REAL TIME VEHICLE COUNTRY OF ORIGIN CLASSIFICATION BASED ON COMPUTER VISION

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Abstract

In order to efficiently monitor and control road traffic, relevant traffic parameters values are needed in real time. Traffic parameters include traffic flow speed profile, vehicle type classification, vehicle gap, vehicle length, origin-destination matrix, etc. Using these parameters advanced traffic control approaches from the domain of intelligent transportation systems (ITS) can be applied. Additionally, traffic planners can incorporate more accurate traffic forecasts when planning new roads. Also ITS related services can be provided to users, especially precise real time traffic information. Surveillance video cameras combined with advanced computer vision (CV) algorithms are nowadays becoming a tool used more frequently to obtain mentioned traffic parameters. They are used as standalone sensors or in combination with other sensors like radars, inductive loops, etc. In this article architecture of a computer vision based road traffic surveillance system is proposed. Application of such a system for vehicle counting and vehicle country of origin classification using license plate recognition is described. Implemented system is tested using real world road traffic video footage from a Croatian highway near the city of Zagreb. Proposed system quality is analysed using vehicle detection processing time and accuracy.

Keywords

Road traffic monitoring, Vision sensor, Vehicle detection, License plate recognition,

INTRODUCTION

Recent decades can be characterized by a significant increase of the number of road vehicles accompanied by a build-up of road infrastructure. Simultaneously various traffic control systems have been developed in order to increase road traffic safety, road capacity and travel comfort. Such control systems need high quality traffic data in real-time, especially control systems from the domain of intelligent transportation systems (ITS).

While analysing traffic on a road traffic network various parameters can be monitored. Such parameters include traffic flow speed profile, distance between vehicles, velocity of vehicles, vehicle classification, etc. They can be measured using various sensors like inductive loops, radars, video sensors, etc. Analysis results can be applied for planning and management of road networks in urban and rural areas including highways.

Development of computing power and cheap video cameras enabled today's traffic safety systems to more and more include cameras and computer vision methods. Cameras are used as part of road infrastructure or in vehicles. They enable monitoring of traffic infrastructure, detection of incident situations, tracking of surrounding vehicles, etc. In urban areas, computer vision applications can also be used in areas of ITS based traffic control management. Such applications include adaptive traffic light control, measurement of queue length, vehicle classification, etc. [1]. On highways cameras can be used in combination with license plate recognition (LPR) methods for statistical analysis of the vehicle country of origin and generation of origin-destination (OD) matrices. Such analyses are useful to improve traffic management and services related to tourism traffic.

In this paper the problem of road traffic analysis using computer vision in real time is tackled with the aim to estimate OD matrices of a larger road traffic network. Emphasis is on needed measurements related to a particular road node. Needed measurements include detection of vehicles and extraction of their license plate data. Whole system is adjusted to work in real time and in out-door conditions. Additionally, appropriate local data base for vehicle data storage is created with possibility to be included as part of a larger system with several nodes covered.

This paper is organized as follows. Second section gives a review of approaches for road traffic analysis. Third section describes proposed vehicle classification system architecture. Fourth section explains the implemented computer vision algorithms for vehicle detection and LPR software development kit (SDK) CARMEN. Fifth section describes speed up of the proposed system. Following sixth section presents obtained results using a real world road traffic video footage. Paper ends with a discussion about open problems and conclusion.

ROAD TRAFFIC ANALYSIS APPROACHES

When developing systems for road traffic analysis, input and output parameters of the system need to be determined first. System inputs described from low level computer vision (CV) aspect and outputs described from aspect of traffic science are presented in Fig. 1. Traffic parameters include various statistical data such as estimated OD

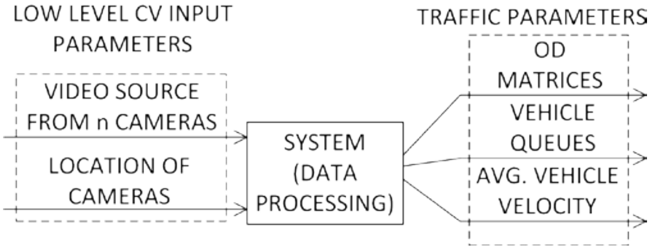

Figure 1: Example of input/output parameters of a system for road traffic analysis.

matrices, vehicles queues, average velocity of vehicles, statistics on vehicle registration plates, etc.

All input data in the system need to be received from sensors. Sensors can be divided into in-roadway sensors and over-roadway sensors. In-roadway sensors can be placed in the pavement or subgrade of the roadway. Sensors of this type can also be taped or attached to the surface which represents less aggressive method of installation. Simplest sensors from this group are pneumatic road tube sensor, inductive loop detector, magnetic and piezoelectric sensors. Road tube and piezoelectric sensors are based on measuring mechanical magnitudes which are formed when a vehicle passes over the sensors. They can be used for vehicle counting, determining gaps between vehicles, intersection and sign stop delays, vehicle's weight and velocity measurement, etc.

Inductive loops

Inductive loops are based on measuring changes in loop inductances as vehicle pass above them. Sensors are installed below road surface. They are more robust than previously mentioned road tube and piezoelectric sensors because they are not based on a mechanical interaction with vehicles. Parameters that can be extracted from inductive loops and magnetic sensors are vehicle presence, flow and occupancy. Using a two loop speed trap additional parameter such as vehicle velocity can be determined.

In [2], system with multiple inductive loops has been presented. Besides ability to detect standard parameters extracted by this sensor, proposed system can also distinguish between bicycle, motorcycle, car, bus, etc. System has been built and tested, however no real counting of traffic entities have been performed.

Approach of using neural network in vehicle detection by inductive loops is proposed in [3]. System with neural network has the ability to perform vehicle detection based on knowledge acquired previously in a learning stage. In mentioned work, system was trained in the learning stage by 60 [%] of positive samples and 40 [%] of negative samples. Test results show that average hit rate of such system is about 92.43 [%].

Main disadvantages of all in-roadway sensors including inductive loops are: need for lane to be closed for traffic when installing or maintaining the sensor; cost of installation (additional construction works that need to be performed on the road or lane); difficult maintenance of sensors due to its inaccessibility.

Cameras in road traffic surveillance

In systems which use CV for road traffic analysis, most traffic information is extracted from cameras. In this concept, term "camera" usually implies to colour or infra-red type of camera, although various other sensors can be used such as LIDARs and radars. These devices return as the output measurement a specific matrix data which is interpreted as 2D or 3D image [4].

Radars have the ability to extract position and velocity of a distant object. Basic working principle is based on emitting an electro-magnetic (EM) beam (wavelength between 0.1 – 30 [cm]) to the specific object and then receiving reflected beam from it. It is most widely used in aerospace industry. However it has other applications like in automotive industry. Main advantage of radars is that they are not affected by bad weather contrary to LIDARs and video cameras which require good optical visibility [5].

In [6], a system is proposed based on continuous wave (CW) radar used for simultaneous vehicle detection, velocity measurement and vehicle classification. Carrier frequency of EM beam is on the frequency of 24.125 [GHz] and data sampling is performed using a 20 [kHz] sampling rate. Vehicle detection rate is about 95 [%], while average accuracy of velocity measurement is 97.1 [%]. Average accuracy of vehicle classification is 94.8 [%] although it varies for each vehicle type (bike, car, van, bus, etc.).

Video cameras are often used in CV based systems for traffic monitoring also. Such systems include vehicle counting, vehicle classification, computation of vehicle velocities and trajectories, computing distance between vehicles, and automatic number plate recognition (ANPR) or sometimes referred as automatic license plate recognition (ALPR) [7].

In [8], system for vehicle classification based on optical camera is presented. System recognizes the vehicle class using its computed 3D model. Overall system evaluation shows that its precision is 87.9 [%] and recall 96.1 [%]. Work presented in [9] uses CV system based on optical camera to count vehicles.

In systems that use video cameras, important features which highly influence final performance of the system are video resolution, location where traffic should be monitored and cameras mounting points.

Modern video cameras often use LAN to broadcast video stream (IP cameras) which often rises to full HD resolution. Main problem of using such high resolution cameras for traffic analysis is high computational, memory and communication load. If video stream is encoded with high compression ratio, network bandwidth requirements

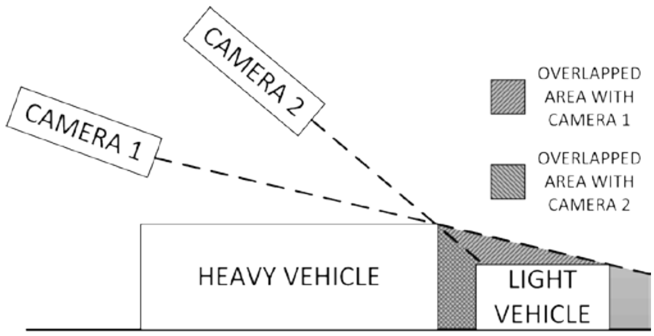

Figure 2: Comparing overlapped area in the image when different camera locations are used.

will be significantly smaller. However there will be higher requirements for processing unit to decode the video. If compression ratio is lower (i.e. video in raw format), processing unit will decode the video more easily but requirements for network bandwidth will be too large for real-time transmission.

Camera must be mounted with such position and pointing direction so that vehicles do not overlap each other in the image as shown in Fig. 2. For this reason cameras are usually mounted on a high place such as a traffic pole. It must be ensured that vibrations in the environment (originating from passing vehicles or strong wind) are not carried out to the camera.

System used for traffic monitoring and traffic analysis needs to perform a variety of tasks such as vehicle detection, ALPR, etc. For vehicle detection ideal location of the camera is high above the road, however this may create problems to ALPR software. ALPR highly depends on the vehicle license plate being visible in the image in good quality. Because camera is mounted above the road, from its perspective license plate will be distorted and therefore results of ALPR software will be significantly worse than if camera was mounted near the road level. The ideal solution in this situation is to perform evaluation of camera's locations and select the one that gives best result [10].

VEHICLE CLASSIFICATION SYSTEM ARCHITECTURE

Proposed vehicle classification system architecture consists of two parts as shown in Fig. 3. The first part is implemented in C++ using OpenCV library [11] for road traffic video footage processing. It contains video processing, image enhancements and vehicle detection techniques which are applied to the road traffic video stream. The task of this part is to detect a possible vehicle, extract it from the video stream as a separate image frame and to transform the separated frame into appropriate form for the second part.

In the second part of the proposed architecture separated video frames are first processed to confirm that detected moving object is a vehicle. If a vehicle is confirmed, the LPR software CARMEN is used to obtain additional information about the vehicle such as license plate number, pixel coordinates where the license plate was extracted, confidence of extracted license plate number, time stamp

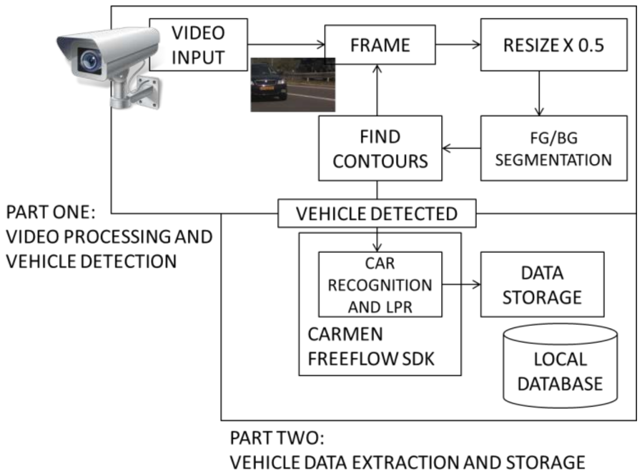

Figure 3: Vehicle detection system architecture.

when and road mark where the vehicle was detected, etc. Obtained information about vehicle is stored in a local database. Proposed local database is configured in a way that it can be used in an augmented road traffic surveillance system where more mutually connected roads are monitored. In such an augmented system each local database conveys data to a central database containing information of a larger monitored road network. In this paper only the system needed to monitor one road segment is described as the first development step for such an augmented system.

VEHICLE DETECTION AND LICENSE PLATE RECOGNITION

For the purpose of video based road traffic flow monitoring various methods can be used. Approach strategies can be based on following methods [12]: active contours; models; features; appearance; stereo-vision.

To determine optimal methods, main objectives of the application need to be defined. It can be assumed that for determining vehicle's country of origin in real-time, input video for developed computer vision algorithm will be obtained from a static (non-moving) camera. Algorithms and methods used in this system will be limited in the scope of this assumption.

First objective of the application is to efficiently detect vehicles in the video. Objects of interest in this application will be only moving vehicles. Second objective of the application is to track vehicles even if they are not moving. Third objective of the application is to recognize vehicle license plate through the LPR software which can be used for further traffic analyses.

Vehicle detection

For detecting vehicles in road traffic videos, methods like foreground/background (Fg/Bg) image segmentation and optical flow can be used. With the Fg/Bg image segmentation method, moving objects are separated from static part of an image. This is based on comparing current image with the image that contains only background objects (non-moving objects) as shown in Fig. 4. If images are in grey scale, only pixel intensity will be compared. In images where 3 channels are used for colour (RGB), all three channel values will be compared. If differences between pixel values exist, they are filtered with specific threshold. If after threshold difference still exists on certain pixel, it will be classified as foreground pixel or otherwise background pixel. Drawback of this method is that object will not be detected if it stops for a certain amount of time. OpenCV framework contains large collection of classes and functions which are used in computer vision applications. In OpenCV framework, class *BackgroundSubtractor* is used to perform Fg/Bg image segmentation based on the algorithm described in [13].

System described in [14] uses Fg/Bg image segmentation method. It performs computation of OD matrix at road intersection. After reading an image from video stream, system performs image pre-processing using Gaussian blur filter. Second step is to update background model using Fg/Bg image segmentation method. In the image with foreground objects, method for morphological opening is performed which consists of dilation and erosion filters. Last step of the system is to detect vehicles, link them to appropriate nodes and create the OD matrix. This is achieved using markers and object tracking. After computation of OD matrix is complete, systems will contain numbers of incoming and outgoing vehicles on the specific intersection entrance or exit.

Regardless of object tracking, after certain object has been detected, its image coordinates can be computed. If coordinates of the object are followed through certain time, object trajectory can be derived. In [12], a Kalman filter is used to construct linear motion model. Position of the object in the next frame is estimated using the Kalman filter. Further processing consists of counting the number of vehicles passed through a certain surveillance region. This can be achieved by monitoring vehicles passing through specific point in an image or by tracking whole trajectories of vehicles in the image. Trajectory tracking starts when a vehicle enters the surveillance area and ends when it leaves the surveillance area.

Proposed applications in this paper perform object detection based on Fg/Bg image segmentation and LPR CARMEN Freeflow software. First version of developed application uses functions and classes for Fg/Bg image segmentation from OpenCV framework. Second version of application also performs Fg/Bg image segmentation for vehicle detection where algorithms are executed mostly on GPU using DirectX 3D framework. Fg/Bg image segmentation method used in second application is based on the already described concept presented in Fig. 4.

License plate recognition

When a vehicle passing through a monitored road network node is caught in an image obtained from camera, extraction of its license plate number can be valuable to the system for traffic analyses. After parsing the license plate number, monitoring application can determine from which country the vehicle comes from. With this data it is also possible to make statistics which show origin countries that are most frequent on the monitored road segment.

LPR algorithms can have difficulties when extracting license plate data caused by variability in license plate and environmental properties such as:

- Location of license plate in the image;
- Quantity (one or more license plates in the same image);
- Size (if camera pan-tilt-zoom function is enabled this parameter will be variable in large scale);
- Colour of license plate;
- Font for different languages and nations (i.e. European countries, Asian countries);

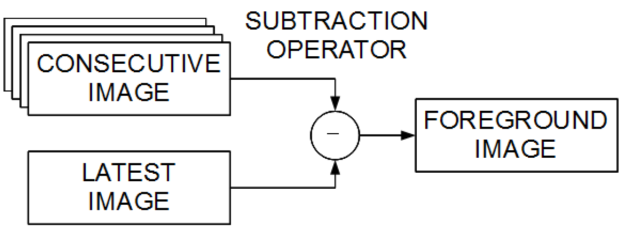

Figure 5: Basic concept of Fg/Bg image segmentation.

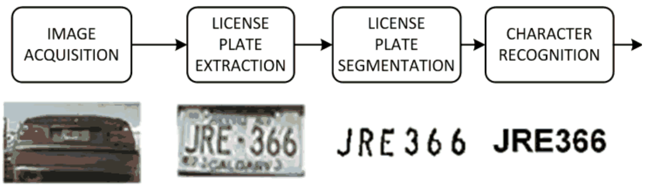

Figure 4: Basic work flow chart diagram of general LPR algorithms [15].

- Custom license plate (non-regular format defined by owner);
- Occlusion (caused by environment – dense traffic with overlapping vehicles, snow, dirt, rain, fog);
- Inclination (caused by camera perspective);
- Environment illumination problems (especially during night);
- Background noises (other textures on vehicles or in the road environment which LPR algorithm can misinterpret as a license plate).

Basic work flow of LPR algorithms can be described by four stages as shown in Fig. 5. In the first stage, part of an image with the whole vehicle is located. After vehicle position in the image is known, second stage begins with locating the license plate on a region of the image with the vehicle. Third stage consists of segmenting only license plate numbers, filtering out other image features. Last stage finally performs optical character recognition (OCR) and extracts license plate data [15].

Developed application described in [16] performs last stage of LPR that is based on artificial neural networks. Application can process single character with resolution 34×22, where execution time on PC Dual Core 2.4 [GHz] is 8.4 [ms], while on embedded FPGA platform is 0.7 [ms] as shown in Tab. 1. In [17], LPR method robust to environmental weather conditions is presented. For computing license plate location on the vehicle, image is first converted to grey channel. After conversion, edge detection is performed followed by image morphology and other filters. After license plate is localized, characters are segmented and finally OCR is performed. Method was tested on 392 images where character recognition rate is 95.6 [%] and average execution time is 500 [ms]. In scope of current work, CARMEN Freeflow software was also tested for performance comparison. From test results

OCR technique	Character recognition rate [%]	Platform	Execution time [ms]
System on FPGA	97.3	Vertex-4 FPGA	0.7
System on PC	97.3	PC 2.4 GHz	8.4
SVM	97.03	PC 1.8 GHz	18
Self-organising map	90.93	Virtex-4 FPGA	not available
SVM	94	DSP C6416	2.88
CARMEN	not available	PC 2.4 GHz	15

Table 1: Performance comparison of single character

performing LPR with CARMEN Freeflow software requires approximately 290 [ms] with an image of 690 × 440 resolution, where OCR per single character in resolution 34×22 is 15 [ms] as shown in Tab. 1. This represents too long execution time for real-time processing and therefore different approach needs to be considered.

Implemented approaches

Developed applications in this paper use two different approaches for vehicle detection. Both applications have the goal to obtain road traffic parameters of a road segment using a surveillance video stream as input. First approach is to use OpenCV framework for Fg/Bg image segmentation and LPR algorithms defined in CARMEN Freeflow framework. In the first approach vehicles in an image are first detected and localized by Fg/Bg image segmentation method and contour extraction. After vehicles are localized their license plates are read by CARMEN Freeflow ANPR software. Image region that contains vehicle is sent to the mentioned software after which it can extract information such as license plate number, confidence of LPR, country of origin related to recognized license plate, etc.

Second approach presented in this paper consists of optimized speed-up methods for image processing. Methods are developed to execute mainly on GPU architecture. Using this technique execution time is significantly decreased and real-time execution has been made possible. Application first performs Fg/Bg image segmentation using GPU. After vehicles have been extracted in an image they are represented in binary format. As such data is insufficient for vehicle detection, they are further translated into clusters where each cluster represents moving vehicle. From this data further parameters can be extracted such as vehicle velocity, distance between vehicles, etc.

VEHICLE DETECTION SPEED UP

As mentioned, first version of the implemented algorithm for vehicle detection has shown to be efficient from accuracy aspect. Further development consists of optimizing it for faster execution and increasing its accuracy. This is trying to be achieved using second approach. Speed up optimization can be performed using two basic strategies: the use of modern system architecture features such as multi-threading (MT) and Streaming SIMD Extension (SSE) support on CPU including parallel processing on GPU, and simplification of all mathematical operations which also includes trade-off between results precision and execution time. Basic work flow of application which uses MT, SSE and GPU support is shown in Fig. 6. Main guidelines for proposed execution speed up development are following:

- Algorithms that process large amount of data (image matrices) should be performed on GPU if possible;
- If small amount of data needs to be processed, it should be preferred to perform it on CPU with SSE support where possible;
- If the algorithm cannot be executed on GPU because of its complex design and it requires a large amount of processing resources, it can be executed on multiple threads in parallel which can significantly improve its execution time.

Algorithms that process every pixel in the image can be time consuming for CPU even with use of SSE support. Modern GPU architecture consists of many stream processors that can process data in parallel execution (SIMD instructions). This represents main reason for considering use of GPU in further development of proposed application regarding real-time properties.

EXPERIMENTAL RESULTS

The experimental tests were carried out with two real world outdoor traffic videos. First video is a traffic node corresponding to the entrance of the parking lot of the Faculty of Transport and Traffic Sciences with a low traffic flow. Second video corresponds to a highway entrance of the city of Zagreb, Croatia. This highway traffic video contains a denser and more variable traffic flow compared to the first video.

Developed application

The application was developed in different stages. In the first version of the program, the area where the moving object is detected is extracted from the image and processed with CARMEN LPR software using the implemented method Recognize. This process is repeated every five frames to ensure needed vehicle detection accuracy. Using the CARMEN software, a vehicle is detected by its license plate number and stored in the local database. To store a license plate the confidence provided by CARMEN software must be higher than the chosen threshold. Value of 50 [%] is used and is derived from experiments made. CARMEN software also provides license plate country of origin recognition, coordinates where the license plate is placed, etc. To test this development stage simpler first video was used.

In the second development stage the aim was to improve the performance in a real world scenario like described with the second road traffic video. Compromise between real time processing and accuracy had to be kept. To accomplish this goal, license plate number registration and aspects like environmental effects (sun shines, shadows, rain, etc.) or

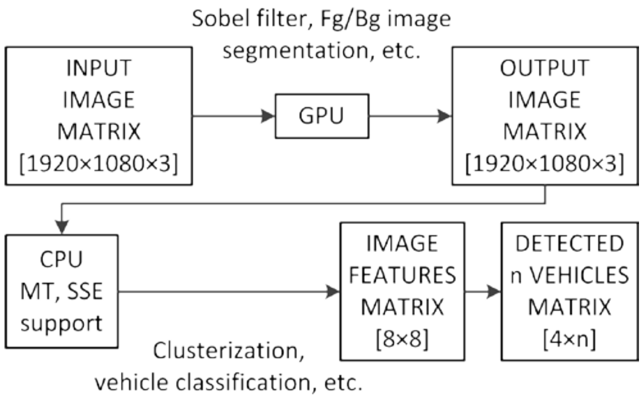

Figure 6: Proposed work flow using modern system architecture features.

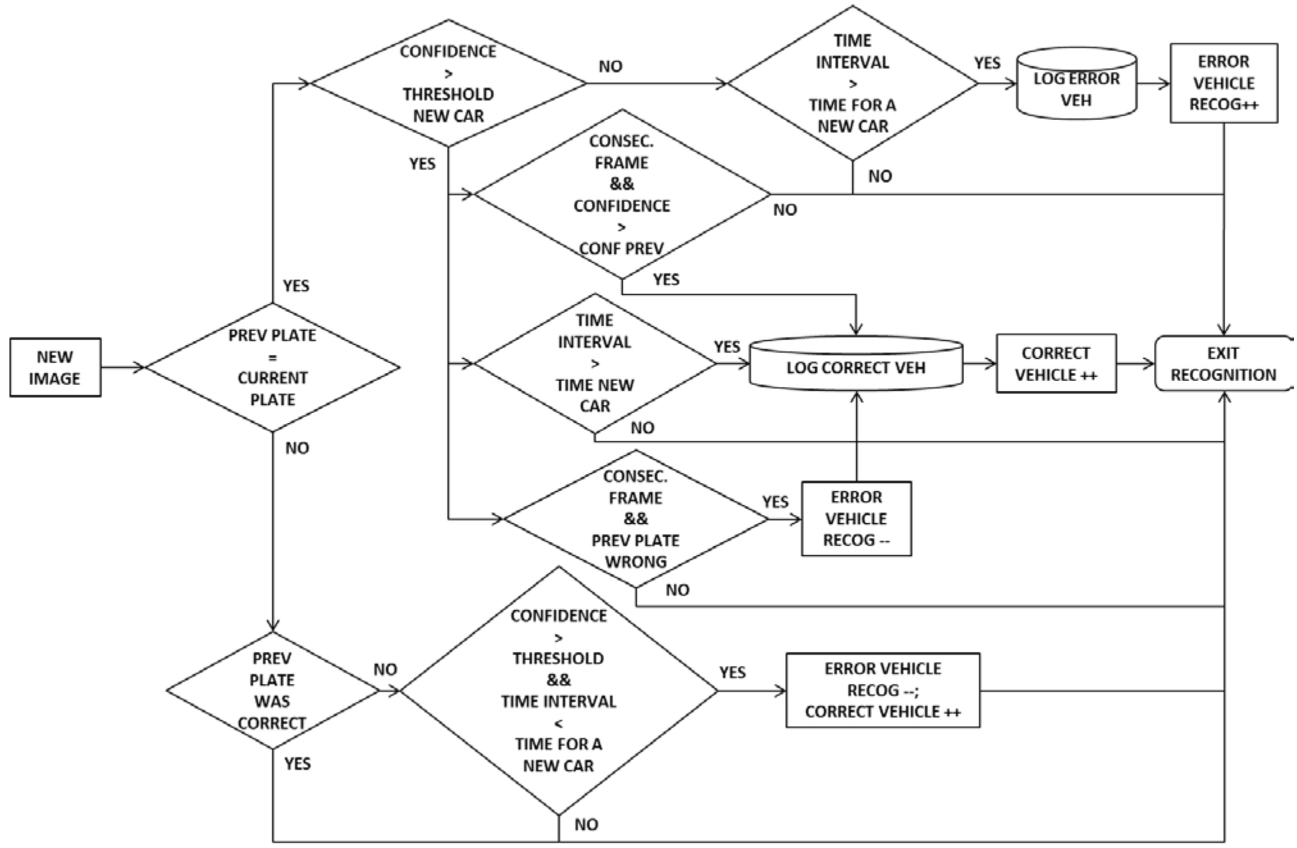

Figure 7: Work flow diagram for license plate registration.

moving objects extraction were studied from the second available highway traffic video footage.

The cases where license plate registration can be improved are: (i) registration of two different license plates in a small time interval; (ii) registration of a license plate when CARMEN software confidence is too small; and (iii) differentiate two different license plates in a short time interval due to real highway traffic speed.

From these cases the algorithm was improved to register one license plate per vehicle and correct wrong license plate recognized according to CARMEN software confidence. The confidence was reduced to forty percent due to high speed and environmental conditions. Time threshold of proximity between two different vehicles is set to one second and automatically adjusted during the execution of the program. The final algorithm is shown in the work flow diagram in Fig. 7.

To mitigate the environmental effects that can influence in the license plate recognition, sharpener filter was used. Sharpener filter amplifies pixels with high frequency (pixels that have large differences in intensity compared to other near pixels). This filter was first applied on images extracted from the original video to evaluate whether performance improvements can be made in the algorithm.

Speed up using extraction of a fixed image area is proposed as part of the module for detection of moving objects. From the second video footage, the coordinates of the detected moving objects bounding boxes were collected. Average values of these coordinates were calculated and set in the program to extract a fix image cut. In Fig. 8 points given by the contour method are marked in red, blue, black and green. They denote the extracted image area sent to LPR. Yellow points represent the average of these points. Finally cyan points represent the adjusted points used in the implementation.

Experimental setup description

The first video was used to get familiar with the software CARMEN, set the basis of the behaviour of the program, so it can be tested in a controlled environment. Second video is used to improve the performance of the program with a real world example of highway traffic.

The first version of the program implemented was tested with the first video footage. The video frames are analysed with contour method from OpenCV library [11] to filter the moving objects with a range of areas. The second version of the developed program was tested using the second video

Figure 8: Point scatter where images are extracted for LPR.

Sharpen filter used		Yes	No
Resolution		320x180	320x180
Contours recognition	Avg. time [ms]	1	1
Moving object detection	Avg. time [ms]	18	16
Recognize method	Max time [ms]	282	300
	Min time [ms]	16	12
Vehicle detection and recognition	Avg. time [ms]	25	23

Table 2: Execution time analysis.

footage. The goal of the testing is to get execution time results and vehicle data collection accuracy.

Execution time and accuracy analysis

First analysis was performed to compare the execution time with an image extracted from contours method and the fixed image cut. The analysis proves that a fixed area keeps the accuracy and reduces the algorithm execution time for about 46 [%]. A fixed area does not need to calculate coordinates, and the area covered allows accurate license plate recognition.

Second analysis was performed to compare the execution time with sharpen filter and without it. Table 2 shows that execution time in average increases with filter performance and Tab. 3 shows accuracy about recognized license plates. The total number of counted vehicles increases when filters are implemented in the algorithm. On the other hand, the number of incorrectly registered vehicles is higher than the analysis done without filters.

The number vehicles that can be registered in the video footage are 529. The developed application recognizes vehicles that do not correspond to the lane that is being analysed. With these results, a fix image cut without filter performance to carry out the license plate recognition is chosen as configuration to be implemented.

Vehicle country of origin distribution

Table 4 contains part of extracted numbers which represents vehicles/country found in the video analysed. Based on the video footage, traffic flow is estimated to be 1088 [vehicles/hour].

In the second video footage vehicles from 18 different countries were registered. From the total number of detected vehicles, the application was not able to recognize the origin country of only 8 vehicles. Germany is the country with the most recognized vehicles. Bosnia and Herzegovina, Bulgaria, Lithuania and Netherlands were the countries with the least recognized cars. We can conclude that this is an important node of the Croatian traffic network for the tourists, due to the variety of countries recognized and the traffic flow.

Sharpen filter used	Yes	No
Total time evaluated [s]	1760	1760
Total vehicle count	534	532
Correct vehicles registered	507	515
Wrong vehicles registered	27	17
Corrected vehicles	94	80
Mean Confidence [%]	70.96	74.76

Table 3: Vehicle count statistics results.

Country of origin	Number of vehicles registered	Percentage [%]
Austria	83	15.6
Croatia	47	8.8
Czech Republic	72	13.5
Germany	166	31.2
Poland	88	16.5
Slovenia	17	3.2
Others	51	9.7
Unknown	8	1.5
Total Vehicles	532	100

Table 4: Vehicle country of origin data obtained from the road traffic video footage analysis.

CONCLUSIONS AND FUTURE WORK

In this paper a computer vision based framework for road vehicle country of origin classification is proposed. Used approaches are simple to implement and have real time capabilities. The development phase produced two applications. First application depends on OpenCV and CARMEN Freeflow frameworks where all functions for image processing are called from mentioned frameworks in order to detect road vehicles. Although accuracy results were sufficient, further optimization had to be considered because real time execution was not guaranteed. Most of the applied algorithms are fast enough to be run in real time. However applied LPR method created problems in this matter. Further development made it possible to significantly improve execution times. Performance improvement was gained in road vehicle extraction and detection algorithm that uses a fixed image size, and in executing part of the algorithms on GPU instead on CPU. Based on image processing and CARMEN software performance, the algorithm was optimized for road nodes characteristic for highway traffic.

First results show that proposed system can collect road vehicle data accurately enough for one road network node. Collected data can be used for detailed road traffic analysis. Country of origin distribution was used as test case. Further development of the proposed system will tackle monitoring and vehicle tracking of a larger road traffic network to enable estimation of OD matrices, measurement of vehicle mean speed and estimation of traffic flow.

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