

VDIS: A System for Morphological Detection and Identification of Vehicles in RGB Images

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With the growth of urban centers worldwide, the number of vehicles in and around these areas has also increased. Traffic-related data plays an important role in spatial planning, for example, optimizing road networks and in the estimation or simulation of air and noise pollution. This information is important as it reflects the changes taking place around us. Additionally, data collected can be used for a wide array of applications including law enforcement, fleet management, and supporting other analyses at varying scales. In this paper, we present a method for the detection and identification of vehicles from low altitude, high spatial resolution Red Blue Green (RGB) images, utilizing both object spectra and image morphology. Results show an identification performance upwards of 62% with false positives occurring from the use of images with sun glare and vehicles with similar spectra values.

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With the increasing growth of urban centers around the world, the number of vehicles within and near these areas is also on the rise (Gaurav and Khisty, 1998). This has led to issues in urban areas, including increases in traffic congestion, accident rates, air pollution, and commute times (Drakakis-Smith, 2000). As a result, data on vehicles plays an important role in many transportation and urban planning applications, provides a useful indicator of expanding economic growth and consumption (East-West Center, 2002), and can provide useful insight on

crisis or disaster severity. There is, therefore, considerable attention being placed on the development of intelligent traffic control systems (Eslami and Faez, 2010; Stilla et al., 2004).

Presently, systems to capture transportation data mainly use ground sensors like induction loops, bridge sensors and stationary cameras (Hasan et al., 2014; Eikvil et al., 2009; Zheng and Li, 2007). These sensors are often located long distances from each other (Eslami and Faez, 2010) and provide only local measurement of traffic (Stilla et al., 2004). This configuration, along with the limited viewing angles of most sensors in use today, leads to gaps in data collection. Larger areas of collected data could be useful to better understand traffic dynamics (Eikvil et al., 2009); however, this may be cost prohibitive if relying on traditional sensor networks alone. Newer methods of collecting transportation data use sensors mounted on various air and spaceborne platforms, which produce images that represent data captured for a wider geographic area (Mahabir and Al-Tahir, 2008; Poli, 1999) along with the possibility for multiple viewing angles.

Images captured from sensors like other forms of data must be processed in order to be useful in any context. The goal of such processing is the extraction of information permitting the detection and discrimination of vehicles in various image sets. High and very high resolution, less than 4 meter ground sampling distance (Moeller 2005), visible Red Green Blue (RGB) imagery is more readily accessible because of Google Earth and similar image visualization platforms. Therefore, RGB images offer a suitable option, or at least an alternative, for collecting transportation data.

In this study we examine the problem of vehicle detection and identification from RGB images. The study area is a major highway in the United States for which several segments of road were available. We propose a method using object spectra and image morphology for first detecting the locations of vehicles in RGB images, followed by an identification process to separate vehicles. In section 2, an overview of data and software used is given. Section 3 discusses the methodology, while section 4 presents the results and analysis from various experiments. Finally, section 5 concludes this paper with a brief discussion on areas for future research.

Data and Software

Data on four segments of a highway in the United States were collected from the Center for Geospatial Intelligence and Geoinformatics at George Mason University, Fairfax, Virginia. Segments were both overlapping and disjointed, and represented different sequential images of the road at different times. The data were collected at low altitude and provided in RGB format (.jpg) at a spatial resolution of about 1m, with atmospheric and radiometric corrections already applied on acquisition. The geospatial software package ENVI, version 4.7 (ITT Visual Information Solutions, Colorado, USA), was used for processing the data.

Methods

The methodology used is divided into two main parts: vehicle detection followed by vehicle identification. Figure 1 gives an overview of the main components of the Vehicle Detection and Identification System (VDIS) and the first two sub-sections provide a summary of each component applied to a control image. In the third sub-section, references are given with respect to the various steps used to test the VDIS method.

Vehicle detection

Training classes consisting of pixels representing regions outside of roads were first selected from the RGB image. These training classes were then used as input into a parallelepiped classification algorithm to create a binary mask for extracting the areas of interest (AOI), that is, areas containing roads and vehicles only. Following the removal of non-road areas, morphological operations of opening followed by dilation were applied to the output to further remove unwanted noise from the AOI binary mask.

Next, the parallelepiped classifier was used once again with the RGB image. Also included as inputs were the use of the binary AOI mask of vehicles and roads, and selected road ROI pixels, used for creating a composite binary mask for eliminating both roads and the non-AOI areas that existed outside the extent of roads. Results of this process created a binary mask with vehicle regions being detected with values of 1 and contained within the extent of roads. Noise from small objects and the median between road lanes contained within vehicle regions is also present in the output of this stage of the process. A median image filter, typically used for removing noise in images, could not be used at this point because of similarity in the size of objects represented by noise and by some positive AOI output. To remove noise the values of

the output were first inverted. This resulted in the locations of vehicles now being represented as regions of 0 values. Next, a morphological chain of operations – opening and eroding, followed by dilation, were used to completely remove unwanted noise.

In the final stage of the vehicle detection process, the inverted and cleaned image is used to create a binary mask. This mask consisted of the combined product of the output of the morphological opening operation used to clean the data and its improved successor. Morphological dilation was then applied to the mask. The output of this final step of the detection process was a mask that showed regions where vehicles were located in the image with pixel values of 1, and everything else with pixel values of 0.

Vehicle Identification

Object spectra for various vehicles in the control image were used to build a spectral library. Two colors for vehicles were chosen: red and white. The spectral library was then used as input into a minimum distance classification process in order to detect vehicles represented by different colors. Red vehicles were targeted first. A median filter was applied to the result of the classification process to reduce noise, and histogram stretching was applied to threshold the output and further reduce unwanted noise. A second median filter was then used to remove noise from the new output, following which the mask resulting from the vehicle detection process was applied. The final output of this process produced vehicle regions with values of 1, identifying red color vehicles, and pixel values of 0 for everything else. The processes outlined were then repeated to locate white vehicles in the image scene.

Testing

The vehicle detection and vehicle identification processes were applied to three test RGB images collected for different segments along the same road network as the control image. Confusion matrices were then generated for each of the test cases for determining the identification performance of VDIS.

Results and Analysis

Figures 2 to 7 show the outputs of the various steps outlined in section 3 for the control image used. Figure 6 shows that one region (highlighted in red) was wrongly detected as a vehicle region. This figure also shows that the shadows of vehicles are detected as regions. In Figure 7, all vehicles matching the color vehicle being searched for (highlighted in green) were

identified using VDIS without any misidentifications. The omission and false positive results of using VDIS on three different test images for the detection process are shown on Table 1, while Figures 8 to 10 show the end results of the identification process. For each image in Figures 8 to 10, the associated confusion matrix used for deriving identification performance is also shown.

The results in Table 1 show that the detection process missed smaller vehicles, like motorcycles. It also wrongly detected part of a truck's shadow as a separate vehicle region. In Figures 8 to 10, the overall identification performance values of test images were 75%, 83%, and 62%, respectively. Closer examination of the results showed that the RGB image with the lowest identification results (Image 3) contained a larger number of vehicles of similar spectral value and higher sun glare content.

Discussion and conclusion

Transportation data, for example, on traffic density, location and trajectory, is a valuable resource for understanding the dynamics of road networks and the interlinked processes taking place around them. This is especially important since the number of vehicles on roadways has been increasing. Analysis of such data has already led to critical findings supporting changes in policy, including traffic modeling and simulation, emission reduction, efficient use of infrastructure, and extension planning of road networks (Kozempel and Reulke, 2009; Gerhardinger et al., 2005). China, for example, has implemented an auction and lottery of license plates to control the number of road vehicles (Feng and Li, 2013). This system was introduced in response to the growth of greenhouse gases emitted from the vehicle population. In the United States, the increasing number of vehicles has been linked with degradation of air quality and aquatic sediments (Van Metre et al., 2000). In Turkey, work by Yalmaz et al. (2009) suggests that the increase in road vehicles has contributed considerably to increases in city temperature, a leading cause of urban heat islands. The problem of increasing numbers of vehicles is expected to be especially acute in Asian countries, where road congestion and accident levels are some of the worst in the world (East-West Center, 2002) and where growing poverty continues to be a daily challenge (Lall et al., 2008). Vehicle data can provide information on how well an affected area is recovering from disaster or crisis (Gerhardinger et al., 2005). Images collected at various locations are especially useful in law enforcement to

assist in tracking selected objects across multiple scenes which vary with location. It is therefore for critical to collect information on transportation networks.

This paper presented a method for the detection and identification of vehicles from low altitude RGB images, using a series of morphological operations and classifications based on object spectra, to uniquely target selected color vehicles. Images can be captured at both high spatial and temporal resolutions, important properties for separating vehicles from other objects in images. Such applications of data capture are especially useful during mass events or disasters, which result in huge congestions or road blocks. Additionally, snapshots along entire road networks could offer more insight into the distribution of vehicles in a region and overcome challenges in using traditional counting equipment (Eikvil et al., 2009). Results show that the VDIS method performs well: upwards of 62% accuracy in identifying vehicles in images that contain lower amounts of sun glare and higher contrast between vehicular spectra. In the image with the lowest identification performance there exists a strong presence of vegetation compared to other images; however, this would not affect final results, because the series of morphological operations were used to remove the median separating roadways, where vegetation usually exists. The processing of the images is not straightforward. For example, there are problems with heterogeneity of vehicle properties (e.g. body styles and colors), uncontrolled lighting, partial occlusions (e.g. by trees), and other undesired phenomena (e.g. strong sunlight reflections from windshields) (Krawiec et al. 2010). Also, separation of objects becomes increasing difficult with increased degradation of image quality, leading to cross contamination of object spectra values. One possible solution for overcoming this challenge is the acquisition of spectral signatures for a wider variety of objects contained in images, that is, extending data collection along more electromagnetic wavelengths. However, this option is not always available and provides a challenge for developing countries around the world with already constrained budgets. Reduction in the detection results across test images occurred as a result of similar spectral values of vehicles and their respective shadows. This becomes a problem since operations were arranged in such a way as to first capture vehicles and their shadows as a single object. This larger (combined) object was then used to remove smaller noise objects. The detection process also did not pick up regions representing smaller vehicles, like motorcycles. The settings used for morphological processes would have identified these small areas as noise

and removed them. Furthermore, shadowed areas behind trucks in the image were wrongly detected as separate objects.

The findings of this research suggest various possibilities for VDIS. It can first be used as an image compression method for reducing the amount of data being stored. This is especially helpful if only the locations of vehicles are of interest. VDIS can also be implemented as a low budget approach for the detection of vehicles to supplement or corroborate data from existing sources, or data currently being collected, such as data collected by traditional sensor networks. Furthermore, VDIS may even provide a suitable option for processing data collected between successive high quality data collection events, including natural disasters, such as floods, or riot events, such as the Occupy Wall Street movement, using low altitude airborne platforms such as unmanned aerial vehicles.

Finally, several areas for future work were identified for improving VDIS. The method can benefit from becoming more flexible, compared to the rigid chained sequence of morphological operations used in this study. This will require investigation into other methods used for detecting vehicles in imagery, including the use of background subtraction and Kalman filters (Jun-Wei et al., 2006; Morris and Trivedi, 2006; Tseng et al., 2002; Young-Kee and Ho, 1999), shape features (She et al., 2004), bayesian background transformation (Sharma et al., 2006), multiple kernel learning (Liang et al., 2012), and pairing of headlights in the case of nighttime imagery (Cheng and Hsu, 2011). The goal would be working towards a fully automated approach as demonstrated by Hinz et al. (2003) and Der et al. (2004). Second, only limited vehicular spectra were collected and used for both calibration and testing purposes. Given the wide spectrum of colors of vehicles on roadways today, the use of much larger spectral libraries and better quality images with higher spatial and spectral resolution would be expected to improve the performance of VDIS. Third, a greater number of test samples, using more images, needs to be used to further test the robustness of VDIS in order to provide more conclusive results. Finally, the approach used to detect and identify vehicle regions could be enhanced by better segmentation approaches.

Author Note

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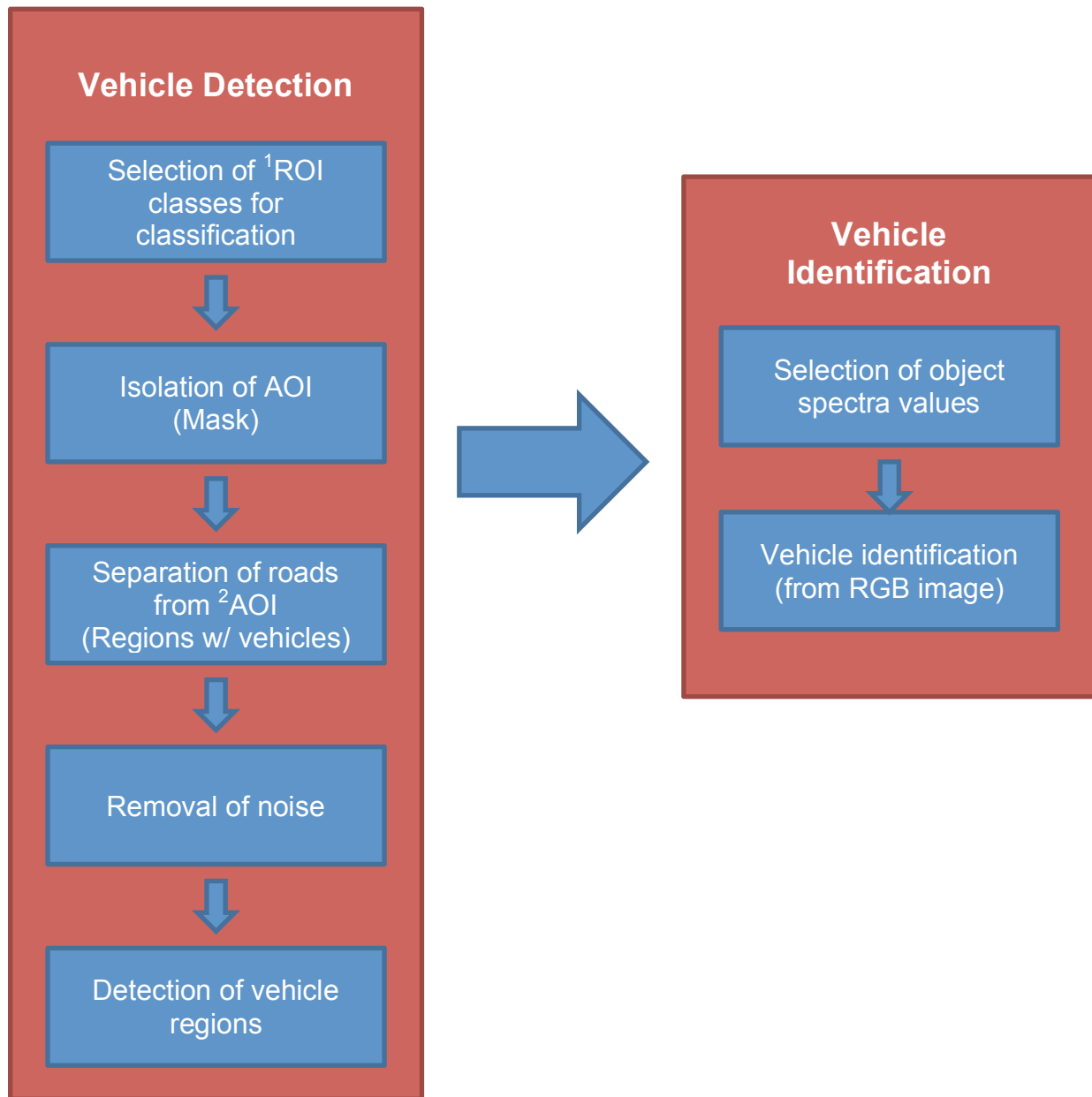
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Tables and Figures

Table 1: Results of detection process for test images

Test image	Wrongly identified regions	Missed regions
1	1 (part of truck shadow)	1 (motorcycle)
2	1 (vehicle with high sun glare)	1 (motorcycle)
3	0	0

Figure 1. Vehicle detection and identification system (VDIS)

¹Region of interest; ²Area of interest

Figure 2. RGB image



Figure 3. Mask showing the isolation of AOI in black

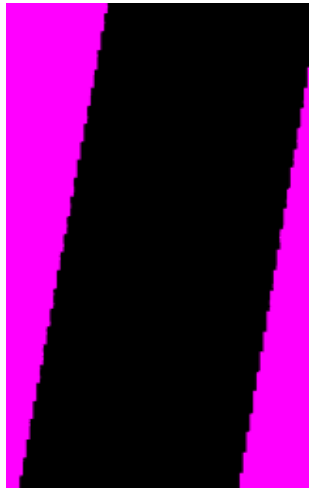


Figure 4: Removal of non-image elements (contains noise)

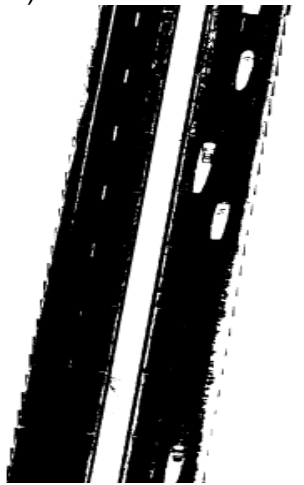


Figure 5: AOI with noise removed

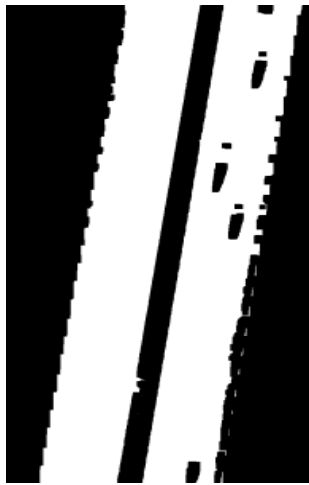


Figure 6. Vehicle regions (left) with clipped RGB image (right)

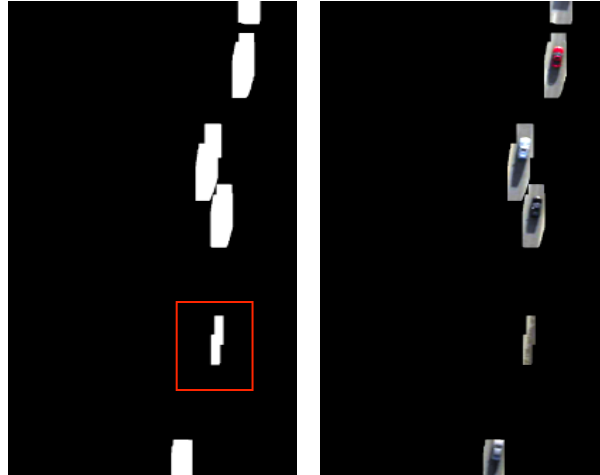


Figure 7. Red and white cars detected

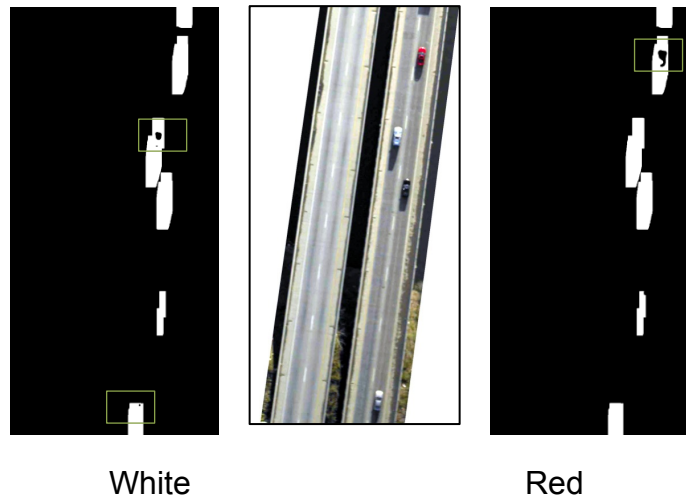


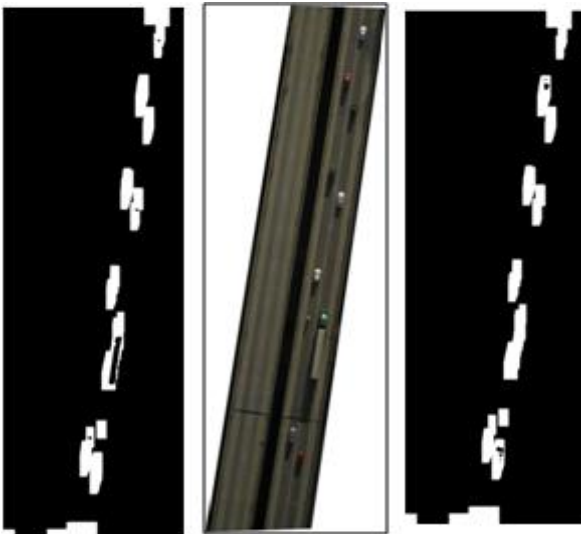
Figure 8. Reported results for test image 1



		Actual			Total
		Red	White	Other	
Predicted	Red	1	0	0	1
	White	0	2	1	3
	Other	0	1	0	1
	Total	1	3	1	4

Identification performance = $3/4 = 75\%$

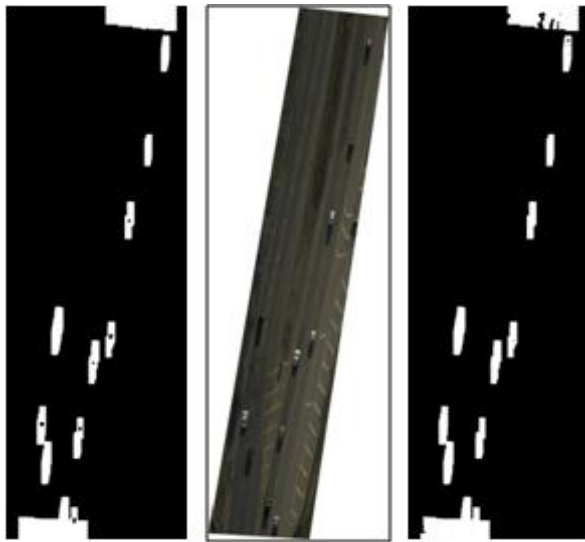
Figure 9. Reported results for test image 2



		Actual			Total
		Red	White	Other	
Predicted	Red	2	0	0	2
	White	0	3	1	4
	Other	0	0	0	0
Total		2	3	1	6

Identification performance = $5/6 = 83\%$

Figure 10: Reported results for test image 3



		Actual			Total
		Red	White	Other	
Predicted	Red	1	0	1	2
	White	0	4	2	6
Other		0	0	0	0
Total		1	4	3	8

Identification performance=5/8= 62%