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Implementation of cognitive perception functions in fuzzy situational control model

Anatolii Kargin[a,*], Sergej Panchenko[a], Aleksejs Vasiljevs[b], Tetyana Petrenko[a]

[a]*Ukrainian State University of Railway Transport, Feierbakh Square 7, 61050, Kharkiv, Ukraine*
[b]*Transport Institute of Riga Technical University, Azenes Street 12-316, Riga, LV–1048, Latvia*

Abstract

In autonomous transport systems, it is useful to be able to continue interrupted traffic after removing the obstacle that caused deviations from the route. This article describes a control model in which cognitive functions, such as context and attention are embedded. The fuzzy situational control model of an autonomously moving machine along a route with obstacles is expanded by tracking context and switching attention mechanisms. Additionally, it describes a knowledge representation about the route, the surrounding space and how to avoid collisions with obstacles.

Keywords: Cognitive robotics; Fuzzy situational control; Context; Attention; Autonomously moving machine

1. Introduction

In the era of the fourth digital revolution, many industrial automation solutions are based on the concepts of the Internet of Things (IoT) and Smart Machines (SM) [1,2]. The implementation plan for the strategic development of the railway industry [3], as one of the leaders in the implementation of Industry 4.0 technologies, involves a wide range of digital solutions based on the concept of SM. These are intelligent trains, smart railway coach, telepresence robots and others. Leading automotive companies are working to create and improve smart cars [4]. Many tasks in different industrial areas are assigned to wheeled robots [5]. A common task for all the listed applications is

* Corresponding author. Tel.: +38-050-478-9421.
E-mail address: panchenko@kart.edu.ua

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Autonomous Moving Machines (AMM) movement control along a given route. There are two possible approaches to the creation of such systems. The first is the preliminary ordering of the environment in which the AMM operates, and the second approach is the creating intelligent control systems that support the task performance when various obstacles appear. The first approach is used in mass production systems, in the processes of servicing automated warehouses and conveyor lines, for example, in the delivery of production parts to workplaces. The second approach is preferable when, in automation projects, the costs of streamlining the environment are significant or put in order the environment is completely impossible due to the peculiarities of the AMM application. For example, the safe passage of a crossroad with heavy traffic or pedestrian crossing by an AMM cannot be ensured only by streamlining the environment. For such applications, the AMM should have the intelligence sufficient to solve the problem of avoiding collision with it [6,7,8]. The intellectualization of the AMM application considered in the article is based on information perception models. Embedded cognitive systems and cognitive robots [9,10] is a form of implementation of such systems. In cognitive robotics, in contrast to traditional methods of artificial intelligence, robotic capabilities necessarily include input data processing based on such cognitive models as perception, attention, and context. Intellectual AMM (IAMM) based on the perception model was proposed in [11,12]. In this paper, on the basis of a generalized representation of the robot environment model, it is possible with the help of fuzzy rules to form control reactions for previously unfamiliar situations. However, the problem of organization rules for making control decisions in accordance with the route description remains unresolved, which limits the ability to control the movements of the robot as it receives data from sensors about the route features. The purpose of this article is to introduce into the above-mentioned model of generalized perception of data from sensors the mechanisms of context and attention borrowed from cognitive psychology and cognitive sciences [13,14]; to investigate the possibility of the IAMM control system in the tasks of moving the robot along a given route in the conditions of obstacles.

2. Problem discussion

Information processing in cognitive robotics is divided into three main tasks [15]. Perception is data from sensors mapping into internal structures that comprehensively represent the situation in which the IAMM is located. Planning movements of the IAMM is the second task and the third is the implementation of movements, which is the direct task of control. Today, the following concepts of information processing in robotics are known: rigid program control; program control with feedback; reflexive or reactive control [15,16]. Consider these approaches as a basis to implementing the concept of uniform knowledge-oriented model for all stages of information processing. Let the robot must to follow one of the routes passing through the nodal points A_1, A_2, A_3, A_4 shown in Fig. 1(a). An Ultrasonic Sensor (US), which is mounted on a turntable, gives the IAMM information about obstacles in any of the four directions around it. An example is being considered with a limited set of control commands: *forward*, *right*, *left*. IAMM constant movement speed is a prerequisite for using the rigid program control concept. Based on this assumption, the required time to move the IAMM between adjacent node points, for example, A_1 and A_2 is calculated. It indicated as $t_{A_1A_2}$, see Fig. 1. The IAMM moving plan in the form of a rigid control program is shown in Fig. 1(b), where t_L and t_R are the times for the execution of turn commands to the left and right. The control program (Fig. 1(b)) will be considered as a model of knowledge representation about the IAMM movement plan. The rigid program control method is demanding on the preliminary environment ordering: compulsory initial conditions and strict requirements on the speed of movement and acceleration and deceleration modes. If the first requirement can be fulfilled with a certain organization, then the second is almost never satisfied. These limitations are removed in the method of program control with feedback. Here, to identify situations when the IAMM is in certain states, data from the sensors is used, and the values of time intervals are not used. Fig 1(c) shows the control program for the program control with feedback method similar in functionality to the program shown in Fig. 1(b). Data from the US about the distance to the obstacle is denoted by l. The command execution completing condition in a control program with feedback is specified on a data from sensors. The IAMM control system will form a *forward* command until the condition is met. In this form, the IAMM plan is not sensitive to variations in speed and acceleration, however, it is still intended to control in a well-ordered environment: the parameters are rigidly tied to the medium in which the IAMM moves. Cognitive robotics applications are focused primarily on disordered environments tasks under conditions of unforeseen interference and obstacles [9]. In this regard, both the above concepts of information processing in robotics can’t be used as a basic for supporting IAMM cognitive functions.

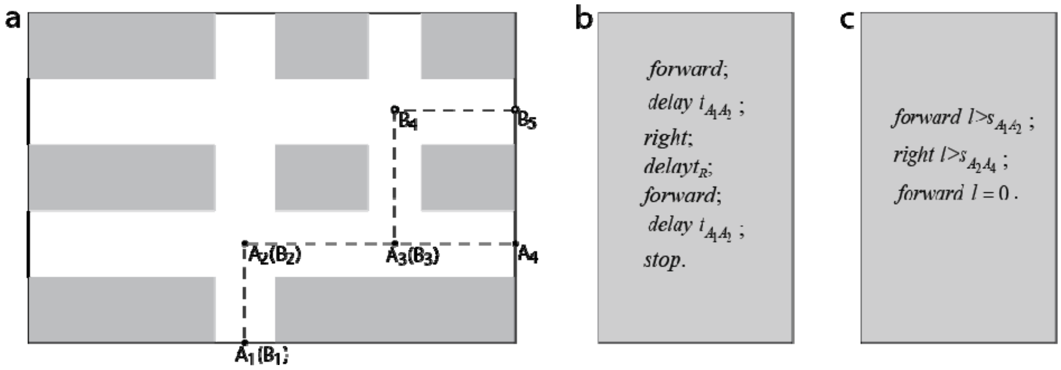

Fig. 1. (a) IAMM moving route; (b) rigid control program; (c) control program with feedback.

The concept of reflexive or reactive control is based on the assumption that the environmental model is initially unknown or only some of its general characteristics are known, which are not enough to preliminarily build a plan for achieving the goal and, moreover, how to implement it. Behavior is formed mainly on feedbacks from the medium [7,8]. The emergent behavior description in such applications of cognitive robotics and embedded cognitive systems is based on the concept of rule-based systems (RbS). For the example considered in the article, knowledge about route *A* (Fig. 1(a)) in a simplified form can be represented by an unordered set of rules (1):

$$
\begin{array}{lll}
R_1: & \textbf{\textit{if}}\ Route=A,\ Pos=A_1 & \textbf{\textit{then}}\ forward; \\
R_2: & \textbf{\textit{if}}\ Route=A,\ Pos=A_2 & \textbf{\textit{then}}\ right; \\
R_3: & \textbf{\textit{if}}\ Route=A,\ Pos=A_2,\ l_L=near,\ l_R=near,\ l_F=far & \textbf{\textit{then}}\ forward; \\
R_4: & \textbf{\textit{if}}\ Route=A,\ Pos=A_3 & \textbf{\textit{then}}\ forward; \\
R_5: & \textbf{\textit{if}}\ Route=A,\ Pos=A_4,\ l_L=near,\ l_R=near,\ l_F=near & \textbf{\textit{then}}\ stop.
\end{array}
\qquad (1)
$$

Knowledge in embedded RbS (ERbS) are represented by rules (1) and facts that describe the current situation based on data from sensors. In rules (1) in the *if* part, a prototype of a situation is described as a subset of facts: *Route=A* is a fact that describing route, $Pos = A_i$ is a fact that indicating the location of the IAMM, l_L, l_R, l_F are a fact that linguistic estimates the distance to the obstacle on the *left*, *right* and *forward* away from the IAMM, respectively. It is assumed that using the system of sensors, the IAMM receives information about its location and environment (distance to the obstacle). At the first perception stage of information processing in systems based on rules data from sensors are mapped into knowledge in the form of facts. At subsequent stages, on the basis of this knowledge, a control response is formed according to the rules (1). In the knowledge base (1) it is easy to introduce new rules. Thus, at the conceptual level, systems based on rules implement a homogeneous mechanism for representing and processing information at all three stages: perception, planning and motion control for IAMMs. However, the use of rule-based systems, including fuzzy ones, in the tasks of situational control encounters two problems. The first problem is related to the task dimension. In classical systems based on rules, it is necessary to fulfill the requirement of pairwise distinguishability of rules. This requires the introduction of new facts and rules with distinguishable combinations of facts in the *if* part [12]. In meeting this requirement, there is a duplication of rules that have the same meaning. Thus, the group of rules (1) must be supplemented with a similar set with the fact *Route = B* to introduce knowledge of the movement along route *B* (see Fig. 1(a)). The second problem is low resistance to various kinds of disturbances that violate the movement IAMM along the route. For example, in a regular situation, the rules R_1-R_5 in (1) must be consistently triggered in time for the IAMM to complete its task. However, if an obstacle appears on one of the route sections, forcing the IAMM to deviate from the route, then after the interference is eliminated, the IAMM will not be able to continue move along the route.

This article proposes to solve this problem with the help of two mechanisms: context and attention. To do this, fuzzy rules based situation control model encapsulates context tracking and attention switching mechanisms.

3. Event-based situational control model with tracking context and switching attention mechanisms

3.1. Conceptual model

The context in cognitive sciences is understood as the general meaning of a fragment of written or oral speech, which makes it possible to clarify the meaning of its individual words and sentences [13]. This paper discusses the context model in rule-based systems. In the ERbS model, the effect of context and attention is proposed due to the following. First, the actualization of facts that uniquely describe the route nodal point are carried out taking into account the current context and attention. Secondly, for each Route Nodal Point Fact (RNPF), enter one special fact-satellite (Satellite of Fact, SoF), the processing of which has the following features:

- SoF information processing is carried out only at that time moment when an event occurs (change in the characteristics of the own RNPF). Thus SoF status is not explicitly dependents on data from sensors. Only the above-mentioned events initiate a mechanism that explicitly actualizes or deactualizes a SoF
- The rule in which there is a SoF in the *then* part is activated by an event that occurred and described by corresponding RNPF

In the rule, a reference to an event that is generated by RNPF status changes, for example, $Pos = A$, will be denoted as *event* (A). In this case, the rules pairwise distinguishability requirement weakens and reduces to the requirement of dynamic distinguishability of the rules. Only those rules that are activated by the same event should be distinguished. The event processing mechanism significantly reduces the number of rules in the ERbS.

The context tracking mechanism is illustrated on Fig. 2. In the figure, the RNPFs are ordered according to the route. These facts are labeled A_i. The SoFs are beside RNPFs. They are labeled A_i^{Sat}, respectively. The context model is represented in dynamics. The actualized fact is depicted as a darkened circle, and the irrelevant fact is shown as a light one. The light background surrounding the facts highlights a subset of the facts that come into attention region. A darker ellipse covering a couple of facts points out the current position of the context region: the activation of these facts is facilitated by the activated context. The Fig. 2 shows the facts relevance distribution in time for six time moments. The Fig. 2 (a) shows the distribution at the initial moment before the IAMM began moving along the route. The Fig. 2 (b) shows at the time when the input data about the route number actualized attention. The Fig. 2(c) describes the situation when the data came from the system of sensors about the current position in space when the IAMM is located at the nodal point A_1, see Fig. 1(a).The Fig. 2(d) corresponds to the time point when the IAMM reached the next node point, about which data was obtained from sensors that activated the fact A_2.Activating the RNPF A_2 extends the context region to the A_2^{Sat}, which is depicted in the Fig. 2(e).The context region moves from the A_2^{Sat} to A_3^{Sat}, see Fig. 2(f). From this time point until reaching the next node point, in the absence of obstacle on the route, two facts will be updated. Fact A_2, the relevance of which is supported by data from sensors about the features of the A_2 and A_3^{Sat}, the relevance of which is supported by the context region, until the sub-goal A_3 is reached.

Thus, the essence of the dynamic context model is that a limited subset of facts, which is localized in the context region, for certain events that actualized by data from sensors of a RNPF, move along successively placed facts. The context region is supported in time by the SoF around which it is concentrated. The context region moving is triggered by an event, when data from sensors that describes the RNPF features is appear.

3.2. Knowledge representation

IAMM motion control along a given route with obstacles is based on knowledge. Knowledge is divided into three groups: knowledge of the route, knowledge of possible control reactions, knowledge of obstacle avoidance techniques.

At first describe knowledge of the route. Consider the route, for example, depicted by the dotted line in Fig. 1(a). The route passes through the nodal points A_1, A_2, A_3, A_4. In the IAMM knowledge base, each such point is assigned an RNPF, possibly a structured multilevel [12], describing the unique features of a nodal point. In the knowledge base for each RNPF there is a SoF. It is used to organize the logical processing of information: the current time points to the actual couple of facts (RNPF and SoF), reflecting the location of the IAMM on the route. As the IAMM moves physically from one nodal point of the route to the next, the context region logically moves as a relevant pair of facts in the fact space knowledge base. The actual RNPF at the logical level reflects the current location of the IAMM, and the actual SoF is the target nodal point. The actual pair RNPF and SoF determines the IAMM current control action.

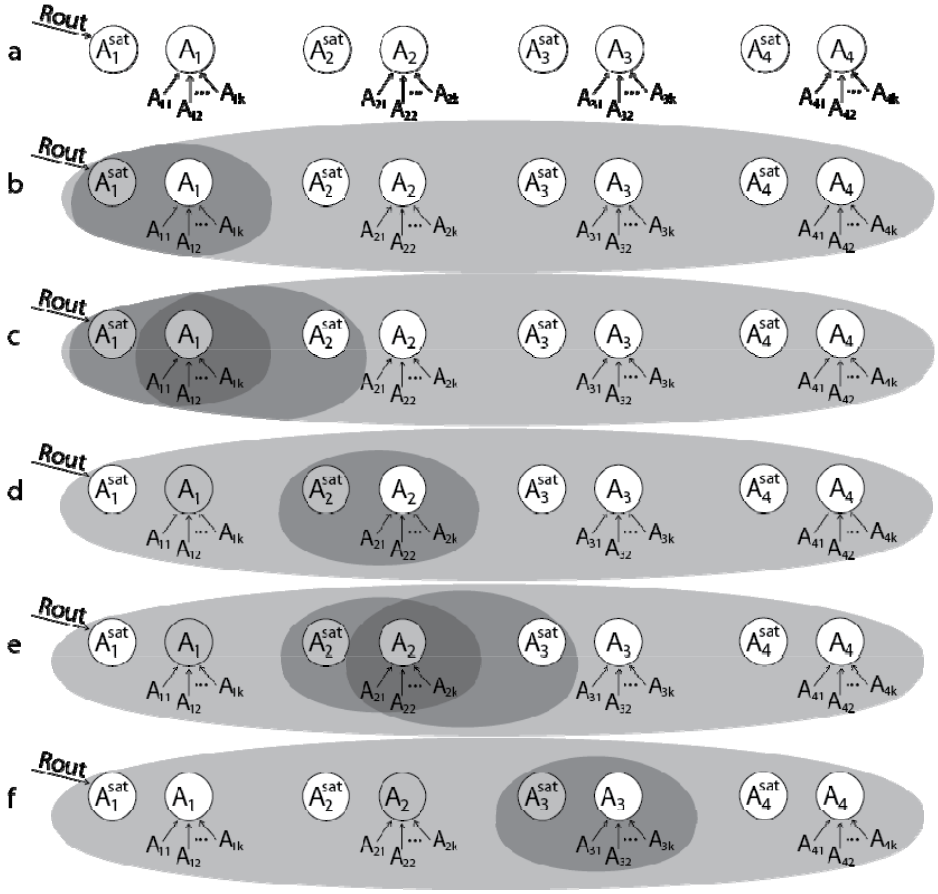

Fig. 2. Context and attention effect: moving of the context region in the facts space.

To assess the fact relevance degree, the confidence factor (CF) is introduced [12,15]. The value $-1 \leqslant cf \leqslant +1$ of CF is a numerical estimate of the fact relevance degree. The actualized fact adequately represents at the logical level the situation that takes place at the physical level. A high degree of relevance is estimated by a confidence factor value $cf = +1$, and a low one by a number $cf = -1$. When, with equal certainty, it can be said that the fact is either adequate or not to data from sensors that obtained about the state of the physical world, then the actuality of the fact is $cf = 0$ (neutral value). Route knowledge, for example, *Rout_1* is defined by the set of pairs of facts (A_i, A_i^{Sat}) for all nodal points of the route $i = 1,2, .. n$ and the set of rules ordering the facts according to the route.

$$\boldsymbol{R_{i1}}\text{: } \textbf{\textit{if}}\ event(A_i)\ \textbf{\textit{and}}\ CF\_A_i^{\mathrm{Sat}}\ is\ high\ \textbf{\textit{and}}\ CF\_Rout\_A\ is\ high\ \textbf{\textit{then}}\ cf\_A_{i+1}^{Sat} = +1,\ cf\_A_i^{Sat} = -1,\ i=1,2,..n. \quad (2)$$

Rule (2) is processed by the reasoning mechanism only at the moment of appearance of the features describing the nodal point A_i (the moment of reaching the nodal point). A rule that is activated only when an event occurs, contains a reference to the *event* (A_i). The occurrence of an event is determined by the value of the CF of the RNPF, which is formed by rule (3).

$$\boldsymbol{R_{i2}}: \textbf{\textit{if}}\ CF\_Attention\ is\ high\ \textbf{\textit{and}}\ CF\_A_{i1}\ is\ high\ \textbf{\textit{and}}\ CF\_A_{i2}\ is\ high\ ..\ \textbf{\textit{and}}\ CF\_A_{ik}\ is\ high$$
$$\textbf{\textit{then}}\ cf\_A_i = 0.5{\cdot}cf\_Attention + 0.5{\cdot}(v_1{\cdot}cf\_A_{i1} + v_2{\cdot}cf\_A_{i2}\ .. + v_k{\cdot}cf\_A_{ik}),\ i=1,2,..n. \tag{3}$$

As can be seen from the rule, the CF can get a high value, provided that attention is actualized (*Attention is high*) and data from sensors that register the different features A_{ij} of the nodal point A_i are relevant (*CF_A_{ij} is high*). In rules (2), (3), *CF_XX* denotes the names of the corresponding linguistic variables. For example, CF_A_{ij} is the name of a linguistic variable that has the meaning "the confidence factor of the *j*-th attribute of the A_i-th node point". The term set of a linguistic variable is {*high*, *neutral*, *low*}. Terms are defined (Fig. 3(b)) on the CF universe $-1 \leqslant cf \leqslant +1$, where *cf* is the numerical value of the confidence factor. The parameter $0 \leqslant v_j \leqslant +1$ is the degree of completeness of the information on the *j*-th feature to identify the nodal point.

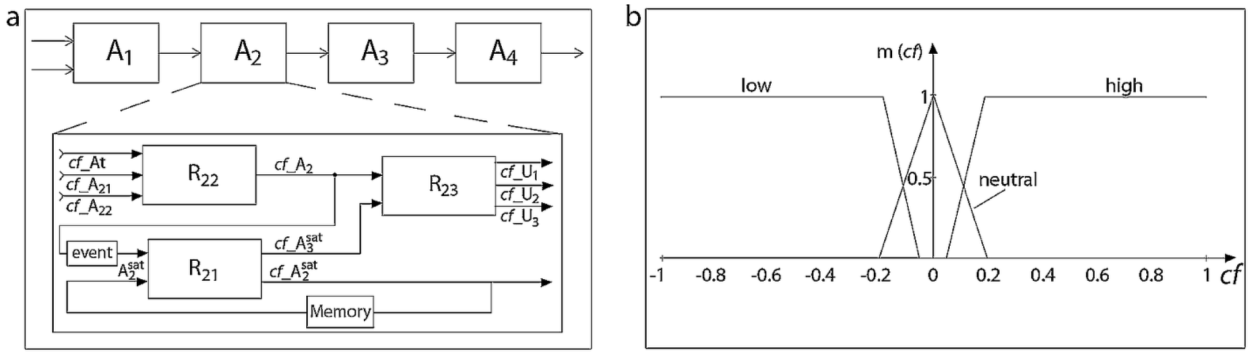

Fig. 3. (a) model structure; (b) linguistic variables definition.

The rules (4) represent the IAMM knowledge about working space: what kind of control is required to achieve the goal (nodal point A_{i+1}^{Sat}), if the IAMM is located in the area in which data of the A_i features are available.

$$\boldsymbol{R_{i3}}: \textbf{\textit{if}}\ CF\_A_i\ is\ high\ \textbf{\textit{and}}\ CF\_A_{i+1}^{Sat}\ is\ high\ \ \textbf{\textit{then}}\ cf\_U_{i1} = +1,\ cf\_U_{i2} = -1,\ cf\_U_{i3} = -1,\ i=1,2,..n. \tag{4}$$

In rule (4), U_{i1}, U_{i2}, U_{i3} are control actions belonging to the set of IAMM possible actions. These can be either elementary actions such as *forward* or *left*, discussed earlier, or macro-command that implement a chain of elementary control actions. The knowledge base stores the rules (4) not only for the nodal points of the route, but the rules connecting any pair of special points of the workspace. Rules (4), as well as rules (3), are not related to a specific route. They can be activated by data from sensors about the any location of the IAMM and form control, leading to the achievement of the actual goal (*$CF\_A_{i+1}^{Sat}$ is high*).This mechanism guarantees that the IAMM moves along the route in case of deviations when obstacle occurs.

Let describe obstacle avoidance knowledge. The IAMM movement control based on knowledge (2)-(4) allows the appearance of obstacles on any part of the route between two adjacent nodal points. The obstacle appearance is detected by the IAMM's sensors, for example, USs. This event activates the attention control mechanism. The field of attention moves from the knowledge base fragment, including the active facts at this time (Fig. 2), to a fragment, the facts of which describe the reaction to this event. This may be a set of rules, similar to (2), which describe the IAMM's route when bypassing an obstacle or avoiding collision with an obstacle. It is possible to use the rules of classical situational control of avoiding an obstacle of type (1), for example, according to the strategy of "feeling the obstacle" on the data from sensors [8]. After the hazard has been eliminated, the attention control mechanism returns the field of attention to a fragment of the knowledge base that was relevant before the appearance of obstacle. The activated attention region, according to (3), makes it possible to actualize the fact A_i that based on data from sensors again. This restores the conditions for activation according to the rule (4) of interrupted control. Thus, the movement to the destination node of the route is restored. Here it is important to pay attention to the fact that after the hazard is eliminated, the IAMM may end up in another place, not where it was at the time of the occurrence of the obstacle. Nevertheless, the IAMM from this position will continue to move towards the target, possibly due to other control actions. Flexibility of control is achieved through the knowledge base of the working space (4). Rules (3) actualize the fact that corresponds to the IAMM physical location. The relevance of this RNPF, in conjunction with the actual SoF, according to (4) actualizes the adequate control reaction necessary to achieve the goal. The mentioned target SoF remained relevant for the entire period of time when the IAMM was circling the obstacle. This became possible because the SoF's state could only be changed by rule (2), and there were no conditions for updating these rules.

3.3. Modeling

Below are the results of step-by-step simulation of the movement control along route A (Fig. 1(a)), which includes four nodal points. The model structure is shown in Fig. 3(a). The fragment of the processing circuit of one nodal point consists of three blocks. The names of the blocks correspond to the names of the rules in (2)-(4). In these blocks, a fuzzy inference is implemented by the Takagi-Sugeno method based on the rules: the R_{21} block contains a complete fuzzy rules knowledge base of type (2); block R_{22} – type (3); block R_{23} – rules of type (4). The designations of the input and output numerical and linguistic variables in Fig. 3(a) correspond to those taken in (2)-(4). All the linguistic variables used in the simulation are defined in the same way: three terms on the universe of the confidence factor (Fig. 3(b)). Possible control set: U_1 *– forward*; U_2 *– turn right and straight ahead*; U_3 *– turn left and straight ahead.* The simulation results are shown in Table 1 and Table 2. Rows of tables correspond to the same points in time. Table 1 shows the values of *cf* for the facts, and Table 2 shows the values of *cf* for the control reactions. In Table 2, the first index *i* in the designation U_{ij} corresponds to the simulation results obtained for the block A_i (Fig. 3(a)). In the last three table columns are the total *cf* control signal values.

Table 1. The values of the confidence factor *cf* of A_i facts.

t	Atten	A_1^{Sat}	A_{11}	A_{12}	A_1	A_2^{Sat}	A_{21}	A_{22}	A_2	A_3^{Sat}	A_{31}	A_{32}	A_3	A_4^{Sat}	A_{41}	A_{42}	A_4
1	-1	-1	-1.0	-1.0	-1.0	-1	-1.0	-1.0	-1.0	-1	-1.0	-1.0	-1.0	-1	-1.0	-1.0	-1.0
2	+1	+1	-1.0	-1.0	0.0	-1	-1.0	-1.0	0.0	-1	-1.0	-1.0	0.0	-1	-1.0	-1.0	0.0
3	+1	+1	1.0	1.0	1.0	-1	-1.0	-1.0	0.0	-1	0.9	1.0	0.9	-1	-1.0	-1.0	0.0
4	+1	-1	0.8	0.9	0.9	+1	-0.9	-0.6	0.1	-1	-0.6	-0.1	0.5	-1	-1.0	-1.0	0.0
5	+1	-1	0.9	0.7	0.9	+1	0.8	0.9	0.9	-1	-1.0	-1.0	0.0	-1	-1.0	-1.0	0.0
6	+1	-1	-0.8	-0.9	0.1	-1	0.9	0.9	0.9	+1	-1.0	-1.0	0.0	-1	-1.0	-1.0	0.0
7	0	-1	-1.0	-0.9	-0.5	-1	-1.0	0.9	0.5	+1	0.9	1.0	0.5	-1	-1.0	-1.0	-0.5
8	-1	-1	-1.0	-0.8	-0.9	-1	-1.0	1.0	0.5	+1	0.9	1.0	-0.1	-1	-1.0	-1.0	-1.0
9	+1	-1	-1.0	-1.0	0.0	-1	0.9	0.9	0.9	+1	0.9	0.9	0.9	-1	-1.0	-1.0	0.0

From the data analysis it can be seen that time point 3 corresponds to the occurrence of an event associated with obtaining information about the nodal point A_i. In the fourth time point, this event actualized the purpose of the move (SoFA_2^{Sat}), which, in turn, actualized the U_1. At the fifth time point, data appeared on reaching the nodal point A_2. In the sixth time point, this event deactualizes the A_2^{Sat} and actualizes the new target A_3^{Sat}. Then, it actualizes the U_2 control. At the seventh and eighth time points, switching attention to another piece of the knowledge base was modeled. In these time points, despite the ongoing data from sensors processing, control signals are not issued to the IAMM actuators. The value $cf\_U_{22} = 0.5$ is not enough to actualize the control, see Table 2. After returning attention in time point 9, the value of $cf\_U_{22} = 1.0$, which is already enough to actualize this control signal.

4. Conclusion

The proposed event-based situational control model was tested on the IoT and SM training and research polygon of Ukrainian State University of Railway Transport [16]. The proposed model in comparison with traditional has appropriate advantages. First, it becomes possible to use a rule-based model for embedded real-time applications by reducing the size of the knowledge base. It became possible due to mitigating the requirement of pairwise distinguishability of the rules: discernibility is not required on the whole set of rules, but only on subsets actualized by the same event. Secondly, the scope of application of control systems has expanded to IAMM control tasks in a disordered environment. The model makes it possible to implement control of IAMM movements along the route and obstacle avoidance according to different strategies and on the basis of heterogeneous data from sensors due to the mechanisms of context tracking and switching attention.

Table 2. The values of the confidence factor *cf* of control signals U_i.

t	U_{11}	U_{12}	U_{13}	U_{21}	U_{22}	U_{23}	U_{31}	U_{32}	U_{33}	U_1	U_2	U_3
1	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0
2	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0
3	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0
4	+1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	+1.0	-1.0	-1.0
5	+1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	+1.0	-1.0	-1.0
6	-1.0	-1.0	-1.0	-1.0	+1.0	-1.0	-1.0	-1.0	-1.0	-1.0	+1.0	-1.0
7	-1.0	-1.0	-1.0	-1.0	+0.5	-1.0	-1.0	-1.0	-1.0	-1.0	+0.5	-1.0
8	-1.0	-1.0	-1.0	-1.0	+0.5	-1.0	-1.0	-1.0	-1.0	-1.0	+0.5	-1.0
9	-1.0	-1.0	-1.0	-1.0	+1.0	-1.0	-1.0	-1.0	-1.0	-1.0	+1.0	-1.0

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