Solution of Problems to Ensure Road Safety by Means of Intelligent Transport Systems

D G Vasilchenkova¹

¹Department of Functional Analysis and its Applications, Vladimir State University Named After Alexander and Nikolay Stoletovs, Gorky Street, 87, Vladimir, 600000, Russia

E-mail: darya.vasilchenkova@mail.ru

Abstract. The article is devoted to intelligent transport systems based on short-range radio technology (DSRC). The main feature of this type of system is the ability to provide communication between vehicles without the direct involvement of drivers and without access to the global network. This allows to solve a number of problems related mainly to road safety. This article is about collision prediction and the detection of dangerous driving elements. For these problems, mathematical models of their solution are given, a description of the basic terms of the proposed algorithms, and the results of simulation experiments delivered using the traffic simulator Simulation of Urban Mobility are presented. The model for prediction of vehicle collisions is based on methods for approximating vehicle trajectories and their pairwise comparison. The detection of dangerous driving elements is based on the statistical processing of a number of vehicle motion parameters in the visibility range of the such DSRC device.

1. Introduction

Currently, many intelligent transport systems have been developed and a wide variety of products designed to improve road safety and comfort are presented [1-5]. Significant disadvantages of the most common systems of this type are the need for centralized management, stable access to the Internet, a long period of updating information and broadcasting signals.

In the article we consider a promising type of intelligent transport systems based on the technical means of radio communications for vehicles of the Dedicated Short-Range Communications type – DSRC (see IEEE 802.11p, IEEE 1609.x, WAVE, ETSI ITS-G5 standards [6-10]). To implement this technology, it is necessary to install compact short-range radio transceivers on the vehicle (from hundreds of meters to a kilometer). Devices allow cars to “detect” each other and exchange necessary telemetry data in real time. Thus, vehicles interact with each other directly, and it is not necessary to transfer information through the global network. This leads to a significant advantage of DSRC devices, especially in adverse weather conditions and areas of unstable communication of cellular operators.

This work is devoted to the development of mathematical models and algorithms that solve the following problems: prediction of vehicle collisions and detection of vehicles doing dangerous driving maneuvers. Results of a simulation experiment with road traffic obtained using the Simulation of Urban Mobility (SUMO) [11-15] traffic simulator will be presented. During all experiments a real
transport network of one of the Russian cities, located on an area of about 12 km$^2$, will be used to build traffic.

2. Vehicle collision prediction

To create a collision prediction system [16], it is necessary to construct prediction trajectory of the vehicle. There are many different models of motion prediction, for example, based on the probabilistic choice from the set of all possible straight-line trajectories of the vehicle [17], the Kalman filter [18], information about the state of the tilt steering arms of the vehicle [19], Bezier curves [20].

In this paper a kinematic approach is proposed, namely, the approximation of the equation of motion by various types of linear and quadratic regression.

2.1. Quadratic regression of vehicle movement

This approach involves the construction of the classical regression equation of uniformly accelerated motion. Using the vehicle path for a time of about 2 seconds, we build a predicted path of the form

$$\ddot{x}(t) = C_x + B_x t + A_x t^2, \quad \ddot{y}(t) = C_y + B_y t + A_y t^2.$$ 

Parameters $A_x, B_x, C_x, A_y, B_y, C_y$ are calculated by the classical least squares method. The shortcomings of this model were experimentally identified. They were partially eliminated by adjusting the quadratic approximation model.

2.2. Adjusted quadratic regression of vehicle movement

The following model involves the construction of a quadratic regression of coordinates, as in the previous paragraph, with correction of the resulting trajectory. Due to the features of the problem, natural requirements arise for the prediction trajectory, but approximation principle in the general case does not guarantee the implementation of following conditions: firstly, vehicle moving vector along the regression trajectory from the previous position to the present one should have a direction that coincides with the current vehicle direction; and secondly, the curve defined by the regression must pass through the position of the vehicle at the current time. Thus, the correction of the trajectory is carried out by turning a known angle and parallel transfer of prediction points.

Simulation experiments were also constructed for the adjusted regression variant. The most typical prediction errors were identified, among which: building a trajectory in the opposite direction (it is feature of a quadratic curve); acceleration errors associated with the model’s high sensitivity to this motion parameter (the problem does not involve leaps of acceleration). In connection with these remarks, the following conclusions can be drawn. Any one universal form of the curve will not give high accuracy of the prediction trajectory. Each model allows a certain class of situations quite qualitatively, but at the same time does not work at all in other cases. Therefore, an alternative variant of adaptive construction of the interpolation curve from the two previous points of the path and the current position is proposed.

2.3. Adaptive interpolation model

Directly for interpolation, we use only the present $t_0$ and the previous $t_{-1}, t_{-2}$ times to determine the nature of the trajectory curve. We carry out the construction in two stages.

First stage. Using three known values of the $x(t)$ coordinates: $x(t_{-2}), x(t_{-1}), x(t_0)$, two parameters are calculated: the sign of the second derivative (to determine the nature of the convexity): $\text{sgn} \; x''$ and the curvature of the trajectory: $K$. The algorithm for coordinate $y$ is similar.

Second stage. Depending on the convexity of the trajectory, the type of prediction curve is selected. In the case of slight curvature, i.e. curvature not exceeding a certain threshold value $\bar{K}$, a linear interpolation of the coordinate is constructed $x(t): x(t) = At + B$. It was experimentally established that the optimal value of $K$ is in the range 1.2-1.4 sec $\cdot$ m$^{-2}$. In the case of significant curvature ($K > \bar{K}$) and convexity upward, the logarithmic interpolation is chosen: $x(t) = A \ln t + B$. In the case of significant curvature and convexity down, exponential interpolation is chosen: $x(t) = e^{At+B}$.
2.4. Collision prediction simulation results
Let us conduct a comparative analysis of three variants of prediction models regarding the accuracy of the forecast and the number of erroneous collision signals.

An estimate of the forecast error will be obtained by calculating the sample average from the maximum deviation of the predicted trajectory from the real one for all forecast trajectories in road traffic. For the models given in 2.1, 2.2 and 2.3, the error is 3.5 m, 3.2 m, 3.1 m, respectively.

However, note that the construction of the predicted trajectory is only a tool for collision alerts, therefore, the number of erroneous collision signals will be a more significant estimate when comparing models 2.1-2.3. Modification of first model by special adjustment (model 2.2) allowed to reduce the number of erroneous warnings by 2-7% compared to the first model (depending on the parameters of the experiment). Errors of the alternative coordinate prediction model (model 2.3) are mainly related to the acceleration module, and the nature of the trajectory, due to the combination of regression models, is estimated much more correctly. That is why, despite the slight difference in the estimation of forecast errors, the third model generates 48-56% less erroneous collision warnings than the first variant.

3. Detection of dangerous driving elements
The next problem is detection vehicles that perform dangerous driving elements [21] in the local dynamic neighborhood of each car. Analysis will be limited by three vehicle motion parameters in a local dynamic neighborhood of the radius of each car, namely: speed module, acceleration module and module of changing the direction of motion. These parameters can be directly calculated from the primary information. The main idea of the detection is to fix significant deviations of monitored parameters from their average values within the vicinity. If any of them significantly deviates from the average value, the counter of “violations” of the vehicle is increased by one. When the counter reaches a certain threshold value, the vehicle falls into the category of “dangerous”. In addition, in order to exclude random fluctuations of parameters, to assign the vehicle a category of “dangerous”, a duration of violations is required.

There are many statistical criteria for the detection of anomalous sample elements, for example, the criteria of Chauvenet, Grubbs, Wright, Tukey, Titien-Moore [22, 23]. A combination of Wright’s and Tukey’s methods in adapted form is proposed. Both criteria suggest that the analyzed sample has normal distribution. In addition, the classical method of exponential smoothing is used for analysis.

The experiment allows us to draw the following conclusions. In certain ranges of model parameters and with the most probable radius of the radio communication, the proposed algorithm makes it possible to identify about 70% of vehicles performing dangerous driving maneuvers. The share of vehicles mistakenly classified as dangerous driving is about 5%.

It should be noted that the proposed statistical method is aimed primarily at identifying different from average driver behavior, which, obviously, is not always equivalent to “dangerous” behavior. In this regard, one of the directions for development is the addition of the algorithm for detecting dangerous driving with a probabilistic criterion for a possible collision based on a short-term prediction model of movement.

4. Conclusion
The features of considered telematics tools, in particular, the lack of centralized control, the nature of the movement of vehicles and the high dynamics of the information network, determines the specifics of constructing algorithms to solve the tasks. That is why the construction concepts of the proposed models are radically different from the principles of standard intelligent transport systems using global network.

In this paper, models of collision prediction of vehicles and detection of dangerous driving elements have been proposed. Their efficiency has been proven through experiments with simulated traffic.
5. References

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