COMPARISON OF VEHICLE DETECTION USING VERY HIGH-RESOLUTION SATELLITE IMAGES

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Abstract

Traffic can be monitored using data obtained from mobile or permanent sensors such as induction loops, bridge sensors or cameras. This is an opportunity to obtain traffic data on main roads, but data from large parts of the road network is not available. Today´s optical sensors on satellites provide images covering large areas with resolution better than 1 meter and with frequency better 1 week, which can provide us with various information. Such information is important for urban and transport planning, intelligent transport systems, emergency control etc.

Panchromatic imagery from WorldView3 was processed. The pilot area for WorldView3 is located in Prague, close to the Old Town Square.

Panchromatic images were processed in two software. First software was ENVI and second was CATALYST Pro. Object detection was performed, then training data were created and finally classification methods were used. ENVI offers three classification methods (SVM, PCA, KNN) and CATALYST Pro offers two classification methods (SVM, RT).

The detection of vehicles was relatively successful, especially in open public places without shade or vegetation. The detection of dark vehicles had the best results. The detection of vehicles in shadow had the worst results.

Keywords: high resolution satellite images, segmentation, detection of vehicles, supervised classification

INTRODUCTION

Image classification still represents a challenge in remote sensing research [1], [2]. It depends on tasks such as object detection, object tracking, image segmentation and remote sensing image interpretation. Image segmentation is not trivial task because the choice of segmentation parameters is usually subjective and arbitrary, often leading to unsatisfactory results with few image divisions (under-segmentation) or highly fragmented images (over-segmentation), with possible negative impacts on the final classification [2], [3]. Among classification techniques of remote sensing images three groups currently dominate: pixel-based, sub-pixel-based and object-based methods [4]. Object-based image analysis (OBIA) includes two steps: image segmentation and object classification [4], [5]. Typical OBIA classification techniques are SVM (support vector machine), KNN (k-nearest neighbor classifier), PCA (Principal Components Analysis) or RT (Random Trees) [6].

STUDY AREA

Assessment of vehicle detection results is conducted for satellite images provided by WorldView3 in Prague and WorldView4 in Ostrava. Spatial resolution of panchromatic and multispectral image is 0.3 m and 1.6 m, respectively. The full scene (July 23, 2019 morning) of WorldView3 covers 25 km2 and a small subset is selected for this study. The study area is located in the center of Prague, around Old Town Square. The full scene (August 13, 2018 morning) of WorldView4 covers 56 km^2 and a small subset is selected for this study. The study area is located in the center of Ostrava, around Masaryk Square and shopping center Nova Karolina.

Figure 1 Study area (Old Town Square in Prague, WorldView3, panchromatic image)

METHODOLOGY

Vehicle detection is tested in urban environments in open public spaces such as streets, squares, parking places, etc. In such conditions it is appropriate to create a mask of the image for objects different from public space such as roofs, water bodies, etc. Open vector data for buildings and xx terraces? available from cities' web pages enables to construct such masks.

Two different software were used to vehicle detection, their segmentations and classifications - ENVI and CATALYST Pro. The results from both systems are compared and evaluated.

- ENVI

First, a segmentation of the image was performed to obtain objects that correspond to real-world features. It is necessary to set appropriate segment and merge settings for segmentation. Two algorithms for segmentation settings are offered; the first one is the edge detection algorithm suitable for clearly bounded objects and second one is the intensity algorithm, performing best for images with subtle gradients such as digital elevation models. The merge settings offers also two algorithms: Fast Lambda and Full Lambda Schedule. Our segmentation process is performed in an urban environment and therefore Full Lambda Schedule algorithm is used, because it can merge small segments within larger, textured areas. The Texture Kernel Size value was set to 3 because we deal with small but highly variable areas. After these settings and segmentation, we created training data. The next step is classification where ENVI offers PCA, KNN and SVM with four kernel types. We decided to use Radial Basis as the kernel type for SVM classification.

- CATALYST Pro

Again setting appropriate segmentation parameters is essential for successful segmentation in this software. There are three segmentation parameters, scale, shape and compactness. The scale values represent the scale that corresponds to the object size. The shape value represents the weight of the shape for segmentation and the compactness denotes compactness of the shape for segmentation. A lower value places a high emphasis on colour, which is typically the most important aspect of creating meaningful objects. A higher compactness value can produce object boundaries that are more compact, such as crop fields. After these settings and segmentation, we created training data. The next step is classification where CATALYST Pro offers RT and SVM with four kernel types. We decided to use Radial Basis as the kernel type for SVM classification.

RESULTS

Four evaluators conducted manual vectorization of vehicles. Three types of cars were distinguished – dark, bright and vehicles in shadow. Unfortunately, perception of brightness, darkness and shade are personally different and influence such classification. To improve following assessment and validation of classification results, we selected only those objects as a baseline where classification of two and more evaluators matched.

Mean of vehicle area for all vectorization vehicles is 7.89 m^2. Mean of vehicle area for the first ten best-selling cars in Czech Republic from 2019 is 7.94 m^2. The detected vehicles had to cover at least 50% of the mean area of these two values.

Table 1. Number of vehicles detected by evaluators.

	Count	Mean of vehicle area (m^2)
Dark vehicles	114	7.89
Bright vehicles	104	8.25
Vehicles in shadow	46	7.17

Table 2. Results of classification.

Software	Method	Errors	Dark vehicles	Bright vehicles	Vehicles in shadow
ENVI	**KNN (%)**	**Omission error (%)**	3.51	0.96	0
		Commission error (%)	4.35	1.67	0
	PCA (%)	**Omission error (%)**	4.39	0.96	0
		Commission error (%)	6.25	2.63	0
	SVM (%)	**Omission error (%)**	10.53	0.96	0
		Commission error (%)	11.01	1.72	0
CATALYST PRO	**SVM (%)**	**Omission error (%)**	0.88	0	4.35
		Commission error (%)	1.52	0	25
	RT (%)	**Omission error (%)**	4.39	4.81	2.17
		Commission error (%)	6.17	7.69	9.09

Table 3. Amount of classified area of vehicle.

Software	Method	Dark vehicles	Bright Vehicles	Vehicles in shadow
ENVI	**KNN (%)**	63.04	45.50	12.04
	PCA (%)	56.06	24.33	7.55
	SVM (%)	75.04	45.11	10.54
CATALYS PRO	**SVM (%)**	47.47	38.12	13.57
	RT (%)	57.59	46.49	18.05

Evaluation of errors (Table 2) shows low omission errors for dark vehicles, where almost all vehicles were identified. That is due to significantly lower DN values for dark cars than for any other object on the streets. Only SVM classification in ENVI has an error about 10%. SVM classification in CATALYST has an error less than 1%. Bright vehicle detection also shows low omission errors, where almost all vehicles were identified. The highest error almost 5% has RT classification. Also vehicle detection in the shadows was quite successful where almost all vehicles was identified. The RT classification again has the highest error about 9%, as in the case of light vehicles. Evaluation of errors shows higher commission errors mainly for dark vehicles. This is due to the fact that dark vehicles matched to the shadows of vegetation or buildings, where bright vehicles could be detected as dark. The commission error has a relatively high value for the RT classification because vehicles could contain bright pixels such as the hood of the vehicle. The commission error for vehicles in shadow again has a relatively high value for the RT classification because dark vehicles and vehicles in shadow could match.

Amount of classified area of vehicles (Table 3) was calculated as the ratio of the detected area of vehicles to the size of area of vehicles detected by authors. Four classifications detected at least 50% of the total area of dark vehicles detected by evaluators, SVM in the ENVI even 75%. Only SVM classifications in CATALYST detected less than 50% of total area of dark vehicles detected by evaluators. Detection of bright vehicles was not as successful as detection of dark vehicles. All classifications detected less than 50%, PCA even less than 25%. KNN, SVM in ENVI and RT detected approximately the same area of about 45%. The shadow shows a negative impact on the results of classification. Vehicle detection in the shadows was the worst of all. All classifications detected less than 20% of total area.

Table 4. Best classifications.

	Accuracy	**Coverage**
Dark vehicles	SVM-CATALYST	SVM-ENVI
Bright vehicles	SVM-CATALYST	RT-CATALYST
Vehicles in shadow	ENVI	RT-CATALYST

Relatively best classification for dark and bright vehicles with respect to both errors is SVM in CATALYST. For detection of vehicles in shadow is better software ENVI than CATALYST. The largest amount of total area for dark vehicles was detected by SVM in ENVI, more than 75%. For detection of bright vehicles, KNN, SVM in ENVI and RT have almost same amount of detected area, but RT detected the most, more than 46%. RT is the best for detecting vehicles in shadow but was able to detect only 18% of total area.

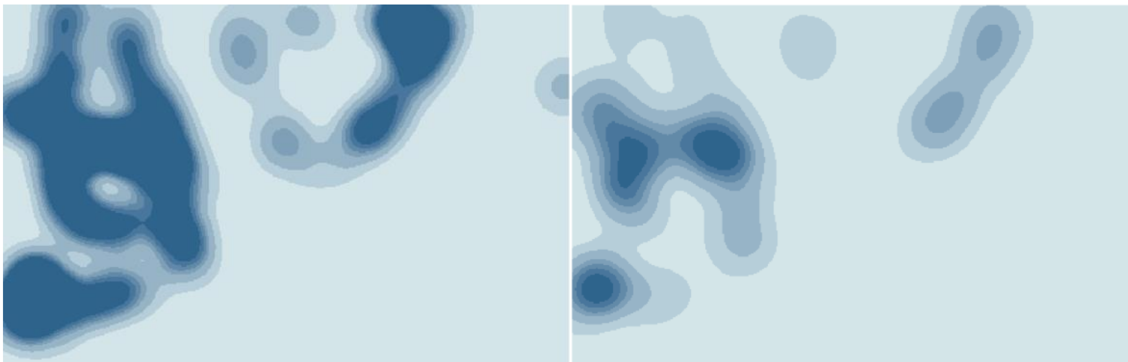

Figure 2 Heat map of detected vehicles (on the left vehicles detected by evaluators and on the right SVM classification in CATALYST)

CONCLUSION

Results from various methods to detect vehicles using very high-resolution satellite images show diverse recommendations depending on the target criteria and conditions. For vehicles detection, we applied OBIA with two different software and five classification methods, KNN, PCA and SVM in ENVI and another two RT and SVM in CATALYST Pro. All these methods detected dark vehicles relatively well in about 50 to 60% of total area, but SVM in ENVI detected up to 75% of total area. Bright vehicles have the best results when KNN, SVM in ENVI and RT classification was used. For vehicles in shadow, RT classification was the best, but only with 18% of detected area. In the future, we would like to focus on detection using neural networks, specifically Faster RCNN.

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