Computer vision and intelligent systems in road traffic control

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Abstract - Intelligent traffic control systems tackle today's most significant problems in road transport, i.e. periodical road congestions. To ensure minimal losses related to congestion and optimal use of existing road infrastructure new approaches from the domain of intelligent transport systems (ITS) are applied. Today's road traffic problems emphasis the need of cooperation between more standalone systems to achieve desired optimal use of the existing infrastructure. Development of such intelligent cooperative control systems presents an open challenge today. In order to implement such approaches, reliable measurements of traffic parameters and appropriate control algorithms are required. Trend in today's traffic control systems is an broad increased use of cameras as the main sensor. From the video footage of traffic surveillance cameras several traffic parameters can be estimated like flow, vehicle gap and type, traffic speed, origin-destination matrices, etc. In this paper new approaches to road traffic control based on intelligent methods and computer vision proposed by the authors are described and newest acquired results are presented. For testing of the system real road traffic video footage was used from Croatian highways. Use case for testing of the proposed ramp metering framework was bypass of the city of Zagreb, Croatia. Section between problematic nodes with many on- and off-ramps was simulated in an augmented version of the macroscopic simulator CTMSIM.

Keywords – Computer vision, moving object detection, trajectory estimation, Kalman filter, intelligent cooperative ramp metering, ANFIS, variable speed limit control, intelligent transport systems (ITS).

I. INTRODUCTION

Intelligent traffic control systems tackle today's most significant problems in road transport, i.e. periodical road congestions. Such congestions appear mostly in urban environments and are related to local urban roads, urban highways and they interconnections (on- and off-ramps). Urban environments have the drawback that they lack the needed space for infrastructural build-up. To ensure minimal losses related to congestion and optimal use of existing road infrastructure new approaches from the domain of intelligent transport systems (ITS) are applied. Such approaches include variable speed limit control (VSLC), ramp metering (RM), optimization of traffic lights signal planes, various driver information systems, etc. They can work standalone or in cooperation. Today's road traffic problems emphasis the need of cooperation between more standalone systems to achieve desired optimal use of the existing infrastructure. Development of such intelligent cooperative control systems presents an open challenge.

In order to implement such approaches, reliable measurements of traffic parameters and appropriate control algorithms are required. Trend in today's traffic control systems is an increased use of cameras as the main sensor. From the video footage of traffic surveillance cameras several traffic parameters can be estimated like flow, vehicle gap and type, traffic speed, origin-destination (OD) matrices, etc. Problem of available commercial traffic cameras is that they can only cover one road lane. Real-time surveillance of multiple lanes with one camera presents also an open challenge. In this paper new approaches to road traffic control based on intelligent methods and computer vision proposed by the authors are described and newest acquired results are presented. In [10] and [11] authors proposed a system that can cover several road lanes in real time and can measure flow, vehicle trajectories and estimate vehicle country of origin using license plate recognition. For testing of the system real road traffic, video footage from Croatian highways was used. Obtained accuracy of the system is over 95%. Mentioned traffic parameters measurements are input for intelligent traffic control systems.

In [3] authors proposed cooperation of RM and VSLC to obtain optimal usage of urban highways. Proposed new learning based framework for RM enabled decrease of travel time on urban highways. Used RM algorithm learned the optimal ramp metering rate using results of standard RM algorithms applied in a wide variety of traffic demands. Use case for testing of the proposed RM framework was bypass of the city of Zagreb, Croatia. Section between problematic nodes with many on- and off-ramps was simulated in an augmented version of the macroscopic simulator CTMSIM.

This paper is organized as follows. In the second section problems related to urban road traffic control are briefly described. Third section presents proposed solution of road traffic parameters measurement based on computer vision. Fourth and fifth section present proposed approaches for cooperative ramp metering and variable speed limit control. Paper end with a discussion about obtained results, conclusion and future work.

II. URBAN ROAD TRAFFIC CONTROL PROBLEMS

Urban road traffic presents a very complex problem for control, planning and management. Open problems are related to measurement of traffic parameters (OD matrices, queue length, traffic flow) and robust distributed traffic control algorithms [14]. Underlying traffic process is of large scale, non-linear, stochastic with time dependent parameters, inter-coupled, and prone to various influences originating from human behaviour, weather, etc. In order to cope with such properties nowadays control methods from the field of ITS are being successfully employed [15, 16]. To affect the urban road network in order to enable optimal usage of traffic lights, variable message signs and traffic information systems are used. In order to do this, reliable measurement of traffic parameters is crucial. Classic sensors like inductive loops are mostly used in the field but nowadays traffic cameras are getting more attention. They, as the one sensor, provide additional information about the traffic like the vehicle type, detect incident situations, OD matrices of intersections [17], driver behaviour [18], etc. For effectiveness of such measurement and control systems various measures are used.

To test the effectiveness of various measurement systems, accuracy and processing time are used. Accuracy describes how close the value obtained by measurements is close to the true value. Usually a standard or a more accurate approach is used to obtain the true value. In case of the video camera based measurement systems the true value of traffic flow i.e. number of vehicles currently is mostly obtained by manual counting. Processing time describes how fast can the change in the traffic network be detected and this information be available to the overlying control system. In computer vision systems this parameter is of significant importance since large amount of data have to be processed and often parallelization of computational processes is used as the solution.

One important part of urban road network are urban highways. They are built as a bypass of the wider city centre or to alleviate transit traffic. Despite the fact that urban highways are originally planned to provide high Level of Service (LoS), almost every day it is possible to observe traffic congestions or at least slowdown on them. LoS is one way to measure the quality of the road network wherein six LoS letters designate each level, from A (best level) to F (worse level) [1]. LoS takes into account mean density or/and speed of the mainstream so it is necessary to use additional measures for highway service quality assessment that take into account also other travel quality evaluation parameters. Travel Time (TT), queue length and Delay are such measures. TT gives the information how much time one vehicle needs to travel through observed highway segment and it is measured in minutes. Queue length presents the number of vehicles waiting in a queue on intersections, congested highway parts or on-ramps. Delay is defined as the difference between the actual time spent by all vehicles on a congested highway and the time spent in case they have travelled at free flow speed. Delay also considers vehicles which are waiting in on-ramp queues or in mainstream queues caused by the bottlenecks and is measured in vehicle-hours [2].

III. ROAD TRAFFIC PARAMETERS MEASUREMENT USING COMPUTER VISION

Combination of state-of-the-art computer vision algorithms and modern video cameras can offer new types of road traffic parameters to ITS. New types of road traffic parameters include origin-destination matrices of wide road traffic network, average travel time from point A to point B, driver aggressiveness factor, classification of vehicles present in road traffic network, etc. Mentioned parameters can be obtained by processing road traffic images with computer vision algorithms. Most often used algorithm for video image processing can use one or combination of the following methods: background subtraction method, methods based on computing optical flow, and methods based on image descriptor and classifiers.

Background subtraction methods consists of classifying pixels in the image as part of foreground (moving) or background (static) object as described in [9]. When all foreground pixels in the image are known, they can be clustered into segments where each segment will represent one object (vehicle). This method is used in the proposed approach. Optical flow method is based on computing direction and velocity of specific segment of pixels in the image. For this computation two or more consecutive images are processed. Method based on image descriptor and classifier use different approach for object detection. Image descriptor algorithm processes the image or segment of the image and computes specific features from it. After these features are known, classifier performs computation to found if a specific object (vehicle in this case) is present in the image or if there is no object in the image. Before mentioned process, classifier needs to learn to distinguish between positive (with object) and negative (without object) images and this is called learning process [13].

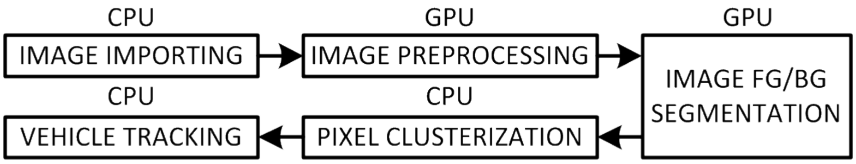

Figure 1: Work-flow of proposed computer vision system for road traffic parameters measurement.

Work proposed in this paper process the video footage of a road traffic network in order to obtain number of passed vehicle on one or two lanes according to the work-flow presented in Fig. 1. First step in every vehicle detection algorithm, besides of importing an image from a video stream is image preprocessing. After image is imported it contains a certain percentage of noise. Noise complicates the vehicle detection process and significantly reduces the accuracy of the proposed system so it needs to be minimized. In the proposed system a 5x5 matrix is used for the implemented Gaussian blur filter. Workflow of image preprocessing wherein renderings are distributed on the Central Processing Unit (CPU) and Graphical Processing Unit (GPU) is given in Fig. 2. So real time capabilities of the proposed system are achieved. After preprocessing of the imported image, system uses the background subtraction method. Workflow of the background subtraction method is shown in Fig 3. Process consists of creating a background model of the scene and comparing computed background model with the latest preprocessed image imported from the video [11].

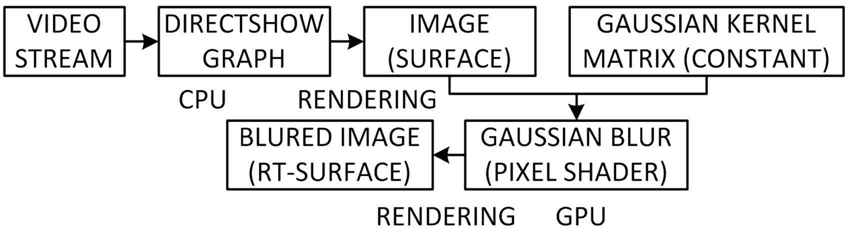

Figure 2: Basic workflow of blur image preprocessing filter [10].

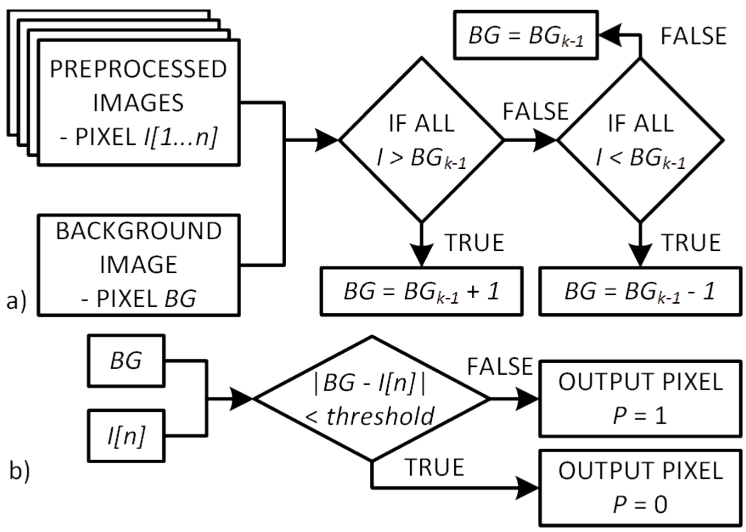

Figure 3: Fg/Bg image segmentation workflow: a) background model creation, and b) background model and current image comparison [10].

To create the background model following equation is used:

$$BG_k = BG_{k-1} + \left\lfloor \frac{\sum_{i=1}^{n} \operatorname{sign}(I_i - BG_{k-1})}{n} \right\rfloor, \tag{1}$$

where BG_k represents value of the specific pixel in the background model for current frame and BG_{k-1} is value of the specific pixel in the background model for the previous frame, I_i is value of a certain pixel in i^{th} image, and n is the number of stored images. By comparing mentioned pixels in imported images, every pixel in the currently processed image can be classified. If difference between current image pixel value and background model pixel value is larger than specified threshold constant, pixel is classified as a part of a foreground object. Otherwise it is considered as a part of the background model. Result of preprocessing and Fb/Bg image segmentation is given in Fig. 4.

Figure 4: Original image (a) passed through preprocessing algorithm (b) and after Fg/Bg segmentation (c).

When a moving vehicle is detected by the described method, its location in the image is obtained also. Detected vehicle location is given with x, y pixel coordinates and it contains information about vehicle true location corrupted with noise. Noise disturbs vehicle tracking algorithm as measured vehicle location gets shifted for a certain value which is different for each image. This requires further processing of measured data. Proposed system in this work processes object location by modified data association algorithm mentioned in [12] and Extended Kalman Filter (EKF) algorithm. First step in data association algorithm is pixel clustering performed in the latest image obtained from vehicle detection algorithm. Pixel clustering combines all adjacent pixels in the image into clusters. After all clusters are computed, they are compared with clusters from the previous image. If there is a positive match between two clusters in two consecutive images, both clusters are set to belong to the same object. If a cluster from the latest image has no match with any of the clusters in the previous image, it is considered to be a new object. If a cluster from the previous image has no match with any of the clusters in the latest image, it is considered that it has left the current scene. Matching criteria for cluster association in two consecutive images is given by the weights defined with the following equations:

$$w_{dist} = 1 - \frac{d - d_{min}}{d_{max} - d_{min}}, \tag{2}$$

$$w_{area} = 1 - \frac{a - a_{min}}{a_{max} - a_{min}}, \tag{3}$$

$$w_{cover} = \frac{a_{is}}{\max\,(a_{obj}, a_{cl})}, \tag{4}$$

$$w = \frac{w_{dist} + w_{area} + w_{cover}}{3}, \tag{5}$$

where d is distance between location of the specific cluster and estimated object location in pixels, d_{min} and d_{max} are minimum and maximum distance between all clusters and processed object in pixels, a is difference between the cluster area (size) and estimated object area, a_{min} and a_{max} are minimum and maximum difference between all clusters area and estimated object area respectively, a_{is} is intersection area between cluster and object, a_{obj} is area of the object, and a_{cl} is the cluster area. All areas are expressed in pixels [px].

To compute the distance between the location of a specific cluster and corresponding estimated object location their geometric centers are used. Cluster and object areas are computed as their surrounding bounding box area. Matching gives a positive result only for cluster with the highest weight w and if $w_{cover} \geq 2/3$. EKF combines measured data with predicted state estimate. Result of this process can give more accurate trajectory then the one obtained by using measured data only. Basic workflow of the vehicle trajectory estimation part of the system is given in Fig. 5.

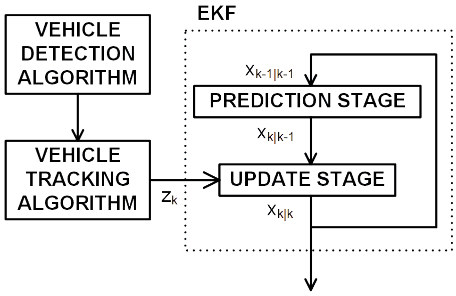

Figure 5: Basic workflow of implemented EKF for vehicle trajectory estimation.

IV. Intelligent cooperative ramp metering

In spatial and temporal aspects congestions are common in parts of the urban highway near on- and off-ramps during the early morning or late afternoon, [2]. In order to mitigate influence of congestions at highway on-ramps - ramp metering is applied as the most used control method under the ITS domain. Ramp metering uses road signals at on-ramps to control the rate or size of vehicles platoons entering mainstream traffic according to current traffic conditions, [3].

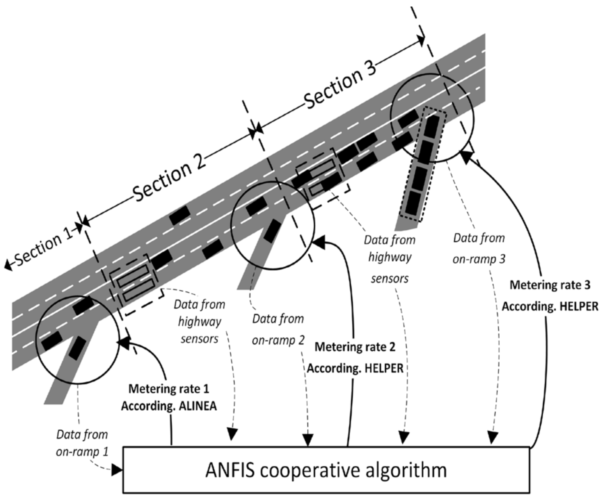

Figure 6: ANFIS based working principle for cooperation between on-ramps

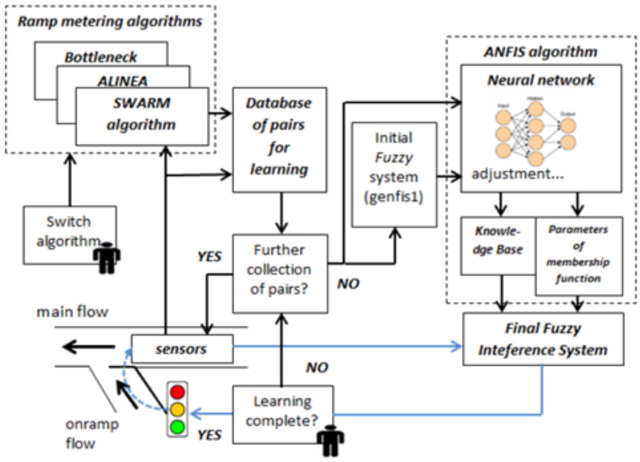

Figure 7: ANFIS based framework for learning ramp metering control algorithms

Locally based ramp metering strategies takes into account only traffic conditions on particular on-ramp and nearby segment of highway where they are applied. Most representative member of this algorithm category is ALINEA. Main working principle of ALINEA is to keep the downstream occupancy of the on-ramp at a predefined value using a closed loop control structure [4].

Optimization of on-ramp metering rates at urban highway with many on- and off-ramps placed at small distances can be difficult and insufficient with local ramp metering control algorithms. In order to mitigate that problem coordination between isolated on-ramp controls is established [4]. This paper will use two types of coordinated algorithms: cooperative and competitive. Cooperative ramp metering algorithms adjusts metering rate, previously computed by local ramp metering algorithm, for every on-ramp according to overall highway traffic state. Intelligent system which enables cooperative ramp metering is achieved through an Adaptive neuro-fuzzy inference system (ANFIS) algorithm. Proposed ANFIS based working principle for cooperation between on-ramps is shown in Fig. 6. This control structure is built on top of the HELPER cooperative ramp metering algorithm which exploits several downstream on-ramp queues capacity in order to mitigate back-propagation of upstream “shock waves” [5]. In other words HELPER algorithm creates virtual queues on several downstream on-ramps. Mentioned action consequently decreases the number of incoming vehicles from the upstream on-ramps regarding the current bottleneck location.

Application of intelligent systems in ramp metering is the latest approach in order to perform adaptive mitigation of congestion which is varying in spatial and temporal context. In some cases it is possible to predict characteristic behaviour of traffic demand during the day in spatial and temporal context (e.g. peak hours). Furthermore, traffic demand on the one of urban highway on-ramps can significantly exceed traffic demand at an unforeseen interval of the day. Reason of such traffic demand can be for example summer sale in shopping centres or any other event of high public interest. For such a traffic scenario HELPER ramp metering algorithm is suitable also. It can effectively suppress upstream propagation of "shock waves" due its ability to create upstream virtual queues. It is possible to conclude that one ramp metering algorithm cannot equally efficiently respond on every traffic situation on urban highway. This is the reason for development of ramp metering algorithm with an intelligent system which will be based on summarized knowledge from several different ramp metering algorithms into one control structure.

Proposed ANFIS based control framework uses an artificial neural network (ANN) to modify parameters of a fuzzy inference system (FIS) [7]. First phase in ANFIS learning includes selection of appropriate teaching ramp metering algorithms. Three teaching ramp metering algorithms (local - ALINEA, competitive - SWARM and cooperative - HELPER) are selected and simulated under the same highway conditions. After all simulations are conducted database of different types of traffic parameters is created. Exhaustive search was used to select appropriate parameters from database which would be used in the input/output teaching set of the ANFIS algorithm [8]. Database with traffic data selected by exhaustive search and appropriate criteria function is used for ANFIS algorithm learning process. Criteria function selects one solution for particular traffic scenario between solutions derived by three teaching ramp metering algorithms according to the balanced ratio between Delay and TT. ANN optimizes its interconnection structures trough unsupervised learning methods and provides optimization capabilities. During the learning process every element of the training data set (inputs only) is presented to ANN. After learning process FIS for cooperative ramp metering is created. Learning framework of the propose ANFIS based ramp metering algorithm is presented in Fig. 7.

V. COOPERATIVE VARIABLE SPEED LIMIT CONTROL

Standalone Variable Speed Limit Control (VSLC) has the main task to gradually decrease speed of the upstream flow before congestion starts. Such approach firstly gradually decreases mainstream speed, but enables higher mainstream speed during the congestion period unlike the scenario without VSLC [5]. It is possible to conclude that main purpose of VSLC is homogenization of mainstream vehicle speeds what enables better control over them. Standalone ramp metering is ineffective in two cases: (i) traffic demand is too low and (ii) traffic demand is extremely high, in which case traffic breakdown will happen anyway. VSLC is useful in order to mitigate second case by limiting the inflow into the area where the traffic breakdown starts. By this action of VSLC the ramp metering algorithm can have more time to control on-ramp flows before traffic breakdown arise. This is the most common case of VSLC cooperative behaviour. In cooperation with the core ramp metering system it is possible to include several other highway management strategies: VSLC, line prohibiting changes and various driver information services.

In this paper, additional cooperation is established between VSLC and ramp metering. As mentioned, HELPER is used as the cooperative ramp metering algorithm which works independently regarding VSLC. VSLC monitors HELPER work and decreases mainstream speed shortly before HELPER creates virtual on-ramp queues and ends when the congestion is reduced [5]. Decreased speed of mainstream vehicles contributes to the lower values of density in the area between congested and last downstream on-ramp affected by virtual queues. Lower upstream density of the congested on-ramp leaves additional mainstream capacity to accept vehicles which have origin from congestion back-propagation. In such a way the appearance of the congestion build conditions can be postponed. Additionally, the congestion build-up start phase can be prolonged resulting in a shorter congestion phase.

VI. EXPERIMENTAL RESULTS

To test the proposed measurement and control system tests using real world date have been conducted. Vision based measurement systems has been tested using real world road traffic video footage in an off-line working mode. Only the vehicle trajectory estimation part has been tested using a synthetic video since the authors currently have no access to accurate vehicle trajectory data. The control system has been tested using real world traffic data and the CTMSIM macroscopic simulator. Prior to simulation, used CTMSIM simulator was upgraded to enable cooperative control and VSLC [5].

A. *Vision based road traffic parameters measurement*

The proposed road traffic parameters measurement system has been tested using real world road traffic video footage captured on a highway with two lanes near the city of Zagreb in Croatia. Camera was mounted above the highway and passing vehicles were recorded using a top view camera perspective as given in Fig. 8. Duration of the test video was 10 [min]. Obtained original video resolution was 1920x1080 [px] in RGB format.

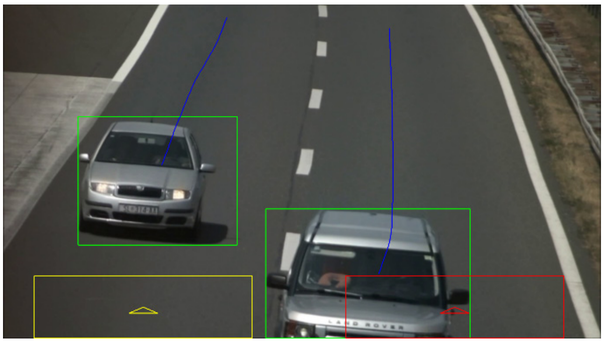

Figure 8: Vehicle tracking and counting on two lanes.

For vehicle detection results verification, two approaches for vehicle counting were tested. Both are based on markers (virtual vehicle detectors). Yellow and red rectangle markers are placed in the bottom part of the scene on each lane as shown in Fig. 8. Edges of markers are perpendicular to the image x and y axis. When vehicle passes through marker and a hit is detected, counter for that marker is incremented. First approach checks if an object is passing through marker with its trajectory and second approach performs check if an intersection between marker and object exists. Both approaches discard all objects whose trajectory direction is outside of a specific interval. In performed test, all objects need to have their direction between 90 – 270 [°] in order not to be discarded. Objects also need to be on the scene for more than 30 frames. Value of the threshold constant used in Fg/Bg segmentation method is 10 and number of consecutive images used when creating background model (n) is 105. Blue lines in Fig. 8 represents estimated vehicle trajectory. Experimental results are given in Tab. 1. FP represents false positive and FN represents false negative hits. True vehicle count is acquired by manually counting all passed vehicles.

Table 1: Obtained vehicle detection test results.

Approach		**Vehicle count per lane**		
		Total	**Left**	**Right**
Overlap check	**Hits**	126	65	61
	FP / FN	0 / 6	0 / 5	0 / 1
	Accuracy	95,6%	92,9%	98,4%
Trajectory check	**Hits**	129	68	61
	FP / FN	1 / 4	0 / 3	1 / 1
	Accuracy	96,2%	95,8%	96,8%
True vehicle count		132	70	62

In Fig. 9, execution time is given for various resolutions tested on a Windows 7 (64 bit) computer with CPU Intel Core i7 – 2.4 GHz, GPU NVIDIA Quadro K1000M and 8 GB RAM. In the experimental testing, both approaches (overlap and trajectory check) for vehicle counting had the same execution time. From the acquired results it can be concluded that real time vehicle detection can be performed on SVGA 800x600 [px] resolution and lower using a standard PC computer. On SVGA resolution, 17 [ms] is required to process a single frame. This enables maximum frame rate of 58 [fps]. At QVGA 320x240 [px] resolution, 142 [fps] can be achieved with 7 [ms] required to process a single frame. It can also be concluded that approach with trajectory check gives better results regarding accuracy than approach with overlap check.

For testing of the implemented EKF based vehicle trajectory estimation, a synthetic road traffic video was made in Autodesk 3ds Max. Video of synthetic environment simulates passing of one vehicle on a road with two lanes. As the true position of vehicle in the synthetic environment is known, implemented EKF can be tested for its trajectory estimation accuracy. In Figs. 10 and 11, different trajectories obtained by various methods are compared. Real trajectory represents movement of vehicle geometric center defined during development of the synthetic video. Measured trajectory is computed by taking data (vehicle trajectory) from vehicle detection algorithm and adding noise to it. Noise is defined by standard uniform distribution in interval [-2.5, 2.5] and it is added to each vector of vehicle trajectory. Mean trajectory is computed by taking last 3 of the x and y coordinates of measured trajectory and computing mean value of them. So measurement noise can be reduced without significantly affecting vehicle location estimation accuracy. EKF trajectories are obtained by using two different state models. First model is already described in previous section. The second model is based on first model with the angular velocity component removed.

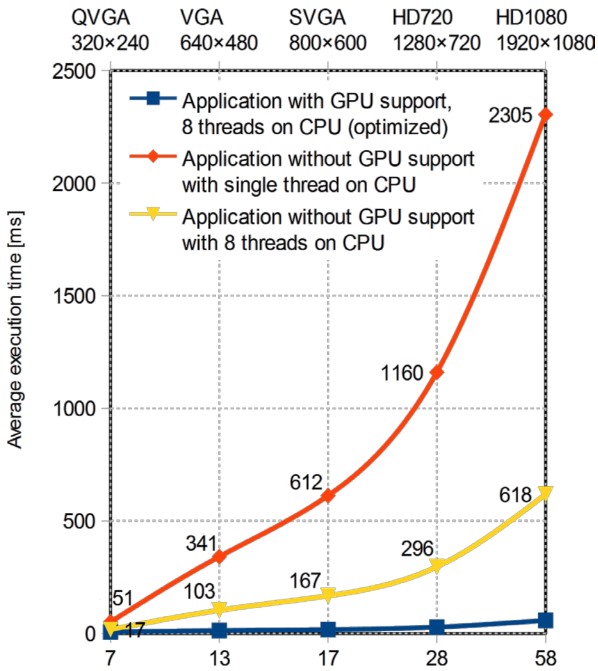

Figure 9: Execution time of the proposed system.

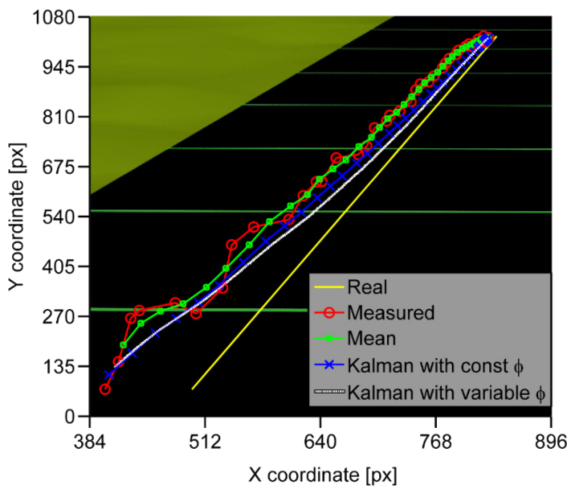

Figure 10: Comparison of real, measured, mean and EKF vehicle trajectory.

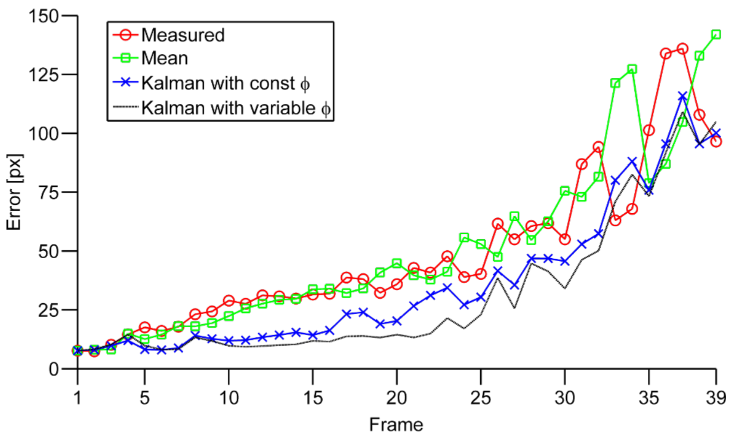

Figure 11: Comparison of error in measured, mean and EKF vehicle trajectories.

In Fig.11, x-axis represents number of frame for which error is computed and y-axis represents amount of error in [px]. Vehicle position error can be computed for any frame using the following equation:

$$err(k) = \sqrt{\left(x_r^{(k)} - x_f^{(k)}\right)^2 + \left(y_r^{(k)} - y_f^{(k)}\right)^2}, \qquad (6)$$

where k is the frame number, $x_r^{(k)}$ and $y_r^{(k)}$ are real measured values in [px] of x and y coordinates for specific trajectory vector, $x_f^{(k)}$ and $y_f^{(k)}$ are filtered values in [px] (using mean value method or EKF) of x and y coordinates for specific trajectory vector. Mean error value for the measured trajectory is 48.4 [px], for trajectory obtained by mean method is 50.2 [px], for trajectory obtained by EKF with constant vehicle direction angle φ is 35.9 [px] and EKF with variable vehicle direction angle φ is 31.2 [px].

B. *ANFIS based cooperative ramp metering*

Zagreb bypass between nodes Lučko and Jankomir is used as test site as presented in Fig. 12. Due to unavailability of real Zagreb bypass traffic data, on-ramps traffic demand characteristics and in-flow of the simulation model are reconstructed according to interpolated Ljubljana bypass traffic data [3]. Use case scenario on mentioned section involves an expressed traffic load at peak hours at nodes Lučko and Jankomir. So this use case scenario is adequate for evaluation of cooperative ramp metering algorithms and VSLC. In order to evaluate highway traffic behavior under the control of mentioned highway strategies an interactive highway simulator CTMSIM is used. CTMSIM is based on a macroscopic Asymmetric Cell Transmission Model (ACTM) specifically designed for highway traffic flows simulations which is in detail described in

[6]. CTMSIM only provides local ramp metering and on-ramp queue control so it is augmented to support simulation of cooperative ramp metering and VSLC as it is shown in Fig. 13.

Figure 12: Zagreb bypass with marked nodes

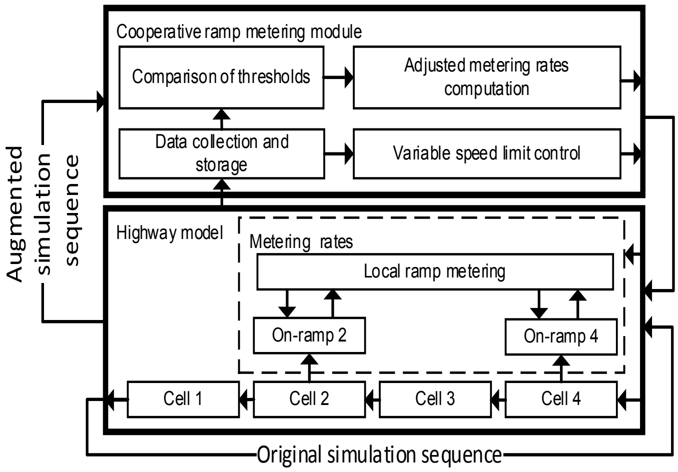

Figure 13: Augmented CTMSIM simulation structure in order to support cooperative ramp metering and VSLC

According to Table 2 it is possible to conclude that with increased average TT, average Delay decreases its value and it's also applies the other way around. LoS is related with TT since it takes into account only traffic situation at the mainstream. In Fig. 14 it is possible to conclude that ANFIS ramp metering based approach has produced highest TT values compared to the other ramp metering algorithms involved into analysis except for VSLC and no control applied. Additionally, average TT values of ANFIS ramp metering are more similar to the lower average TT values achieved by teaching ramp metering algorithms than in case of VSLC and no-control applied. Balanced values between ANFIS average TT and Delay enables second best LoS categorization among all involved control strategies. Higher values of TT achieved by ANFIS algorithm are key feature which enables lowest Delay values in contrast to the other teaching ramp metering algorithms what can be seen in Figs. 14 and 15.

It is possible to assume that ANFIS algorithm has learned from the teaching ramp metering algorithms set of rules which govern relations between TT and Delay values. Criteria function used into ANFIS learning database is set to select inputs and outputs derived by all teaching ramp metering algorithms which enabling balance between Travel Time and Delay. According to Table 2 it is possible to conclude that ANFIS based ramp metering algorithm has achieved balance between TT and Delay values due to similar average values of TT and Delay.

Table 2: Type Size for Results of cooperative analysis between different ramp metering algorithms

No Control	No Control	ALINEA	SWARM	HELPER	VSLC	HELPER + VSLC	ANFIS
LoS (according to [1])	E	D	A	C	E	C	B
Average TT [min]	14.32	5.61	3.99	4.41	11.01	4.63	6.42
Average Delay [vh]	5.42	20.53	24.18	10.94	4.51	7.62	6.75
Average Queue [v]	0	79	89	58	13	57	38

C. Cooperation between ramp metering and variable speed limit control

Standalone VSLC has only noticeable effect on TT, since it is applied to the mainstream flow. VSLC produces vehicle platoons which are traveling at lower speeds in comparison to the free flow speed by decreasing mainstream speed. This produce decreased speed of process which induces mainstream congestion back-propagation. Additionally, this feature can potentially induce small queues at downstream on-ramps regard to the congested on-ramp due to increased mainstream density in downstream segments. Increased mainstream density in downstream segments is induced by influence of slower vehicles platoons which are moving toward congestion location. Generally it is possible to conclude that lower speeds of previous congestion arise, enable higher speed in time when congestion is most expressed. Sometimes VSLC prevented traffic standstill during most of the congested period [5]. Mentioned behaviour can be seen in Fig. 16. Furthermore, standalone VSLC has achieved the same LoS categorization as scenario with no control applied. This suggests that application of standalone VSLC in traffic scenarios with increased traffic load is often not enough.

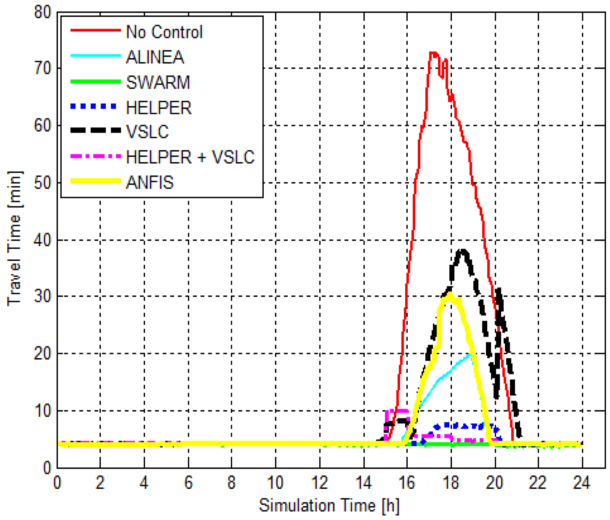

Figure 14: Results of comparative analysis according to TT

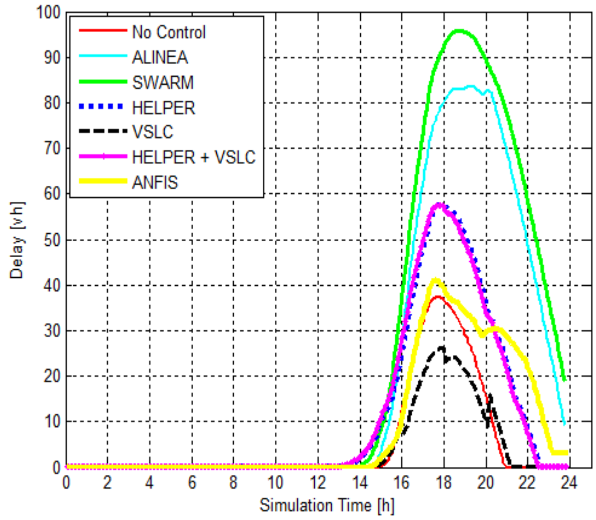

Figure 15: Results of comparative analysis according to Delay

Main goal of the cooperation between ramp metering and VSLC is to significantly reduce traffic density upstream of the congested on-ramp by use of virtual queues provided by cooperation between HELPER and decrease speeds of incoming vehicles to the congested region by use of VSLC.

Cooperative based control strategy second best average TT value was achieved by HELPER and in the situation with cooperation between HELPER and VSLC. Cooperation between HELPER and VSLC decreases TT curve in the period of heaviest traffic congestion (16:00 h – 20:00 h) in contrast to the HELPER stand-alone ramp metering algorithm as it can be seen in Fig. 14. Additionally, solution which includes cooperation between HELPER ramp metering algorithm and VSLC produce same LoS categorization as the standalone HELPER ramp metering algorithm. In the other hand mentioned cooperative solution produces significantly lower average Delay values in contrast to the standalone HELPER ramp metering algorithm. According to Table 2 among the stand-alone ramp metering algorithms, SWARM has achieved lowest TT and best LoS categorization due to its restrictive nature which also has resulted with highest Delay.

D. Discussion about obtained results

Obtained results related to road traffic parameters measurement by one camera that cover two lanes present that traffic flow can be measured with high accuracy. Implemented parallelization of image processing algorithms resulted with significant improvement of processing time to ensure real time capabilities. Additionally, enough processing time is available to conduct vehicle trajectory estimation on part of the monitored road and the implemented EKF is capable to reduce the estimation error. In this implementation phase the system has problems with traffic video footage quality and with a somewhat larger trajectory estimation error in image parts closer to the camera.

According to results related to traffic control it is possible to conclude that ANFIS algorithm has successfully adopted control knowledge which enables balanced ratio between TT and Delay values. With mentioned knowledge ANFIS has achieved second best LoS categorization. Cooperation between HELPER ramp metering algorithm and VSLC has achieved slightly higher average value of TT in comparison with standalone HELPER. Additionally, cooperation between HELPER and VSLC has achieved significantly lower average value of Delay due to VSLC in comparison with standalone HELPER. VSLC into cooperation with HELPER decreases the number of incoming vehicles into the congested zone what consequently induces lower mainstream density in mentioned zone. With lower mainstream density in congested zone HELPER control logic creates shorter virtual queues and consequently achieves lower average Delay. In order to achieve better results of cooperation between HELPER and VSLC it is necessary to conduct optimization. Optimization parameters should be number and locations of highway segments affected by VSLC and number of the on-ramps which provides virtual queues.

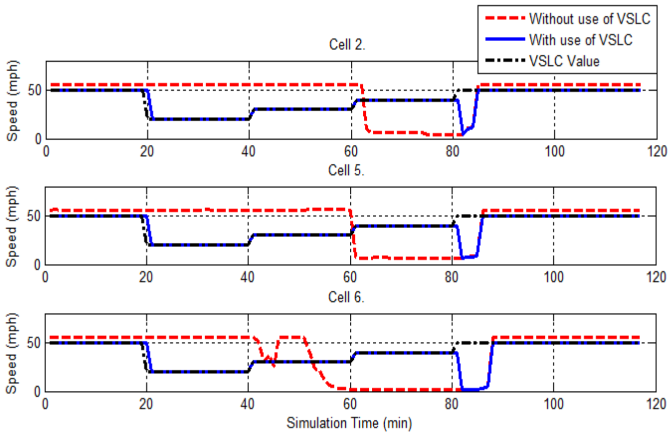

Figure 16: Analysis of mainstream speed with and without VSLC

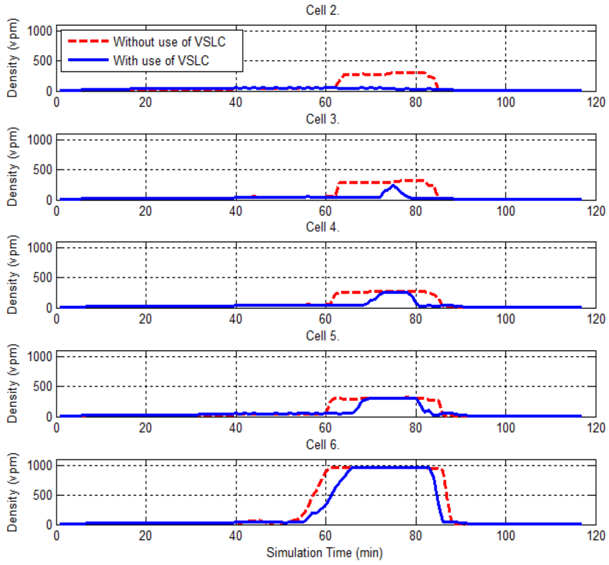

Figure 17: Analysis of mainstream density with and without the use of VSLC

VII. CONCLUSION

In this paper two new approaches to road traffic parameters measurement and cooperative intelligent ramp metering are presented. Proposed approach for road traffic parameters measurement is based on computer vision and is capable to detect and track vehicles on multiple lanes using only one camera. It can measure traffic flow and be easily integrated in existing road traffic measurement systems. The proposed cooperative intelligent ramp metering approach can ensure cooperation between several on-ramps and additional traffic control systems. VSLC was chosen as the additional traffic control system. Evaluation results show that this control approach can ensure improvement of the traffic situation.

Future work of the authors on these two topics will be related to vehicle type classification from road traffic video footage and augmentation of the intelligent ramp metering systems with on-line learning abilities. Additional emphasis will be put on improving the robustness of both approaches.

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