The Estimation of Traffic Flow Parameters based on Monitoring the Speed Values using Computer Vision

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Abstract: Most of the previous works dealing with road traffic organization have been focused on optimizing the setup of traffic signals, assuming that the traffic flow speed is fixed or adheres to a given distribution. In our study, we focused on real-time determining the vehicle speed and assessing its influence on the vehicle delay time. Vehicle detection and speed determination are based on real-time processing of video streams by a convolutional neural network (YOLOv3). The developed system can identify and classify traffic flows into eleven types, as well as track the motion path and speed of vehicles throughout the entire functional area of a signal-controlled intersection. While analysing the data, we identified two important factors corresponding to the presence of a queue of vehicles waiting for the green traffic light: 1. We identified the nature and statistically significant measure of reducing the free vehicle movement speed, depending on the size of the queue; 2. We determined the acceptable queue size, which does not affect the dynamics of crossing the intersection by group vehicles moving from the previous intersection. The obtained data allows us to optimize the operation of the adaptive traffic light control of intersections and to optimize the synchronization of road network signals based on speed indications.

1 INTRODUCTION

Most of the previous studies on the optimization of road traffic parameters (Wong et al., 2010; Wong et al., 2011), including methods for the synchronization of coordinated signals (Skabardonis and Geroliminis, 2008; Liu et al., 2011; Makarova et al., 2020) are focused on the optimization of signal timings ignoring the speed of traffic flows (Wu et al., 2015; Makarova et al., 2017). The real-time movement speed depends on several factors, including the condition and quality of the road surface, the driver behaviour, the vehicle performance characteristics, and road conditions (Burkhardt et al., 2021; Tian et al., 2021). Variable speed can be used on highways to control the traffic flow to increase the traffic capacity in open highway sections. In particular, the procedure for detecting road accidents is considered in (Allaby et al., 2007; Hadiuzzaman et al., 2013; Škorput et al., 2010; Beymer et al., 1997). In the studies focused on monitoring the level of traffic flow emissions, the key input variables are instantaneous measurements of the

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vehicle speed and acceleration (Ahn et al., 2002; Pavlovic et al., 2021). Therefore, it is essential to closely monitor the flow speed, which can facilitate making effective management decisions, as well as predicting the influence of vehicle emissions on the ambient air quality (Agarwal and Mustafi, 2021). There are methods for detecting anomalies and interpreting road traffic analysis using the Global Navigation Satellite System (GNSS). The method is based on measuring the Euclidean distance between the STM (Speed Transition Matrices) centre of mass (COM) and the mean STM, which represents normal driving conditions. Space and time-related events are combined into so-called traffic congestion propagation patterns. These patterns provide a high-level description of traffic congestion and its propagation in time and space (Tisljaric et al., 2020; Wang et al., 2013). This approach is characterized by a significant data transmission delay and averaging, which does not allow one to instantly receive and respond to any deviations in traffic parameters.

The vehicle speed determines the time the vehicle needs to cross the functional area of the intersection. The authors of (Wang, 2007) considered a general approach to the development of universal means for assessing the state of road traffic for highway sections based on stochastic macroscopic traffic modelling and extended Kalman filtering. Vakili et al. (2020), Czajewski and Iwanowski (2010) present a speed calculation method based on the use of geometric information and the distance travelled by vehicles. The algorithms are based on processing a video image taken by a single camera on the road to extract the license plate in the image.

In this study, we focused on developing a method for traffic speed monitoring to determine the delay time of the vehicle queue. The main objectives of this paper are: 1) to highlight the nature and statistically significant measure of reducing the free vehicle movement speed in the presence of a queue in front of a traffic light; 2) to determine the size of the queue, which does not affect the dynamics of crossing the intersection by group vehicles.

Although speed is very important to ensure the safety and efficiency of setting road traffic control systems (Choi et al., 2013; Makarova et al., 2018), and there are known advantages of integrating speed into traffic signal synchronization programs (Abu-Lebdeh, 2010; Daganzo and Pilachowski, 2011), there remain technical difficulties in a reliable real-time determination of the driving speed and interpretation of big data.

2 DEVELOPMENT OF A METHOD OF DETERMINING THE VEHICLE SPEED

Our approach is based on the use of street video surveillance cameras with a viewing angle providing visibility of the entire functional area of the intersection and the adjacent roads (Online broadcast). We used the architecture of the YOLOv3 neural network, which consists of 106 layers and is a modification of the Darknet-53 neural network (Khazukov et al., 2020). Besides, it includes 53 more layers with two N-dimensional output layers providing for the detection at three different scales. This modification contributes to more accurate vehicle recognition and classification. As input data, YOLOv3 accepts an image represented as a three-dimensional tensor $h \times w \times 3$, where h, w is the height and length of the input image. We used OpenCV open-source library to work with machine vision algorithms and process images and general-purpose numerical algorithms. To track traffic flows, we used the Sort library built on elementary data associations and methods for assessing the state of objects. To calculate the vehicle speed, we need to find the distance travelled based on the change in the latitude and longitude of the object location, using the change in coordinates. To solve this problem, we calculated the perspective transformation matrix (1) by selecting reference points in the map and comparing their corresponding points in the image (Figures 1, 2) (Khazukov et al., 2020).

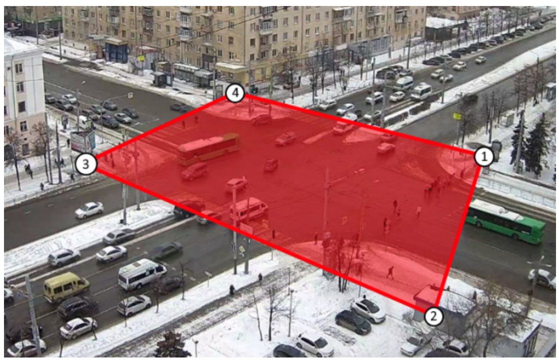

Figure 1: Reference points in the image.

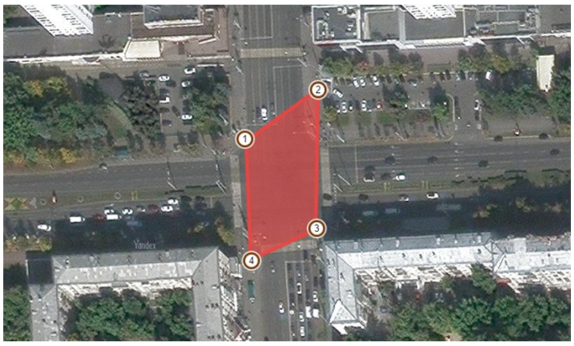

Figure 2: Reference points in the image.

$$A \times \begin{pmatrix} x_i \\ y_i \\ 1 \end{pmatrix} = \begin{pmatrix} x'_i \\ y'_i \\ t_i \end{pmatrix} \quad (1)$$

where A is the perspective transformation matrix, x_i, y_i are the pixel coordinates in the image; x'_i, y'_i are the latitude and longitude of a point in the image.

We will calculate the distance between two points based on the formula of inverse haversine presented explicitly through the arcsine:

$$D = 2r \cdot \arcsin\left(\sqrt{\sin^2\left(\frac{\varphi_2 - \varphi_1}{2}\right) + \cos(\varphi_2)\cos(\varphi_1)\sin^2\left(\frac{\lambda_2 - \lambda_1}{2}\right)}\right) \quad (2)$$

where D is the measured distance; φ_i, λ_i are the latitude and longitude of the i-th point; r =6.371 km is the earth radius.

We will find the average speed by the following formula:

$$v = \frac{D}{t_2 - t_1} \quad (3)$$

where t_1, t_2 is the time of the beginning and the end of the object movement at a distance.

The distance measurement accuracy is calculated and verified based on a perspective transformation determining the area of the used pixels transmitting the road section (Figure 3).

The actual size of the marked distance is 88.5 m, in the image this segment is transmitted as 91px.

One pixel in this section covers an area with a length of 0.97 m. Taking this area as a square, we can estimate the maximum projection error of a point within this area of 1.37 m. Thus, the error in determining the speed does not exceed 1.7 km/h.

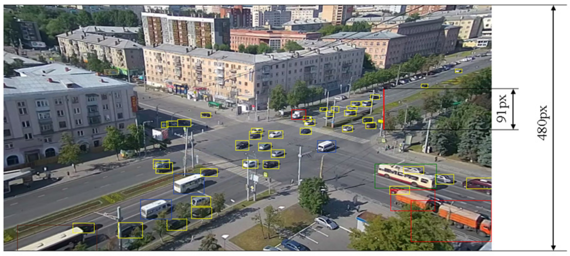

Figure 3: The distance transmitted by pixels.

2.1 Statistical Significance of Differences

In statistical analysis, it is generally accepted to consider the revealed regularity to be statistically significant when the empirical level of significance is less than the generally accepted critical value of 0.05 (5%) (Byul, 2005; Tyurin and Makarov, 2016). For the considered problem of estimating the statistical significance of reducing the time spent on crossing the intersection in the presence of a queue, we should make sure that the calculated mean values of time (Table 1), from the standpoint of statistics, are not in the same confidence interval, i.e., they do not represent the same numeric value.

We used the professional SPSS Statistical Analysis Package for the calculations. According to Table 1, the empirical significance levels of deviations are much lower than the limiting ones, which indicates the statistical significance of the vehicle speed deviations in the presence of a queue before the intersection.

The SPSS package additionally calculates paired Pearson correlation coefficients between the same variables (Table 2), which show a weak correlation between them.

This additionally confirms the legitimacy of the conclusion that the changes in the vehicle speeds are statistically significant - due to the absence of hidden regularities in empirical data, which could distort the analysis results.

The recommended verification of the results of the statistical significance of the differences in the speed of the vehicles passing the intersection in the interpretation of the nonparametric approach also confirmed the high significance of its change. Table 3 presents the results of the calculations using the Wilcoxon nonparametric signed-rank test.

Table 1: Statistical significance of the deviations of the intersection crossing speeds.

		Paired differences		t	Degrees of freedom	Significance
		Mean	Standard deviation			
Pair 1	Och1 & OchN	1.43704	1.33611	12.497	134	0.00
Pair 2	Och1 & NoOch1	2.02133	1.403367	16.732	134	0.00
Pair 3	Och1 & NoOchN	3.00489	1.37474	25.397	134	0.00
Pair 4	OchN & NoOch1	0.58430	1.11680	6.079	134	0.00
Pair 5	OchN & NoOchN	1.56785	0.96799	18.819	134	0.00
Pair 6	NoOch1 & NoOchN	0.98356	1.10166	10.373	134	0.00

Table 2: Correlation of paired samples.

		N	Correlation	Significance
Pair 1	Och1 & OchN	135	0.230	0.007
Pair 2	Och1 & NoOch1	135	0.199	0.020
Pair 3	Och1 & NoOchN	135	0.067	0.438
Pair 4	OchN & NoOch1	135	0.284	0.001
Pair 5	OchN & NoOchN	135	0.286	0.001
Pair 6	NoOch1 & NoOchN	135	0.177	0.041

Table 3: Statistical significance by the Wilcoxon test.

	Z	Asymptotic significance (two-sided)
OchN - Och1	-8.584[a]	0.00
NoOch1 - Och1	-9.456[a]	0.00
NoOchN - Och1	-10.048[a]	0.00
NoOch1 - OchN	-5.515[a]	0.00
NoOchN - OchN	-9.644[a]	0.00
NoOchN - NoOch1	-7.666[a]	0.00

2.2 Analysis of the Vehicle Queue Size

This study is based on the video camera data on the operation of 22 urban intersections and, similarly, assumes the solution of the following tasks:

1. additional processing of the initial data to make them homogeneous;
2. analysis of the mean values of the intervals between the vehicles located in different initial positions in the queue in front of a traffic light when they enter the intersection;
3. determination of the queue size, when the last vehicle in the queue passes the intersection as if there is no delay in the queue.

2.2.1 Formation of a Homogeneous Sample

The previous clustering of the analysed intersections showed a contrast in the empirical data for the two intersections containing tram lines. Therefore, for further analysis, we use about 30 observations for each of the twenty intersections quite similar in the way they are passed by vehicles. Eventually, for the analysis in this task, we used 590 records of passing the vehicle queue only on the green traffic light.

Similar to the first study, we removed the observations for the transport categories other than M1 (vehicles, which are used to carry passengers and have no more than eight seats in addition to the driver's seat), M2 (vehicles, which are used to carry passengers, have more than eight seats in addition to the driver's seat, the technically permissible maximum mass of which does not exceed <5 t), and N1 (small trucks with the technically permissible maximum mass not exceeding <3.5 t.) from the empirical data (Classification of vehicles according to technical regulations, 2018). The size of the vehicle queue considered in this study is limited by the availability of a sufficient amount of the empirical data – these are 13 vehicles. According to the final results, it turned out to be sufficient to form reliable conclusions.

2.2.2 Mean Values of the Time Needed to Pass the Intersections by the Vehicle Queue

The summary calculated data on processing the sample of observations of passing twenty intersections by a vehicle queue are presented in summary Table 4.

Notably, the table clearly shows the difference between the intersections in the dynamics of crossing by vehicles. This has been shown earlier when the intersections were clustered into homogeneous groups. However, in this task, this difference does not affect the distortion of the general trend but only emphasizes the generality of the conclusions obtained for various intersections.

The processing results are graphically shown in Figure 4, where the horizontal axis indicates the position of the vehicle in the queue before the intersection, and the vertical axis indicates the mean time of the interval this vehicle needs to enter the intersection.

Table 4: Mean time of the intervals the vehicles need to enter the intersection.

Intersections	Position of the vehicle in the queue												
	1	2	3	4	5	6	7	8	9	10	11	12	13
Prkr01	3.0	2.9	2.7	2.3	2.6	2.5	2.4	1.8	2.2	2.3	2.8	2.0	2.0
Prkr02	3.5	3.6	2.5	3.1	2.7	2.3	2.1	2.1	2.0	2.1	2.0	2.0	1.5
Prkr03	3.4	2.8	2.7	2.4	2.2	2.3	2.4	2.0	2.5	2.0	1.9	1.6	1.6
Prkr04	3.0	3.0	2.7	2.1	2.4	1.5							
Prkr05	2.6	2.8	2.2	1.7	2.4	1.8	2.0	1.5	1.5	2.0			
Prkr06	3.0	2.8	2.3	2.5	2.0	2.0	2.2	1.6	2.0				
Prkr07	4.2	2.3	2.1	2.1	2.0	2.0	1.8	2.2	1.6				
Prkr08	3.4	3.5	2.8	2.8	3.0	2.0	2.4	2.7	2.3	2.5			
Prkr09	4.5	2.8	2.7	2.1	2.0	2.0							
Prkr10	4.1	2.2	1.9	1.8	2.1	2.1	2.0	1.6	2.0	2.0	2.4	2.2	1.8
Prkr11	3.1	2.4	2.2	2.0	1.9	2.0	2.0	1.8	1.7	2.6	1.7	2.0	2.2
Prkr12	2.9	2.5	2.5	2.5	2.0	2.4	1.9	1.8	2.2	2.1	2.5	2.2	1.7
Prkr13	3.0	2.8	2.3	2.7	1.5	2.0							
Prkr14	3.0	2.6	2.4	2.3	2.6	3.0	2.0	2.0	2.0				
Prkr15	4.6	2.2	2.3	2.3	2.2	2.0							
Prkr16	5.1	2.1	2.0	2.0	2.0	2.0							
Prkr17	4.6	2.8	2.5	2.7	2.5	3.0	2.0						
Prkr18	3.7	2.6	2.8	2.4	2.1	2.8	2,2	2.2	2.9	1.8	1.5	2.0	2.0
Prkr19	3.8	1.9	1.9	1.7	2.0	1.8	1.6	1.7	1.6	2.6	1.3	2.0	
Prkr20	5.2	2.2	1.9	2.0	2.1	1.8	1.7	1.8	2.2	1.5	1.5		
Mean:	Sr1	Sr2	Sr3	Sr4	Sr5	Sr6	Sr7	Sr8	Sr9	Sr10	Sr11	Sr12	Sr13
	3.72	2.69	2.41	2.31	2.24	2.19	2.07	1.96	2.08	2.16	1.97	2.01	1.86

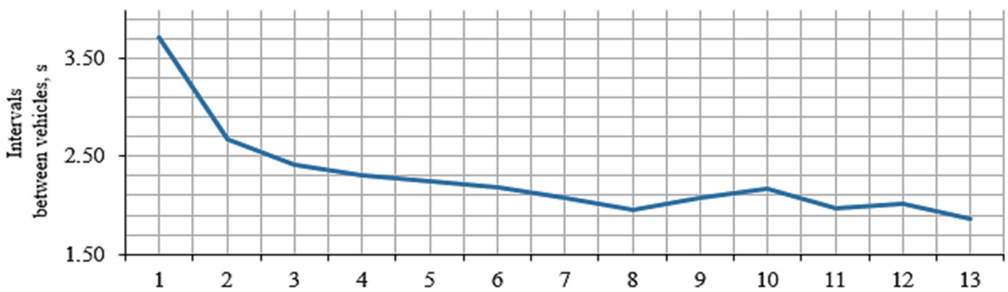

Figure 4: The intervals a vehicle needs to enter the intersection, depending on its position in the queue.

We can assume a priori that the dynamics of the vehicles passing the intersection, starting from the 7th vehicle in the queue, becomes stable.

That is, a queue of six vehicles or more already does not slow down the time of passing the intersection by subsequent vehicles. The mean time of the interval between vehicles entering the intersection is two seconds.

However, these preliminary conclusions should be confirmed in terms of their statistical significance.

2.2.3 The Size of the Queue Stabilizing the Interval between Vehicles

Taking into account the significant influence of the human factor in fixing empirical data, as well as their major gradation by an observer within one second, a nonparametric approach used in similar conditions will be more suitable for statistical analysis. Moreover, the normal distribution of the initial data is out of the question.

Notably, the samples are linked through the observed intersections. Therefore, the statistical analysis method most suitable in this study is the Wilcoxon nonparametric signed-rank test for two linked samples (SPSS statistical analysis package). We will use this method to check the possible pairs of differences of all the calculated mean values of the Sr1-Sr13 intervals from the a priori assumed SR0 value of two seconds.

The calculation results are presented in Table 5.

According to the calculations, the mean values, starting from Sr6, fall into the confidence interval of the a priori expected value of two seconds, i.e., they become statistically indistinguishable. This means that in the queue before the intersection, vehicles, starting from the 6th position in the queue, pass the intersection with the time intervals corresponding to the absence of a queue. This time interval corresponds to the generally accepted estimates of two seconds.

Table 5: Statistical significance by the Wilcoxon test.

	Z	Asymptotic significance (two-sided)
SR0-Sr1	-3.922[a]	0%
SR0-Sr2	-3.885[a]	0%
SR0-Sr3	-3.696[a]	0%
SR0-Sr4	-2.940[a]	0.3%
SR0-Sr5	-2.728[a]	0.6%
SR0-Sr6	-1.790[a]	7.4%
SR0-Sr7	-1.716[a]	8.6%
SR0-Sr8	-1.171[b]	24.2%
a. Positive ranks are used		
b. Negative ranks are used		

Notably, the mean values of the intervals corresponding to the vehicles' positions from 9 to 13 are not considered due to the decreasing amount of the initial data and because their absolute values are much closer to the a priori expected SR0 value than for SR6.

3 CONCLUSIONS

In the course of the study, we identified two important factors corresponding to the presence of a vehicle queue before the intersection on the red traffic light.

First, we revealed the nature and statistically significant measure of reducing the free movement vehicle speed in the presence of a queue in front of the traffic light.

Second, we determined the size of the queue, which does not affect the dynamics of passing the intersection by the vehicles following the queue. We also determined their mean interval of movement equal to two seconds.

In addition to these two factors manifested and studied in this paper, which correspond to the presence of a vehicle queue, we can note other interesting areas of research, such as a heterogeneous structure of the category of vehicles in the queue, their location in the queue, and several other important situations. These areas are the subject of our further research generally intended for task-oriented vehicle flow management.

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