An Artificial Immune Approach for Vehicle Detection from High Resolution Space Imagery

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Summary
Vehicle targets extraction is a new research issue for high resolution satellite imagery application in transportation. In this paper, an artificial immune approach is presented to extract vehicle targets from high resolution panchromatic satellite imagery. This approach uses the antibody network concept inspired from the immune system to learn a set of templates called antibodies for vehicle detection. Based on learned template antibodies, an immune detection strategy is proposed to locate vehicle targets in satellite imagery, and a morphology based preprocessing algorithm is also developed to generate candidate template antibodies. Experiments on 0.6 meter resolution QuickBird panchromatic images are reported in this paper. The experimental results show that the proposed approach has a good detection performance.

Key words:
Vehicle detection, space imagery, antibody learning, immune network

1. Introduction

With the development of traffic there is high demand in traffic monitoring of urban areas. Currently the traffic monitoring is implemented by a lot of ground sensors like induction loops, bridge sensors and stationary cameras. However, these sensors partially acquire the traffic flow on main roads. The traffic on smaller roads – which represent the main part of urban road networks – is rarely collected. Furthermore, information about on-road parked vehicle is not collected. Hence, area-wide images of the entire road network are required to complement these selectively acquired data. Since the launch of new optical satellite systems like IKONOS and QuickBird, this kind of imagery is available with 0.6-1.0 meter resolution. Vehicles can be observed clearly on these high resolution satellite images. Thus new applications like vehicle detection and traffic monitoring are raising up. This paper intends to study the vehicle extraction issue from high resolution satellite images.

Some vehicle detection methods have been studied using aerial imagery [1][2][3][4]. In the existing methods, two vehicle models are used. They are explicit model and appearance-based implicit model. They describes a vehicle as a box or wire-frame representation. Detection is carried out by matching the model "top-down" to the image or grouping extracted image features "bottom-up" to create structures similar to the model.

Few research on vehicle detection from high-resolution satellite imagery with a spatial resolution of 0.6-1.0m has been reported [5][6]. At 0.6-1.0 meter resolution, vehicle image detail is too poor to detect a vehicle by model approaches. Thus, it is necessary to develop specific approaches to detect vehicles from high resolution satellite imagery.

The immune system is one of the highly evolved biological information processing systems and is capable to learn and memorize. Many kinds of immune systems have been studied by mathematical methods. In recent years, applications of artificial immune system have been proposed in many engineering problems [7,8,9]. In our study, we attempt to use them for target recognition. Observed targets are regarded as foreign antigens, and a template is regarded as an antibody. Complementary template matching is considered to be exactly the same as the binding of the paratope and epitope. This paper proposes the technique using the artificial immune network concept to extract the vehicle targets in space imagery.

In this paper, we concentrate the vehicle detection on roads and parking lots, which can be manually extracted in advance. In order to collect antibody samples, a morphology based preprocessing algorithm is developed. The algorithm implements morphology operations on images to enhance vehicle features. Some of sub-images in the processed images are selected as the vehicle and non-vehicle training samples for antibody learning. The learned template antibodies are tested on real road segments and parking lots. The performance results are also discussed in this paper.

The paper is organized as follows. In Section 2, the details of our vehicle detection approach are described. In Section 3, experimental results are given and conclusions are provided in Section 4.

2. Immune Vehicle Detection Approach

2.1 Definition of immunological terms

In this paper, the immunological terms are defined in the following manner:

• *Antigen*: Vehicle targets.

•*Antibody*: Vehicle template images extracted from processed images by the morphology transform.

The used morphology transform is to enhance vehicle features. It is defined by

$$G(f) = f \oplus g - f \tag{1}$$

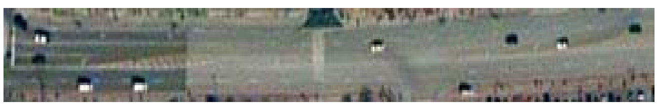
where g is a structuring element , f is a gray scale image, $f \oplus g$ means dilate operation, i.e.

Dilation:

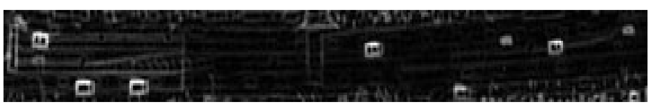
$$(f \oplus g)(x) = \max\left\{ f(z) - g_x^*(z) : z \in D\left[g_x^*\right]\right\}$$

(2)

where $g_x(z) = g(z - x)$, $g^*(z) = -g(-z)$ and $D[g]$ is the domain of g.



(a) An original image



(b) The morphology preprocessing result

Fig.1 An original image and its morphology preprocessing result

Fig.2 Antibody examples

Fig. 1 shows an original image and its morphology processing result. It can be clearly seen that all vehicle bodies or contours are enhanced. These enhanced features can be used to discriminate vehicle targets and non-vehicle targets.Fig. 2 shows some antibody examples collected from the morphology processed image, and each example image has same size.

• *Affinity:* Matching index. It is inspired from image correlation concept. It is defined by

$$R = \frac{\sum_{x=0}^{L-1}\sum_{y=0}^{K-1}(w(x,y)-\overline{w})(f(x,y)-\overline{f})}{\sqrt{\sum_{x=0}^{L-1}\sum_{y=0}^{K-1}(w(x,y)-\overline{w})^2}\sqrt{\sum_{x=0}^{L-1}\sum_{y=0}^{K-1}(f(x,y)-\overline{f})^2}} \tag{3}$$

$w(x, y)$ is the template antibody image of size $K \cdot L$, $f(x, y)$ is the antigen image of size $K \cdot L$, $\overline{w}$ is the average intensity value of the pixels in template antibody image w , $\overline{f}$ is the average intensity value of the pixels in template antigen image f.

The greater the value of R, the higher the antibody's affinity.

2.2 Antibody Learning

For antibody learning, we setup an image database which includes vehicle samples and non-vehicle samples. In the database, all samples are collected from morphology processed images using same sampling window.

We randomly select N vehicle samples from the database as the initial antibody population, the rest samples are regarded as training sets. According to the immune network theory, antibodies interact with each other and with the environment (antigens). The interaction property lead to the establishment of a network. When a antibody recognizes an epitope or an idiotope, it can respond either positively or negatively to this recognition signal. A positive response would result in antibody activation, antibody proliferation and antibody secretion, while a negative response would lead to tolerance and suppression. According to these antibody properties, we develop an immune network for vehicle detection. A set of rules are proposed for antibody selection and updating in the immune network. These rules are as follows.

Rule 1. Eliminate the antibody if the maximum affinity of the antibody to vehicle samples is under the threshold (< 0.6).

Rule 2. Eliminate the antibody that has high similarity over the threshold (>0.9) to other antibodies.

Rule 3. Eliminate the antibody if the affinity of the anti-body to any non-vehicle sample is over the threshold (> 0.6).

Rule 4. Add a vehicle sample from training sets into the antibody population as a new antibody if the affinity of the vehicle sample to any antibody is under the threshold (< 0.6).

Based on above rules, the antibody learning procedure in the immune network is described as follows:

Step 1: Randomly select N vehicle samples from the database as the initial antibody population;

Step 2: Evaluate the affinity of each antibody in the popu-lation with Eq. (3);

Step 3: Eliminate the antibody according to Rule 1-3;
Step 4: Update antibody population according to Rule 4;
Step 5: Repeat Steps 2–4 until none of antibodies is eliminated and none of new antibodies is added.
Step 6: Save final antibody population for vehicle detection use.
Fig.3 shows the flowchart for antibody learning.

2.3 Strategy of Detection

After learning the antibody population, the learned antibody population can be used to detect vehicles in the imagery.

Firstly, according to Eq.(1), implement morphology transform on the original image. Secondly, calculate the maximum affinity to all template antibodies at each pixel point (i,j) by Eq.(3). Thirdly, compare the maximum affinity value R at every point with the given threshold. If the R is greater than the threshold, the point belongs to a vehicle target and is set as 255. Otherwise, it belongs to a non-vehicle target and is set as 0. Finally, a post-processing based on morphology dilation and erode operations is employed to merge neighborhood vehicle target pixels and locate the center of a vehicle [10].
Fig. 4 shows the flowchart of the proposed vehicle detection based on the antibody learning.

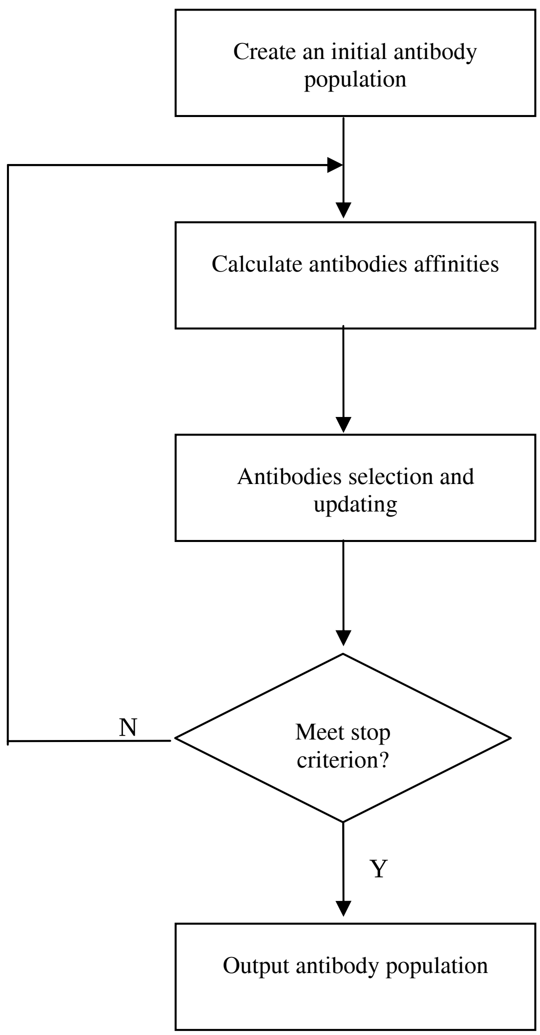


Fig.3 The flowchart for antibody learning

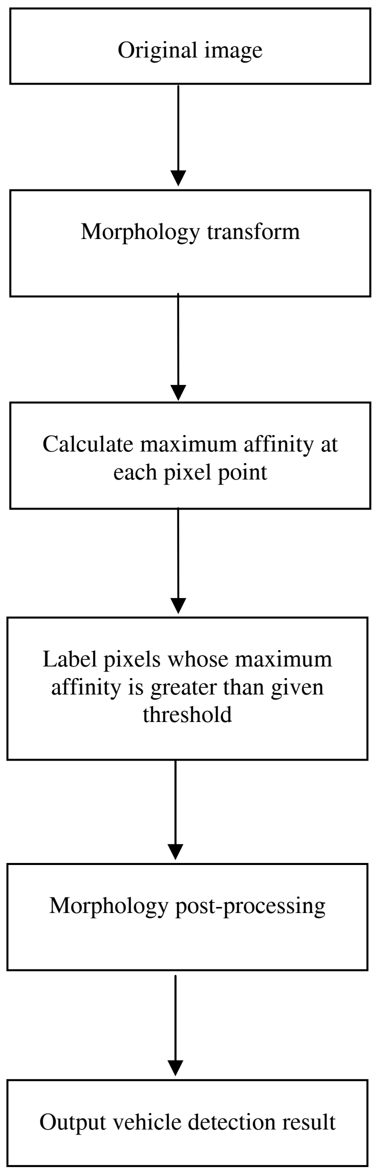


Fig.4 The flowchart for vehicle detection

3. Experimental Results

QuickBird panchromatic data set used in our study was collected from Space Imaging Inc. web site. The data set contains different city scenes. A total of 12 road segments and 5 parking lots segments containing over 1000 vehicles were collected. Most vehicles in the images are around 5 to 10 pixels in length and around 3 to 5 pixels in width. Since the vehicles are represented by a few pixels, their detection is very sensitive to the surrounding context. Accordingly, the sample database consist of vehicle and non-vehicle samples in a variety of conditions, such as road intersections, curved and straight roads, roads with lane markings, road surface discontinuity, pavement material changes, shadows cast on the roads from trees, etc. These represent most of the typical and difficult situations for vehicle detection.

For each selected road segment image or parking lot image, roads and parking lots were extracted manually in advance and vehicle detection was performed only on the extracted road surfaces. To build the vehicle example database, a human expert manually delineated the rectangular outer boundaries of vehicles in the imagery. A total of 400 vehicles delineated in this manner from 5 road segments. An image region with size 6×6m can cover most vehicles in the imagery. Hence, sub-images of size 10×10 pixels centered at vehicle centroids were built into the vehicle example database. In addition, 400 non-vehicle sub-image samples covering different road surfaces were also collected to build the non-vehicle example database.

After building sample databases, sub-image samples were used to learn antibodies and validate the vehicle detection approach. We randomly select 100 vehicle samples from the database as the initial antibody population, the rest samples are regarded as training sets. According to selection algorithm in Section 2, we finally got an antibody population including 32 template antibodies.

Taking vehicle orientations into account, each template antibody was rotated every 45° and the resulting template antibodies were also collected in the antibody population. As a result, the antibody population consisted of 32×4 =128 template antibodies.

After learning, the antibody population was tested on 12 road segments and 5 parking lots. The detection statistical results are shown in Tables 1. Fig. 5 shows some images of vehicle detection results.

From Table 1, it can bee seen that the missing detection rates (number of missing vehicles/number of vehicles) for road segments are from 0% to 13.8%, and average detection rate is 6.3%. The missing detection rates vary with the complexity of road surfaces, as well as the false alarm. The false alarms are due to vehicle-like “blobs” present in some of complex urban roads such as the presence of dust and lane markings (see Fig. 5). Some of these “blobs” are very hard to distinguish from actual vehicles, even to a trained eye. Most missing detections

Table 1 Vehicle detection results

Site	No. of vehicles	No. of detected vehicles	No. of missing vehicles	No. of false alarm	Missing detection rate %	False detection rate %
Road1	5	5	0	0	0	0
Road2	8	8	0	0	0	0
Road3	10	10	0	1	0	10
Road4	15	15	0	1	0	6
Road5	19	17	1	1	5.3	5.2
Road6	16	15	1	0	6.2	0
Road7	25	23	2	2	8	8
Road8	60	56	6	5	10	8.3
Road9	52	47	5	4	11.5	7.6
Road10	92	84	8	4	8.7	4.3
Road11	140	123	17	2	12.1	1.4
Road12	202	174	28	8	13.8	3.9
Parking1	6	5	0	0	0	0
Parking2	14	8	3	0	21.4	0
Parking3	16	9	7	0	43.7	0
Parking4	30	20	10	3	33.3	10
Parking5	41	25	16	6	39	14.6

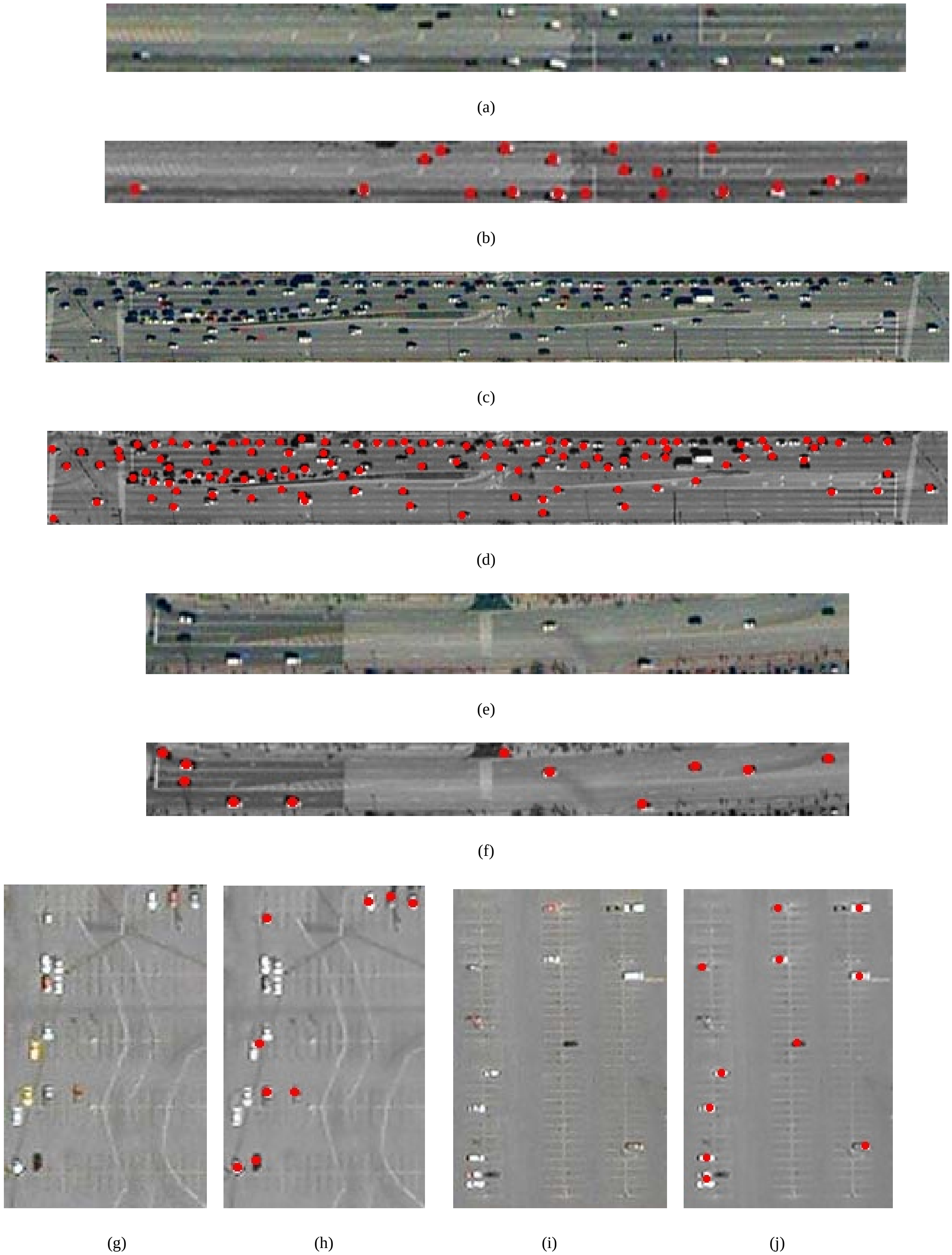


Fig. 5 Vehicle detection results. (a)(c)(e)(g)(i) The sample images of road segments and parking lots. (b)(d)(f) (h)(j) The vehicle detection results for images shown in (a)(c)(e)(g)(i), where red dots represent detected vehicles.

occur when the vehicles have a low contrast with the road surface or vehicles are too close. For the vehicle detection on parking lots, the missing detection rates are high. It is because the vehicles are too close to separate due to the resolution limit. How to detect vehicles on parking lots is still an open issue.
Comparing with other vehicle detection approaches [5][6], the proposed method directly detect vehicles in single satellite image, while Sharma's method needs a set of multi-temporal images at the same site to reach good detection performance [5]. A. Gerhardinger proposed the detection method based on Features Analyst Module for Arc/Gis [6]. The method could obtain over 90% correct detection rate. However, some interactive workload are needed and cost is relatively expensive due to using commercial software. In addition, their methods were mainly tested on simple road scenes, tests on heavy traffic roads and parking lots were not discussed in Sharma and Gerhardinger's study. In contrast, our method was tested not only on heavy traffic roads but also on parking lots, and experiment results show that our method has good performance both on simple road scenes and on heavy traffic roads.

4. Conclusions

In this paper, we focus on the issue of vehicle detection from high resolution satellite imagery. We present an immune detection approach for vehicle detection from 0.6 meter resolution panchromatic QuickBird satellite imagery. The concept of immune learning was introduced in our approach and was found to have good vehicle detection performance. Further work could include more training samples, better pre-processing method such as adaptive image enhancement and filtering, and fusing more information like edge shapes to improve the correct detection rate.

Acknowledgments

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