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Testing the Immune Algorithms for Electrical Transport Using Mathematical Methods

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Abstract

Objective of this paper is to test the immune algorithms for an intelligent rolling stock safety system which could provide a possibility for railway transport to avoid dangerous situations. The authors examine the algorithms used in artificial immune systems and ways how they can be used together and provide data for each one other via communication protocols, then create a simulation for further analysis with mathematical methods.
The authors review data analysis methods used to detect, predict and control undesirable rolling stock travel conditions.
KEY WORDS: *immune algorithms, classification, railway transport.*

1. Introduction

The research aims to develop a way for the electric railway transport to avoid dangerous situations.

Objective of this paper is to test the immune algorithms for an intelligent rolling stock safety system which could provide a way for railway transport to avoid dangerous situations.

Artificial immune systems (AIS) were mentioned in some papers in mid 1980s but became a subject in its own right in 1994 in papers on negative selection by For-rest et al. [1] and Kephart et al. [2]. Currently the systems are actively explored for possible use cases. Dasgupta et al. [3] investigated a real-valued negative selection algorithm for aircraft fault detection. Watkins et al. [4] presented a simplified version of a clonal selection algorithm called AIRS (Artificial Immune Recognition System) and Negi [11] implemented an AIS for urban traffic control which responds to undesirable situations.

The authors examine the algorithms used for data analysis in artificial immune systems and ways how they can be used together and provide data for each one other, then create a simulation for further analysis with mathematical methods.

2. The system analysis and design

During journey the rolling stock driver may experience many undesirable situations and have to make decisions on how solve them. The situations may include such examples as:

- the last car from the flow is still on the level crossing 25 seconds before the train arrival, while the safety regulations require the crossing to be cleared at least 35 seconds before train arrival;
- a daredevil is running across the tracks somewhere in the urban zone;
- there is a red signal on the railway traffic light;
- there is a wide but harmless rod lying between the tracks, etc.

Each of these situations requires different actions or no action at all. The driver may have to apply brakes, speed up, continue the steady movement and in any case communicate the information to the control center and other drivers.

The desired result conforms to at least two require-ments:

- there are no casualties;
- the train is on schedule.

A common situation is illustrated on Fig. 1, where L is a locomotive and I is an invading object on tracks.

The authors offer the intelligent rolling stock safety system functional design which is presented on Fig. 2.

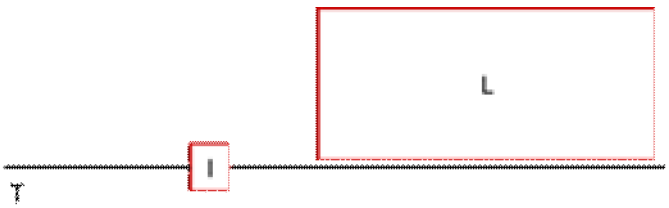

Fig. 1. A common unwanted situation on the railway tracks

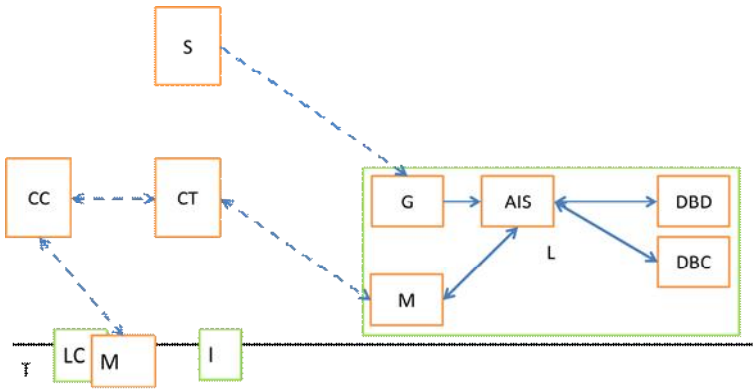

Fig. 2. The intelligent rolling stock safety system functional design

The invading object I is picked up by sensors S and the data is transmitted to the nearest cell tower CT, which relays it to the control center CC and nearest locomotives wireless modems M. Through the same modem the locomotive L receives data about closest neighbors' rolling stock position and status, railway segment profile and maximum allowed speed.

L also hosts: a positioning receiver G which receives data from a positioning satellite ST; data analysis module AIS which communicates to the immune detector database DBD and control cell database DBC. Depending on the results of control cell maturation the module makes a decision and executes it by sending a control signal or displaying an alert to the driver.

The information is also communicated to the device on a level crossing LC through a similar modem M.

The principles behind AIS, DBD and DBC are discussed further in the article.

3. Mathematical formulation

Let $U \in R$ be problem space:

$P \in U$ – set of known "good" situations;

$S(t) \in U$ – current situation which changes with time t;

$D = \{D_1, D_2, \ldots, D_n\} \notin P$ – set of detectors;

$C = \{C_{D1(1)}, C_{D1(2)}, \ldots, C_{D1(p)}, C_{D2(1)}, \ldots, C_{Dn(p)}\}$ – set of control cells affiliated to detectors;

$E = \{E_1, E_2, \ldots, E_m\}$ — set of encountered situations;

$W = \{W_{E1D1}, W_{E1D2}, \ldots, W_{E1Dn}, W_{E2D1}, \ldots, W_{EmDn}\}$ – set of detector weights in different situations;

Distance between two points on a sphere:

$$d = 2R \arcsin\left(\sqrt{\sin^2\left(\frac{lat_A - lat_B}{2}\right) + \cos(lat_A) \times \cos(lat_B) \times \sin^2\left(\frac{lon_A - lon_B}{2}\right)}\right)$$

Conditions intriduced by using embedded device:

$T = \{t_1, t_2, \ldots, t_n\}$ – the embedded device must work in real time;

$V = \{v_1, v_2, \ldots, v_n\}$; $v_i = x_i \times y_i \times z_i$; V^* – min V – size of the device;

$T_{test1} < T_{test2}$ – time to test prototypes;

$E = \{e_1, e_2, \ldots, e_n\}$; E^* – min E – energy consumption;

$IZ = \{iz_1, iz_2, \ldots, iz_n\}$; IZ^* – min IZ – install and use costs;

$P = \{p_1, p_2, \ldots, p_n\}$; P^* – min P; $AT = \{at_1, at_2, \ldots, at_n\}$; AT^* – min AT – speed and memory.

Additional limitation outside of mathematical scope is input and output UI.

The requirements for the chosen algorithm A_n:

$T_{An} \rightarrow$ min – completion time for the algorithm

$Pr_{An} \rightarrow$ max – precision of the algorithm's result

$E_{An} \rightarrow$ min – energy consumption while running the algorithm

$(x_B \times y_B \times z_B) \rightarrow$ min – embedded device dimensions

$ST_B \rightarrow$ max – reliability of the device and algorithm

$IP_B \rightarrow$ min – install and use costs

Hypothesis: the immune algorithm will complete faster and give more precise answers.

4. The general algorithm

The possibilities for learning implementation are the following: either make the system fully automatic and let it discover all the data by itself; or set two-stage learning with the initial training and continuous self-improvement.

Therefore the intelligent rolling stock safety system general algorithm is such:

1. Fill in the initial values *D* for DBD by running the negative selection training routine.
2. Run in real time the detection routine using the negative selection algorithm.
3. Determine the possible situation identifiers (detectors which matched above a given threshold).
4. Assign weights to the detectors based on their «distance» to the situation.
5. Retrieve a population of control cells *C* from DBC which are related to the activated detectors.
6. Run the control cell maturation routine using the clonal selection algorithm.
7. Execute the found optimal solution.
8. Communicate the information to the control centre CC.
9. Continue from step 2.

The most feasible way to implement such a safety system would be, like in case of hybrid IDS [5], through the two phases of anomaly detection and determination of their type to draw a conclusion. In this case the incoming data from the sensors is the set of antigens. The data includes but is not limited to speed, acceleration, voltage, rotation and operational temperature.

The algorithm uses AIS negative selection and clonal selection algorithms as the basis. The problem in AIS is represented as an antigen and solution candidates as antibodies which are randomly generated from the library of available solutions or genes. The evaluation of affinity or degree of binding between the antigen and the anti-body is similar to complementarity level in biological *IS* and it defines the fate of each individual antibody as well as termination of the whole algorithm.

Negative selection algorithms need training samples only from one class (self, normal), thus, they are especially suited for the tasks such as novelty, anomaly or change detection including those in engines and other devices. The key advantage of anomaly detection systems is their ability to detect novel attack patterns for which no signature exists, while their most notable disadvantage is a larger false positive rate. This algorithm produces a set of detectors capable to recognize non-self patterns. The action following the recognition varies according to the problem under consideration. In the case of transport safety control system it could be an alarm or issue of an immediate stop signal depending on the detected situation.

The detectors and the caught dangerous conditions are stored in immune memory for further processing and to provide further information about the consequences of the attack and possible future actions instead of simply reporting the incidents.

In clonal selection algorithm, individual antibodies are replaced, cloned and hypermutated until satisfactory level of affinity is reached. Partial replacement of the solutions' population with fresh randomly generated candidates maintains diversity which allows solving a wider set of problems. The probability of cloning or hypermutating a candidate depends on its affinity. While usually cloning is proportional and hypermutation is inversely proportional to each candidate's affinity, there's also a version of this algorithm called AIRS [4], which is a bit closer to a genetic algorithm and where hypermutation happens on an independently random rate.

5. The experiment

The computer experiment plan was such:

- build a computer model for each of the solution methods;
- input data about the device;
- simulate various road situations;
- run the models for many iterations;
- statistically analyze the output and draw conclusions about the devices and algorithms with such methods as t-tests and z-tests.

The test run of the real-valued negative selection algorithm on the computer in 2-dimensional problem space shows the detectors showed good coverage of the nonself space and stable detection of nonself antigens. The population should have stayed the same but after 3 generations the detector population decreased but still detected the pathogens. The chosen actions did not differ much probably because of implementation which needs further research and improvement.

The field experiment involved controllers on the locomotive and in the railway traffic light control box interacting with a server and each other. The data set for the experiment was taken from the two controllers in the field attached to a locomotive and a traffic light control box. The data exchange scheme is presented on Fig. 4.

The communication between the controllers was facilitated by GPRS modules and a server running on a PC; the data was exchanged using a set of custom text messages on top of an open protocol which facilitates observation and control of the whole process with a wide range of tools for PCs and mobile phones. Through the chain of software tools – communications and data collection server, an instance of PHP script (could be anything capable of network and database communication) – the data was piped from the controllers to the database tables.

Upon receiving the data about its own and the traffic light location the locomotive embedded device calculates the distance between them according to the formula of distance between points on a sphere.

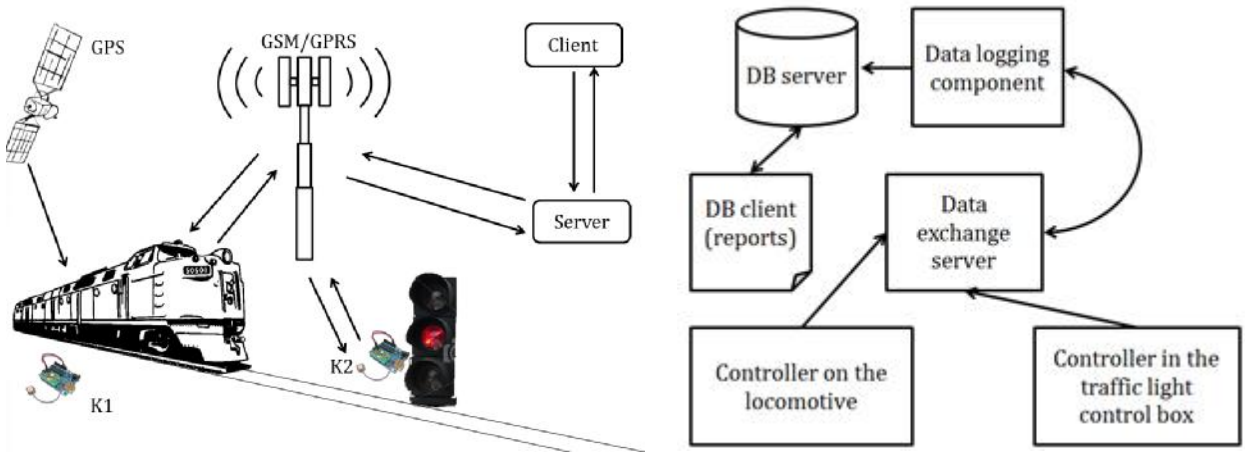

Fig. 3. The experiment overall and data exchange plan

When the braking distance matches or exceeds the calculated distance and the traffic light is set to red, the device immediately activates the train brakes.

Some signal instability was detected in the GPS feed and some data overflow in the exchange process.

6. Conclusions

- Learning process for the intelligent rolling stock safety control system should consist of two phases:
  - Initial training and detection – immune negative selection algorithm,
  - Classification and improvement – clonal selection algorithm;
- The embedded program needs a position and distance prediction routine to handle lost or late data due to unstable radio signal;
- An alternative protocol should be established to avoid flooding the serial link with all the devices variables' values;
- The authors need to assess the possibility to run the data analysis on the embedded devices themselves using these algorithms in real time.

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