Using Multiple Viewpoint Templates For Target Detection In High Resolution Images

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Abstract

In this paper, we present a novel method to detect geospatial targets in high resolution remote sensing images by using a class of target templates with multiple viewpoints. The proposed method involves modeling the target by a collection of target models with multiple viewpoints. Initially, the image is segmented into several regions. The contour information of each segmented region image and templates are obtained. Then the seed regions are identified by computing the similarity of segmented image with the target template and missing regions are identified. Finally, the regions are extracted and combined to get the exact target.

Keywords:*Contour information, Geospatial targets, Spatial relationship, Template matching.*

1. Introduction

Now-a-days,target detection in High Resolution Remote Sensing Images becomes a challenging task due to lack of structural information. This is mainly because of difficulty in segmentation and to identify required and more identical segments (regions) which are correlated to the target image by comparing the segmented regions.A method was proposed for target detection using Contour representation and spatial relationship concepts[1].By learning the contour-based features, objects are detected by creating a location-sensitive classifier using a discriminative set of features from a randomly chosen dictionary of contour fragments[2].

Then geospatial objects are detected by learning taxonomic semantics by applying segmentation tree[3].Lots of studies and research has been done for classification and segmentation. As a result, many new methods have been proposed for classification. One such method has been proposed using support vector machine [4].Objects are detected using structural information and after multiplesegmentation[5]. Another method was proposed for object detection achieved using texture motifs [6].Every method has a flaw due to lack of information and these methods can be applied to certain type of images only.

The normalized cut algorithm could result in a near-optimal clustering and delineate the objects regions more accurately[7].It segments the image into larger segments.Hence there will be minimal chance of getting target itself. A combined technique, for object categorization and segmentation using implicit shape modelis described in [8].Objects are also detected using group of adjacent contour segments[9] and contour fragments[10].Further, a Hierarchical Shape matching is done by a Bayesian model[11]. All these methods have some drawbacks.Objects are also detected using gradients within the Bandwidth [12].In futurework, objects are detected using shape context matching[13].

The main drawbacks in the existing system are

- Expensive to compute, due to the level of complexity and detail often found in geospatial objects.
- Hard to segment and compare.
- When the extreme viewpoint changes, it will not work properly.
- Can work well only in fixed shape model.

In this paper, we proposed a combined technique of template matching and contour matching. Initially, the image is partitioned into multiple segments. This process is used to obtain sufficient candidate regions of the image. Segmented regions are represented with contour information using the edge representation. Then similarity is computed between the template and segmented image to get target seed regions.Then by using spatial relationship missing regions are identified. The process is applied for class of templates to detect efficiently.

The rest of this paper is organised as follows. The process of segmentation, modelling templates and seed region identification are introduced in section II. The process of similarity computation is described in section III. Modelling spatial relationship is presented in section IV. The algorithm for target detection process is described in section V. Experimental results are shown and discussed in section VI, and then conclusions are given in Section VII.

2.Seed Region Identification

Segmentation

Using k-means clustering method, the image is partitioned into multiple segments. This process is used to obtain sufficient candidate regions of the image. With a large number of variables, K-Means is computationally faster than hierarchical clustering and produce tighter clusters than other clustering.Then segmented regions are represented with contour information using edge representation.

The K-means algorithm is an iterative technique that is used to partition an image into P clusters. The basic process is:

- It picks P cluster centers, either randomly, manually or based on some other heuristics.
- Calculates distance between each pixel in the image and cluster centers and assign the pixel to the cluster centre which is nearer.
- Re-computing the cluster centers.
- Steps 2 and 3 are repeated until no pixel change.

Here, the distance is the squared or absolute difference between a pixel and a cluster centre. The difference is generally based on properties like pixel colour, their intensity, texture, and location, or its combination.

Creating Template Model

Class of target templates is modelled in such a way that it could able to identify the target efficiently. It includes models which supports the properties like translation, scale, rotation, and slight shape variation.

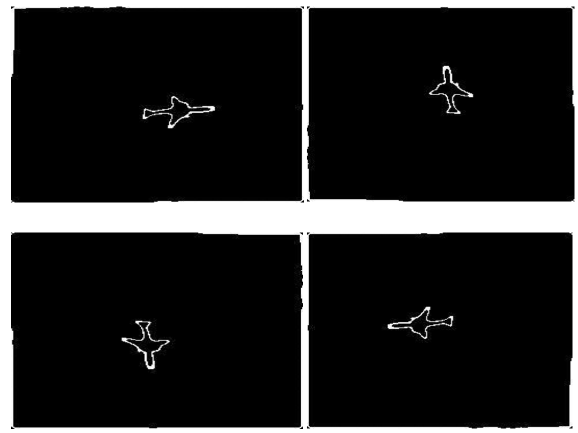

Fig.2 Sample Template Models.

Contour Representation

After the image segmentation, the segmented information is retrieved. The noise and other disturbances are removed by using median filter. Finally the edges of the image are obtained and represented using canny edge detection method.

3. Similarity Computation

After contour representation, Similarity between the image and target template is computed to get the seed regions.The similarity of the two points(for example p and q) is defined as the distance between their descriptors. The distance between two histograms is defined using X2 statistic

$$\textbf{Dist(p,q)= X2(hp,hq)=} \frac{1}{2}\sum \frac{[\mathbf{hp(k)-hq(k)}]2}{\mathbf{hp(k)-hq(k)}}$$

where K is the number of Shape Context (SC) bins, hp(k) and hq(k) are the normalized shape descriptors at points p and q respectively.

Given two contours P and Q, i.e., P = {pi, i = 1,….,Np}and Q = {qj, j = 1,….,Nq}, the match cost matrix between them is denoted as

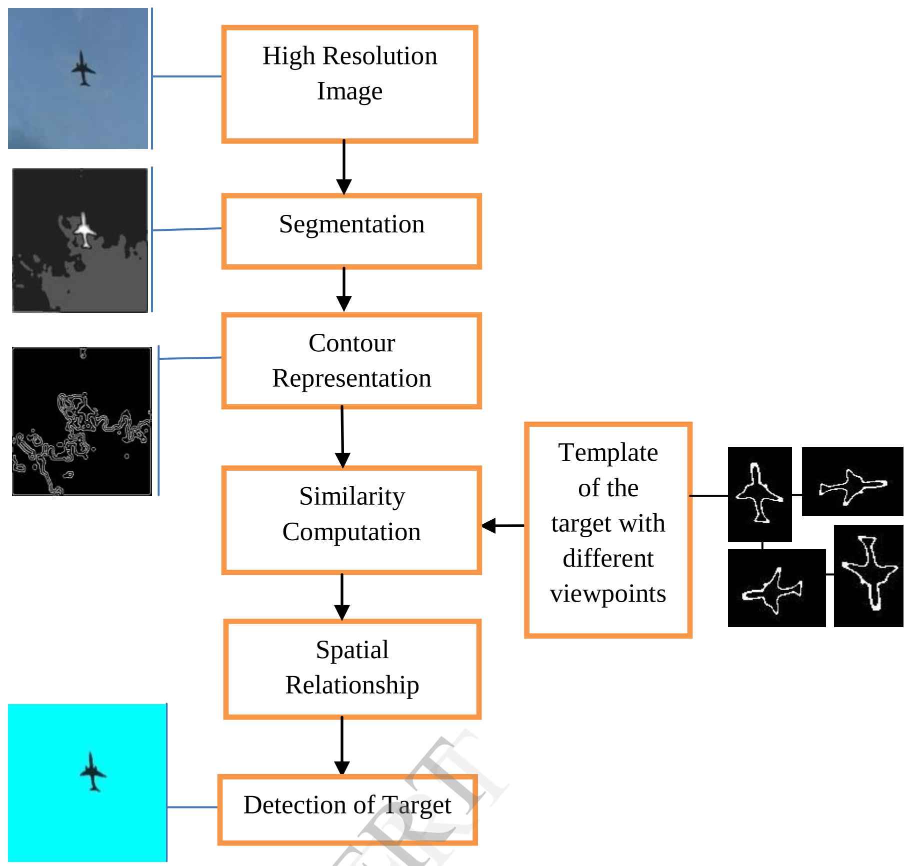

Fig.1Overview of our target detection method.

$$\textbf{Dist(P,Q)}=\begin{bmatrix} dist(p1,q1) & dist(p1,q2) & \cdots & dist(p1,qN_q) \\ dist(p2,q1) & dist(p2,q2) & \cdots & dist(p2,qN) \\ \vdots & & \vdots & \vdots \\ dist(pNp,q1) & dist(pNp,q2) & \cdots & dist(pNp,qNq) \end{bmatrix}$$

The matching cost can be used to measure the similarity between a segment P and the template Q. Seed regions are obtained using the above described formula.After the seed regions are identified, spatial relationship is applied to get remaining parts.

4. Spatial Relationship

After seed regions are identified,remaining regions are obtained by applying spatial relationship. For each seed region,it computes the indexes of eight neighbours of every contour point.It is calculated using by computing the Euclidean distance.

The Euclidean distance between (x1,y1) and (x2,y2) is $\sqrt{(\mathbf{x_1}-\mathbf{x_2})^2+(\mathbf{y_1}-\mathbf{y_2})^2}$.

The spatial relationship between all regions in an image can be represented by a region relationship matrix. For a pair of regions, we first compute the following:

- Areas of each region çiand çj .
- Common area between two regions çij computed as the number of shared pixels between two regions.
- Ratio of the common area to the minimum area ηij = çij / min(çi, çj).

5. Target Detection

Given an input image, segmentation is built, and the target candidate regions are obtained as described in Section II. Then, the target seed regions are identified by matching the candidate regions with the target reference model. The matching algorithm is reported in Section III.

Since there are the lack of spatial contextual information in segmentations and background interference, the seed region pieces ordinarily are not whole targets and miss some parts of the targets. The missing parts of targets are extracted according to their spatial relationships in the image described in Section IV.

In the missing part extraction process, we select the missing parts by a criterion function

$$\lambda = ws - \tau$$

Where w is the weight according to spatial relationship, s is the shape similarity, and τ denotes the threshold. The value of criterion function λ is compared with zero. Positive value means that the piece is the target missing part. The threshold is initialized as the similarity of seed regions and adjusted during the process as described hereinafter.

Suppose that S denotes the target seed region and R denotes the set of image pieces. The combination scheme alternates between the following two steps.

Search step: Fix the threshold τ, and search the image pieces R according to the criterion function. For every image piece, calculate its response value of the criterion function. Extract the image pieces 'rtarget' whose response is positive. This routine can be implemented efficiently using dynamic programming.

Update step: Fix the image pieces that belong to the target, compose them together forming the new seed region $S = S \cup rtarget$ and $R = R - rtarget$, and update the threshold. The algorithm ends when no missing piece is obtained at the search step. This target piece selection procedure can be shown to converge to a local maximum of contour similarity.

The process is repeated for all templates and targets are obtained concurrently.

6. Result

Due to the lack of standard data sets of high-resolution remote sensing images for target detection, we evaluate the proposed method on Quick Bird images for aircraft detection. There are 120 images approximately from 200 × 200 pixels to 600 × 500 pixels in size with a resolution of 60 cm/pixel. These images contain both the images with good contrast and clutter images, as well as some occluded target images.

Fig. 3 Results of our method for aircraft accurate detection.

In order to quantify the evaluation, let Area(region) be the area of a region; then, a detection is marked as true positive(TP) if the Area(target) agrees with the Area(ground_truth) based on the criterion.

$$\frac{\text{Area (groun d}_{\text{truth}} \cap \text{target)}}{\text{Area (groun d}_{\text{truth}} \cup \text{target)}} > 0.6$$

The Plots for false positive per image (FPPI) in accordance to precision is shown in Fig.4. where precision and FPPI are calculated as

$$\text{Precision} = TP/(TP+FP), \text{ and}$$

$$\text{FPPI} = FP/NP,$$

Where FP is False Positive and NP is Number of testing images.

To Evaluate the scalability of the our model when the multiple segmentation parameters vary, we compare the detection performance of our method when the values of α and β vary. The values of segment coefficients are the only variables. The results are summarized in Table I.

We evaluate the performance variation when the number of contour samplings is set to be 50, 100, 150, and 200 and shown the result in Fig.4.It shows how the detection performance can be improved by adding spatial relationship.

TABLE I
Comparison Of Precision For Different Numbers Of Segments

	FPPI	α=0.015 β=0.015	α=0.015 β=0.05	α=0.05 β=0.05	α=0.015 β=0.100
Hu Moments	0.2	19%	46%	38%	49%
	0.4	23%	53%	42%	61%
Our Method	0.2	35%	72%	49%	83%
	0.4	37%	76%	52%	86%

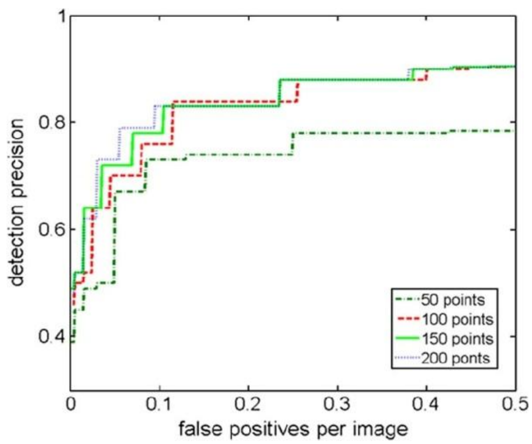

Fig. 4 Detection Performance with varying number of Sample Contour Points.

We observe that our method can achieve good performances, even in some difficult cases such asthe variability in the appearance of targets and shadow effects,targets surrounded by complex background.

7.Conclusion

In this paper, a method has been proposed to solve the problem of detecting geospatial targets present in high-resolution remote sensing images under multiple view pointaccurately and automatically. Segmentations are employed to produce target seed regions. By using template matching and according to their contour similarities, the seed regions are identified. Spatial relationship is used to obtain missing parts of the target instances. The process is repeated for the class of template models and concurrently target regions are identified. The experimental results with aircraft t image as example shows the robustness and effectiveness of the proposed method.

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