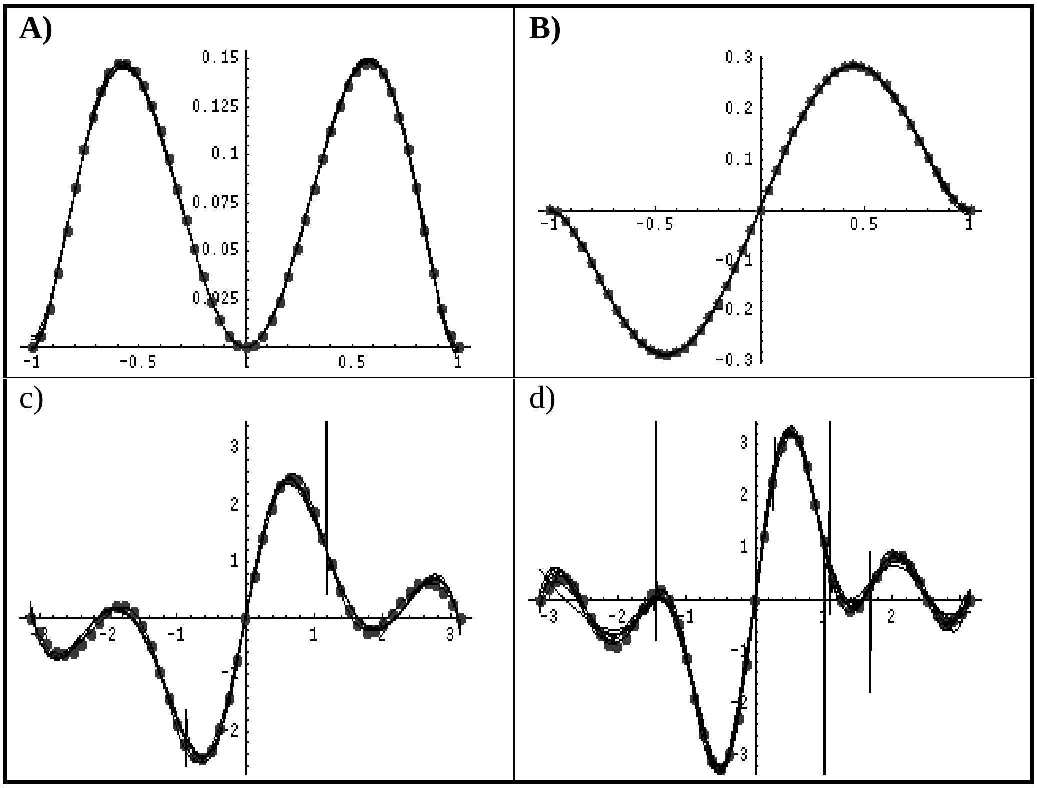

Figure 2: Examples of results – a) Quintic, b) Sextic polynomial, c) Three Sine, d) Four Sine problem for SOMA algorithm

Santa Fe trail for an artificial ant

This task was used to prove that AP is able to work also with linguistic terms which in real words means some commands for robot like move straight-forwardly, turn left, turn right, look before and find what is there, etc. [21], [22]. To try to see, if it works, we chose a task Santa Fe Trail for artificial ant from Koza's Genetic Programming [10]. Such task is possible to replace by a robot in a real world in industry, space, etc.

The problem was designed so that an artificial ant should go through a defined trail (Figure 3) and eat all the food that was there. The trail was set up as 31 x 32 fields where black field means food, grey and white is basically the same, i.e. there is nothing. But the grey colour was used to highlight the problems on the way for the ant which are e.g.:

– one simple hole (position [8,27] in Figure 3)

– two holes in the line (positions [13,16] and [13,17])
– three holes ([17,15], [17,16], [17,17])
– holes in the corners
  - one hole (position [13,8]]
  - two holes ([1,8],[2,8])
  - three holes ([17,15], [17,16], [17,17])

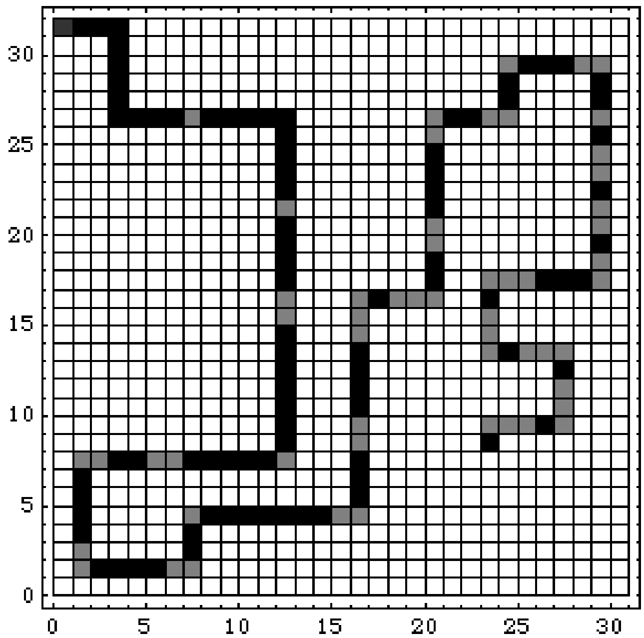

Figure 3: Santa Fe Trail for artificial ant

Simulations in [37] pointed out that usage of linguistic terms for AP is possible and works well. Even our solution by means of AP was carried out in a better way then GP, as less number of steps to clear all „food“ was reached.

Evolution and/or metaevolution

This part can be demonstrated on one study case with two approaches. The study case comes from the field of deterministic chaos. Interests about deterministic chaos increase day by day. To control these kind of systems is not easy and specialists look for the way of effective control tool every day. One possibility is to use some classical optimization techniques but we have used evolutionary techniques for faster and better optimization [38]. Used chaotic systems were Logistic equation, Hénon map and others.

The logistic equation (logistic map) is a one-dimensional discrete-time example of how complex chaotic behaviour can arise from very simple non-linear dynamical equation. This chaotic system was introduced and popularized by the biologist Robert May [39]. It was originally introduced as a demographic model as a typical predator – prey relationship. The chaotic behaviour can be observed by varying the parameter *r*. At $r = 3.57$ is the beginning of chaos, at the end of the period-doubling behaviour. At $r > 3.57$ the system exhibits chaotic behaviour. The example of this behavior can be clearly seen from bifurcation diagram – Figure 4.

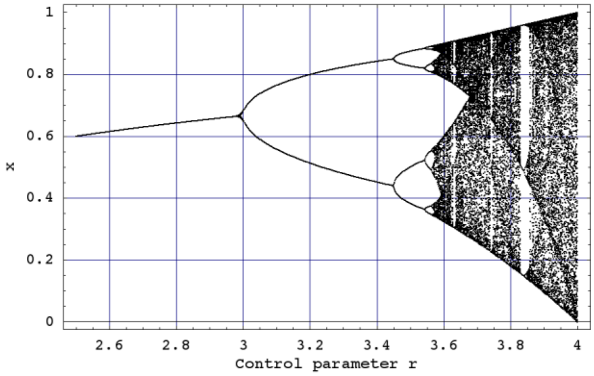

Figure 4. Bifurcation diagram of Logistic equation

Evolutionary techniques were used in all above-mentioned chaotic systems for optimization of parameters, which can be accessed from Pyragas method: Extended delay feedback control – ETDAS [38].

There exist also another approach – not only to use a predefined control law and to find suitable coefficients but also to synthesize the whole control rule including the values of coefficients [140] - [42] in a similar way, as in the case of data approximation described above. Therefore the second evolutionary algorithm was used for coefficients estimation, this method is called metaevolution [37].

Examples of synthesized solution are given in following notations (5 -6) and a stabilized system for 1-orbit for the logistic equation is depicted in Figure .

without Ks estimation

$$F_n = (K_1 + K_2) * (x_{n-1} - x_n + \frac{x_{n-1} - x_n}{1 + x_{n-1}}) \qquad (5)$$

with Ks estimation

$$F_n = -0.377047 * (x_{n-1} - x_n + \frac{x_{n-1} - x_n}{1 + x_{n-1}}) \qquad (6)$$

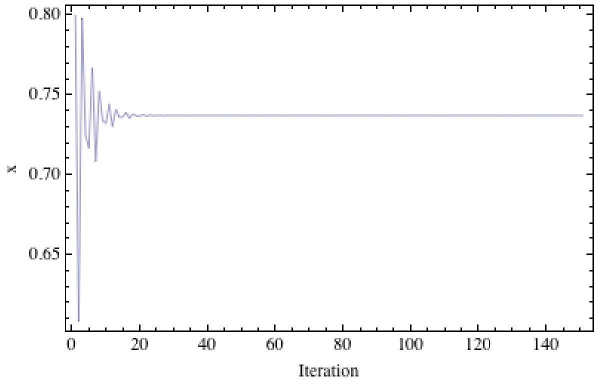

Figure 5: Example of a stabilized system for 1p-orbit

Steganalysis by means of neural networks

Steganalysis is connected with information security. Mainly in companies, information security is a very spoken problem nowadays. All employers have to pay attention to their employees if company secrets and know-how are not spread out of the company. One of the possibilities how to leak the information is to use a steganography [43]. Steganography [43] and cryptography [44] are connected together more or less. Cryptography is strong in the usage of the key and the message is somehow coded. But if it is sent unsecure, attacker will notice it very soon and will try to break it. Therefore steganography helps with secure transfer of secret messages. It codes a message inside the picture or other multimedia files which can be sent e.g. via emails. If you see such a picture, normally you do not recognize that there is a secret message. And this is the point. Crackers will go through and will not give the attention to the message.

Therefore to have a detector of steganography content in the multimedia files is very important. To reveal a steganography content is called steganalysis, i.e. a detection of files with hidden information of without hidden information, which was inserted by means of steganography.

Neural works need some numerical value for its run so Huffman coding was used for extracting useful information which helps to classify images with a hidden information from the cover (clear ones) [45] - [48].

It is not easy to recognize by human eyes the change caused by inserted message as can be seen in Figure 5. Our method was successful and on selected steganographic tools the results of testing (images which neural network has not seen before) finished with almost 100% (Tab. 1).

Figure 5. Example of images a) without and b) with inserted message

Tab. 1: Example of results for steganalysis by means of neural networks

	A	B	**C**
Cover (x = 4068)	0	0	**100**
Stego OutGuess (x = 3644)	0	0	**100**
Stego Steghide (x = 9933)	0	0	**100**
Stego F5 (x = 2709)	0	0	**100**

Conclusion

This paper presents introduction into softcomputing methods - evolutionary algorithms, symbolic regression and neural networks. Presented applications demonstrate different fields of usage of these techniques. One of application examples is also description of differences between evolutionary and metaevolutionary approach. Applications mentioned here are only a small part of simulations and tasks performed out at our department in this field of research. As described, these techniques have a wide range of possibilities of application.

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