Implementation of Smart Parking Solution by Image Analysis

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Abstract: Modern smart city concept implies various smart aspects including smart parking management. Searching for a free parking lot can be a challenging task, especially during major events, therefore automatic system, which will help drivers to find a free parking is very valuable. There are many intrusive and non-intrusive technologies available for smart parking development, but authors of this paper developed a system based on video processing and analysis. Authors developed Python application for real-time parking lot monitoring based on video analysis of public video stream. Five classifier models (Logistic Regression, Linear Support Vector Machine, Radial Basis Function Support Vector Machine, Decision Tree and Random Forest) were compared for parking lot occupancy detection. Logistic regression classifier showed better results and was chosen for real-time parking monitoring application. System shows good performance and correctly predicted parking lot occupancy almost in all test cases.

1 INTRODUCTION

Smart City concept is highly dependent on the use of Information and Communication Technologies (ICT) for a more efficient use of existing resources, with main aim to improve citizens quality of life (Albino et al., 2015). As far as the livability of cities is concerned, traffic is one of the most frequent and complex factors directly affecting citizens (Sevillano et al., 2014).

In Latvia more than 3 000 new vehicles are registered each month, but road infrastructure is not developing so quickly. There are 664 177 of passenger cars on the Latvian roads (based on Road Traffic Safety Directorate statistics: *https://www.csdd.lv/en/vehicles/statistics-of-registered-vehicle*) and there are insufficient car parking facilities especially during the major concerts or sport events. Development of Smart parking can minimize the parking problem in modern cities (Pham et al., 2015).

Smart parking systems are implemented worldwide, mainly in Europe, United States and Japan (Shaheen, 2005; Kuran et al., 2015; Lan and Shih, 2014). Implementation of smart parking systems has many advantages for municipality, parking owners and drivers. Drivers can easily find vacant parking lots and avoid driving to fully occupied parkings (Shoup, 2006; Idris et al., 2009; Polycarpou et al., 2013), this also minimizes the air pollution (Arnott and Inci, 2006).

Smart parking systems usually are divided into several categories: parking guidance and information system (PGIS), transit based information system, smart payment system, E-parking and automated parking (Shaheen, 2005). Each system has its advantages and disadvantages. This paper deals with parking guidance and information system sub-component, named parking lot occupancy detection.

Critical point in smart parking operation is parking lot occupancy detection. There are many technologies available for this, which are mainly divided into two categories: intrusive (inductive loops, piezoelectric cables, active infrared sensors, etc) and non-intrusive (passive infrared sensors, ultrasonic, video image processing, etc).

This paper describes software solution for parking lot occupancy monitoring using video processing and image interpretation methods. Many authors tried to develop smart parking system based on video analysis (Sevillano et al., 2014; Al-Kharusi and Al-Bahadly, 2014), but still there are no one universal system, which can be used in all parking cases. This solution can extend the existing Smart parking solutions in Jelgava city[1], which are based on inductive sensors

[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: Frame example from live video stream.

for each parking lot monitoring and video monitoring of entering and exiting cars (Zacepins et al., 2017).

For demonstration purposes the live video is obtained from public video stream (https://balticlivecam.com/cameras/estonia/narva/) from fix camera positioned above the parking in Narva, Estonia (see Figure 1).

2 MATERIAL AND METHODS

Figure 2 shows basic workflow of solution for parking lot monitoring on live stream video. Input images are extracted directly from FullHD stream (1920×1080), cropped to area of interest and used for further processing and analysis, described in subsections below.

Solution is implemented and tested in Python 3.5.2 environment using different provided libraries (cv2, sklearn.linear_model, numpy, matplotlib, etc). OpenCV 3.2.0 library (Bradski, 2000) is used for low level image manipulations and processing (image scaling, resizing, changing image color schema, image saving and opening, etc).

2.1 Model Development

This paper describes parking lot status (free or occupied) detection approach based on machine learning techniques. Extensive phase of sample image preparation is crucial for precise model development.

First of all variety of example images where captured from live stream video camera. Authors used custom made automated utility which connected to the video stream and downloaded FullHD frames (1920×1080 px) on defined interval (every 10 minutes). More than 2 100 images where captured during two weeks, which gave good variety in weather and parking conditions (different time of the day, day of the week).

Next, manual region of interest identification took place. The captured frames contain overhead view of

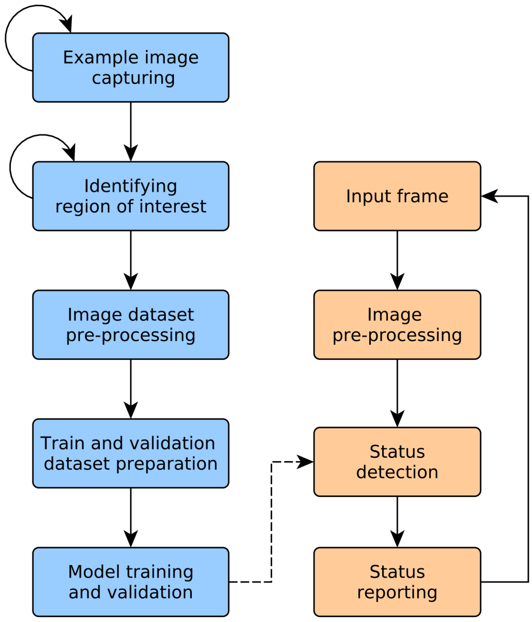


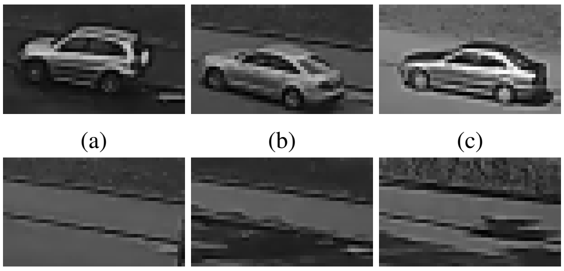
Figure 2: Parking status monitoring process workflow.

parking with about 130 lots. Vehicles are oriented in different angles and occlusions are common. During daytime a lot of buses are using the parking. Moreover car drivers often disobey parking lot markup (two cars in one lot, parking outside and across lots). For demonstration purposes few parking lots were selected and analyzed as described below. All other parking lots can be processed following the same procedure.

Defined areas of interest (selected parking lots) are cropped from example images and pre-processed. First, parking lot images are scaled down to uniform size of 50×30 px which allows generic processing of different lots. In order to decrease number of input parameters for further modeling images are also converted to gray-scale color schema.

Training and validation datasets are created from normalized gray-scale images (pixel color values $c \in [-1:1]$) of specific parking lots. Due to lack of night mode in selected live camera images captured from 20:00 till 8:00 where excluded from datasets. Images are manually separated into two classes: positive (car exists, parking lot is occupied) and negative (parking lot is free without car) (see Figure 3). There are 2 000 samples in positive and 1 000 samples in negative datasets. 25% of randomly selected samples are used for validation purposes, while others are used for model training. For better handling training and validation image sets were converted to numeric arrays.

Five classification models from *sklearn* package were trained for image classification by two classes:



(a) (b) (c)

(d) (e) (f)

Figure 3: Positive (a, b, c) and negative (d, e, f) image samples.

either parking lot is free or occupied. Authors compared classifiers modes without any tuning or improvement. Selected models with parameters are:

- Logistic Regression (LR) with default parameters;
- Linear Support Vector Machine (l-SVM) with $kernel = linear$ and $C = 0.025$;
- Radial Basis Function Support Vector Machine (r-SVM) with $gamma = 2$ and $C = 1.0$;
- Decision Tree (DT) with $max\_depth = 5$;
- Random Forest (RF) with $max\_depth = 5$ and $max\_features = 1$.

Due to model implementation specifics input images (matrices) are converted to vectors. Model comparison and precision analysis are described in details in results section. Finally based on comparison results one model with highest precision was chosen for real-time parking monitoring.

2.2 Parking Lot Monitoring

The model selected in previous phase is used for online parking status monitoring. Current input frame is captured from live video stream. Then it is preprocessed in a way similar to model building phase: regions of interest (parking lots) are cropped out of the frame, scaled to uniform size and converted to gray-scale color schema.

Next each captured region is processed through the model, which returns its prediction: probabilities of each class indicating either certain parking lot is free or occupied. Regions with "occupied" probability $P(car) \geq 0.6$ are considered as occupied (this parameter can be manually adjusted depending on user requirements).

Results of classification are reported as status of parking lot. All analysis and processing take less than 1 sec (connection establishment to the live stream takes most of the time) and therefore such system is applicable for real-time parking lot monitoring.

Table 1: Comparison of classification models by scores (%).

Num of samples	Classification model				
	LR	l-SVM	r-SVM	DT	RF
100	90.8	84.0	65.8	85.7	76.7
500	93.5	88.8	70.6	87.7	86.8
1 000	93.4	90.4	75.0	88.8	89.9
1 500	93.1	90.4	77.2	90.1	89.6
2 000	92.9	90.4	77.7	92.0	85.5

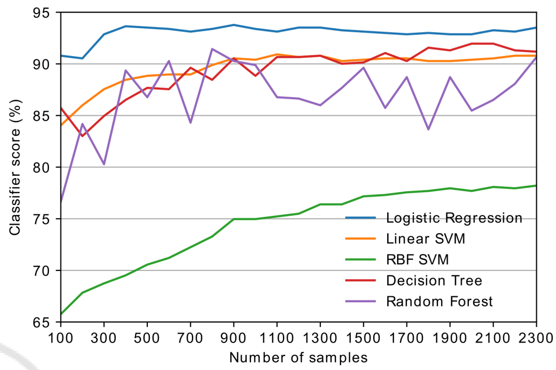


Figure 4: Classifier score depending on number of training samples.

3 RESULTS AND DISCUSSION

Model development and classifier selection is important task. To select appropriate model for given task five classifiers were trained on the same dataset and evaluated. Training and testing datasets are distinct and image samples do not overlap over datasets. Table 1 summarizes scores (mean accuracy of prediction) of all selected classifiers trained with different numbers of sample images.

Logistic regression (LR) classifier has highest average score and is not significantly affected by number of sample images. Linear SVM (l-SVM) and Decision Tree (DT) classifiers has comparable scores and slightly improve average score depending on number of samples. RBF SVM (r-SVM) has significantly lower score compared to others, while it shows noticeable increase of score for whole range of tested sample numbers. Random forest (RF) classifier has fluctuations of scoring values and is comparable with l-SVM and DT. Detailed plot of classifier score depending on number of training samples is shown on Figure 4.

Based on classifier comparison Logistic regression were selected for live parking status monitoring application. According to obtained results there is no significant increase of classifier precision after 300 training samples, therefore smaller training set can

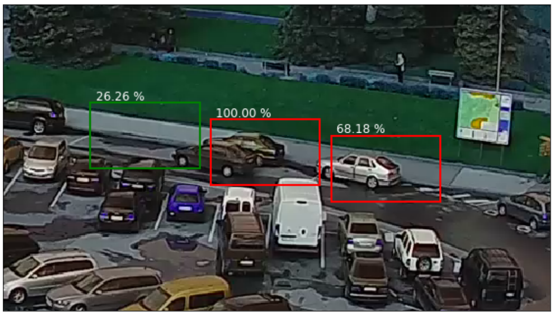


Figure 5: Parking lot status report.

be used for parking status detection with precision of 90% and more.

Results can be considered as good taking into account camera position, parking lot configuration and drivers' parking habits. Figure 5 shows an example of parking status report. Frame colors indicate either parking lot is free (green) or occupied (red). Percentages show probability of lot occupancy $P(car)$ calculated by model.

4 CONCLUSIONS

Results show that classification precision is not significantly dependent on number of image samples used for model training (about 300 samples is enough for desired precision).

Disadvantage of video based parking monitoring approach is that if car is not parked directly at considered lot, than system will not detect car correctly. In case parking lots are differently oriented to camera, than several models have to be trained for each parking lot orientation. In future it is planned to extend this solution for whole parking monitoring.

Significant advantage of video based parking monitoring is that existing infrastructure can be used: already installed surveillance, security or other cameras can be used for image acquisition.

For better results pixel spatial location aware models should be used (e.g. convolutional neural networks, histogram of oriented gradients, etc).

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REFERENCES

Al-Kharusi, H. and Al-Bahadly, I. (2014). Intelligent parking management system based on image processing. *World Journal of Engineering and Technology*, 2(02):55.

Albino, V., Berardi, U., and Dangelico, R. M. (2015). Smart cities: Definitions, dimensions, performance, and initiatives. *Journal of Urban Technology*, 22(1):3–21.

Arnott, R. and Inci, E. (2006). An integrated model of downtown parking and traffic congestion. *Journal of Urban Economics*, 60(3):418–442.

Bradski, G. (2000). The OpenCV Library. *Dr. Dobb's Journal of Software Tools*.

Idris, M., Leng, Y., Tamil, E., Noor, N., and Razak, Z. (2009). park system: a review of smart parking system and its technology. *Information Technology Journal*, 8(2):101–113.

Kuran, M. Ş., Viana, A. C., Iannone, L., Kofman, D., Mermoud, G., and Vasseur, J. P. (2015). A smart parking lot management system for scheduling the recharging of electric vehicles. *IEEE Transactions on Smart Grid*, 6(6):2942–2953.

Lan, K.-C. and Shih, W.-Y. (2014). An intelligent driver location system for smart parking. *Expert Systems with Applications*, 41(5):2443–2456.

Pham, T. N., Tsai, M.-F., Nguyen, D. B., Dow, C.-R., and Deng, D.-J. (2015). A cloud-based smart-parking system based on internet-of-things technologies. *IEEE Access*, 3:1581–1591.

Polycarpou, E., Lambrinos, L., and Protopapadakis, E. (2013). Smart parking solutions for urban areas. In *World of Wireless, Mobile and Multimedia Networks (WoWMoM), 2013 IEEE 14th International Symposium and Workshops on a*, pages 1–6. IEEE.

Sevillano, X., Màrmol, E., and Fernandez-Arguedas, V. (2014). Towards smart traffic management systems: Vacant on-street parking spot detection based on video analytics. In *Information Fusion (FUSION), 2014 17th International Conference on*, pages 1–8. IEEE.

Shaheen, S. (2005). Smart parking management field test: A bay area rapid transit (bart) district parking demonstration. *Institute of Transportation Studies*.

Shoup, D. C. (2006). Cruising for parking. *Transport Policy*, 13(6):479–486.

Zacepins, A., Komasilovs, V., Kviesis, A., Gatins, A., Skudra, M., and Pierhurovics, A. (2017). Implementation of smart parking system in jelgava city in latvia. In *Application of Information and Communication Technologies (AICT), 2016 IEEE 10th International Conference on*, pages (in–print). IEEE.