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Video detection data as important factor for transport systems safety improvement

Keywords

discrete transport system, road monitoring, vehicle recognition, AR, AV, ANPR, MMR

Abstract

The paper presents the analysis and discussion of video detection data usage for discrete transport systems safety improvement. The Autonomous Vehicles (*AV*) and the Augmented Reality (*AR*) research in connection with a Driving Assistance (*DA*) are presented. This article is going to show where the border between those two fields of interest is and how they are going to influence on the future of automotive. The proposal of the *AR* system - based on soft-computing methods used for an object classification problem – is given. The input data are taken from the real traffic monitoring system located at the set of roads in Poland. Data from the monitoring devices are used to analyze the travel time of vehicles – elements of the transportation system. The travel time model taking into account the real road situation is built. The proposed solution can be an essential tool for the owner and administrator of the transportation systems.

1. Introduction

In transport systems management, modelling and simulation generates very wide spectrum of sophisticated problems. The challenge to solve them with the required level of detail is not a trivial task at all. The complex structure of each transportation system is the main reason of the situation. The performance of the system can be impaired by various types of faults related to the transportation vehicles, communication infrastructure or even by traffic congestion or human resources [3]-[7]. Each part of the system is characterised by an absolutely unique set of features. It is hard for an administrator, manager or an owner to understand the system behaviour and to combine the large scale of variant states in a single, easily observable and controlled global metric which could be used as an indicator, to make proper decisions in short time period. This is the reason why we propose a functional approach. The data used to describe the features related to the vehicle movement are collected from the road monitoring system located at the set of roads in the central part of Poland. The monitoring devices (described in section 6) are able to use automatic number plate recognition (*ANPR*) techniques to capture and store the various parameters for vehicles recognised in automatic way by the video detection techniques. The registration numbers, the make and model (*MMR*) of vehicles are recognised and stored in the database. The collected parameters are the basis for analysing real travel time problems related to the trucks operating with the commodities among the nodes of the transport system (section 7). We try to observe the changes during the consecutive days of a week, as well as for much longer time-horizons, taking into account the traffic jam problems and other extraordinary situations like crashes, or extremely bad weather conditions, which can have significant influence on the typical time travel. The next step is to generalize the results of travel time analysis into the travel time model (section 8). Such a model, based on the real data taken from the road monitoring system, can be a very important part in a larger simulator for discrete transport systems, as its behaviour very closely resembles the real system. On the other hand such data can provide very significant assumption for the Augmented Reality (*AR*) and the Autonomous Vehicles (*AV*): two approaches, two different types of understanding of the future of automotive. *AR* solutions give driver a chance to change a way of driving (make it easier, safer and much more reliable), whereas *AV* eliminates driver at all. This paper also presents main features of both approaches and gives a necessary background to show a driving assistance system created to recognize road events and inform a driver about (for example) road signs, pedestrians, unidentified dangerous objects only using some voice (specialized voice alerts).

2. Augmented Reality for Vehicles

2.1 AR Basics

AR solutions have to be integrated with a natural user's environment. This paradigm enhances interaction between user and system. The major advantage of *AR* approach is an intuitive perception of information - real objects coexist with the virtual ones in the same space. It allows user (driver) to recognize the content of information without any additional abstract interface which can delay each kind of perception process. *AR* is strictly connected with a personal recognition of shapes, colours, object's locations or movements and sound which can be set as an *AR* element too [11].

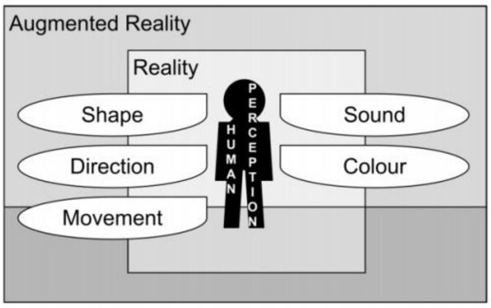

Figure 1. Perception in both realities

2.2. Head-Up Display (HUD) as AR Device

Technology of HUD comes from the aircraft solutions. Nowadays it is also rarely used in cars to display basic information (on windscreen) such as: speedometer, tachometer, and navigation system - showed in *Figure 2*. The potential of this solution is unused. HUD is the best way to augment a reality during driving a car [11].

Figure 2. Information on a head-up display

2.3. AR with Navigation and Driving Assistance

Nartzt and partners in [13] constructed prototype of AR a navigation system which connects GPS data with video from a front camera. The proposal of a future solution is to connect assumptions of a driving assistance system created to recognize road events and inform a driver with the Nartzt prototype and set *HUD* as a main information source for a driver - *Figure 3* [10].

Figure 3. A supplementary solution

3. Autonomous Vehicles

3.1 Road Trains

Trains have locomotives. So can cars be like a railway wagons? The idea of setting one leading car (with the driver) and "catching on" it and getting autonomy in driving is shown by Coelingh and Solyom in [5]. Volvo engineers adapted their active cruise control system to give a car some autonomy. They used additionally different Volvo systems: pedestrian detection system and road signs detection system. This mixed solution was fully developed and successfully tested (2009-2010). Except leading car, the rest was fully autonomous [2].
Technology (in prototype):

- a short-range system of three laser beams, which measures distances of up to 8 meters ahead;
- 76GHz radar in the active cruise control, which measures the ranges of objects up to 200 meters ahead;
- side-to-side movement of the car up ahead - forward-looking camera used in Volvo vehicles to detect pedestrians and recognize road signs;
- two rear- and side-looking radars 76GHz;
- wireless system, based on the 5.9GHz IEEE 802.11p Wi-Fi standard, to allow direct data links among all the vehicles.

3.2. DARPA Urban Challenge

The *DARPA* Urban Challenge [6] is an autonomous vehicle research and development program. The most interesting rules for the teams were:

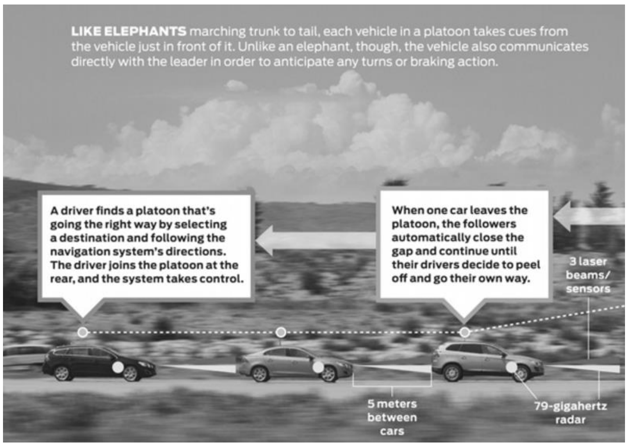

Figure 4. Road train part 1

Figure 5. Road train part 2

- vehicle must be entirely autonomous, using only the information it detects with its sensors and public signals such as *GPS*;
- vehicles must operate in rain and fog, with *GPS* blocked;
- vehicles must avoid collision with vehicles and other objects such as carts, bicycles, traffic barrels, and objects in the environment such as utility poles;
- vehicles must be able to operate in parking areas and perform U-turns as required by the situation.

The winner of the challenge was a group from Carnegie Mellon University (USA). From the local (European) point of view, the most interesting team which took a part in a final was Team *CarOLO* from Braunschweig (Germany). Researchers from the University of Braunschweig [4] constructed vehicle based on Volkswagen Passat using similar devices as in a famous Google autonomous car.

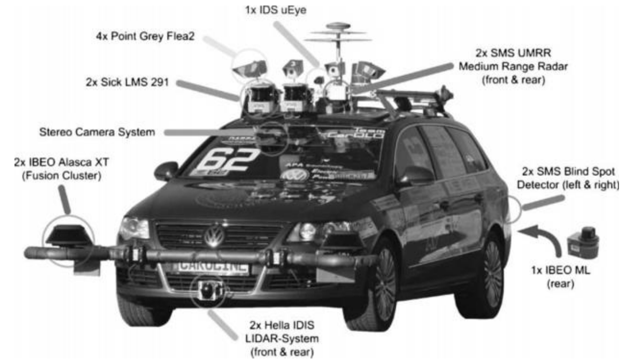

Figure 6. Autonomous car Caroline

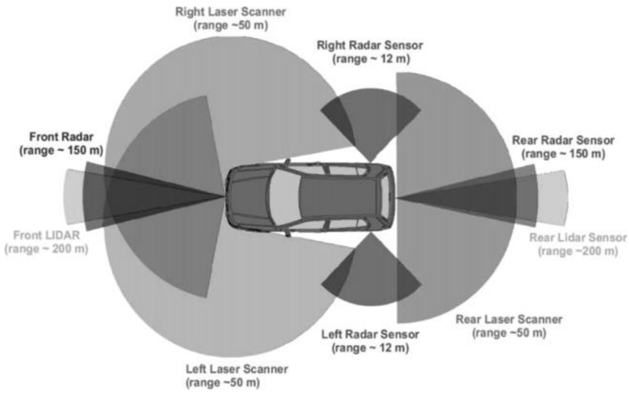

Figure 7. Caroline's perception

4. AR in Opposition to AV

According to the complexity of road traffic, many fast changing conditions with a strong influence to any driving process, there is a chance to set *AR* in opposition to *AV*. The biggest problem for *AV* researchers is not a technology and algorithms. The main problem with any autonomous automotive system is a changing environment which needs extensions for each road, traffic scenario and weather conditions. Each extension needs a long and expensive process of development. As an example can be used a learning process for object recognition systems (computer vision based systems) which needs thousands of patterns for each atomic object, for each separated scenario (real life), to learn a classifier. Volvo [5] collected 3TB of data and needed to drive over 500000km to confirm, that in its Pedestrian Detecting System (the main function is autonomous breaking) a risk of inadvertent breaking is acceptably low [8]. Nevertheless *AV* should not make any mistakes - there is no place for any acceptance level. For the automotive industry, there is no sense in production of semi-autonomous cars. Coelingh and Solyom determined other *AV* issues [5]. They tested their solution wintertime. The biggest problem was not a gasoline consumption or wrong system behaviour. The problem was windscreen full of salty spray. It caused the problem with a camera view. For instance washing fluid consumption and necessity of cleaning was unacceptable. The last problem in *AV* research is a legal use of autopilot solutions for road traffic. It is not allowed in Europe and North America. The situation comes from the lack of consensus that would be responsible for a potential accident. The elimination of a driver is not possible nowadays, so *AR* solutions are much more useful and many of them are released (road signs recognition systems, line assistants, distance assistants, park assistants, and adaptive cruise control).

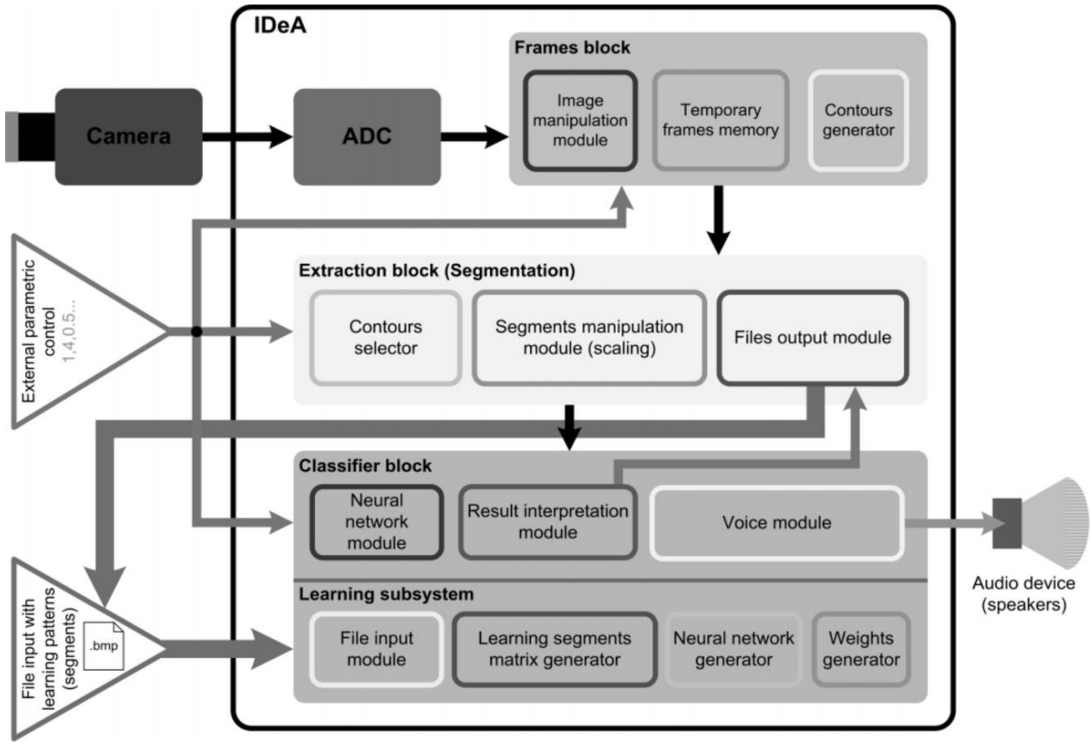

Figure 8. IDEA architecture

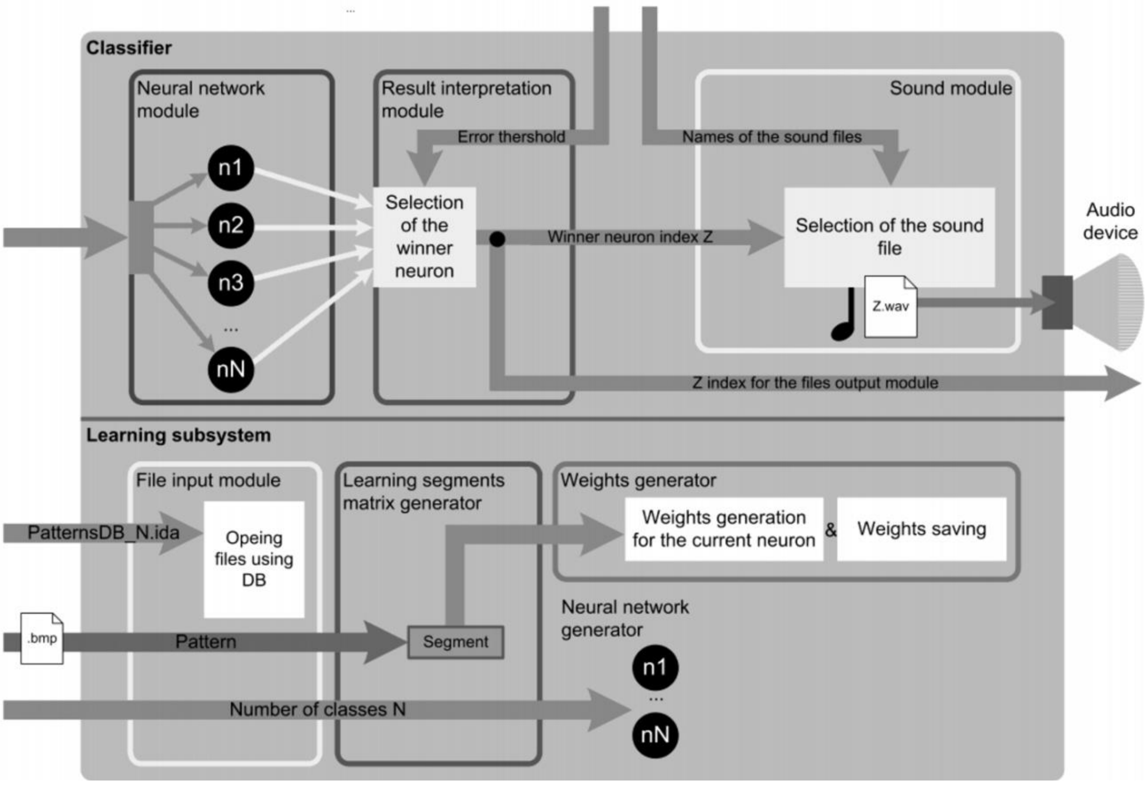

Figure 9. Classification module

5. IDEA System

5.1. Specification

IDEA is going to be an autonomous solution without any connection to any database or other remote resource. This system should be able to learn in its whole life cycle. Each "turning on" should start a learning procedure based on patterns collected previously. General Assumptions:

- *IDEA* informs a driver about various types of road events e.g. recognises speed limits, traffic jams, obstacles;
- system is autonomous, works in a real time and needs only a power supply;
- *IDEA* cannot have any direct influence to a driving process;
- software developed for *IDEA* should use most known algorithms adapted for special tasks.

An application developed for *IDEA* system is modular. Each module is a part of the application responsible for a special task. Modules are grouped into functional blocks (*Figure 8*). Functional blocks and modules communicate to each other using some specified data and parameters. Each module can be controlled outside the application by control parameters without which its processing is impossible. The control parameters are very important. Their values determine a correct *IDEA* processing. *ADC* is a device which converts a camera signal to digital frames in a specified format (readable for the application). Extraction block is a set of modules which processes frames. Contours selector is responsible for finding and selecting contours in a frame which is processed [12]. On the other hand a number and type of contours is controlled by external parameters. Moreover a segments manipulation module starts working when the contours selector gives its output. The manipulation on the specified segment is understood as a scaling process (scaling is an equivalent of a normalization process). After this process, selected and normalized segments are an input for a classifier block and if a classification process matches some segments to some classes, it sends them to a files output module (it is a part of a self-learning process). Classifier block is a set of modules which consists of two subsystems: a classifier and learning subsystem. The first one works in "a real time". The learning subsystem starts working after *IDEA* is turned on and is responsible for a system initial learning (from patterns collected in bitmaps stored on a hard disk: a file input module). A result interpretation module is connected with a voice module and file input module. After matching segment to a specified class, it sends information about the segment to store on the hard disk (in a specified class folder) – it will be used for a next learning procedure. Simultaneously it gives a specified class name to a voice module and then a sound with an alert is played (*Figure 9*).

5.2. Research

From the *AR* point of view, the most important issue in the *IDEA* research process was finding *ROIs* (Regions of Interest), which are named segments in *IDEA* system. After many experiments with steering parameters, authors got satisfactory results in a segmentation process calibrated to find road signs. Examples from the real environment tests are shown in *Figure 10* and *Figure 11* (segments are normalized, after thresholding and ready for being classified).

Figure 10. Segments from the frame in *Figure 11*

A satisfactory effect was gained using a simple algorithm:

1. get a frame and do a threshold;
2. find contours in a binary scene;
3. eliminate contours bigger than *par_max* and smaller than *par_min*;
4. set selected contours as segments and normalize them.

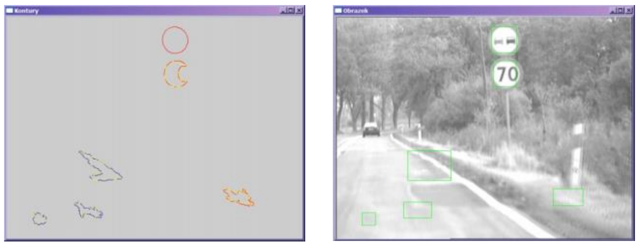

Figure 11. Input frame and ROIs

This algorithm is really simple. It just needs setting proper parameters *par_min* and *par_max* which needs to be found according to a frame resolution, camera point of view and type of objects needs to be found. *Figure 12* shows how such a simple segmentation algorithm can give satisfactory results. There is an interesting fact, that bigger frames are better for finding the most suitable *ROIs*, but a risk of not finding some *ROIs* is bigger. *IDEA* segmentation algorithm gives the most suitable input for the Classifier Block, where a cascade of neural networks classifies segments.

Number of analysed frames	Frame size	Average number of ROIs per frame	Average % of missed ROIs	Average % of ROIs with road signs shapes
100	320x240	21.8	2.2%	91.5%
100	640x480	19.4	4.7%	96%

Figure 12. Segmentation algorithm results

6. Road Monitoring System

The data used for simulation analysis has been gathered from the system used for road traffic monitoring in the vicinity of Polish capital city of Warsaw. There are few similar systems installed in other areas (e.g. Wroclaw and Wloclawek) used for over weighted vehicle detection, but the system installed near Warsaw is the biggest one so far. It consists of several data collection points installed along two major roads (*DK7* from Grojec and *DK8* from Mszczonow) where they connect at the southern suburbs of Warsaw in Raszyn, as well as *DK50* from Grojec to Mszczonow, forming a triangle (*Figure 13*). *DK7* and *DK8* are two main roads approaching Warsaw from the south/south-west direction and they can be treated as alternative routes in case of major traffic problem in one of them. The data collection system has been set up to monitor current traffic situation and provide drivers with the travel time estimations and allow intelligent traffic management [1], [9] based on current traffic volumes.

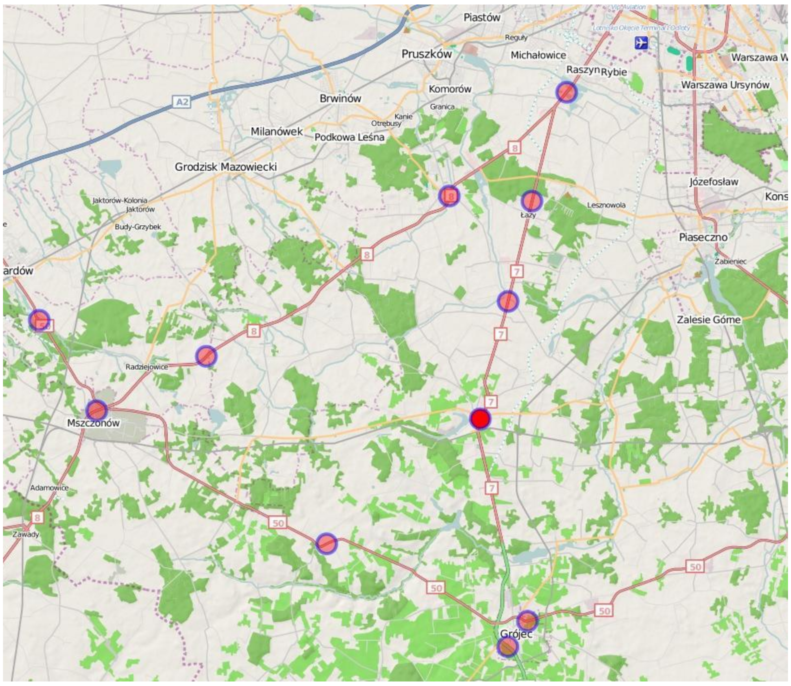

Figure 13. Data collecting points

Data collection is based on license plate recognition [1] – there are 11 different data collection points and in each of them there are cameras installed over each traffic lane in both directions (plus one overview camera). The incoming video stream from each camera is sampled 25 times per second, generating separate frames, which are then segmented, and run through the neural network classifier to recognize the plate number. As the vehicle moves through the image window, its license plate gets recognized in each captured frame. So at the end, the best one is chosen automatically, based on the confidence level of the particular recognition (*Figure 14*). Another neural network process samples the front view of the car to find the make and model of the car, allowing for vehicle class recognition (i.e. car, pickup, bus, truck). After each successful recognition a time-stamped image capture is saved, as well as the text-based file with the recognition results. These are sent from the collection points to the central server using GSM-based GPRS or WiMax data connection. The images can be used later for verification of the system operation and for retraining the neural network, while the textual data is used online for real-time traffic monitoring and generating alerts.

Number plate recognition allows for exact vehicle identification along a given path, thus making it possible to record the exact times needed for travel between consecutive points along the route. This opens possibility to not only gather traffic volume information at observation points, but also to collect exact travel times on per-vehicle basis, that allow getting not just the estimated values, but also drawing conclusions about their distribution during the day or in any arbitrary time-span. However, the volume of data stored by the monitoring system requires a careful design of the data aggregation algorithms. Data from different observation points are collected independently from each other, but in order to find travel times, records regarding the same vehicle spotted in different locations must be correlated to find possible paths the vehicles have travelled. Several constraints, such as the maximum travel time between consecutive points, have to be established to eliminate false positives showing up in path detection algorithm. Additional parameters, such as colour, make and model matching may be further used to assure the correctness of the *ANPR* and path detection.

Figure 14. Monitoring system results

7. Traffic Monitoring Results

Data collected by the road monitoring system allow us to analyse the travel times. *Figure 15* presents results of travel time distribution for one of monitored road segments for different days within one month. It is easy to notice that in case of Sunday the distribution has two modes. After detailed analysis of the collected data, the reason of the second mode was identified as a traffic jam that happened on one of the Sundays in the analysed month. The sample distributions of travel jam during traffic jams are presented in *Figure 16*. It could be noticed that the shape of distributions are similar in both cases but the mean values are different. Therefore, to model the transport time by a random value, one has to distinguish between the normal and traffic jam situation. So, a simple algorithm was developed that allows to divide data into two sets of *normal* and *jam* traffic.

The algorithm consists of the following steps:

1. calculate the mean time (*mt*) and standard deviation (*std*) of travel time in a given road segment
2. for each 15 minutes interval of traffic data $\{time_i\}$
    a. calculate traffic coefficient
    $$trc = \frac{sum(time_i < mt + std)}{length(time_i)}$$
    b. if *trc* < 0.3, assign as *normal* traffic else *jam* traffic
    c. remove too long journeys - for which
    $$time_i > mean(time_j) + 3std(time_j) \quad (14)$$

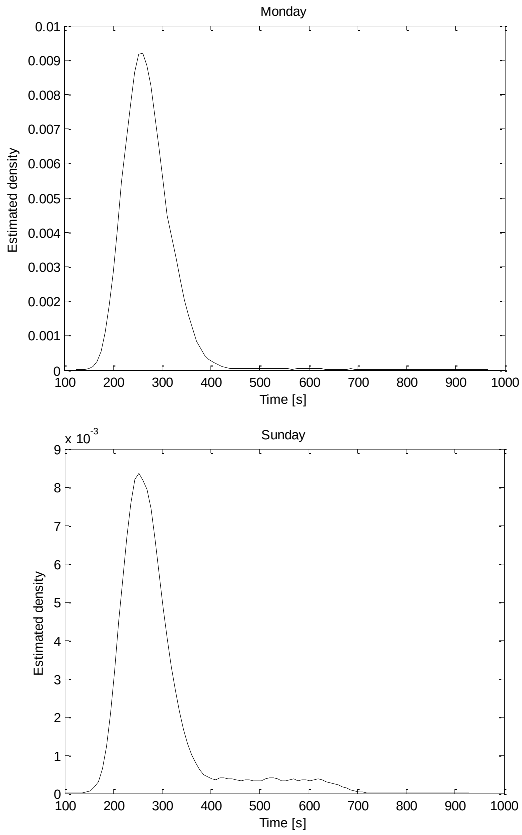

Figure 15. Travel time distribution for Mondays and Sundays

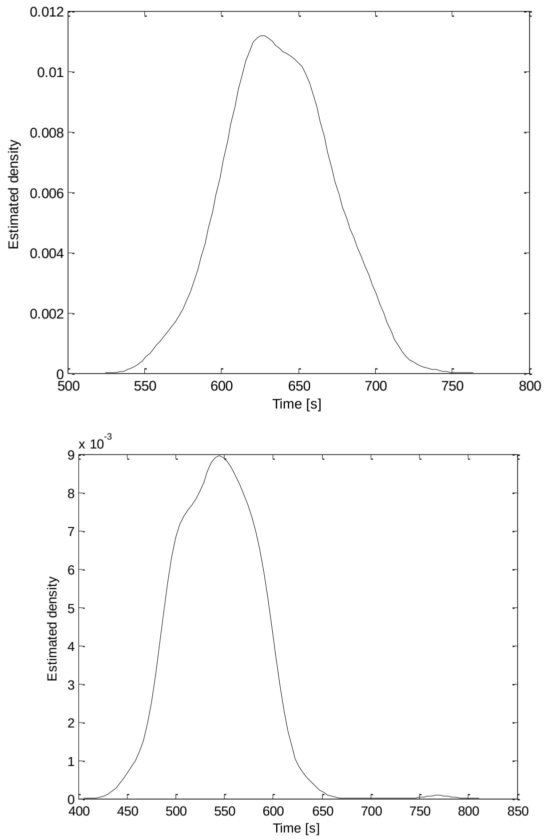

Figure 16. Travel time distribution for two different traffic jams (recorded in 15 min slots)

8. Travel Time Model

After selecting the data classified as normal traffic, it has been analysed to check the dependencies of the week day and day time on travel time distribution. The results for mean value are presented in *Figure 17*.

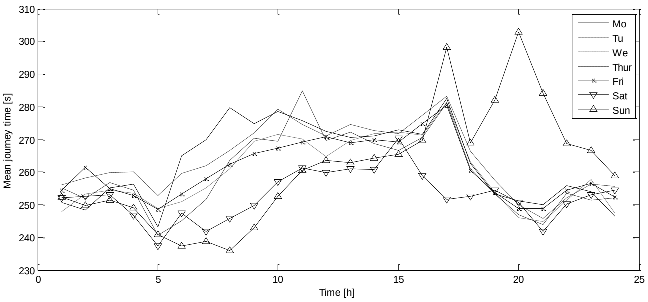

Figure 17. Mean journey time for normal traffic in function of week day and time during day

One can notice, that on workdays the mean values undergo very similar changes, whereas Sundays and Saturdays are very similar until 4 pm. The longer mean travel time on Sunday afternoon and evening is caused by larger traffic, when people are coming home (Warsaw) and the end of weekend. Based on data presented in *Figure 17* we propose to model workdays by the same distribution and to have different models for Sunday and Saturday.

The next question to be answered is the type of distribution to be used for modelling travel time. Three different types of probability function were considered: Gamma, Normal and Beta. In case of Beta, data were scaled to (0,1) range. The results for workdays are presented in *Figure 18*. The best solution is the Gamma distribution. However, according to Kolmogorov-Smirnov statistical test, the data are not from any of analysed distributions.

In *Figure 19*, for data within one hour it could be noticed that the Gamma distribution is not fitting ideally to real data, since one could notice a small second mode around 430 s (for 9 am data) and 370 s (for 9 pm data). It suggests that the travel time for normal traffic should be modelled by a mixture of distributions. However, for the simplicity of parameter estimation and simulator implementation we will assume the Gamma distribution.

Taking into consideration mentioned facts, we propose to divide roads into segments. Next, based on the real data, estimate the Gamma distribution parameters for normal traffic separately for working days, Saturdays and Sundays for each hour. The second step is to estimate parameters for traffic jams. Due to relatively small rate of traffic jam occurrence and a need to analyse large amount of data, the full analysis of these data has not been performed yet. But we could assume some probability of traffic jams which depend on weekday and hour and use it within simulator for modelling traffic jam occurrence. The distribution of travel time during traffic jams could be modelled also by gamma distribution. Its parameters differ however in each case (see *Figure 17*) so we propose to generate them in random way (from unity distribution).

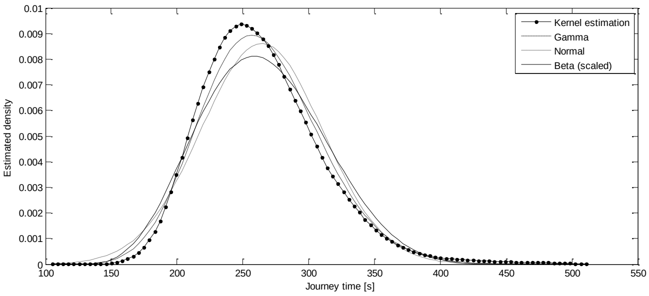

Figure 18. Travel time for normal traffic and Gamma, Normal and Beta density function fitted to real data

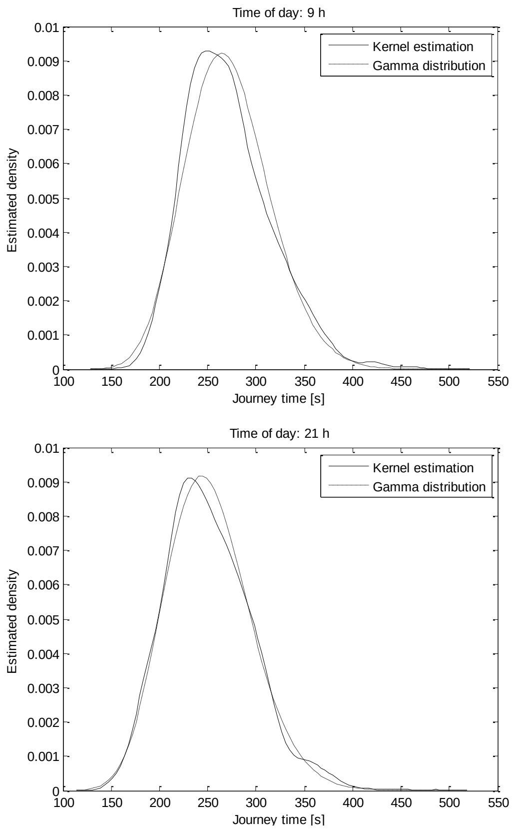

Figure 19. Travel time for normal traffic within one hour (9 am – left side and 9 pm – right side) and fitted Gamma distribution

In summary – at the beginning of each hour the traffic jam occurrence for a group of segments is randomly established. Next, the travel time distribution parameters have to be set. In case of normal data, they are selected from the estimated parameters (from real data) and in case of traffic jams they are randomly generated (to model different traffic jam situations). It could be noticed (such analysis was performed on the real data) that the journey time of the same vehicle consecutive road segments falls in similar quintiles. To model this case, we propose to generate on random value from (0,1) interval for each truck starting its journey and use it for estimating travel time for each road segment using inverse of Gamma cumulative distribution.

9. Conclusions

The future of *AR* solutions for an automotive industry is strictly connected with head-up displays. They need to be cheaper and easier to obtain. Compilation of: object recognition systems (pedestrian, road signs, buildings and institutions), *GPS* based navigation, set of sensors monitoring vehicle environment, adaptive cruise control systems, simple sensors such as park sensors in connection with a head-up display and sound device can increase traffic safety, give the chance to drive the easiest way and does not eliminate a driver. The future of *AV* is to collect as much data as possible to cover the biggest number of road traffic scenarios. Based on gathered data we analysed the travel time. We are able to find the travel time distribution of monitored road segments for different days within required time-interval. We also generalize the results of travel time analysis into travel time model. Our model can be incorporated into complex simulators for discrete transport systems. Thanks to the real-life data methodology used for its creation, the reliability and functional analysis in these simulators can be improved, yielding more realistic and precise simulation results. This is why the proposed solution may become the essential tool for owners and administrators of transportation systems. The solution presented here can be used as a practical tool for improving vehicle maintenance and transportation system logistics, allowing for better fleet usage, fuel savings, and reduction of CO_2 emission.

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