Antilock Braking System Fuzzy Controller Optimization with a Genetic Algorithm in a Form of Cellular Automaton

Alexey Fedin, Yaroslav Kalinin and Evgeniy Marchuk

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Alexey P. Fedin
Department of Technical Maintenance and Repair of Automobiles
Volgograd State Technical University
Volgograd, Russia
0000-0003-0495-0516

Yaroslav V. Kalinin
Department of Applied Mathematics
Volgograd State Technical University
Volgograd, Russia
0000-0001-6068-0886

Evgeniy A. Marchuk
Department of Theoretical Mechanics
Volgograd State Technical University
Volgograd, Russia
0000-0002-3758-9643

***Abstract* — This paper is devoted to the issue of efficient and intuitive visualization of optimization processes. The problem is considered on the example of ground wheeled vehicle antilock braking system fuzzy control element optimization using a genetic algorithm in the form of a cellular automaton.**

Keywords* — *braking, fuzzy control, optimization, genetic algorithm, cellular automaton

I. Introduction

Antilock braking system can be considered as a classic example of the use of various methods of automatic control which are described in popular works, e.g. [1], [2], [3]. At the same time, the process of improving the antilock braking system is an urgent task in the automotive industry [4], [5], [6]. Throughout the entire period of existence of antilock braking systems, both methods of automatic control of these systems and methods of optimization of the designated systems have been improved. In previous works the authors considered the possibility of implementing antilock braking control system in the form of artificial neural network (ANN) [7], [8]. The optimization process was considered in a setting of antagonistic differential game [8]. In this paper the autors propose the implementation of the control element of antilock braking system in the form of a fuzzy controller. The optimization process is proposed to be implemented using a genetic algorithm (GA) in the form of a cellular automaton. The choice of a fuzzy controller is justified by the relative ease of intuitive perception of the modeling process. The choice of a cellular automaton is justified by the relative ease of intuitive perception and clarity of the optimization process, which is undoubtedly useful.

II. Antilock Braking Systems

Antilock braking system is one of the most important elements of the active safety system of wheeled vehicles. The main aim of the antilock braking system is to keep the steerability of a vehicle in a braking mode, especially emergency braking. In the context of this research, the main focus is on the development of a control element for the distribution of braking forces of antilock braking system. In general, the system of distribution of brake efforts is used not only in the work of antilock braking system, but also for traction control and stability systems. The principle of operation of the antilock system is as follows. The mathematical model of antilock braking system uses the concepts of wheel slip coefficient and wheel friction coefficient [9]. There are various formulations of the functional dependency of the wheel friction coefficient on the wheel slip coefficient [10], [11]. It is experimentally and analytically established that the maximum value of the functional dependency of the wheel friction coefficient for various road surfaces is located nearly of the value 0.2 of the wheel slip coefficient function argument [12]. Based on the data of wheel angular velocity sensors, the electronic control unit (ECU) distributes the braking forces to each wheel in such a way as to achieve the desired value of the wheel slip coefficient. At the same time, on the one hand, due to the nonlinear nature of the transient response of transformation of rolling friction into braking friction, and on the other hand, due to the non-linearity of the processes of operation of the executive elements of the braking system, the characteristics of the model acquire a pronounced non-linearity. In addition, it is necessary to take into account the influence of uncertainty arising from various factors: noise and errors of sensor data, heterogeneity of the road surface, hydraulic system delays, etc. As mentioned above, the antilock braking system is a classic example in descriptions of the use of various automatic control methods. Free accessed descriptions of the principles of operation of the antilock braking control system are methods based on PID control [13], optimal [13], adaptive [13], [14], robust [15], fuzzy [16], [17] intelligent [18], [19] and various combinations of these methods [13], [15], [19], [20]. As a rule, these simplified models are used usually neglect all the real factors. Thus, implementing an adequate mathematical model of antilock braking system and control element becomes a non-trivial task.

III. Fuzzy Controllers

Since this study originally announced the use of a fuzzy control element, let's look at the principles of fuzzy control in more details. Fuzzy control is based on the principles of fuzzy logic by Lotfi Zadeh [21], [22]. The principles of fuzzy logic determine the degree of belonging of an object to a fuzzy set. The concept of linguistic variables is introduced. At the first stage, input data is fuzzified, then data is processed with the connection of the knowledge base, then aggregation is performed, and at the final stage, output data is defuzzified. The most famous algorithms are Mamdani [23] and Sugeno [24], and there are other algorithms for logical inference in fuzzy systems [25], [26], [27]. Various models of fuzzy controllers are known, both SISO and MIMO. Kosko's research has shown that fuzzy systems can be used as universal approximators [28]. Further development of fuzzy set theory has led to the possibility of identifying fuzzy systems with artificial neural networks [29], [30], [31]. Fuzzy systems have become capable of

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learning and storing information [32]. Fuzzy methods are well and appropriate to apply in cases where the creation of a strict mathematical model is impossible either due to the complexity of the described process, or due to the presence of uncertainties. Fuzzy control is successfully applied in complex economic, social, and technical models. Fuzzy control and modeling are discussed in detail by Piegat [25] and Wang [26]. An approach that takes into account both fuzzy and stochastic processes is described by Bellman, Zade [33]. The theory of fuzzy control in matrix form is described by Tanaka, Wang [34]. Engineering problems formalized in fuzzy logic are discussed by Ross [35], [36]. There are known examples of fuzzy control systems used in serial models of japanese cars [37], [38], [39], including antilock braking system controllers.

IV. Genetic Algorithms

Note that fuzzy systems, artificial neural networks, and genetic algorithms interact closely both in terms of theoretical development and in problems of an applied nature. Genetic algorithms belong to the field of evolutionary modeling theory. The very idea of GA was developed by Holland [40], among later significant works we will mention the authors [41], [59]. The principles of GA are based on comparing models to natural processes of evolution and selection. Concepts similar to the terms of genetics are introduced: genes, chromosomes, genotype, phenotype, crossover, mutation, etc. GA do not process the values of the parameters of the problem itself, but their encoded form. At the first stage, the initial population of chromosomes is selected, then the parents are selected, then genetic operators are applied (for example, crosses and mutations), and at the final stage, the best chromosome is selected (the most appropriate for the specified criteria). GA are well suited for solving a wide class of optimization problems. The main differences between GA and traditional optimization methods are that they operate with the encoded form of the problem parameters and search for a solution based not on a single value, but on a certain set (population). In addition, GA use probabilistic selection rules not deterministic ones, and use the objective function itself not the derivatives [27]. As a rule, GA solve optimization problems for a single criterion. However, they can also be successfully applied to multi-criteria optimization problems. In this case, the solution is chosen not as a single chromosome, but as a set of chromosomes that are optimal in the sense of Pareto. GA are widely used for solving optimization problems, searching for solutions in artificial intelligence systems, artificial neural network systems, fuzzy systems, etc [42], [43]. Examples of practical use of GA are given in [49]. A description of fuzzy controllers of antilock braking systems using GA in optimization processes can be found in [44], [45].

V. Cellular Automata

The ideas of cellular automata were independently developed by J. fon Neumann [46] and K. Zuse [47]. Cellular automata were understood as a universal computing environment for constructing, analyzing and comparing the characteristics of algorithms, in some way equivalent to a Turing machine [48]. The principles of operation of cellular automata can be described by the example of a space represented as a uniform grid, in which time passes in discrete steps, and each cell contains some information and at each step determines its new state depending on the state of neighboring cells. There are well-known the "Life" type automata whose principles were proposed by J. H. Conway [50]. Thus, cellular automata are discrete dynamical systems whose behavior is completely defined in terms of local dependencies [51]. Here we can draw an analogy with continuous dynamical systems defined by partial differential equations. We can say that the concepts of cellular automata in computer science are analogous to the concept of fields in physics. Cellular automata are widely used in modeling physical, biological, social, economic, and other processes [52], [53], [54]. The theory of cellular automata in application to GA is described in the works of Schiff [59], and others. There are a number of papers describing the construction of models of various processes using GA in the form of cellular automata [55], [56].

VI. Fuzzy Controller Design and Model

Next, we will consider an example of optimization using GA in the form of cellular automaton for a model of a fuzzy PID-type Sugeno controller for the distribution of braking forces of a wheeled vehicle. We will enter the observer model into the automatic control system and use the value of the deviation of the slip coefficient from the target value as an input parameter. The control law can be written as:

$$u_c(t) = \begin{cases} u = F_p\big(e(t)\big) + F_i\left(\int e(t)dt\right) + F_d\left(\frac{de(t)}{dt}\right), \\ u < P_{max} \\ P_{max}, \\ u \geq P_{max} \\ 0, \\ e(t) \leq 0 \end{cases}$$

where P_{max} – maximum value of a brake pressure; F_p, F_i, F_d – configured functions of fuzzy control; $e(t)$ – a deviation.

Genetic algorithms allow you to adjust most fuzzy models. In the context of a genetic algorithm, the range of each variable is considered as a space divided into a finite number of intervals. Let's look at one of the encoding methods. If the interval contains the maximum of the membership function, it is coded with number 1, otherwise – 0. Encoded string, suitable membership functions for one variable will be the chromosome (10110001011), and its elements (0 and 1) genes. An example of encoding the membership functions of a deviation in the form of a chromosome is shown in figure 1.

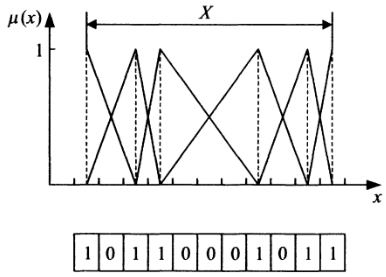

Figure 1 – An example of chromosome of fuzzy model

In the case of MIMO, all input and output parameters of the model are subject to genetic encoding. So, to increase the adequacy of the proposed antilock braking system fuzzy controller to the real process you can add a second input parameter, for example, a time derivative of the deviation. In this case the genetic representation of the fuzzy MISO model takes the form shown in figure 2.

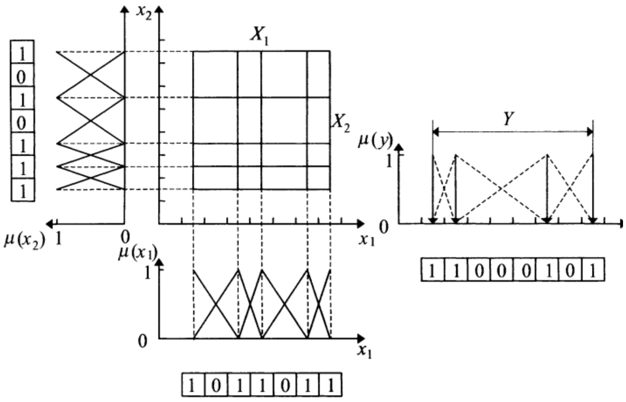

Figure 2 – An example of chromosomes of fuzzy model with two inputs and one output

It should be taken into account that an increase in the number of genes (i.e., the intervals that make up the chromosome) leads to an increase in the resolution of the search for the optimal solution. However, higher resolution leads to a fast increase in the number of potential solutions (combinatorial explosion) [25]. Genetic operations are applied to generations of populations until the degree of fitness of the resulting representation meets the specified requirements. In case of the fuzzy controller sample under consideration the specified requirements can be determined, for example, by minimizing the step response, minimal overshoot, etc.

VII. Cellular Automaton Model

Now let's look at the visualization of a genetic algorithms for optimizing a fuzzy controller for the distribution of braking forces in the form of a cellular automaton. In general, visualization of the optimization process is possible in a variety of ways to represent cellular automata. In this case we will not use one-dimensional automata due to their simplicity and dimensions greater than two due to their complexity. Let's imagine the model in the form of a two-dimensional cellular automaton. To determine the cell among neighbors we use the Moore model. The implementation of GA model in the form of a cellular automaton is carried out with the Matlab software, figure 3. As we can see from simulations, the ordering of chaos begins to become noticeable after several thousand iterations. In general, strictly speaking, on the one hand, the initial chaotic state in this optimization model is human-made, i.e. artificial. However, on the other hand, evaluating the uniqueness of the human-made fuzzy model, we can still talk about some of its natural chaotic nature. Here, you should also consider the probabilistic principles of GA, which also imply a chaotic process. Cellular automata are a kind of unique representation of dynamic processes. Cellular automata are most effective to observe in dynamics, because photos, while preserving the specific beauty of the cellular automaton, do not convey the full effect to the viewer. Working with cellular automata and understanding them undoubtedly contributes to understanding the phenomena of chaos in complex systems.

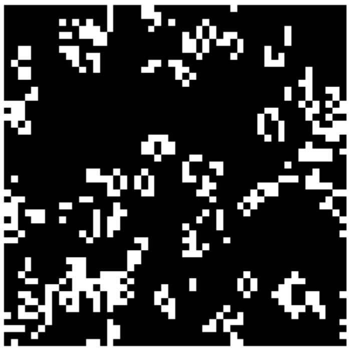

Figure 3 – Cellular automaton simulation

The authors believe that the design of a genetic algorithm in the form of a cellular automaton is one of the best examples of visualization of fuzzy controller optimization processes.

VIII. Summary

In the process of visualization of braking forces distribution fuzzy controller optimization described above, the transition from the initial chaotic state to organized chaos is presented. Cellular automata make a significant contribution to the understanding of complex systems. As professor T. Toffoli noted in his preface to the book by editors Hoekstra, Kroc, and Sloot [60], models of systems based on cellular automata are basically a conceptual tool for cognition.

The further direction of research is seemed to work on the representation of a neurofuzzy controller for the distribution of braking forces in the form of a cellular automaton. It is also interesting to consider the stability and appearance of chimera states [57], [58] for ANNs of braking forces distribution controllers. In area of particular interest is also consideration of optimization process in the form of antagonistic differential game for the visualization of a cellular automaton.

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