

Neural network model for recognition and classification of types of interactions in road traffic

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ABSTRACT: The article presents neural network for recognition of driving strategies based on interactions between drivers in road traffic. It analyzes the architecture of the model implemented as a self-organizing map (SOM), consisting of a group of neural networks based on radial basis functions (RBF). It is a training model grounded in the biological foundations of artificial neural networks, in which the training set should consist exclusively of input vectors; wherein the network training algorithm adjusts itself the network's weights to obtain consistent output vectors (i.e. to make presenting sufficiently close input vectors result into the same outputs).

The article presents the results of using a new generation of the neural network developed by us, which includes an adaptive learning algorithm to reduce the effect of re-training (overfitting) and false recognition, as well as to improve the determination of the boundaries between clusters.

The aim of the research is to outline architecture and structure of the neural network model that allows recognizing strategical characteristics of driving and can identify strategies of interactions between vehicles (their drivers) in road traffic as well as identify behavioral patterns. This paper considers driving strategies that characterize the interaction of

dyads of vehicles (drivers) moving in road traffic. The research results show that the SOM RBF neural networks can recognize and classify types of interactions in road traffic based on modelling of the analysis of vehicle movement trajectories. Experimental results demonstrate the neural networks architecture and networks learning involving 400 iterations of streaming the training data representing 500 possible simulated interaction situations. This paper presents a novel neural network model for recognition of drivers' behaviour patterns and for classification of driving strategies into five general classes: (1) competition strategy, (2) contest strategy, (3) evasion strategy, (4) compromise strategy, and (5) active confrontation strategy. This neural network has demonstrated a high rate of recognition and concise clusterization of similar driving strategies. The key contribution of this paper: it proposes a neural network model based on Kohonen's Self-Organizing Map (SOM) for detecting drivers' behaviours from vehicle movement patterns – driving strategies – instead of monitoring driver's specific activities.

KEYWORDS: Neural network model; Self-organizing map (SOM); Driving strategies; Traffic participants' interactions strategies.

1. INTRODUCTION

One can state that in recent years a high interest in artificial intelligence and machine learning has been increasingly penetrating into various fields of science. Today the works on recognition and classification of visual images (Efremova et al., 2012) or "patterns of form and motion" can be found in different researches (Giese and Rizzolatti, 2015, Parisi et al., 2017). These studies are based on the cognitive modeling methodology and serve as the basis for the development of neural network models.

It should be emphasized that more and more research works in which neural networks serve the purposes of road safety appear at the junction of various fields: engineering, transportation, traffic psychology (Olayode et al., 2021). Of course, the development of intelligent vehicle technologies allows integration of complex traffic safety analysis systems and statistical analysis of highway accident data (Mannerling et al., 2016) with the aim to reduce the rate of collisions related to human error (Costela and Castro-Torres, 2020).

However, as some authors assert some systems monitor solely the driver behaviour (Galarza et al., 2018), whereas others monitor the driver status combining the driver behaviour, the vehicle state and the road environment (Al-Sultan et al., 2013). Also a larger part of driver behaviour monitoring systems detect only a specific abnormal behaviour (Shahverdya et al., 2020).

Today it is often noted, that some studies have been done on driver behaviors, which monitor the drivers' body and use

the deep learning techniques to classify their actions (Galarza et al., 2018, Sabet et al., 2012, Shahverdya et al., 2020).

A literature review shows that researchers are actively engaged in exploring data on characteristics of various aspects of drivers' behaviour (Brackstone and McDonald, 1999, Chliaou-takis et al., 2002, Kochetova, 2018, Miles and Johnson, 2003).

However, there is still no effective monitoring system to detect different behaviour patterns as "driving strategies" (Efremov, 2017, 2018) or "traffic interaction strategies" (Wilde, 1976). In this regard, it is of interest to develop a neural network capable to recognize drivers' strategies relative to one another.

Such patterns may include stylistic features, and some authors analyze vehicle control style (Efremov, 2017, Polikarpova, 2017) which is connected to personal activity style (Klimov, 1982) – a system of psychological means that are consciously or spontaneously used by a personality (West and Hall, 1979) to better adjust his/her individual characteristics to objective conditions of a driver activity.

Quite obviously, emphasis on investigation of stylistic features of driving does not imply investigation of socio-psychological aspects of interactions between drivers as road traffic participants. Since road traffic is a complex social system, which includes multiple participants – transportation subjects, it is necessary to pay attention at the analysis of driving features that characterize a driver's behavior in a wide range of interactions with the other traffic participants (Efremov and Kochetova, 2018, Efremov, 2018). We consider such interactions to be the contents of a driver's behavior in the

context of his movement in relation to other drivers nearby in traffic.

In other words, driving strategies differ from vehicle control styles since they are stable patterns of traffic behavior characterized by certain ways and means for solving so-called "driving tasks" in traffic and interactions with other drivers (Wilde, 1976), for instance, while changing lanes or overtaking. Based on this perception of strategic behavioral characteristics, by a "driving strategy" we will mean steadily recurring patterns of a driver's traffic behavior (Kochetova and Meinhard, 2020, Wilde, 1976) that characterize his interactions with other traffic participants.

The given concept of driving strategies and studies in the neural networks development (Chonga et al., 2013, Gipps, 1981, Ossen and Hoogendoorn, 2008) provided the ground for creating a neural network model (Osipov, 2009, Efremov, 2017, 2018) to recognize the types of drivers' behaviour patterns in road traffic.

Thus, in this paper we propose a novel neural network model for recognition of drivers' behaviour patterns and for classification of driving strategies into five general classes: (1) competition strategy, (2) contest strategy, (3) evasion strategy, (4) compromise strategy, and (5) active confrontation strategy.

The key contribution of this paper is as follows: we propose a neural network model based on Kohonen's Self-Organizing Map (SOM) (Kohonen, 2001) for detecting drivers' behaviours from vehicle movement patterns of interactions – driving strategies – instead of monitoring driver's specific activities.

Experimental results in this paper demonstrate not so much the neural networks architecture that was presented in the previous papers (Efremov, 2017, 2018), but the results of neural networks learning involving 400 iterations of streaming the training data representing 500 possible simulated interaction situations.

The fundamental differences between this article and those previously published (Efremov, 2017, 2018) are: (1) presentation of the results of using a new generation of the neural network developed by us, which includes an adaptive learning algorithm to reduce the effect of re-training (overfitting) and false recognitions, as well as to improve the determination of the boundaries between clusters; (2) introduction of the concept of "canonical trajectories" for each type of vehicle interaction.

When simulating road situations, we, when developing a neural network, set different initial vehicle speeds (vehicles) and different distances before interaction. At the same time, from each array of correctly recognized types of road interactions, we use the trained network to determine the trajectories to which the neural network gives the best response. We call these trajectories canonical, and further use them when displaying graphic information reflecting the recognition results (Graphs 1-5.).

2. MATERIALS AND METHODS

By "interactions" we mean situations when two moving vehicles cause changes in each other's speed and/or movement trajectory. Thus, we "separate" the whole traffic flow into vehicles' (drivers') dyads that meet the following conditions:

- An overtaking vehicle has higher speed (otherwise no interaction would take place).
- One or both vehicles (drivers) have to change their speed and/or movement trajectory under the influence of each other (Figure 1).

As one can see in Figure 1, the vehicles A1 and A2 dyad are demonstrating interaction. The stable and recurrent pe-

culiarities of such interactions will be considered as driving strategies (Efremov and Kochetova, 2018), and their recognition will be regarded as the main task for developing a neural network and training it in recognition (Efremov, 2017).

In this paper, we are not performing the task of implementing the network training on data from traffic cameras, since this problem has been already solved and there are several systems capable to recognize objects on the road and to build trajectories of their movement.

We simulate this situation and feed the following data on the selected (interacting) dyads of vehicles (drivers) to their input of the neural network.

We work with neural network based on Kohonen's Self-Organizing Map (SOM) (Kohonen, 2001), consisting of a group of Radial Basis Functions (RBF) networks as well as a 256 (16 x 16) networks map. This architecture has been implemented in the developments by the Artificial Intelligence Laboratory of the Massachusetts Institute of Technology (Kosslyn, 1994, Riesenhuber and Poggio, 1999, 2020), and in the developments by a group of researchers from Kyoto University (Tokunaga and Furukawa, 2009).

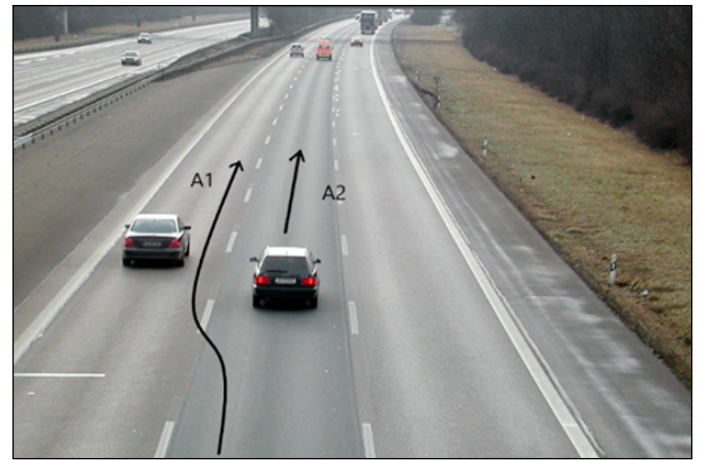


Figure 1. Traffic participants' interactions strategies

The use of a self-organizing map, consisting of RBF networks, allows to create a multidimensional topology between all analyzed data, using the training of neural networks "without teacher" and project it onto a two-dimensional space.

Training a neural network without teacher forcing is a training model grounded in the biological foundations of artificial neural networks, in which the training set should consist exclusively of input vectors; wherein the network training algorithm adjusts itself the network's weights to obtain consistent output vectors (i.e. to make presenting sufficiently close input vectors result into the same outputs).

It is necessary to emphasize the biological credibility (Fujita, 2002) of such a neural network and its structure (Efremova et al., 2011; Efremova et al., 2012, Efremov, 2017).

Our neural network is organized as SOM, consisting of 256 functional RBF-modules (Tokunaga & Furukawa, 2009), structured into a square 16 x 16 grid.

The SOM algorithm includes four main processes: evaluative, competitive, cooperative and adaptive ones (Fujita, 2002).

The neurons in hidden layers of each module are Gaussian functions (Efremov, 2017). Initially, weights are determined randomly in the interval [0.25-0.75]. During the evaluative process the outputs of all functional modules are calculated for each pair of input-output vectors (Efremov, 2017, 2018):

$$o(x) = \sum_j^n w_j \times \exp \left\{ \frac{-(x - u_j)^2}{2\sigma_j^2} \right\}$$

In the training process, the module with the minimal error is designated the winner module. The error is calculated as follows:

$$E_i^k = \frac{1}{2} \left(y - \frac{1}{1 + \exp^{-o(x)}} \right)^2,$$

where y defines the output to be made (here $y = 1$). During the cooperative process the coefficients in training are calculated using the neighborhood function:

$$\alpha(r_i) = \frac{\exp \left\{ \frac{-(r_i - r_p)^2}{2\sigma_j^2} \right\}}{\sum_{i=1}^n \exp \left\{ \frac{-(r_i - r_p)^2}{2\sigma_j^2} \right\}}$$

where r_i is the position of a RDF-module number on the map, r_p is the position of the module with the minimal error, and σ is the parameter of the neighborhood function. In the training process, all the elements are changed according to the back error propagation algorithm.

$$\Delta u_j = k \times \frac{\partial E}{\partial u_j(t-1)}$$

and

$$u_{ij}(t) = u_{ij}(t-1) + \Delta u_{ij} \cdot \alpha(r_i)$$

Thus:

$$\Delta w_j = k \cdot \left(y - \frac{1}{1 + e^{-o(x)}} \right) \cdot \left(y - \frac{e^{-o(x)}}{(1 + e^{-o(x)})^2} \right) \cdot \exp \left\{ \frac{-(x - u_j)^2}{2\sigma_j^2} \right\}$$

The back error propagation algorithm is repeated until all the elements are trained. In the training process, the radius of the neighborhood function gradually decreases until the network reaches a stable state.

$$\Delta u_{ij} = k \cdot \left(y - \frac{1}{1 + e^{-o(x)}} \right) \cdot \left(y - \frac{e^{-o(x)}}{(1 + e^{-o(x)})^2} \right) \cdot w_{ij} \cdot \frac{(x - u_j)}{2\sigma_j^2} \exp \left\{ \frac{-(x - u_j)^2}{2\sigma_j^2} \right\}$$

Due to the heterogeneity of the data, we had to increase the number of neurons in the inner layer from 2 to 3 that, in turn, allowed us to increase the level of the network's recognition accuracy.

3. RESULTS

Our model implies that we take five snapshots from a stationary camera on a certain section of the road for each dyad of

vehicles and use the distance between the vehicles, as well as the change in the position of the vehicles in relation to one another as orientated along the road axis, as input vectors – see Figure 2.

Then we generate 500 situations relating to five various types of strategies of interactions between two vehicles in traffic (Efremov, 2017, 2018).

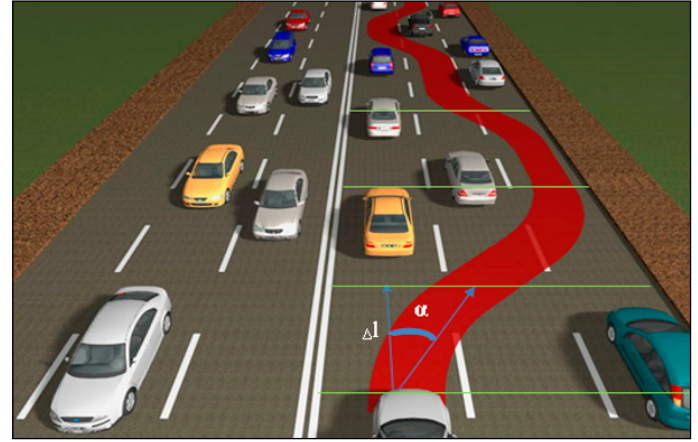


Figure 2. Traffic participants' interactions strategies

Hereinafter in the schematic pictures of driving trajectories the higher (grey) rectangle represents the vehicle A, which moves with the higher speed than the vehicle B with the intention to overtake it; the lower (black) rectangle represents the vehicle B.

Vehicle A – the higher rectangle (grey). The vehicle B – the lower rectangle (black) – see Graphs 1-5.

To achieve a more realistic simulation, the initial speeds of the interacting vehicles are randomly assigned in the range of 40 to 80 km/h and are calculated at random.

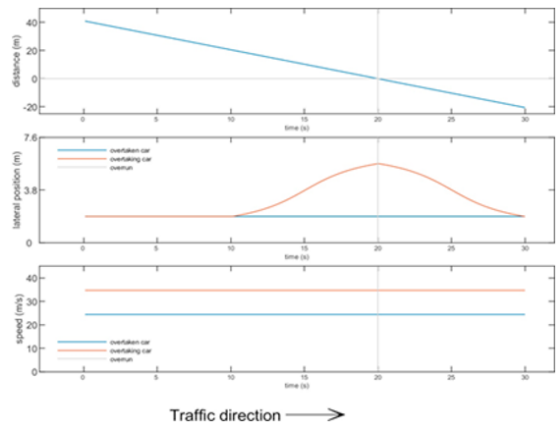
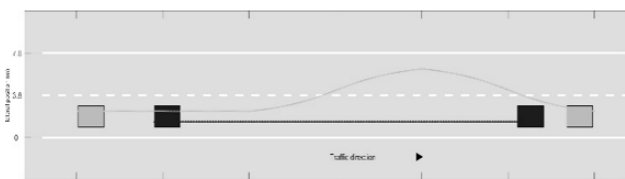
Training the neural network

In the new version of the neural network, we increased the number of iterations to 400, but starting from the 200th iteration, we begin to proportionally lower the learning rate from 1 to 0.25. Thus, the training accuracy increases and the re-training effect, which we periodically encountered in the previous version of our neural network, decreases (Efremov, 2017, 2018). In other words, using the methodology presented in previous studies, in the present work, the main focus was on ensuring the accuracy of the results of recognition and training of the neural network.

This reduces: (1) the error rate for recognizing each of the canonical trajectories of interaction and (2) the overall re-

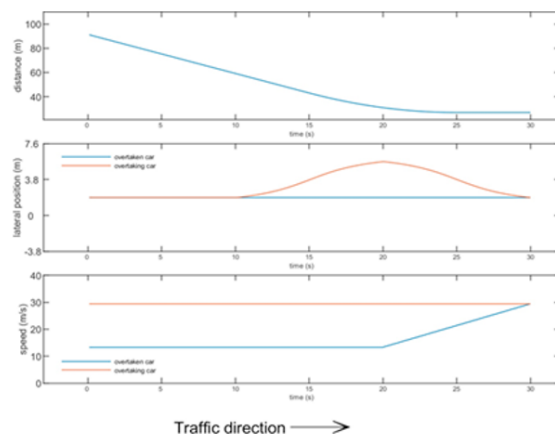
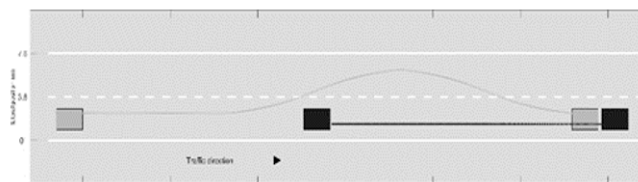
Vehicle A moves faster than vehicle B. The driver of vehicle A overtakes vehicle B and returns to the previously occupied lane after this maneuver.

After a while the driver of vehicle B does not change speed.



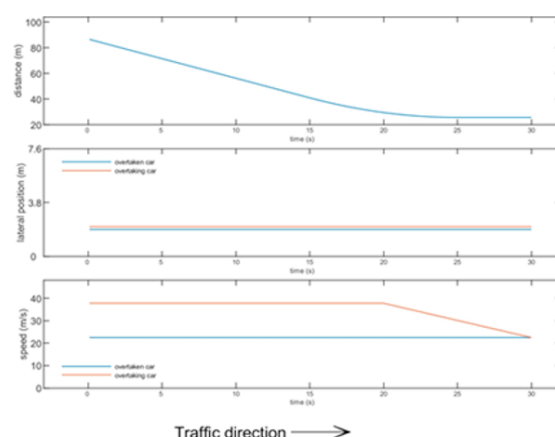
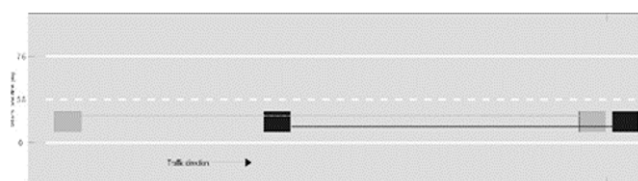
Graph 1. Competition strategy

Vehicle A moves faster than vehicle B and starts overtaking. The driver of vehicle B accelerates which causes vehicle A to abort the maneuver and return to the lane at which it started.



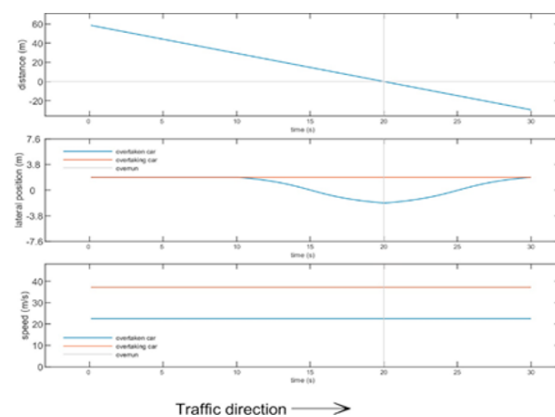
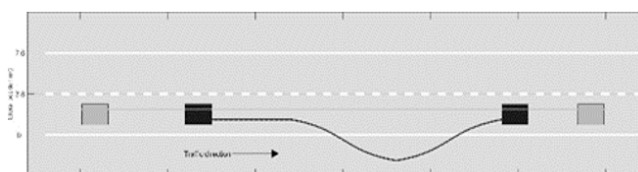
Graph 2. Contest strategy

Vehicle moves A at a faster speed than vehicle B. When approaching vehicle B, the driver of vehicle A slows down to bring it to the speed of vehicle B and follows it.



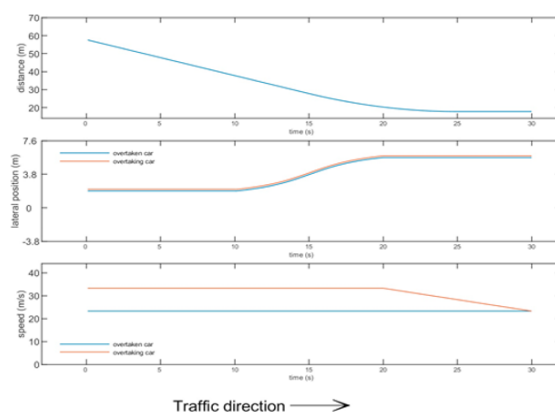
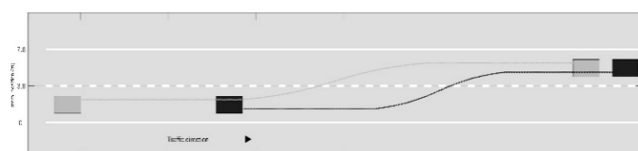
Graph 3. Evasion strategy

Vehicle A moves at a faster speed than vehicle B. The driver of vehicle B changes lane to give vehicle A, and returns to the previously occupied lane after vehicle A drives by.



Graph 4. Compromise strategy

Vehicle A is moving at a faster speed than vehicle B. Approaching vehicle B, the driver of vehicle A begins an overtaking maneuver. The driver of vehicle B moves to the left, changing lanes without changing speed. The driver of vehicle A is forced to brake to the speed to adjust it to the speed of vehicle B.



Graph 5. Active confrontation strategy

sponse of the network to all non-standard interactions, and also improves the quality of classification of each type of interaction.

The control of such training can be displayed at the graph of the mean error decrease through the entire cluster of networks.

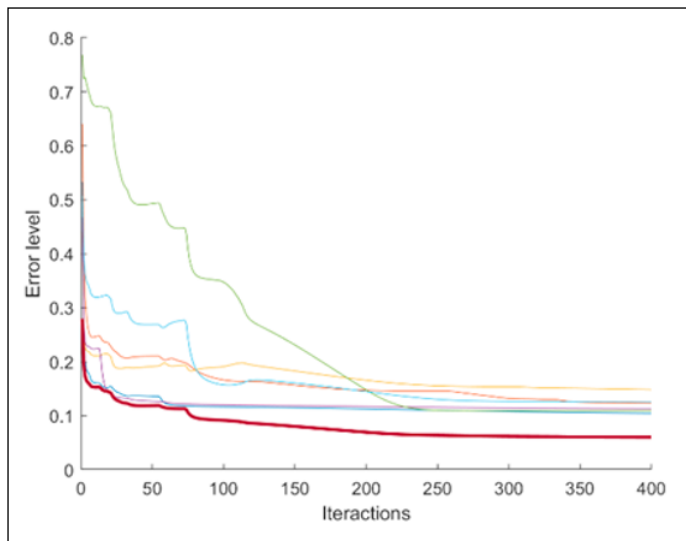


Figure 3. The graph of the mean error decrease through the cluster of networks with 400 iterations

As mentioned above, in this new version of the neural network, the number of iterations has been increased from 250 to 400, and starting from the 200th iteration, the learning rate has been proportionally reduced to 0.25.

Visual borders between the between the SOM-network clusters are represented in Figure 4.

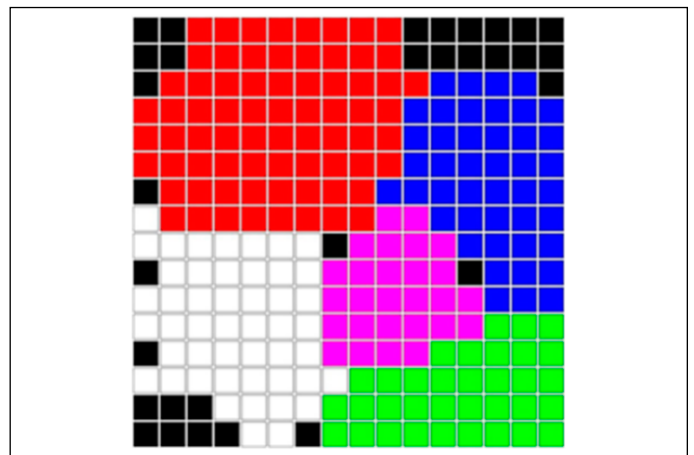


Figure 4. The borders between the SOM-network clusters: the recognition zones for each type of a strategy are marked with different colors

The further graphs illustrate the recognition zones for each of the five driving strategies presented in the five aforementioned traffic situations: the networks with zero response to data are highlighted in black, the lighter is their color the higher is the response – see Figure 5.

The described neural network can be used as a basis for the development of more complex models capable of recognizing other patterns of road behaviour, for example, behaviours associated with the choice of speed, operating at the maximum speed of traffic flow, and many others.

As we have already noted, the described algorithm is a modification of SOM; it includes the basis for constructing a self-organizing map consisting of RBF modules. Thus, a neural network model of recognition and classification of types of interactions in road traffic was obtained.

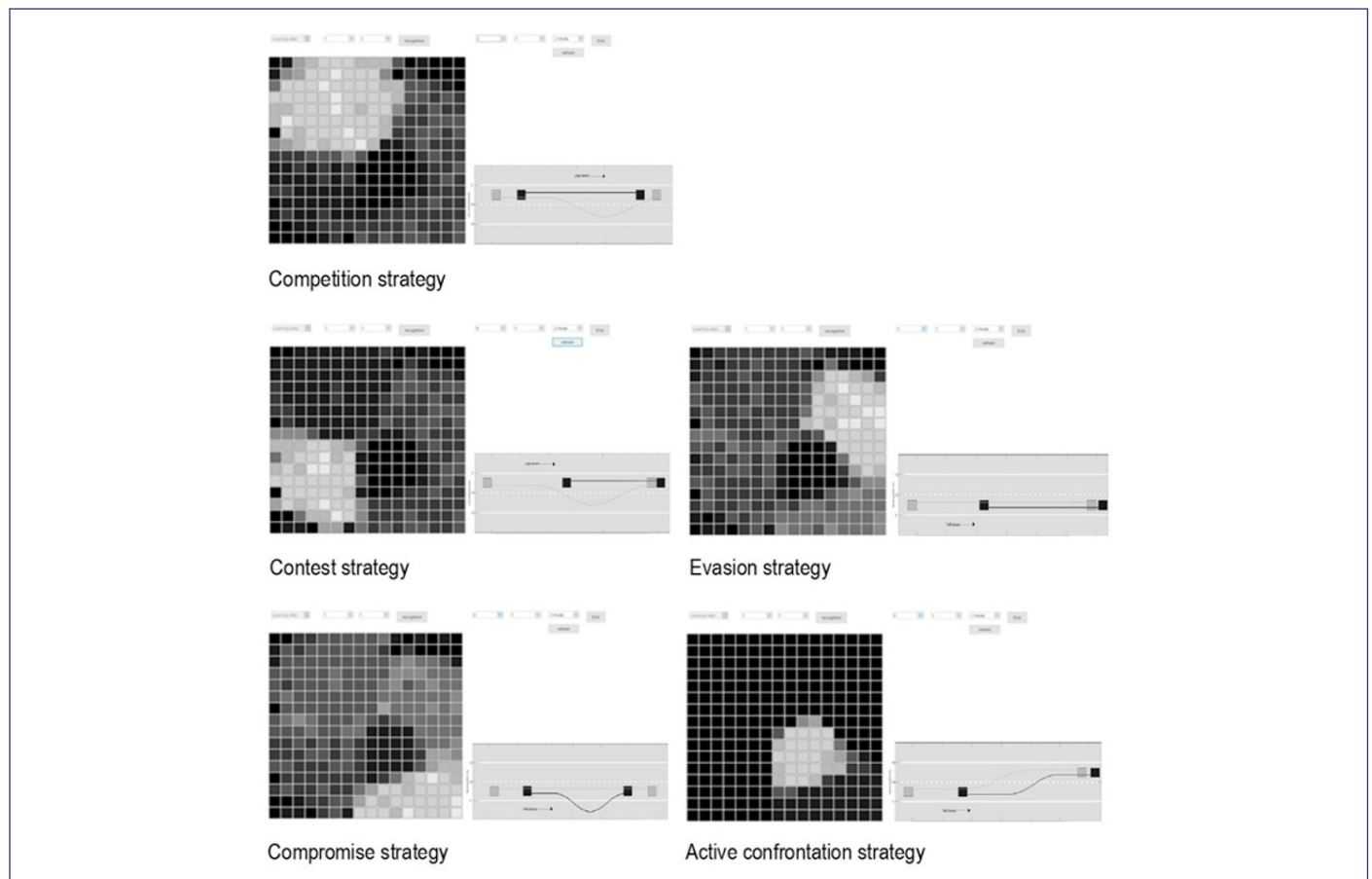


Figure 5. The classification of five types of interactions in road traffic

4. CONCLUSIONS

This article presents the results of training a neural network model based on the Kohonen self-organizing map (SOM). and consists of a group of Radial Basis Functions networks as well as a 256 (16 x 16) networks map. We used this model to create a neural network that allows us to recognize types of driving strategies as types of vehicle interactions.

It can be concluded that the proposed model for recognizing driving strategies that characterize the interaction of dyads of vehicles (drivers) moving in road traffic, based on the architecture of SOM has been successfully implemented. Unlike previous research (Efremov, 2017, 2018), this neural network is trained using 400 iterations of streaming training data representing 500 interaction situations. The created neural network makes it possible to recognize and classify the types of interactions (driving strategies) in road traffic.

Thus, the neural network demonstrates a high precision of recognition and classify types of interactions in road traffic. The proposed SOM model not only inherits many of the properties of classic self-organizing maps, but adds some new properties (Yin, 2008).

We must emphasize that our development of the neural network model cannot be considered complete; further work may be required.

Nevertheless, it can be considered as a certain intermediate result of an interdisciplinary scientific synthesis of neuroscience, cognitive science, social psychology and transport psychology (Velikhov and Chernavskii, 1987), aimed at studying the processes of interaction between participants in a wide range of social systems.

Such a synthesis can both significantly expand the understanding of a person and his/her behaviour on the road and lead to important practical applications, since the study and further recognition of strategies / behavioral patterns in drivers can help achieve the goal of reducing the number of traffic accidents. Indeed, the recognition of driving strategies makes it possible to clearly identify patterns of, for example, dangerous or risky behavior of drivers in traffic.

It is important to emphasize that the neural network cannot be considered as fully complete and requires further refinement development in the future. So, for example, with an increase in the number of classifications in the future, we can use the canonical trajectory of interaction as a kind of basis for evaluating potential intermediate transactions and / or transactions that have signs of several strategies (for example, with the participation of more than two drivers in the same traffic situation).

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Conflict of interests

The authors declare no conflict of interests.

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