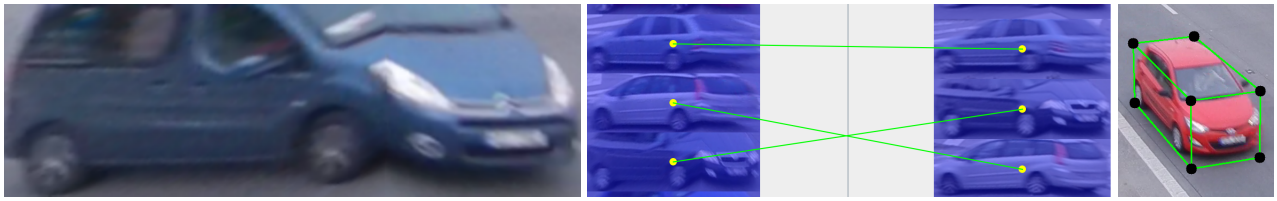
Excel@FIT 2015
http://excel.fit.vutbr.cz

# Vehicle Re-identification in video

Dominik Zapletal*



**Abstract**

In this paper an approach to the vehicle re-identification problem in a multiple camera system is presented. We focused on the re-identification itself assuming that the vehicle detection problem is already solved including extraction of a full-fledged 3D bounding box. The re-identification problem is solved by using color histograms, histograms of oriented gradients by a linear regressor. The features are used in separate models in order to get the best results in the shortest CPU computation time. The proposed method works with a high accuracy (60 % true positives retrieved with 10 % false positive rate on a challenging subset of the test data) in 85 milliseconds of the CPU (Core i7) computation time per one vehicle re-identification assuming the fullHD resolution video input. The applications of this work include finding important parameters like travel time, traffic flow, or traffic information in a distributed traffic surveillance and monitoring system.

**Keywords:** Vehicle re-identification — Reacquisition — Multiple camera system — Vehicle signatures — Real time systems — Video surveillance — Computer vision — Feature extraction — Image matching — Road traffic

**Supplementary Material:** Downloadable Code

*xzaple34@stud.fit.vutbr.cz, *Faculty of Information Technology, Brno University of Technology*
herout@fit.vutbr.cz, *thesis supervisor, Faculty of Information Technology, Brno University of Technology*

## 1. Introduction

Obtaining accurate and up to date traffic information and statistics is increasingly in demand for multiple reasons – for collecting statistical data [1], for immediate controlling of traffic signals [2], for law enforcement [3, 4], for traffic density reduction and traffic flow optimization [5], for on-line route calculation in Global Positioning System navigators [6], etc. In most traffic-busy areas, many surveillance cameras are already installed. It would be advantageous to use these devices for analysis of traffic flows with no need of replacing them with some special hardware. To achieve this, re-identification on existing simple video surveillance cameras is necessary. To maintain anonymity and because of the inability to obtain all vehicle number plates from video recordings in some cases, it is desirable to base the re-identification only on visual characteristics of the vehicle [7].

The problem of re-identification consists of extraction of sufficient information from the detected vehicle in the video and of efficient use of this information to find an identical vehicle in a different set of detected vehicles. One aim of solving the problem is to minimize the cases of false positive and false negative re-identifications and to maximize the cases of positive re-identifications.

Some existing works are concerned with the re-

**Figure 1.** Examples of detections. Data received from the detection system are represented as seven points describing the 3D bounding box around the detected vehicle. Under the detection examples are results of image extraction from the 3D bounding box.

identification issue. Arth *at al.* [8] created a decentralised vehicle re-identification engine working on a non-calibrated surveillance camera network. They used PCA-SIFT [9] features as an appearance-based method for a vehicle data extraction. Their system represents the data extracted from a vehicle as a vocabulary tree, a so called signature. However, their approach does not take into account colour information of the vehicles. Also, a simple 2D bounding box was used in their solution.

Other works are concentrated on people re-identification [10, 11]. Oliveira *at al.* [10] based their solution on local appearance features; colour (HSV histograms) and SURF description [12].

The solution described in this paper is based on the assumption that the vehicle detection in the video is already solved. In our approach, a detection system that creates 3D bounding boxes around detected vehicles is used [13, 14]. The input information for vehicle re-identification is a vector of points describing the 3D bounding box (Figure 1).

Our approach is based on linear regression which uses two trained models: a model using colour histogram [15] and a model based on histogram of oriented gradients [16]. The side and front of the bounding box of the detected vehicle are projected by warping into the plane and combined together. Then, the combined image is split into a grid and colour histogram values for each of the RGB channels and histogram of oriented gradients values are computed for each grid cell. Both of the models are created by training on a large amount of positive and negative data samples. The re-identification itself is performed by finding the most suitable vehicle in a detected vehicle database based on the data previously obtained.

Besides proposing the vehicle re-identification methodology, we invested effort into collecting a dataset for training and evaluation of the method. We manually annotated pairs of corresponding (identical) cars in videos captured from different cameras and different viewpoints. Then, we crowd-sourced another dataset of vehicle pairs, where human subjects annotated their perception whether the given pair "could be the same vehicle". This dataset allows for stratification of clear cases of match, clear cases of non-matching vehicles, and borderline cases, where even human observers doubted.

In our work, we were able to find a way of solving the vehicle re-identification problem which can be built upon in our future work and studies. We achieved accurate results that can be found useful in many ways in traffic surveillance.

This paper was also submitted to the ITSC 2015 – The IEEE Intelligent Transportation Systems Conference.

## 2. Vehicle Fingerprinting

It is necessary to properly represent the data describing key visual characteristics of the vehicle for maximal re-identification accuracy. It is also very important to minimize the background parts of the image behind the detected vehicle in order to increase the signal/noise ratio. The data extracted has to be efficiently stored in order to speed up the whole re-identification process.

In order to reduce the amount of unwanted data extracted from video we use 3D bounding boxes as the vehicle detection representation (Figure 1). The side and front faces of the bounding box are used only, because the rooftop does not typically contain any additional useful information. These two parts are projected on a 2D surface and then combined together for a compact and practical single-image representation (Figure 1, bottom three rows). The advantage of this approach is efficient background noise reduction without any extra usage of CPU computation time which would be necessary for background noise removal if simple 2D bounding box was used. Around 5 % of the combined image content is background by using 3D bounding box instead of 25 % as is illustrated by Figure 3.

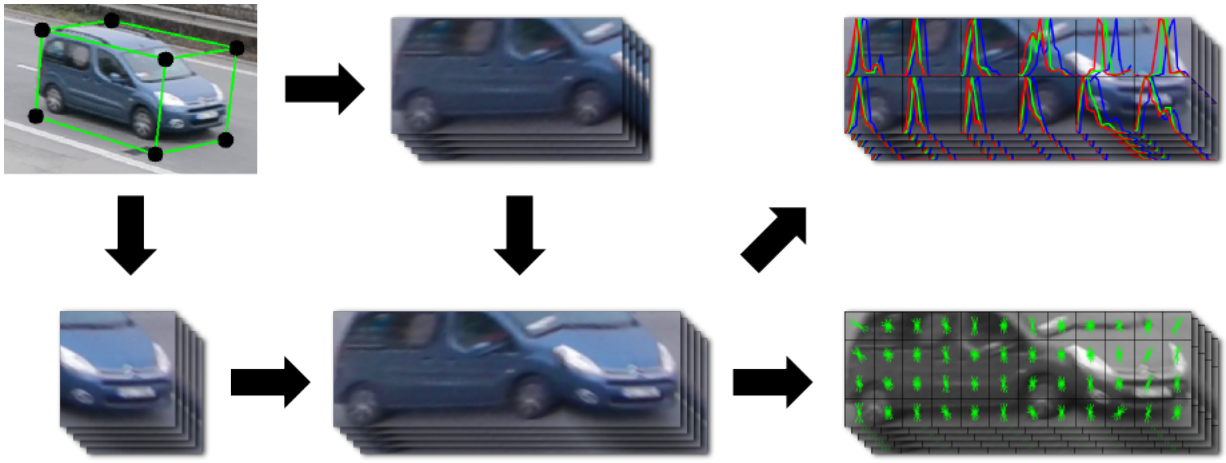


**Figure 2.** A simple illustration of the data extraction and fingerprinting process. Firstly, a vehicle is detected in the video. The detection result is represented as a 3D bounding box (green block in the top left picture). Then the side and front faces of all bounding boxes belonging to the vehicle are extracted and warped into a plane. Corresponding pairs of rectified side and front 3D bounding box faces are combined together. By this point, a vehicle combined images set is created. Combined images are deformed because of video scene perspective. Finally, colour histograms and histograms of oriented gradients are computed from the combined images set. The number of elements in the combined images set depends on the video shot taken and on the vehicle detection accuracy. HOG and colour histograms are plotted without overlap for clarity.

**Figure 3.** An illustration of a typical "unwrapped" image. The representation used in re-identification (bottom) is much more compact compared to the original and it contains very little of the background clutter. The extraction is very efficient and preserves majority of the visual information of the vehicle.

The detection system is not perfect and up to 5 % of vehicles (depending on traffic density, camera viewpoint, etc.) could be mis-detected (Figure 4). These detections are unrolled into 2D representations which do not match with actual vehicles and besides introducing small extra computational load, they do not constitute a considerable harm to the system performance.

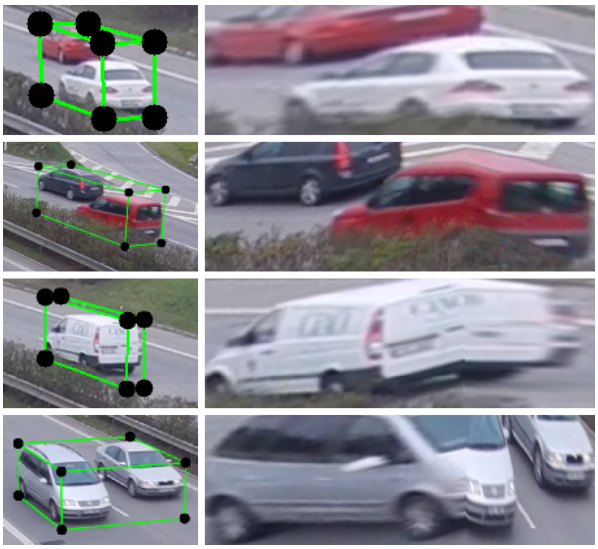


**Figure 4.** Some detection errors examples which can negatively affect resulting re-identification. **left**: Incorrect detection results. The bounding box is created over a group of vehicles or is deformed within a vehicle. **right**: Results of the inaccurate side and front 3D bounding box faces combination.

The main steps of the fingerprinting and data extraction process are visualized in Figure 2. Most of the existing solutions previously mentioned have not taken into account information about the colour characteristics of the vehicle. In some cases, it could be reasonable mainly in order to reduce the data amount that has to be stored. We decided to use this informa-

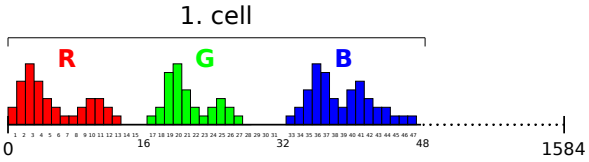



**Figure 5.** A colour histogram vehicle fingerprinting representation result. A vector of 1,584 features (48 features per one $6 \times 2$ grid cell with 50 % overlap makes $11 \times 3$ extractions) per one side-front combined image is created. Grid cell colour 16 bin histogram RGB values are concatenated consecutively into the vector.

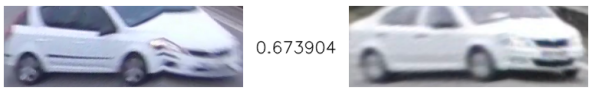



**Figure 6.** Colour histogram, regression result only. Relatively high regression result was computed (1.0 is the best match result, -1.0 the opposite). Colour information is not sufficient for deciding the re-identification problem.

tion because of two reasons: it significantly speeds up re-identification process (colour histogram is one of the fastest appearance-based methods to be computed and is used as first re-identification-match criterion in the presented approach) and reduces false positive re-identification cases. Colour histograms are computed for each of the RGB channels of the vehicle image. More precisely, colour histogram consisting of 16 bins for each of the $6 \times 2$ grid cell is computed. Each neighboring cell has a 50 % overlap in both of the $x$ and $y$ axes. It follows that 1,584 colour features per one side-front combined vehicle image from overall 33 grid sub-cells are computed. The number of combined images per one vehicle depends on the video shot taken (scene, frames per second, ...) and on the vehicle detection accuracy. On average, it is around 25 combined images per one vehicle. The color histogram feature vector is shown in Figure 5 for illustration.

The information about the vehicle colour only is not sufficient in order to achieve a successful re-identification as can be seen in Figure 6 (though it is fast and eliminates many candidate pairs based on the vehicle colour). Therefore, we added histogram of oriented gradients [16]. This information is stored separately. The histogram of oriented gradients is computed for all combined images belonging to a vehicle. The image is divided into a $12 \times 6$ grid. For each cell, the 9-bin HOG is computed with 50 % grid cell overlap. Overall, 1,449 features for one combined image from total of 161 grid sub-cells are computed.

In order to speed up the re-identification process (mainly the search in the vehicle database) an average

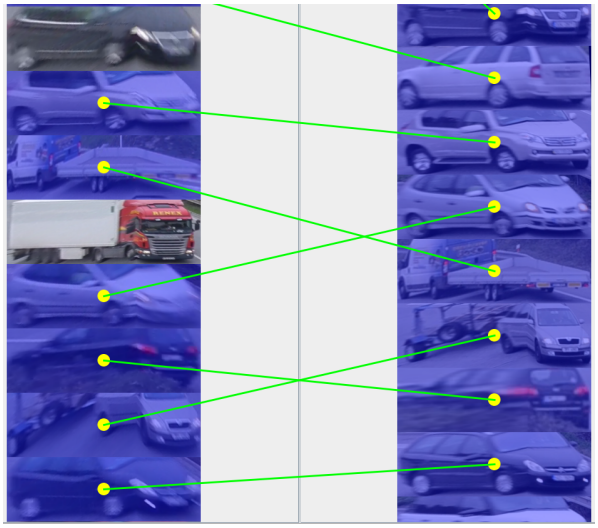


**Figure 7.** Ground truth annotation GUI. Creation of pairs of the same vehicles obtained from different cameras. Blue coloured vehicles connected with the green line are paired. Unselected vehicles do not have its counter part and can not be paired. Data created by the GUI is used for training the linear classifier.

information of all combined images belonging to the vehicle for both of the colour histogram and histogram of oriented gradients is computed. Using this information helps to reduce unnecessary deep-regression (several regressions based on a combination of randomly chosen feature vectors belonging to a vehicle) amount.

## 3. Ground-Truth Training Data Annotation and Linear Classifier Training

In our approach we used a linear SVM classifier [17] for learning the recognizer of vehicle matches. Its advantage is that it can be quickly trained on a large amount of training data with a large amount of features per one training instance. The regression is also faster using the linear classifier compared to non-linear support vector machine regression.

Five video shots taken from the same spot, from a different angle, captured by different camcorders and differently zoomed were recorded to obtain a sufficient amount of training data simulating different environments. Overall over 800 vehicles were captured.

A simple GUI interface was created for annotating the ground-truth training data. It allows to pair the same vehicles easily, while minimizing time per vehicle (Figure 7). Information about these pairs is stored and used for training afterwards.

As previously mentioned, each vehicle is described by the colour histogram and the histogram of oriented gradients vectors created from a set of combined images belonging to the vehicle and one average vector

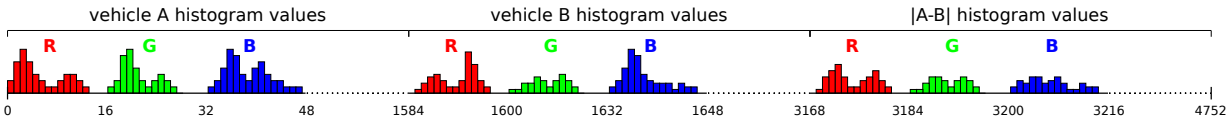



**Figure 8.** The colour histogram feature vector concatenated from A and B vehicle feature vectors used for the training and for the regression. Vehicle A, vehicle B, and their differential colour histogram feature vectors are concatenated. The resulting vector contains 4 752 values. The histogram of oriented gradients feature vector concatenation is constructed identically.

**Figure 9.** Randomly generated positive pairs of the same vehicle for the linear classifier training. **left:** Camera A, **right:** Camera B.

for both of these kinds of vectors. Training data are based on these vectors. Respectively, they are concatenated together plus one differential vector is added (Figure 8). Concatenated vectors are created for positive vehicle pairs and negative vehicle pairs. Positive vectors are randomly combined together choosing from positive vehicle pairs (Figure 9) vector set only. In this case, there were around 12,000–16,000 of them generated. Negative vector concatenations are created from randomly generated vehicle pairs chosen from camera A and B. Two times more negative pairs were created than the positive ones in order to tighten and refine the resulting regression. HOG and colour histogram models are stored separately after the training procedure.

## 4. Regression and Re-Identification Experiments

The re-identification itself consists of several steps. First, the average colour histogram vector of a vehicle that is to be found in another vehicle set simulating a different camera is used for the first round regression. Vehicles with positive first round regression results are tested in the second round regression where the average HOG vector is used. Vehicles with both of the regression results positive are added to another set and are considered as highly potential positive re-


**Figure 10.** Results (numbers in the middle) of deep regressions (several random regressions per one vehicle pair) from 10,000 randomly generated vehicle pairs. The more similar the vehicles are, the higher regression result is computed. From the experiment it can be assumed that almost all positive regression results belong to similar-looking vehicle pairs.

identification results. For example, when searching in around 300 of vehicles, the potential set contains between 5–10 vehicles depending on their unique visual characteristics. All vehicles in the set are then deeply regressed with the B-camera vehicle. Deep regres-

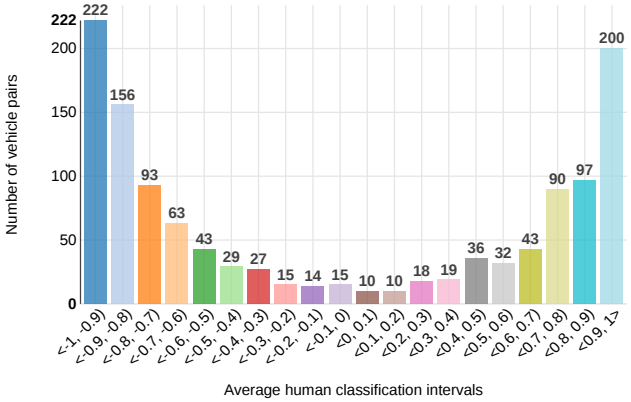



**Figure 11.** Histogram showing the results of people's opinion about 1,232 vehicle pairs whether "are likely to be the same vehicle". An average annotation result for each pair was computed from obtained -1 (different) and 1 (the same) values.

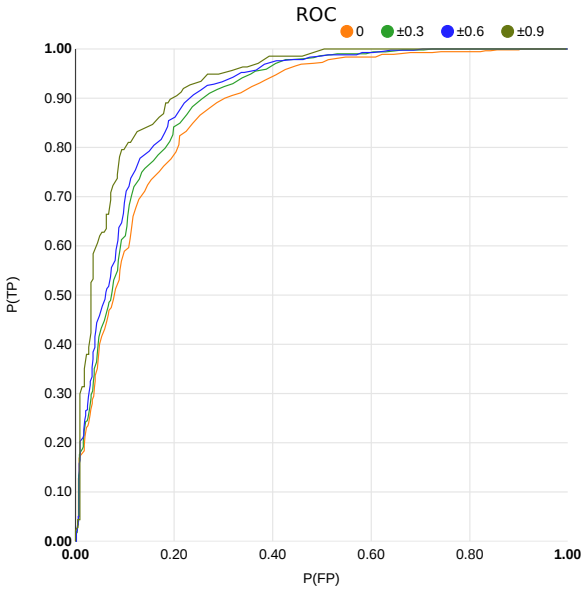



**Figure 12.** Receiver operating characteristic which shows the relationship between true-positive (TP) and false-positive (FP) rate. Four ROC curves were computed with different positive/negative average classification thresholds. For example, the blue curve was computed using an interval $< -1, -0.6)$ for negative average human classification and $(0.6, 1 >$ for positive average human classification.


**Figure 13.** Examples of pairs wrongly identified as identical by the algorithm. The differences are very subtle and difficult to cover by the simple (and fast) linear model.

sion denotes the concept that several randomly chosen non-average HOG and colour histogram vectors of a vehicle in the set are concatenated with randomly chosen vectors of the vehicle to be re-identified. A continual score from the regressions is computed for each vehicle in the set during the deep regression. A vehicle with the highest score above a positive re-identification threshold is considered to be successfully re-identified.

Figure 10 shows an example of an average result of the deep regression consisting of five random sub-regressions between 10 000 randomly chosen pairs of vehicles. This illustration is meant for visual assessment of the performance of the algorithm and for showing the meaning of the regressed responses.

In order to perform a quantitative evaluation of the algorithm, we pre-selected semi-automatically 1,232 pairs likely to be matching vehicles. We constructed a web interface and crowd-sourced people's opinion of vehicles that "are likely to be the same vehicle". This way, we obtained 24,000 individual annotations by approximately 500 people. The annotation results are visualized in Figure 11. The figure shows that about one third of the data were annotated unanimously, and majority of pairs were recognized with a high majority. However, the dataset is quite challenging in the sense that a non-negligible part of the data was labeled ambiguously. This kind of labeling shows to be useful, because it stratifies the data according to the confidence level of the human annotators.

Figure 12 shows the receiver operating characteristic – ROC [18]. The ROC curve shows the performance of the trained classifier on the human-annotated dataset of difficult cases. It should be noted that the dataset consists of 1,232 most similar vehicles out of the 645,840 possible pairwise combinations which can be made from the original vehicle samples – 828 (camera A), 780 (camera B). The performance of the classifier (in terms of ROC) in natural use would be therefore "close to ideal" and hard to read. This dataset therefore provides a challenging and pessimistic estimation of the classifier performance. Despite that, 60 % of matches can be retrieved (TPR) with only about 10 % of false positives included. Such performance on the difficult dataset promises reliable analysis based on the proposed re-identification method. Some of the false positive re-identification results are shown in Figure 13.

The re-identification time depends on a number of vehicles stored in a database and on a positive/negative

re-identification threshold setting. It takes around 70 milliseconds of the CPU computation time to compute HOG and colour histogram feature vectors for one vehicle combined image set. When searching in a database of 400 vehicles another 15 milliseconds (on average) for an attempt to find the corresponding vehicle is needed.

## 5. Conclusions

In this paper, we presented a simple and effective solution to the vehicle re-identification problem. Having 3D bounding box from the vehicle detection (obtainable from an existing real-time method), we are able to extract maximum of the useful vehicle data which are represented as colour histogram and histogram of oriented gradients feature vectors. The main part of the re-identification process is based on regression by a linear classifier.

Using this approach, we were able to achieve 60 % re-identification true positive rate at 10 % false positives accuracy (on a challenging subset of the test data) in 85 milliseconds of CPU (i7) computation time per one vehicle. Meaning that in the worst scenario, it is possible to fluently re-identify 12 vehicles per second.

An accurate vehicle re-identification in video brings a new view on obtaining real-time traffic information, traffic statistics and other important traffic-related data.

A few questions are open and leave space for future work. The combination of the feature-based data representation used in this paper is surely worth attention and can be a valuable inspiration for other similar works. The solution presented in this work has a high potential to be deployed into full operation by constructing a higher-level system observing traffic streams and measuring interesting characteristics of the traffic flow.

## Acknowledgment

This paper is based on my bachelor thesis which is supervised by Doc. Ing. Adam Herout, Ph.D. By this I thank him for his valuable advice and suggestions, which helped the successful completion of the work.

## References

[1] J de Ortuzar and Luis G Willumsen. *Modelling transport*. 2011.

[2] Stefan Lämmer and Dirk Helbing. Self-control of traffic lights and vehicle flows in urban road networks. *Journal of Statistical Mechanics: Theory and Experiment*, 2008(04), 2008.

[3] Shunsuke Kamijo, Yasuyuki Matsushita, Katsushi Ikeuchi, and Masao Sakauchi. Traffic monitoring and accident detection at intersections. *Intelligent Transportation Systems, IEEE Transactions on*, 1(2):108–118, 2000.

[4] David Vallejo, Javier Albusac, Luis Jimenez, Carlos Gonzalez, and Juan Moreno. A cognitive surveillance system for detecting incorrect traffic behaviors. *Expert Systems with Applications*, 36(7):10503–10511, 2009.

[5] Sylvie Charbonnier, A. Pitton, and A. Vassilev. Vehicle re-identification with a single magnetic sensor. In *Instrumentation and Measurement Technology Conference (I2MTC), 2012 IEEE International*, pages 380–385, May 2012.

[6] Chih-Chieh Hung and Wen-Chih Peng. Model-driven traffic data acquisition in vehicular sensor networks. In *Parallel Processing (ICPP), 2010 39th International Conference on*, pages 424–432, Sept 2010.

[7] M.A. Saghafi, A. Hussain, M.H.M. Saad, N.M. Tahir, H.B. Zaman, and M.A. Hannan. Appearance-based methods in re-identification: A brief review. In *Signal Processing and its Applications (CSPA), 2012 IEEE 8th International Colloquium on*, pages 404–408, March 2012.

[8] Clemens Arth, C. Leistner, and H. Bischof. Object reacquisition and tracking in large-scale smart camera networks. In *Distributed Smart Cameras, 2007. ICDSC '07. First ACM/IEEE International Conference on*, pages 156–163, Sept 2007.

[9] Yan Ke and R. Sukthankar. Pca-sift: a more distinctive representation for local image descriptors. In *Computer Vision and Pattern Recognition, 2004. CVPR 2004. Proceedings of the 2004 IEEE Computer Society Conference on*, volume 2, pages II–506–II–513 Vol.2, June 2004.

[10] Icaro Oliveira de Oliveira and J.L. De Souza Pio. Object reidentification in multiple cameras system. In *Embedded and Multimedia Computing, 2009. EM-Com 2009. 4th International Conference on*, pages 1–8, Dec 2009.

[11] K.-E. Aziz, D. Merad, and B. Fertil. People re-identification across multiple non-overlapping cameras system by appearance classification and silhouette part segmentation. In *Advanced Video and Signal-Based Surveillance (AVSS), 2011 8th IEEE International Conference on*, pages 303–308, Aug 2011.

[12] Herbert Bay, Tinne Tuytelaars, and Luc Van Gool. Surf: Speeded up robust features. In *Proceedings of the ninth European Conference on Computer Vision*, May 2006.

[13] Markéta Dubská, Jakub Sochor, and Adam Herout. Automatic camera calibration for traffic understanding. In *Proceedings of the British Machine Vision Conference (BMVC)*, 2014.

[14] Markéta Dubská, Adam Herout, Roman Juránek, and Jakub Sochor. Fully automatic roadside camera calibration for traffic surveillance. *IEEE Transactions on Intelligent Transportation Systems*, PP, 2014.

[15] T.S.C. Tan and J. Kittler. Colour texture analysis using colour histogram. *Vision, Image and Signal Processing, IEE Proceedings* -, 141(6):403–412, Dec 1994.

[16] N. Dalal and B. Triggs. Histograms of oriented gradients for human detection. In *Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on*, volume 1, pages 886–893 vol. 1, June 2005.

[17] Rong-En Fan, Kai-Wei Chang, Cho-Jui Hsieh, Xiang-Rui Wang, and Chih-Jen Lin. LIBLINEAR: A library for large linear classification. *Journal of Machine Learning Research*, 9:1871–1874, 2008.

[18] Tom Fawcett. An introduction to roc analysis. *Pattern Recogn. Lett.*, 27(8):861–874, June 2006.