A Study of the Travel Time of Intersections by Vehicles using Computer Vision

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Abstract: The article deals with the problem of intelligent traffic control at intersections of road networks of large cities. Due to the advances in cyber-physical systems (CPS), autonomous driving, as part of Intelligent Transport Systems (ITS), will obviously be in the centre of future urban transport. However, the existing ITSs do not fully take into account the size, structure, and parameters of the queue of vehicles waiting at inter-sections, which in turn affects the traffic capacity of the intersection. In the study, we used computer vision to interpret a queue of vehicles and record the parameters at the intersection on a real time basis. We studied the mutual impact of two generalized categories of transport standing in the queue before the stop line at the intersection. We developed a general conceptual research model, which includes both the task of forming the original sample and statistical analysis of the time needed to cross an intersection by the vehicles located in different initial positions. The main research results showed a statistically significant reduction in the vehicle speed to 58% in case there are various categories of vehicles standing in the queue at the intersection.

1 INTRODUCTION

Currently, researchers pay much attention to the emerging advanced intelligent transport systems, such as vehicle-to-vehicle communications and the vehicle-to-infrastructure communication system (Azimi et al., 2015; Arsava et al., 2014). Using the advantages of such systems, scientists develop a joint control mod-el which optimizes the speeds of connected vehicles and simultaneously coordinates signals along the artery. This control model divides the connected vehicles into groups so that the vehicles can cross intersections together without stops or with the least stop time. At the same time, it optimizes signal synchronization patterns along the artery to achieve lower signal delays and a higher capacity (Wang et al., 2020; Bakibillah et al., 2019; Makarova et al., 2019).

To solve the problem of traffic jams at road intersections through intelligent systems, it is necessary to form a comprehensive insight into several determining problem factors. The most critical factor in the tasks of setting and modelling intelligent transport systems is the queue of vehicles waiting at the intersection.

Many studies deal with the development of adaptive learning controllers for traffic signals, analyse their studied policies, and compare them with the Webster controller. Using the representation of the state of statistics (i.e., vehicle queues and density), the proposed traffic signal controllers with enhanced training develop an optimal policy in the dynamic and stochastic traffic microsimulation (Tubaishat et al., 2008; Genders et al., 2020). Ghazal et al. (2016) and Mandal et al. (2020) offer a system based on the use of microcontrollers which assess the traffic density using IR sensors.

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The study Kulakarni et al. (2020) proposes a model between the saturation flow and the ratio of a small car, a large car and the road width.

There is a widely used method based on the formulation of the combinatorial problem to structurally optimize the traffic light cycle, which allows us to create the most optimal phase separation schemes according to the set traffic demand (Galkin et al., 2018; Kapski et al., 2019; Kazhaev et al., 2018).

Several studies propose a behavioural view methodology based on the calibration of a microsimulation model for highly heterogeneous traffic at the signalized intersection. The proposed methodology is illustrated through the use of Verkehr in Staedten Simulation - a widely used microsimulation soft-ware based on the psycho-physical car tracking model. Signalized intersections with different transport and geometric characteristics from two cities of India were taken as an example (Mathew et al., 2010).

In (Treiber et al., 2013), the main part, after presenting various categories of traffic data, deals with the mathematical description of the dynamics of traffic flows, covers macroscopic models describing traffic in terms of density, as well as microscopic models of many particles, in which each particle corresponds to a vehicle and its driver. Since the stochastic queue model excludes some realistic traffic flow aspects, the authors propose to adapt maximum pressure control for dynamic traffic assignment based on modelling (Levin et al., 2019)

Some studies dealing with the traffic instability and calibration / validation of models present these topics in a new and systematic way (Solovyev et al.,2020; Makarova et al., 2018; Ertman et al., 2016).

Quek et al. (2006) describes the use of a particular class of a fuzzy neural network, known as a fuzzy neural network of a pseudo-external product, using the truth value restriction method (POPFNN-TVR) for a short-term forecast of the traffic flow.

Considering the effects of queues, (Wu et al., 2020; Dai et al., 2016) offered a method for defining assessment and classification criteria for a supersaturated state based on the distance between the intersections, traffic demand, and intersection capacity.

A study of Kikuzawa et al. (2019) developed a traffic flow measurement system to extract the traffic data by analysing images from fixed-point cameras installed near intersections. The intersection and the speed of recognizing the correspondence for the same vehicle and the accuracy of the average speed are estimated by the difference in the time needed to cross two intersections.

There are a minimal number of studies in the field of investigating the mutual impact of various categories of vehicles in the queue on the capacity of signalized intersections. The most representative works are summarized in the introduction.

The closest study, which describes the headway, speed and acceleration characteristics of vehicles during the queue discharge after the green onset under mixed traffic conditions, is presented by Dey et al. (2013). It has been found that the queue discharge headway shows an unmistakable pattern of gradual compression as queuing vehicles are discharged in succession. This article also analyses the speed at which vehicles move when the queue is discharged for two different categories of vehicles (category I - passenger cars; category 2 - trucks and buses). It also analyses the acceleration characteristics of different categories of vehicles released from a stop after the green onset and explains them by the non-uniform acceleration model in the form of. A probabilistic approach based on the second-order first-moment method was adopted to assess the saturation flow and delay caused by the traffic at signalized intersections under non-uniform traffic conditions (Thamizh et al., 1995).

The presented methodologies available for assessing the capacity of signalized intersections are based on the concept of saturation flow(s). At the same time, the studies do not fully take into account the impact of such factors as the queue structure and its dynamic parameters on the capacity of inter-sections. In this paper, we will focus on these two aspects.

2 METHODS

The purpose of this article is to analyse the impact of heterogeneity of vehicles in the queue on the capacity of intersections using computer vision. To achieve this objective, let us divide the problem into three sub-tasks: to determine how the time needed to cross the intersection crossing time decreases due to the traffic-light stop, to analyse the reduction in the time needed to cross the intersection due to the vehicle stop in the queue, and to determine the statistical significance of changes in the timed needed to cross the intersection crossing time. In the following sections, we will describe in detail each module, together with the data collected for analysis and assessment.

2.1 Dataset

Street surveillance cameras were used to collect data, which provide a stable 25 frames per second, supporting a resolution of 1920 × 1080 (Fedorov et al., 2019).

As shown in Figure 1, images from these cameras differ from those in publicly available data sets, such as KITTI (Cordts et al., 2016) or UA-DETRAC (Wen et al., 2015).

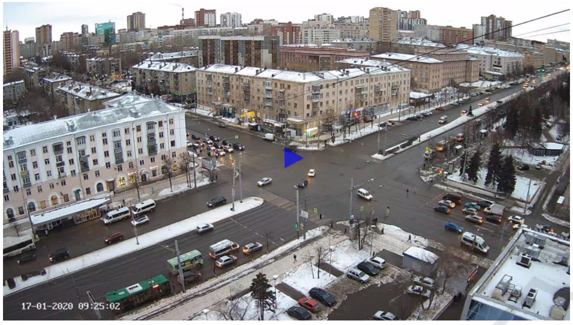

Figure 1: An example of an image from CCTV cameras.

To carry out our research, we focused on one camera, which controls one of the most problematic intersections in the city of Chelyabinsk. It is a conscious choice to maximize detection accuracy and obtain a minimally viable product.

The data on the time the vehicles needed to cross the stop-line section, and the intersection were collected through the use of the YOLOv3 trained neural network (Figure 2).

Stage 1. To determine how the time needed to cross the intersection decreases due to the vehicle stop in the queue.

The general conceptual research model can be presented by the following interdependent stages:

1. Adjustment of the input data to make them uniform;

2. Analysis of the average values of the time needed to cross the intersection by the vehicles located in different initial positions;

3. Determination of the statistical significance of changes in the time needed to cross the intersection due to the traffic-light stop.

The formation of a homogeneous sample.

To minimize distortions of the research results, we selected a sample of the intersection crossing by similar vehicles. For the analysed intersection, these are vehicles of category M - vehicles with at least four wheels and used to carry passengers (Vehicle Categories, 2019). We also rejected the observations with the vehicles of category M3 (which maximum permissible mass exceeds 5 tons), which will also bring distortions into the results due to their size and response rate.

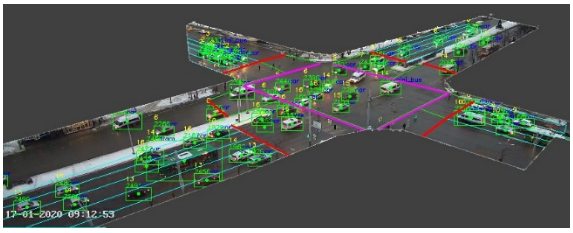

Figure 2: An example of an image from our dataset.

We also rejected the observations falling out of the general intersection crossing structure - which have a short queue without vehicles crossing the intersection non-stop. The initial sample was reduced by 38% and amounted to 1128 observations for the vehicles of categories M1 and M2. A visual illustration of the empirical data accepted for our analysis is shown in Figure 3.

Stage 2. To analyse the decrease in the time needed to cross the intersection due to the vehicle stop in the queue.

In the prepared homogeneous sample of the observations of vehicles crossing the intersection, we also determined the time intervals when the vehicles entered the intersection, which will allow us to solve similar research problems further. The primary information on this study – the time needed to cross the intersection average for the sample - is divided into four positions according to the location of a vehicle and presented in Table 1.

Table 1: Changes in the time needed to cross the intersection.

Position of the vehicle	Time needed to cross the intersection, seconds	Reduction in speed, %
The first vehicle in the queue	6.56	57.8
The last vehicle in the queue	5.25	67.3
The first vehicle passing non-stop	4.62	76.5
The last vehicle passing non-stop	3.53	100

As follows from the calculations, the speed of the vehicle crossing a free intersection decreases by almost a half (up to 58%), depending on the presence of the queue. However, to confirm the reliability of the obtained results, it is necessary to assess the statistical significance of their differences.

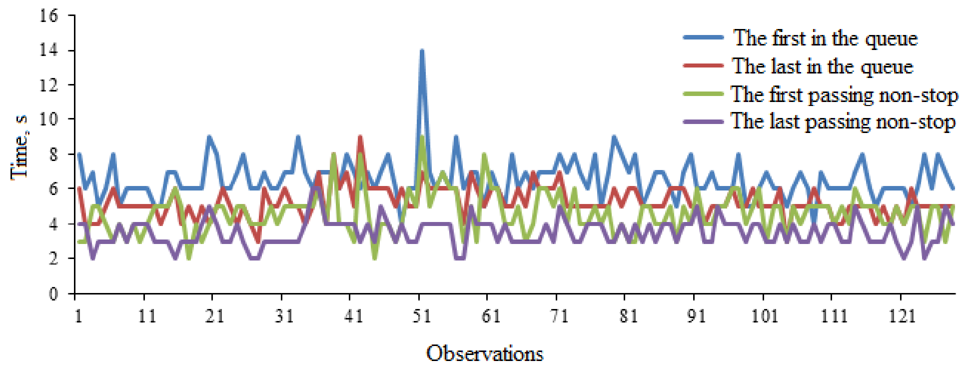

Figure 3: The empirical data on the time needed to cross the intersection.

Stage 3. To determine the statistical significance of changes in the time needed to cross the intersection

In a statistical analysis, a manifested regularity is considered to be statistically significant if the empirical significance level is less than the generally accepted critical value of 0.05 (5%) (Buyul et al., 2005; Tyurin et al., 2016).

For the problem under consideration – to assess the statistical reliability of reducing the time needed to cross the intersection in the presence of a queue, it is necessary to make sure that the calculated average time values (Table 1) in terms of statistics are not in the same confidence interval, i.e., do not represent one and the same numerical value.

To select a statistical analysis method most suitable in this case, it is necessary to determine its following characteristics:

- This is a parametric method since the data measurement scale is at least interval; the distribution law is close to normal (not verified);
- The samples are linked since each quadruple of data in one record is read from one observation.

Given such restrictions, the most acceptable is the method for two linked samples - Student's parametric t-test, which allows us to compare each pair of four calculated time values. Otherwise, we can use the parametric method for several linked samples (>2) - an analysis of variance with repeated measurements, which allows us to evaluate the differences between all the four values simultaneously. A detailed analysis of all pairs of time values is undoubtedly of great interest, so we select the first method.

The statistics calculated by Student's t-test is determined as follows:

$$t = \frac{(\bar{x}_1 - \bar{x}_2) - (\mu_1 - \mu_2)}{S_{\bar{x}_1 - \bar{x}_2}} \tag{1}$$

where $\bar{x}_1, \bar{x}_2$ is the mathematical expectation for the two samples; μ_1, μ_2 are the estimates of the average values of the two samples (it is assumed that $\mu_1=\mu_2$); $S_{\bar{x}_1 - \bar{x}_2}$ is the normalization base formed from the estimates of variances S of these equal samples ($n_1 = n_2 = n = 128$) according to the standard rule.

$$S_{\bar{x}_1 - \bar{x}_2} = \sqrt{\frac{1}{n}\left(S_1^2 + S_2^2\right)} \tag{2}$$

Based on the calculated values of these statistics, we determined the empirical significance levels for all pairs of average time values (Table 1), which are summarized, together with Pearson's paired correlation coefficients, in Table 2.

Comparing the calculated values of the error (these are the selected cells "Difference estimate" in Table 2) with an acceptable level of 5% (5.00E-2), we made the following conclusion - all pairs of the average values of the time needed to cross the intersection (Table 1) differ significantly. I.e., in terms of statistics - the differences between them are statistically significant.

To further confirm the legitimacy of the obtained result, we determined paired correlation coefficients and their corresponding levels of statistical confidence (Table 2). All the links relate to the levels of weak and very weak links, which is confirmed by the absence of hidden regularities in the empirical data, which could introduce distortions into the analysis results.

3 CONCLUSIONS

All the models are based on uniform driving conditions; these models may not provide a satisfactory estimate of delays under non-uniform

Table 2: Changes in the time needed to cross the intersection.

		The first vehicle in the queue	The last vehicle in the queue	The first vehicle passing non-stop	The last vehicle passing non-stop
The first vehicle in the queue	Pearson's correlation Value (2 sides) *N* (sample size)	1 *N*=128			
The last vehicle in the queue	Pearson's correlation Value (2 sides) Difference estimate	0.233** 0.008 1.170E-20	1 *N*=128		
The first vehicle passing non-stop	Pearson's correlation Value (2 sides) Difference estimate	0.169 0.056 3.031E-28	0.360 0.000 2.066E-08	1 *N*=128	
The last vehicle passing non-stop	Pearson's correlation Value (2 sides) Difference estimate	0.073 0.414 3.097E-50	0.236** 0.007 3.308E-39	0.171 0.054 2.084E-16	1 *N*=128

traffic conditions. The average delay caused by various categories of vehicles at signalized intersections is an essential criterion in assessing the capacity of these intersections. The use of neural networks in the tasks covering the recognition and interpretation of traffic flows allows us to obtain the new data needed to optimize intelligent transport systems. As a result of the data analysis at the studied intersection, we have found that the time needed to cross the intersection by the vehicles of categories M1 and M2 reduces in a statistically significant manner to 58% if there is a queue. The interpretation of a bulk of the data in the vehicle-infrastructure system will allow us to introduce advanced solutions for autonomous transport, such as identification of vehicle parameters and queuing at intersections to increase their capacity.

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