Traffic Monitoring System Development in Jelgava City, Latvia

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Abstract: Smart traffic management and monitoring is one of the key aspects of the modern smart city. Traffic flow estimation is crucial for sustainable traffic planning in the city. A requirement for successful planning and optimization of traffic is vehicle counting on the streets. Surveillance video is a suitable data source for precise vehicle counting. A solution for real-time vehicle traffic monitoring, tracking and counting is proposed in Jelgava city, Latvia. It is based on motion detection using background modeling, which is enhanced by statistical analysis. Two-phase assessment is utilized: motion blobs are detected and tracked using custom state machine implementation, then tracking results are passed through number of statistical filters to eliminate false positive detections. The system demonstrates good performance and acceptable accuracy on given test cases (about 97% accuracy for regular traffic conditions).

1 INTRODUCTION

Smart city has no one absolute definition (Anthopoulos and Reddick, 2016). In general, the smart city is identified by the following characteristics: smart economy, smart people, smart governance, smart mobility, smart traffic, smart environment, and smart living (Mahizhnan, 1999). Smart traffic consists of several topics, which are smart traffic light management, smart accident management, smart public transportation systems, vehicle identification, vehicle tracking and counting.

Precise and reliable information about traffic conditions can be used to synchronize traffic lights, assist drivers in the selection of routes, assist governments in planning the traffic system expansion, building new roads, and data for designing better solutions for the urban and road traffic (Barcellos et al., 2015).

Number of researches has been reported on traffic monitoring and congestion analysis in urban areas. Advanced communication technologies and *Internet of Vehicles* concept are used for data acquisition and transfer to analytical systems (Ahmed et al., 2016; Wan et al., 2016). Indirect data sources such as GPS tracks from probe vehicles (e.g. public transport) are analyzed offline and traffic characteristics are extracted for strategical planning purposes (Carli et al., 2015). Multiple data sources (such as GPS tracks, in-road and vision sensors) are fused to provide accurate information about traffic conditions to citizens (Bacon et al., 2011). Social media and other public information (e.g. events, feedbacks) is applied as complementary information for traffic modeling and analysis (Wang et al., 2017).

To this moment, in Jelgava city[1] traffic statistics are collected manually by two approaches: a) operator manually observes the road segment or crossing and writes down the number of vehicles; b) camera is located near the monitored place and a video file is recorded. Afterwards, the operator watches the video and manually counts the vehicles. Theoretically, bus GPS tracks could be applied for traffic analysis, but bus routes are covering very limited set of roads.

The authors propose approach to improve this process by using IT solutions for real-time video analysis without attracting the operator for manual vehicle counting. The use of image-based sensors and computer vision techniques for data acquisition on the traffic of vehicles have been intensely investigated in the recent years (Tian et al., 2011). While intrusive traffic sensing technologies (e.g. inductive loops, sonar or microwave detectors on roads, GPS sensors on vehicles) are considered more precise they have

[1]Jelgava is the fourth largest city in Latvia, is historical center of Zemgales region, distance from Latvia capital Riga is 42 km.

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Figure 1: An example of video frame with marked area of interest.

major disadvantages: installation cost, traffic disruption during installation or maintenance, and usually these methods are unable to detect slow or static vehicles (Mandellos et al., 2011). Contrary, surveillance and/or security cameras are very common in urban areas (e.g. Jelgava municipality serve more then 200 surveillance cameras in the city covering almost all streets of the city) and are subject of access granting negotiation rather than infrastructure installations.

Nevertheless, there are plenty of algorithms and systems for image processing (Zhu et al., 1996; Wu et al., 2001; Rad and Jamzad, 2005; Iwasaki and Itoyama, 2007; Lim et al., 2009), image counting in real situations from real-time video stream is not a trivial task and there are challenges to solve. Unfortunately, there is no one ultimate system, which can be applied in all cases. As well price of the commercial system can be a factor, which limits its application by government.

Authors address underestimated availability of video information on urban roads, which can be utilized for traffic condition recognition using modern image processing technologies. This paper describes a software solution for vehicle tracking and counting using image processing technologies. The live video is obtained from Jelgava municipality web page (http://www.jelgava.lv/lv/pilseta/tiessaistes-kamera/) from stationary camera positioned aside the road on the building wall by the address 5 J. Cakstes Blvd., Jelgava, Latvia (see Figure 1).

Vehicle traffic occurs in the diagonal direction, from top right (farthest from the camera) to bottom left (closest to the camera), and vice versa. Video has FullHD resolution of 1920×1080 px at 30 frames per second. Apart from other objects (e.g. wires, bridge, pedestrians, buildings, etc.) video stream contains regular two-way (one lane in each direction) road of Jelgava city.

Complexity of vehicle counting task is increased by several aspects: vehicle occlusions occur due to camera position, area of interest includes parking lots on both sides of street, speed bumps on a street, bridge cables appear on foreground, semi-hidden turning under the bridge.

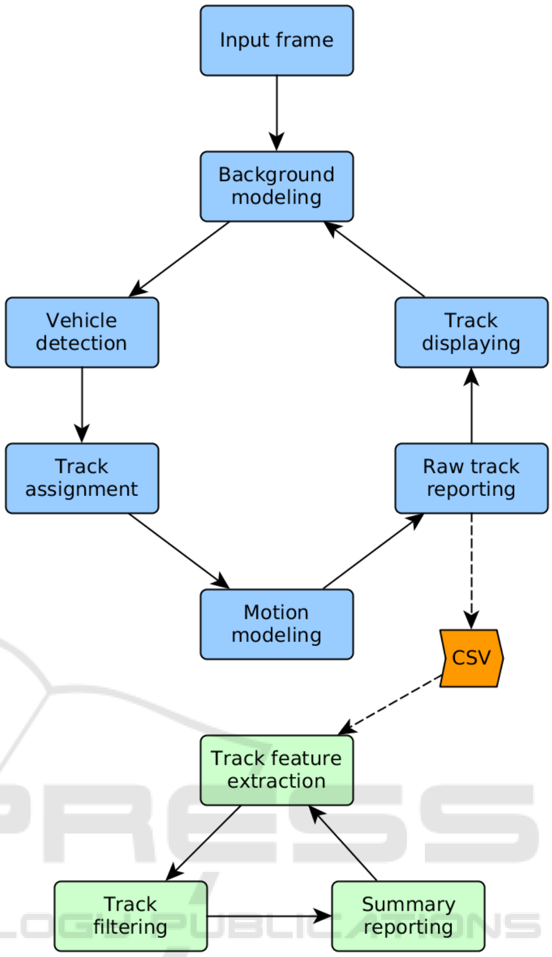
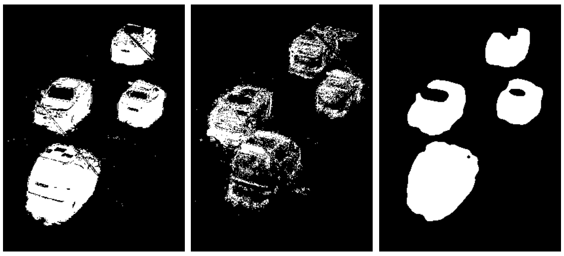


Figure 2: Principal process flow chart.

2 MATERIAL AND METHODS

Figure 2 shows basic workflow of solution for vehicle traffic counting on live stream video. Input frames are extracted directly from YouTube FullHD stream (1920×1080), cropped to area of interest (576×648) and pushed to further processing, described in subsections below. Solution is implemented and tested using Python 3.5.2 environment. OpenCV 3.2.0 library (Bradski, 2000) is used for low level image manipulations and processing.



(a) MOG (b) MOG2 (c) final mask

Figure 3: Moving vehicle masks.

2.1 Vehicle Detection

This stage includes background modeling and vehicle detection. Proposed solution uses background subtraction method for motion detection on subsequent frames. Authors used (KaewTraKulPong and Bowden, 2002) algorithm implementation available in OpenCV (*BackgroundSubtractorMOG*), which gave better results on test cases comparing with (Zivkovic, 2004) implementation (*BackgroundSubtractorMOG2*) as shown on Figure 3(a) and (b) respectively. The parameters used are as follows: *history=50*, *nmixtures=3*, *backgroundRatio=0.1*, *noiseSigma=10*.

For better moving blob segmentation additional mask operations are applied:

- Gaussian blur with kernel size 25×25 px and standard deviation 0;
- binary threshold on level 100;
- single erosion iteration with elliptical kernel 3×3 px.

The resulting final mask after all manipulations is shown on Figure 3(c).

At the next stage contour search is performed on mask. The list of contours is filtered by area threshold $t_{area} = 2000$: contours with area less then 2000 px^2 (number obtained empirically for given frame and vehicle size) are considered as no-interest detections (e.g. birds, tree leaves moving by the wind, walking people, bicycles, scooters) and excluded from further processing. Then center coordinates of each contour is calculated and together with contour area and bounding box coordinates is packed into tracking point data structure and pushed to further processing.

2.2 Vehicle Tracking

Vehicle tracking stage stands for the problem of following same vehicle across multiple subsequent frames and includes track assignment, motion modeling and raw track reporting steps. As an input this module uses list of moving vehicles (contours) detected on current frame and it maintains its internal state of tracked vehicles from previous frames.

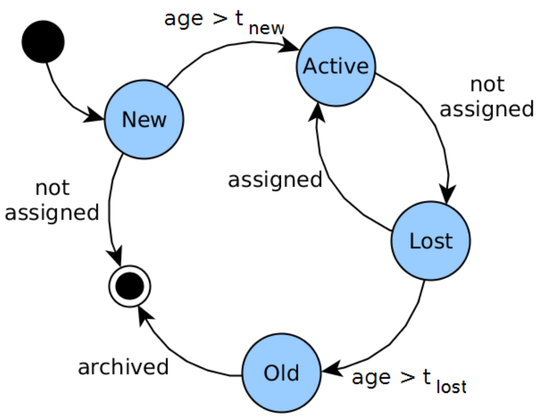


Figure 4: Track status transitions.

First of all detected vehicles are assigned to tracks - the trajectory of the moving vehicle from previous frames. Authors use modification of Hungarian algorithm for linear sum assignment problem and minimize the sum of distances between detections from current and previous frames (1):

$$\min \sum_i \sum_j D_{i,j} X_{i,j} \quad (1)$$

where D is distance matrix between last tracked points and current detected points, X is binary assignment matrix which indicates pairs of detection point and tracked point.

There are cases when between two subsequent frames some tracked vehicles left the current frame and new (yet untracked) vehicles appeared on the frame. For proper handling of such cases authors use distance threshold $t_{dist} = 300$ px and area change ratio threshold $t_{areaRatio} = 0.3$, which in taken into account during assignment step: detection is not assigned to track if distance between those two is more than 300 px or if area has changed by more than $\pm 30\%$. As a result new vehicles are properly assigned to new tracks, while old vehicles are left unassigned.

In addition to increase stability of tracking and reduce false positive vehicle tracking cases authors use status modeling with several time thresholds (see Figure 4) expressed in number of processed frames. Frames are not explicit measure of time, but because video frame rate is considered as constant, it can serve this purpose.

- $t_{new} = 15$: time delay (frames) until newly tracked object becomes active, helps to eliminate shortly appearing detection blobs (e.g. shadows, car occlusions, clouds);

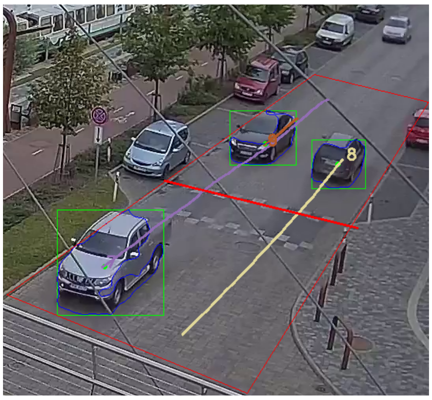


Figure 5: Real time monitor screenshot.

- $t_{lost} = 30$: grace period (frames) while lost track is kept among assignment candidates, helps to eliminate short gaps in detection (mostly car occlusions);

In order to smooth tracked vehicle trajectory and improve detection gap handling authors apply Kalman's filter for vehicle motion modeling and prediction. Internal state of the tracked vehicle is modeled using 6 dynamic parameters:

- x, y: object center coordinates on picture;
- v_x, v_y: object moving speed;
- s, v_s: object contour area and its changing speed, respectively.

As input for filter corrections x, y and s are provided from detection results, while speeds are maintained internally.

Finally, active tracks are displayed on real-time monitor (see Figure 5) and eventually *Old* tracks are archived to external database "as-is" (authors use separate CSV file for every 10 minutes of monitoring for easier handling).

2.3 Post-processing and Filtering

For better accuracy post-processing on reported raw tracking data is performed by separate process. This stage contains feature extraction, track filtering and reporting. First of all for each track following features are created:

- coordinates of tracking starting point;
- vehicle moving direction (*to left* or *to right*);
- number of recorded points in track and its length;
- imaginary mid-line crossing;
- linear motion trajectory interpolation (coefficients for line $y = ax + b$ and R^2).

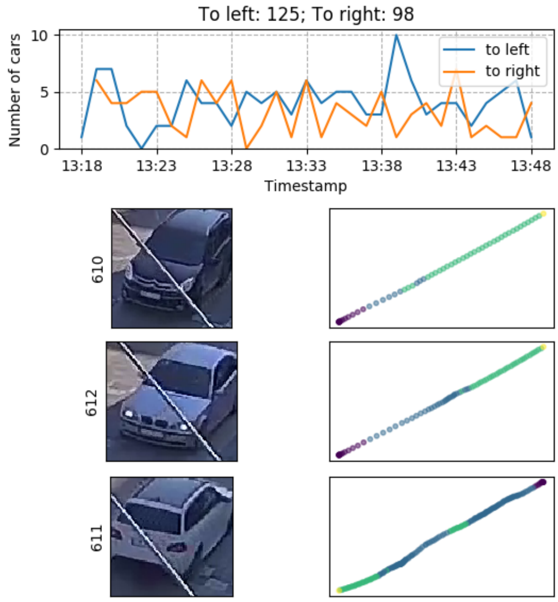


Figure 6: Summary monitor screenshot.

Then statistical analysis is performed on resulting dataset and criteria are derived for filtering ineligible cases. Statistical analysis is described in details in next section.

Finally obtained statistics are periodically (every 5 seconds) displayed on summary monitor (see Figure 6).

3 RESULTS AND DISCUSSION

This section describes results and their evaluation for the proposed solution.

3.1 Experiments Setup

For testing and evaluation purposes eight 10 minutes long video clips were recorded from live stream at different time of the day, every 2 hours from 7:00 till 21:00 (see table 1 for details). On each clip vehicles are manually counted for ground truth reference. Then each clip is processed via the proposed solution and results are collected.

For better statistical analysis another raw tracking dataset is gathered during several afternoons when most of traffic happens on the given street. In total it has about 10 000 recorded tracks.

3.2 Statistical Analysis

Raw vehicle tracking reports obtained from first stage of processing demonstrate poor accuracy: the system

Table 1: Recorded video clips.

Nr.	Time	Description
1	07:00	dawn
2	09:00	partly cloudy, sun reflections
3	11:00	cloudy
4	13:00	sunny
5	15:00	sunny, windy
6	17:00	rainy, congestion
7	19:00	partly cloudy
8	21:00	dusk, headlamp reflections

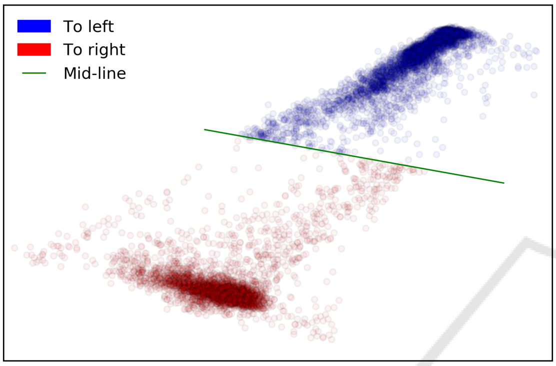


Figure 7: Track starting points and imaginary mid-line.

detects many false positives. Statistical analysis on recorded dataset were performed to develop suitable filtering conditions.

First of all, tracks are filtered by moving direction and starting point coordinates in a way that tracks potentially cross imaginary mid-line. Observations confirm that the majority of tracks started after mid-line by moving direction are either detection errors or duplicates of already tracked vehicles. Figure 7 shows spatial scatter plot of track starting points colored by moving direction.

Next track variation is analyzed by number of developed features (see Figure 8). Number of recorded points in track is not correlating with track quality: there are correct tracks with small number of recorded points (fast moving vehicles) as well as with large number of recorded points (slow vehicles / congestion).

Track length in pixels is good candidate for filtering condition. Whole class of false positives have short trajectories (vehicle occlusions, foreground wires, etc). Observation shows that very long tracks are, in essence, tracks of two vehicles merged into one (track jumps between lines and goes in opposite direction). Such cases can be separated into two independent tracks, but in practice these are very rare cases. Therefore, authors count long tracks as single track.

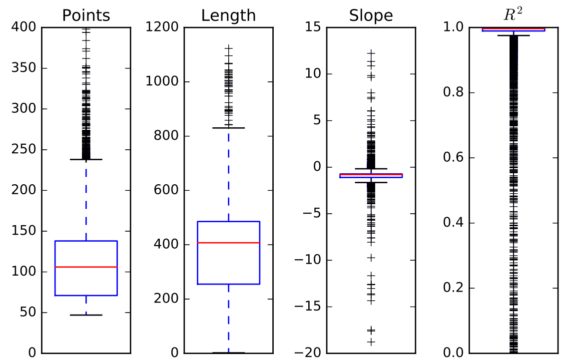


Figure 8: Track variation by selected features.

Another set of features used for raw data filtering is trajectory linear interpolation results (a, b coefficients and R^2 value for line $y = ax + b$). Coefficient of determination R^2 shows how much given track is close to straight line. Despite the fact that R^2 variation is notably close to 1.0 there are a lot of outliners among acceptable tracks, and vice versa, wrong tracks with close to linear trajectory.

Coefficient b affects track pitch on the picture, which in traffic context relates to vehicle position on the street (left or right side of street). Due to presence of speed bumps in the middle of each line drivers tend to drive in-between of bums when there is no oncoming traffic. Therefore this coefficient is not suitable for any track selection.

In contrast, a coefficient shows linear slope of the trajectory, which in turn should correspond to street direction for all vehicles. Figure 8 shows relatively low variation in a coefficient values, and selected outliner cases are clearly incorrect.

Figure 9 demonstrates samples of tracks selected by different criteria. After statistical analysis following criteria is used for selecting acceptable tracks out of raw tracking results:

- track starting point is before mid-line by vehicle moving direction;
- track length $L > 100$ px;
- slope of linear interpolation is in range $-2 < a < 1$

3.3 Accuracy Evaluation

Table 2 shows summarized accuracy evaluation results on all test cases. For each test case ground truth numbers are manually counted and considered as accuracy reference. Total number of raw tracks obtained from the first stage of processing are shown in the table (at this stage they are not divided by direction). Next numbers correspond to tracks left after

Table 2: Accuracy evaluation summary.

	Ground truth		Raw tracks		Statistical analysis		Final accuracy	
Nr.	to left	to right	count	accuracy	to left	to right	to left	to right
1	25	13	39	97%	25	13	100%	100%
2	63	25	96	91%	61	24	97%	96%
3	55	23	82	95%	54	23	98%	100%
4	50	54	107	97%	50	55	100%	98%
5	52	30	85	96%	51	32	98%	93%
6	80	71	188	75%	61	73	76%	97%
7	49	29	82	95%	47	31	96%	93%
8	37	18	78	58%	39	19	95%	94%

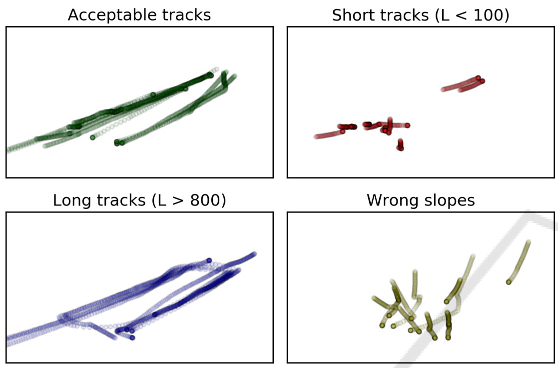


Figure 9: Track types selected by statistical analysis.

analysis and filtering. Last two columns show evaluation of final accuracy of the system. Overall solution has acceptable accuracy for given task and conditions (about 97% accuracy for regular traffic conditions). There are two notable cases worth to highlight.

Test case 6 is recorded at 17:00 when traffic congestion happened on the given street. Proposed solution relies on motion detection via background modeling and due to congestion and slow vehicle movement it was not able to properly track separate vehicles (stopped vehicles were considered as background and movement phase was too short for starting tracking). As results show, statistical analysis does not help to resolve these cases. An improvement option would be to keep tracking even stopped vehicles by implementing difference measure between last seen motion blob and current still frame (e.g. keypoint matching or feature histograms) which is out of scope of current research.

Another notable test case 8, which was recorded at 21:00 shortly after rain. Vehicle headlamps are reflecting from wet street surface, which leads to very high number of false positives in raw tracking results (almost all vehicles going left are counted twice: headlamp reflection and vehicle itself). However statistical analysis and raw result filtering helps to significantly improve results: from 58% to 94%.

In current system implementation the only processing outcome is number of vehicles moving each direction. Given that detailed vehicle tracking information is archived, it is possible to develop and extract more useful traffic features. Vehicle spatial position on camera image could be mapped to geographical position, which gives potential to estimate vehicle speed. Vehicle snapshots could be used for further classification task (e.g. cars, vans, buses, tucks). In case of outputs of multiple cameras are fused into common database there is potential to estimate traffic density and even track distinct vehicles across the city.

4 CONCLUSIONS

Traffic flow monitoring solution for real-time vehicle counting on live stream is proposed, developed and tested for Jelgava city in Latvia. It is based on background modeling, multi-vehicle tracking and statistical analysis. The experimental results show that proposed solution is suitable for variety of traffic and weather conditions, except congestions.

The proposed method detected the number of cars with an accuracy ranging between $93-100\%$ for regular traffic conditions and 76% for congestion.

To extend system functionality it is planned to implement vehicle classification module (e.g. car, van, bus, truck, motorcycle, etc). Also for better congestion handling it is planned to improve vehicle detection approach in addition to background modeling.

Camera positioning is crucial factor for precise traffic monitoring and it should be mounted in more elaborate location without any interfering objects (e.g. wires, pillars, bridges, etc).

Visual image processing and analyzing techniques are improved during recent years. Outdoor surveillance cameras have underestimated potential for non-intrusive traffic monitoring and feature extraction in urban areas.

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