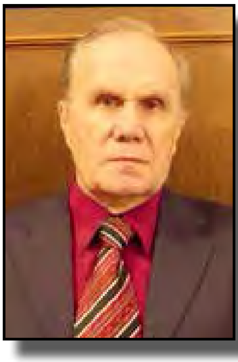
DOI: https://doi.org/10.30932/1992-3252-2020-18-06-26

Application of Models of Probabilistic Situations regarding Railways


Boris A. LYOVIN **Victor Ya. TSVETKOV** **Andrey L. OKHOTNIKOV**

Lyovin, Boris A., *Russian University of Transport, Moscow, Russia.*
Tsvetkov, Victor Ya., *Research and Design Institute for Informatization, Automation and Communication in Railway Transport, Moscow, Russia.*
Okhotnikov, Andrey L., *Research and Design Institute of Informatization, Automation and Communication in Railway Transport, Moscow, Russia*.*

ABSTRACT

The article describes application of models of information probabilistic situations for solving problems of traffic control on the railway. The content of situational control is revealed. The difference between a visual and a «blind» situation during vehicle's movement is shown.

The information situation around a moving object can be deterministic and stochastic. The concept of a stochastic information control situation is introduced. The choice of alternatives in stochastic control situations is characterized by organizational, technological, and informational uncertainties. This motivates development of control methods and algorithms that consider uncertainty and multicriteria in control of moving objects in such situations. Situational control can be used in automated, cyber-physical and intelligent control.

The article proposes a model for controlling mobile objects based on a probabilistic approach in a stochastic situation and on the consideration of a number of stochastic factors. The model is based on calculating the probability of existence of an obstacle in the path of a vehicle. Such a model can be used under the conditions of poor visibility and a probability of receiving erroneous information from sensors. The article gives a systematics of the probabilistic characteristics of a stochastic information situation accompanying a moving object. The application of dichotomous and oppositional analysis in studying obstacles on the route has been substantiated. The model for detecting a foreign object on a traffic route is based on the assumption of the presence of reliable and erroneous information. The analysis is based on Dempster–Schafer theory. The stochastic information situation model uses the probabilistic characteristics of the presence of an obstacle on the track. The probability of an object's existence is estimated using Bayes' theorem. The proposed model considers three factors of the stochastic situation: informational uncertainty in the signal; false signals, sensor measurement error. The field of application of this situational model comprises digital railway, intelligent transport systems, transport cyber-physical systems.

Keywords: transport, detection of objects, stochastic information situation, probability of events, situation analysis, Dempster–Schafer theory.

*Information about the authors:
Lyovin, Boris A. – D.Sc. (Eng), Professor, President of Russian University of Transport, Moscow, Russia, tu@miit.ru.
Tsvetkov, Victor Ya. – D.Sc. (Eng), Professor, Deputy Head of the Centre for Strategic Analysis and Development of JSC Research and Design Institute for Informatization, Automation and Communication in Railway Transport (JSC NIIAS), Moscow, Russia, cvj2@mail.ru.
Okhotnikov, Andrey L. – Deputy Head of the Centre for Strategic Analysis and Development of JSC Research and Design Institute of Informatization, Automation and Communication in Railway Transport (JSC NIIAS), Moscow, Russia, a.ohotnikov@vniias.ru.

Article received 01.02.2020, accepted 19.06.2020.

For the original Russian text of the article please see p. 6.

Background.

Situational management in the field of artificial intelligence is based on the use of semiotic models. Situational management and situation analysis in the field of information management and practical transport management technologies are based on the use of models of information situations [1; 2]. The information situation in the field of transport describes the factors that influence the nature of movement, including the appearance of other objects. The information situation around a moving object can be deterministic and stochastic. Accordingly, the models of the information situation can be deterministic and stochastic. Transport management can be analytical and stereotyped. Analytical control is based on the analysis of parameters of the state of an object and of parameters of the situation. Based on the analysis of all parameters, a solution is developed. Stereotypical control is associated with the analysis of known stereotypical situations for which the control decision is known as a possible alternative.

The deterministic situation is characterized by the presence of cause-and-effect relationships. The stochastic situation is characterized by the presence of uncertainty. The choice of alternatives in stochastic situations is characterized by organizational, technological, and informational uncertainties. This leads to development of methods and control algorithms that consider uncertainty and multi-criteria in decision-making.

Regarding organizational management and automated control, it is appropriate to talk about management methods. Regarding transport cyber-physical control [3], it is appropriate to speak, first, about algorithms and, secondly, about control methods. Regarding intelligent control [4], it is necessary to talk about rules, algorithms, and control methods. Information situation [5; 6] is a model that combines the agent of control (solver), the controlled object (vehicle) and the environment of the controlled object that affects its state.

Situational control is a link connecting automated, cyber-physical and intelligent control. This article presents algorithms for calculating the probability of existence (identification) of an obstacle (object), which are used in organizing control of a vehicle without a person but using «technical vision». An algorithm for calculating the probability of existence at the level of sensors is presented. The mechanism of merging the probabilities of existence from several sensors is shown. At the applied level, the probability of existence can be used in interpretation algorithms [7] of a situation to perform various functions to support decision-making, for example, to help a driver or when driving a driverless vehicle. This paper shows an integrated approach to considering various factors for modelling discrete transport control problems.

Information stochastic situation

A model of the information situation is necessarily used in an explicit or implicit form for unmanned vehicle control (TS). In this case, information situations of different scale are used. Local information situation is a model associated with the state and immediate environment of a vehicle. Visual information situation is determined by the visibility area out of the vehicle. A «blind» information situation is determined by an area that extends beyond the line of sight and can affect the vehicle, and the probability of visual detection of an object in this area is close to zero. Besides, another information situation arises, called stochastic.

To measure the parameters of a «blind» information situation, special measuring instruments are used that allow tracking obstacles in the path of movement: radars, laser scanners, cameras, infrared cameras, ultrasonic sensors, unmanned aerial vehicles (UAV), and others. All these tools allow building a comprehensive system for technical monitoring of the situation and identification of obstacles in the vehicle's path.

One of the main tasks of controlling speed and high-speed railway transport is to recognize objects that impede movement. Since obstacle objects are not planned and arise randomly, this leads to emergence of a stochastic information situation. Stochastic information situation is characterized by probabilistic and technological factors. The probabilistic factors are as follows:

- probabilistic characteristics of the presence of an obstacle on the track;
- probabilistic characteristics of the absence of obstacles on the track;
- probability of detecting obstacles on the track;
- probability of not detecting obstacles on the track;

• probability of systematics of movement;

• probability of violation of systematics of movement.

The dichotomy and oppositionality of pairs of probabilistic assessments draws attention to themselves. This gives rise to application of oppositional and dichotomous analysis for spatial analysis. The technological characteristics of the stochastic information situation are due to errors and failures of monitoring means. In real conditions, data from sensors of TV monitoring systems contain uncertainty. False «echo» signals from sensors are possible. Of course, the measurement error must additionally be considered. All these three factors also characterize the information stochastic situation.

False positives are subject to environmental conditions. A false measurement is a measurement that is interpreted by sensors or information processing algorithms as a measurement of a real object of an obstacle, while in fact this object does not exist. The more often false measurements occur, the larger is the situation, that is, the larger is the observation area. In a local situation, there are few of them. There are few of them in the visible information situation. There are more of them in a blind informational situation.

The measurement of a real object is called true measurement. In real practice, sensors and gauges generate a lot of true and false alarms. False positives also occur from side objects that are not located on the traffic route, but nearby and do not interfere with movement.

When driving a driverless vehicle, it is necessary to filter the side objects that are present near the vehicle's path: pillars, posts, traffic lights, fences. This is important while controlling high-speed transport, during its integral controlling [8].

The stochastic information situation includes the probabilities of existence of the object and the probabilities of false alarms of the sensor. The stochastic information situation sets the conditions for probabilistic analysis. In particular, it analyzes whether the signal about an object is real or false. In other words, a stochastic information situation allows for the presence of uncertainty and requires its disclosure.

The presence of probabilistic characteristics and characteristics of uncertainty of the situation gives ground to speak of probabilistic situational control. Such control is described within the framework of Dempster–Schafer theory (DST) [9].

Probabilistic situational control uses a probabilistic metric for each signal of a detected object. Using empirical probability of accidentally detecting side objects, they can be filtered by setting a threshold (dividing plane) in the parameter space.

One more feature of the stochastic information situation should be noted: visual situation and blind information situation work with parameters of the real space, as well as with probabilistic parameters. If we use multiple assessment of object recognition in real time, then this improves quality of object detection [10–12]. The reason for this is ergodicity of the spatial measurement process. The use of a stochastic information situation requires the use of proven statistical methods that have many implementations in software. Thus, ergodicity and statistical methods are pillars in the analysis of the stochastic information situation.

Estimating the probability of detecting a real object

The Bayesian approach is used to determine the probability of many random and dynamic processes. From the standpoint of logic, this is due to the fact that the basis of the syllogism *modus ponens* is the prototype of Bayes' theorem. Bayes' theorem in interpretation of mathematical logic is an elementary conclusion, which is called *modus ponens* [13]. Bayes' theorem is:

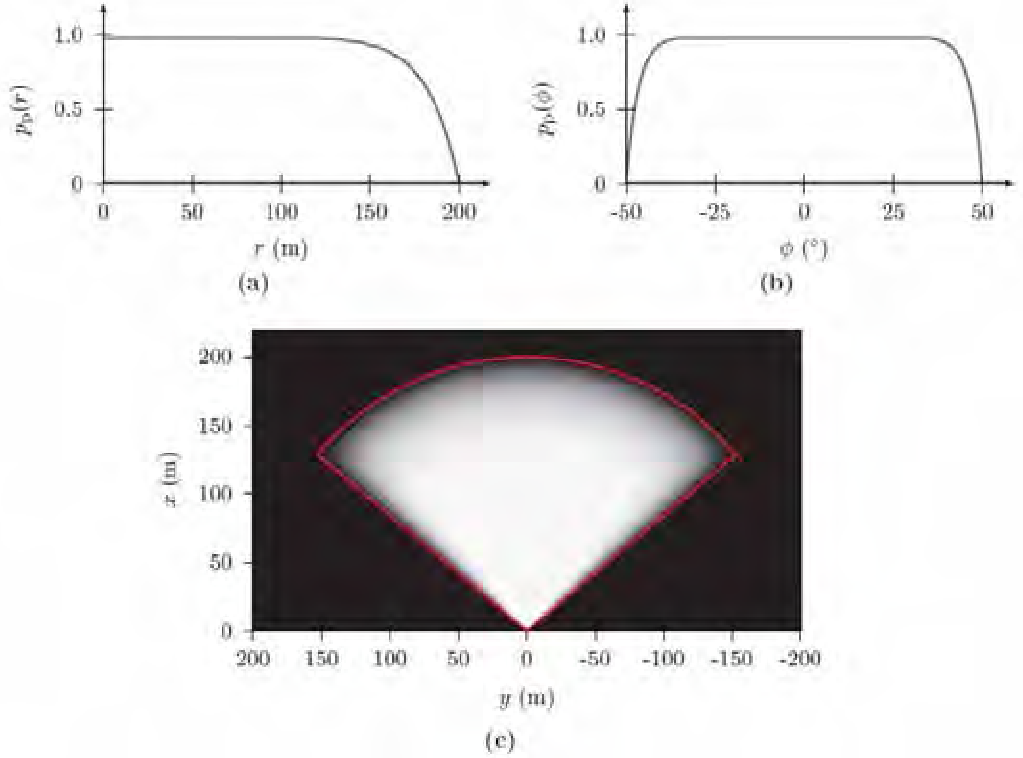
$$p(x|z)=\frac{p(z|x)\,p(x)}{p(z)}\,. \qquad (1)$$

In expression (1), the x-quantity is the quantity to be estimated, $p(x)$ – preliminary probability of the quantity, $p(x|z)$ – next quantity to be estimated after observing the measurement, $p(z|x)$ – measurement made from the estimated values, and $p(z)$ – normalizing factor. To simplify the expression $p(z)$, it is often replaced by a normalizing factor η such that:

$$p(x|z) = \eta p(z|x)p(x). \qquad (2)$$

In expression (2), the value of η guarantees that the result of evaluating the Bayes rules among the value of x and its complement is 1.

For the probability of the existence of an object, the true value is x, and its complement



Pic. 1. Modelling the probability of stability of detection in polar coordinates of the sensor. The model was obtained by the authors on the basis of experimental work.

$\bar{x}$ is the probability of the non-existence of the object. The actual measurement or fact fixing model is z. From (2) we get:

$$p(x|z) = \eta p(z|x)p(x) = p(\exists x_k|Z^k), \quad (3)$$

$$p(\bar{x}|z) = \eta p(z|\bar{x})p(\bar{x}) = p(\nexists x_k|Z^k). \quad (4)$$

The method of detecting objects on the path of movement in stochastic situations is based on the analysis of probabilistic parameters of the situation. These parameters are as follows: probability of occurrence, probability of an object being close to another, probability of detection, probability of detection, probability of disorder (noise or interference).

The probability (persistence) of detection, p_p (p-persistence) is an estimate of the probability of existence of an object. It was used in aerospace radar when IPDA and JIPDA were introduced [14; 15]. It was interpreted as the probability of stability of detecting an object with a field of view of 360° in the Markov process. With automotive sensors, the field of view of a single sensor is more limited. In the conditions of using sensors for a locomotive, the field of view is even more limited and therefore the probability of detection stability in this case is higher. The idea of using the sensor's angle of view to simulate the probability of detection stability was first introduced for road vehicles and then for railway vehicles. This probability is sometimes called the probability of survival. The overall stability probability consists of a combination of the stability probability in polar coordinates:

$$p_d^{mod}(r,\text{ö}) = p_p \bullet (r) \bullet p_p(\varphi)\,. \quad (5)$$

Pic. 1 shows an example of modelling the probability of detection stability for a sensor facing forward.

Practical data are as follows: the maximum distance to the object r = 200 m, and the maximum angle $\varphi = \pm 50°$. The range and cutoff angle were chosen as m_r = 0,4 and m_φ = 0,3, respectively, and α as 0,01, where (*a*) modelling by distance r is shown, (b) modelling by angle φ is shown, and (c) the combined probability of stability in the Cartesian coordinate system is visualized.

The probability of occurrence (birth) $p_b(x_{k|k-1})$, (b-birth) is introduced to predict existence. This probability is used to initialize the probability of existence of a newly discovered object. The easiest way to model the likelihood of an object emergence is to take a reasonable constant value, for example, $p_b(x_{k|k-1}) = 0{,}1$. This constant must be above the threshold. The choice of a constant probability of occurrence is also the most typical approach used in practice in combination with IPDA and general probabilities of related data, JPDA [14; 15].

In [11], the knowledge about the sensor's field of view and other detected objects is used to determine a more accurate probability of occurrence. The probability of occurrence is modelled based on the gradient such that the probability of stability changes in proportion to the higher probability of occurrence. This leads to the fact that high probability of occurrence is selected at the edges of the angle of view of the sensor and visibility of the object.

The probability of appearance of an object that is close to another in [12] is estimated on the assumption that new objects cannot be created in the immediate vicinity of already discovered objects with a high probability of existence. The density function of the hypothesis of probability (PHD – Probability Hypothesis Density) [16] is used to obtain the probability of existence of an object in a certain area. The addition of this probability to all objects in the environment results in the spatial probability of any new hypothesis for appearance of an object. There are many options for modelling the probability of occurrence. When choosing a probability model, one should consider their simplicity or complexity. The type of sensor used also influences the selection. For example, the PHD model presented in [12] works well for sensors that can determine the size of an object. Other sensors, such as the camera, may rely more on a polar probability of occurrence model similar to the model presented in [11].

Detection probability. The probability of detection, $p_d(k)$, (d-detection) is the probability of detecting a valid dimension of the object. The probability of detection affects the probability of existence. There are many ways to simulate this probability, and they vary depending on sensitivity of the sensor.

In [12], the probability of detecting with a laser scanner is modelled by the pitch of the vehicle and the z coordinate of the object being detected, which reduces the probability of detection when the measuring beams of the laser scanner are above or below the object being detected.

The probability of detecting with a camera by the optical sensor is also modelled in [12] using the camera's angle of view, the position of the detected object, length, width, and orientation of the object.

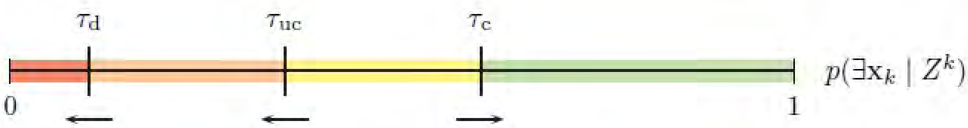
The probability of detection can also be obtained directly from the classifier, for example, using the Adaptive Boosting machine learning algorithms for the camera [11]. The simplest solution for modelling the probability of detection is to choose an appropriate constant.

There is a general approach where the probability of detection is a regarded as combination of three values: the simulated probability of detection $p_d^{mod}(x_{k|k-1})$, the probability of measurement p_d^{meas} (z_k) and the probability of signal reflection from the object $p_d^{track}(x_{k|k})$:

$$p_d(k) = p_d^{mod}(x_{k|k-1})\, p_d^{meas}(z_k\, p_d^{track}(x_{k|k})\,. \qquad (6)$$

If the measurement was not associated with an object, then p_d^{meas} (z_k) and $p_d^{track}(x_{k|k})$ are simply ignored. The simulated detection probability $p_d^{mod}(x_{k|k-1})$ depends on the predicted state of measurements, and information about the measurements themselves is not considered. The idea is to simulate the fact that any location within the sensor's field of view depends on the likelihood that the sensor can actually make a measurement at that location where the object should be. The simplest method is based on the assumption that the sensor can detect an object wherever it exists. This results in a constant value for $p_d^{mod}(x_{k|k-1})$. This assumption may be sufficient in many cases. A model, that considers the sensor's viewing angle sensitivity, improves this model. Other properties of the sensor, such as the prior spatial signal-to-noise ratio, can also be considered, especially for radar sensors. The combination of modelling, measuring, and identifying an object increases the likelihood of correct assessment.

The probability of disorder. The probability of disorder (noise) is often modelled as a spatial process based on the Poisson distribution for detection [11]. This is the probability that a false measurement occurs in a given area or within a given period of time. The Poisson distribution is used to estimate the probability



Pic. 2. Thresholds of existence for confirmation and deletion of objects. The model was obtained by the authors based on theoretical research and the hypothesis of such a threshold ratio.

that *m* measurements are false measurements at time *k*, denoted as the set of false measurements Z^F_k, and is the expression:

$$p_C\left(\left|Z_k^F\right| = m; \text{ë}\right) = \frac{\lambda^m e^{-\lambda}}{m!}, \tag{7}$$

where λ is rate parameter of the Poisson process.

The rate parameter, depending on application of the Poisson process, can be defined as a single occurrence of an event in case of a false measurement. The probability of events that *m* false measurements have occurred is given by the sum:

$$p_c(\mid Z_k^F \mid \leq m, \text{ë}) = \sum_i^{|Z_k^F|} P \frac{\lambda^{m_i} e^{-\lambda}}{m_i!}. \tag{8}$$

To apply expression (8), it is necessary to estimate the number of potential false measurements $|Z^F_k|$ and the level of intensity of λ. All the considered parameters together determine the probabilistic information situation, which is characterized by expression (8).

When obstacles are detected, one of the options for analyzing objects, which are identified by sensors, is executed by discrete enumeration of the probabilities of the existence of an object. Three threshold levels can be introduced to characterize an object: the object confirmation threshold (τ_c), the object non-confirmation threshold (τ_{uc}), and the object deletion threshold (τ_d).

If the probability of the existence of an object reaches the confirmation threshold τ_c, it is counted among the confirmed ones and is included in the list of objects that the sensor accurately identifies and detects. If the probability of existence of an object falls below the non-confirmation threshold τ_{uc}, the object is not considered a valid object, but is still stored in the sensor's internal objects' list.

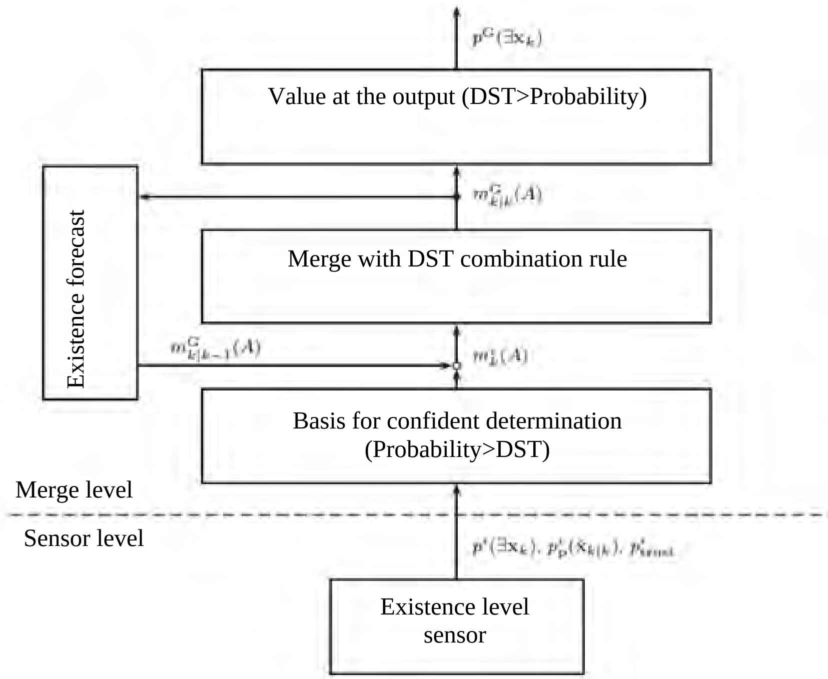
For practical purposes, the non-confirmation threshold should be chosen such that $\tau_{uc} < \tau_c$, that is, there is an effect of detecting objects ever checked over a long period of time if they have already reached τ_c sometime in their history. This is the ergodic factor.

If the probability of existence of an object drops even below, it reaches the deletion threshold τ_d, and will be completely deleted from the list of objects detected by the sensor. Pic. 2 shows the relationship between the various thresholds of existence. Threshold values should be selected in such a way that the detection rate (true positive and false positive values) at the threshold values guarantees a certain desired level in a driving situation for a given vehicle.

Due to this, it is possible to define several confirmation thresholds, especially for vehicles of different speed modes. Each threshold corresponds to a different detection rate. As a result, the probability of existence sets the parameter of «logical reliability» of object detection. This logical reliability can be used as a driver assistance factor, for example, in an intelligent safety system during emergency braking with a delay. This is a case of reacting only to objects that meet the highest threshold values. In comparison, «soft» braking systems [17] such as adaptive cruise control will react earlier when detecting objects that meet the lower confirmation threshold.

In a complex analysis of confluence (merging) of situations, it is necessary to combine the probability of the existence of an object from several sensors into a common list of objects using the strategy of integration of sensors' measurements with the general list.

The object model interface views the probability of existence as a single probability, usually derived from a Bayesian estimation algorithm or from IPDA/JIPDA algorithm [14; 15]. However, to take advantage of the different sensors and handle complex situations such as opacity (occlusion), a single value alone is not enough to model the probability of existence at the merge level. Therefore, the probability of existence is modelled using DST in the merge module, as described below, and then converted back to a single value of the probability of existence at the output of the merge module.



Pic. 3. Estimation of the probability of existence from multiple sensors using Dempster–Schafer theory of proof. The scheme was compiled by the authors based on generalization of the above algorithm.

The processing flow for merging the probabilities of existence is shown in Pic. 3.

Situational modelling using the Dempster–Schafer theory

Simulation and integration with DST theory is described in [18] for transforming measurements from sensor to sensor. In this case, the same probability analysis method is used. A detailed survey of Dempster–Schafer theory of proof (DS) and its many applications is given in [9].

The DS theory defines an object recognition system consisting of mutually exclusive hypotheses or states of the system. To model existence, the simplest set of mutually exclusive hypotheses is that an object exists, ∃, or does not exist, ∄, such that:

$$\Theta = \{\exists, \nexists\}. \quad (9)$$

Then DST defines a set of values 2^{Θ}, which is the set of all subsets of Θ, including the empty set Ø. To simulate existence, as defined in (9), this leads to expression (10):

$$2^{\Theta} = \{\varnothing, \{\exists\}, \{\nexists\}, \{\exists, \nexists\}\}. \quad (10)$$

The set of values contains all combinations that allow assigning confidence values not only for mutually exclusive hypotheses, but also for their combinations. This can be used to simulate ignorance or uncertainty in measurements from multiple sensors that can have different accuracy characteristics (optical cameras, radars, lidars). Uncertainty modelling is acceptable for inference for traditional Bayesian methods. The set of values for the existence of an object includes the subset {∃,∄}, which includes confidence values with information about the existence of an object that is ambiguous. For each set of values, a BBA-Basic Belief Assignment is determined, often also called a mass function, where:

$$m: 2^{\Theta} \to [0,1]. \quad (11)$$

The baseline value of BBA, or mass function, is the number of dimensions, such that each element of the 2 correct ones is considered believable. If BBA is used only for mutually exclusive hypotheses, then DST is equivalent to traditional Bayesian methods. The BBA assignment for a set of values should be adjusted so that:

$$\sum_{A:A\in\theta} m(A) = 1. \quad (12)$$

In addition, DST defines the function of belief (confidence):

$$Bel(A) = \sum_{B:B\in A} m(B), \quad (13)$$

which contains the baseline belief value (BBA) for all subsets of *A*, and that value can be

Pic. 4. Information situation of poor visibility requiring a probabilistic assessment. [Electronic resource]: https://railvision.io/main-line-solution/.

interpreted as *the lower* bound for the probability of indications for *A*. The probability of *the upper* bound for indications within the set of values of *A* is defined as the likelihood:

$$Pl(A) = \sum_{B:B\cap A\neq\varnothing} m(B), \qquad (14)$$

where $Pl(A)$ contains all the sets in (2) that support the measure of confidence in *A*. This difference between confidence and likelihood is the sum of uncertainty in the readings for *A*.

Practical usage

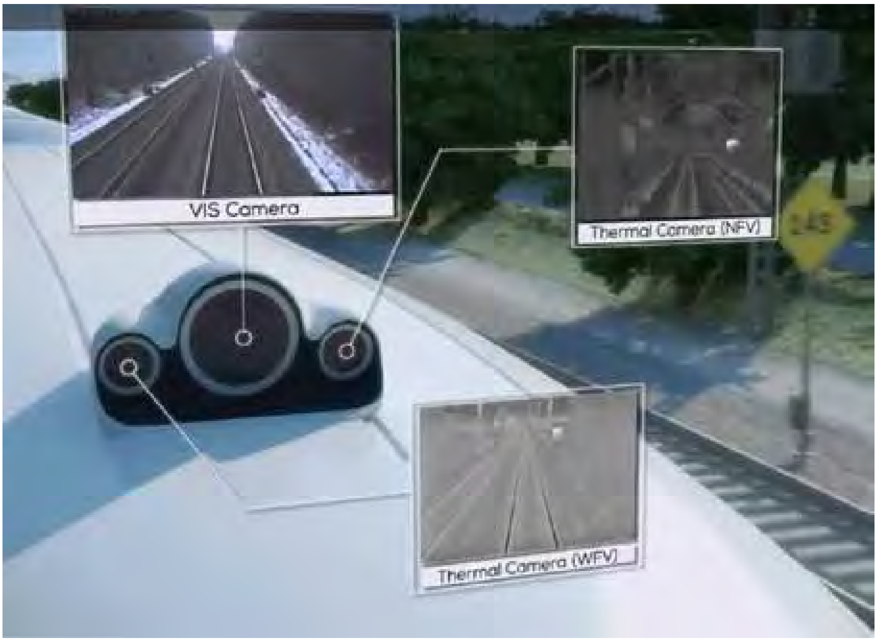
To detect obstacles in practice, it has become mandatory to use «technical» or «machine vision» to help the driver, especially in poor visibility conditions. The human eye is unable to detect certain objects when visibility is not good enough. So, in winter, when snow covers tracks and hides obstacles, it is important to determine exactly how to drive the train. Various algorithms and mathematical models come to the rescue to integrate the data that comes from the sensors. The data has to be filtered by the area of interest relative to the rail track, objects are associated, new objects are initialized, the state of existing objects is updated, and stochastic objects are controlled by modelling using DST, i.e. confirmed or removed from the knowledge base. Pic. 4 shows the information situation of poor visibility, which is between visible and «blind».

According to foreign data, the probabilistic obstacle detection system when a train moves on a railway line can operate at distances up to 2000 m at speeds up to 200 km/h, for example, RODS – Rail Obstacle Detection System[1]. This obstacle detection system on the railway track detects the obstacle and transmits alarms to the train driver in real time.

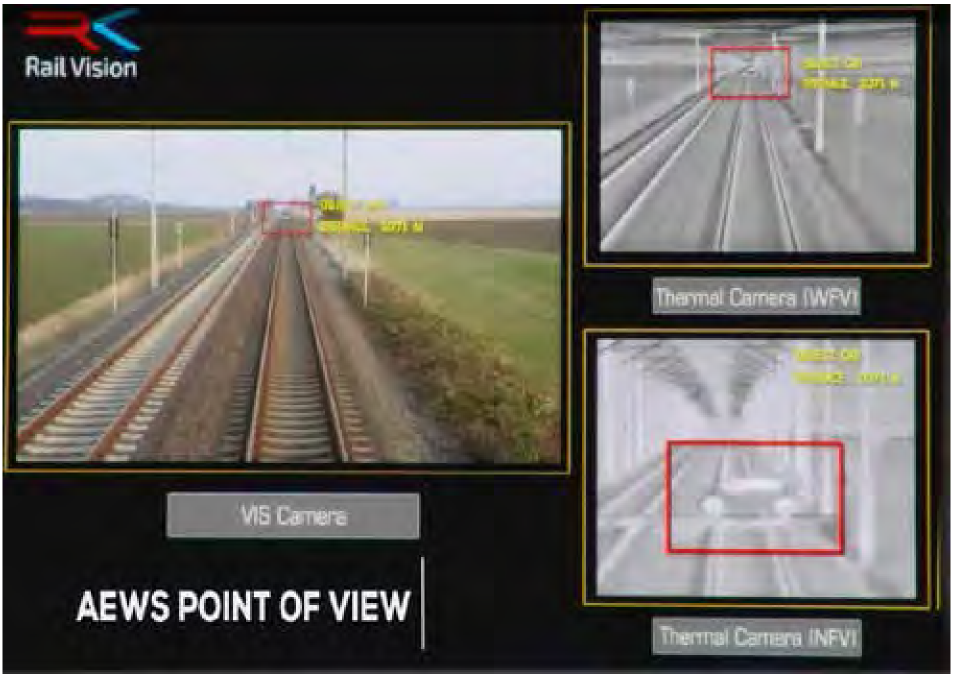
This autonomous system (Pic. 5) addresses more than 80 % of weather-related obstacle detection challenges by quadrupling the operator's visual range, thereby preventing costly and hazardous events, avoiding accidents and ensuring traffic safety.

RODS solution offers assistance to the driver or operator (in case of remote control) with full visual control using a freestanding roof-mounted visualization kit. For this, modern electro-optical sensors (in the visible and thermal ranges) are used (Pic. 6), with the possibility of merging these data. Pic. 6 shows object recognition based on probabilistic models. Such recognition is beyond the power of man. Recognition is based on probabilistic analysis and the use of a library of images.

[1] [Electronic resource]: https://www.railvision.io/the-platform/main-line-vision/. Last accessed 12.01.2020.



Pic. 5. Obstacle sensing driving support system. [Electronic resource]: https://railvision.io/main-line-solution/.



Pic. 6. Obstacle detection system based on situational probabilistic analysis. [Electronic resource]: https://railvision.io/main-line-solution/.

This technology allows the operator and driver to receive real-time emergency alerts for decision making while driving, reducing costs associated with possible injury or loss of life.

Conclusion. The proposed model of an information probabilistic situation and analysis based on it can be used for control in automated and transport cyber-physical systems. In essence, this approach is application of element-by-element (operational) system analysis as applied to the field of probabilistic logic [19]. A feature of the approach described in this work is replacement of the concept of «alternative» by the concept of «alternative information situations», which are then transformed into probabilistic information situations. An alternative information situation is a more structured model with a number of constraints that tie it to the transportation sector. An information transportation situation has a trinitarian essence: side objects, a controlled object, and a semantic environment of a controlled object. The semantic environment of a spatial object and its image is a qualitative feature of this method. It means using the parameter space from the image library to compare with spatial images captured by sensors. The introduction of probabilistic parameters into information situation parameters makes it possible to apply Dempster–Schafer theory and automatically becomes an advisory expert method applicable in transport cyber-physical systems.

REFERENCES

1. Lyovin, B. A., Tsvetkov, V. Ya. Object and situational models in transport management [*Ob'ektnie i situatsionnie modeli pri upravlenii transportom*]. Nauka i tekhnologii zheleznykh dorog, 2017, Iss. 2 (2), pp. 2–10. [Electronic resource]: http://www.vniias.ru/images/img/online_journal/pdf/02_2017/06_2017.pdf. Last accessed 11.05.2020.

2. Titov, E. K. Information situational management [*Informatsionnoe situatsionnoe upravlenie*]. *Gosudarstvenniy sovetnik*, 2019, Iss. 1 (25), pp. 51–56. [Electronic resource]: https://cyberleninka.ru/article/n/informatsionnoe-situatsionnoe-upravlenie/pdf. Last accessed 11.05.2020.

3. Lyovin, B. A., Tsetkov, V. Ya. Cybernetics and Physical Systems for Transport Management. *World of Transport and Transportation*, 2018, Vol. 16, Iss. 2 (75), pp. 138–145. [Electronic resource]: https://mirtr.elpub.ru/jour/article/viewFile/1441/1717. Last accessed 11.05.2020.

4. Kovalenko, N. I. Knowledge extraction for intelligent transport systems [*Izvlechenie znanii dlya intellektualnykh transportnykh system*]. *Perspektivy nauki i obrazovaniya*, 2014, Iss. 5, pp. 45–52. [Electronic resource]: https://cyberleninka.ru/article/n/izvlechenie-znaniy-dlya-intellektualnyh-transportnyh-sistem/pdf. Last accessed 11.05.2020.

5. Tsvetkov, V. Ya. Information Situation and Information Position as a Management Tool. European researcher. Series A, 2012, Vol. 36, Iss. 12–1, pp. 2166–2170. [Electronic resource]: http://docplayer.ru/25906936-Information-situation-and-information-position-as-a-management-tool-viktor-ya-tsvetkov.html. Last accessed 11.05.2020.

6. Pavlovsky, A. A., Okhotnikov, A. L. Information transport situation [*Informatsionnaya transportnaya situatsiya*]. *Nauka i tekhnologii zheleznykh dorog*, 2018, Iss. 2 (6), pp. 16–24. [Electronic resource]: http://www.vniias.ru/images/img/online_journal/pdf/02_2018/2_2018.pdf. Last accessed 11.05.2020.

7. Pavlovsky, A. A. Formal interpretation [*Formalnaya intepretatsiya*]. *Perspektivy nauki i obrazovaniya*, 2017, Iss. 4 (28), pp. 18–22. [Electronic resource]: https://www.elibrary_29904637_56184823.pdf. Last accessed 11.05.2020.

8. Tsvetkov, V. Ya. Integrated Control of High Speed Railway. *World of Transport and Transportation*, 2013, Vol. 11, Iss. 5 (49), pp. 6–9. [Electronic resource]: https://mirtr.elpub.ru/jour/article/view/441. Last accessed 11.05.2020.

9. Okhotnikov, A. L. Application of Dempster–Schafer theory for optimization of transportation [*Primenenie teorii Dempstera–Shafera dlya optimizatsii perevozok*]. *Nauka i tekhnologii zheleznykh dorog*, 2018, Iss. 4 (8), pp. 61–74. [Electronic resource]: http://www.vniias.ru/images/img/online_journal/pdf/01_2019/01_2019.pdf. Last accessed 11.05.2020.

10. Musicki, D., Evans, R. Joint Integrated Probabilistic Data Association: JIPDA. IEEE Transactions on Aerospace and Electronic Systems, Vol. 40, No. 3, pp. 1094–1099, July 2004. DOI: 10.1109/TAES.2004.133748.

11. Mahlisch, M., Ritter, W., Dietmayer, K. De-cluttering with Integrated Probabilistic Data Association for Multisensor Multitarget ACC Vehicle Tracking. IEEE Intelligent Vehicles Symposium, Istanbul, Turkey, June 2007, pp. 178–183. DOI: 10.1109/IVS.2007.4290111.

12. Munz, M., Maehlisch, M., Dickmann, J., Dietmayer, K. Probabilistic Modeling of Sensor Properties in Generic Fusion Systems for Modern Driver Assistance Systems. IEEE Intelligent Vehicles Symposium, San Diego (CA), USA, June 2010, pp. 760–765. DOI: 10.1109/IVS.2010.554804.

13. Kudzh, S. A., Tsvetkov, V. Ya. Logic and algorithms: Monograph [*Logika i algoritmy: Monografiya*]. Moscow, MAKS Press, 2019, 112 p.

14. Wenbo, He; Hoang, Nguyen; Xue, Liu; Nahrstedt, K.; Abdelzaher, T. iPDA: An integrity-protecting private data aggregation scheme for wireless sensor networks. MILCOM 2008–2008 IEEE Military Communications Conference. IEEE, 2008, pp. 1–7. [Electronic resource]: https://www.ideals.illinois.edu/bitstream/handle/2142/11413/iPDA%20An%20Integrity-Protecting%20Private%20Data%20Aggregation%20Scheme%20for%20Wireless%20Sensor%20Networks.pdf?sequence=2&isAllowed=y. Last accessed 11.05.2020.

15. Musicki, D., Evans, R. Joint integrated probabilistic data association: JIPDA. IEEE transactions on Aerospace and Electronic Systems, 2004, Vol. 40, Iss. 3, pp. 1093–1099. DOI: 10.1109/TAES. 2004.133748.

16. Ba-Ngu, Vo; Wing-Kin, Ma. The Gaussian mixture probability hypothesis density filter. IEEE Transactions on signal processing, 2006. Vol. 54, Iss. 11, pp. 4091–4104. DOI: 10.1109/TSP.2006.881190/

17. Okhotnikov, A. L., Dzyuba, Yu. V. Soft situational control [*Myagkoe situatsionnoe upravlenie*]. In: Intelligent control systems for railway transport. Computer and mathematical modeling (ISUZHT-2018). *Proceedings of the seventh scientific and technical conference*, 2018, pp. 62–64. [Electronic resource]: https://www.elibrary_36916645_17254769.pdf. Last accessed 11.05.2020.

18. Aeberhard, M., Paul, S., Kaempchen, N., Bertram, T. Object Existence Probability Fusion using Dempster–Shafer Theory in a High-Level Sensor Data Fusion Architecture. IEEE Intelligent Vehicles Symposium, Baden-Baden, Germany, June 2011, pp. 770–775. DOI: 10.1109/IVS.2011.594043.

19. Gospodinov, S. G. Probabilistic logical analysis [*Veroyatnostno logicheskiy analiz*]. *ITNOU: Information technologies in science, education and management*, 2019, Iss. 1, pp. 3–8. [Electronic resource]: http://www.vniias.ru/images/img/online_journal/pdf/03_2019/03_2019.pdf. Last accessed 11.05.2020.