TARGET DETECTION FROM HIGH-RESOLUTION SATELLITE IMAGES

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ABSTRACT: We present an object-based image classification method to detect aircrafts from high-resolution satellite images. The detection of all varieties of aircrafts is a difficult problem due to the large intra-class variability of aircraft objects, the presence of complex foreground / background scenarios and the large volume of data to be processed. Further as the resolution of data increases the intra-object homogeneity decreases. In the proposed approach we use localised processing and leverage object-level attributes for classification. Localised adaptive segmentation is proposed for segmenting probable aircraft objects from the image and then object classification is performed using *k*NN and SVM. Three band (RGB) data having about 0.5m spatial resolution are used in the experiments. We achieve an accuracy of 81% and 93% using *k*NN and SVM respectively.

1. INTRODUCTION

Detection of various interesting targets including aircrafts, helicopters, vehicles, tanks, field guns, and the like from high-resolution satellite images is an important problem in surveillance. A generic solution frame-work to detect all interesting targets is an open problem. In this work we attempt to detect only aircrafts from high-resolution satellite images using object-based image classification methods. Even in this restricted context, detection of all types of aircrafts is difficult due to the large intra-class variability of aircraft objects in terms of their spectral and spatial properties. For high-resolution satellite images, the presence of complex foreground / background scenarios and the large volume of the data add up to the complexity of the process. Further, as the resolution of data increases, the intra-object homogeneity decreases. This poses more hurdles in the detection process.

Image segmentation, which delineates objects from an image, is the first step in object based image classification technique. Various researchers including (Gonzalez, 2008), (Freixenet, 2002), (Fu, 1981), (Deng, 2001), (Canny, 1986), (Meyer, 1990), (Jianbo, 2000), (Forcadel, 2008), (Grady, 2006a), (Grady, 2006b) and (Blaschke, 2000) give detailed account of different image segmentation techniques. The objective of image segmentation followed by classification is to automatically interpret features / objects in an image. In-depth explanations, comparison of the methods of classification and their applications can be found in (Lu, 2007), (Blaschke, 2003), (Karydas, 2011), (Blaschke, 2010), (Murthy, 2012), (Lillesand, 2008) and (Navulur, 2007).

Image classification methods for satellite images were initially motivated by land-use and land-cover classification applications. Advances in remote sensing and availability of satellite data with high spatial and spectral resolution have fuelled the efforts for detection and identification of smaller objects from satellite images as discussed in Section 2. Target detection from satellite images finds wide applications in military and civilian sectors. In military sector, detection of various types of targets like aircraft, tanks, field guns etc. helps in assessing combat preparedness of hostile forces and in gathering geo-intelligence. Detection of field guns and their orientations can help in computing the coverage zone of the weapons and in the depiction of the same on a Geographic Information System (GIS). So a generic framework to detect various interesting targets from satellite images can be of great aid in military operation planning. In civilian sector, such target detection can find applications like computation of vehicle density on a particular road, number of vehicles in a parking lot etc. Hence it can aid in building intelligent transportation systems and in city planning. Aircraft detection, in specific, helps in monitoring the dynamics in airbases by identifying types and volumes of aircrafts operating from an airbase. In this context, the current paper attempts to detect (aircraft-like) targets from high resolution satellite images.

The paper is organized as follows. In Section 2, we briefly review the prior work in this field and relate them to ours. Localized Adaptive Segmentation (LAS) algorithm to separate out probable aircraft objects from a satellite image is proposed in Section 3. Feature space construction and object classification are presented in Section 4. Results are discussed in Section 5. Finally we conclude in Section 6.

2. PREVIOUS WORKS

In this section we briefly review the existing work on this problem. On the way we try to relate these to our work and comment on the similarity and the dissimilarity.

Classifications of remotely sensed images were initially motivated by land-use and land-cover applications. Later, with the availability of high-resolution data, localization and identification of smaller objects from the satellite images started finding use. For example, Segl and Kaufmann (Segl, 2001) designed an object-based ANN classifier to detect house-plots from 4.5m MOMS-02 images. These plots are much smaller than typical objects in a land-use application; but are still quite large compared to the target objects of our interest. In (Zheng, 2006), Zheng et. al. manually selected the pixels corresponding to roads from 0.6m Quickbird panchromatic images. Classification was then applied on these selected pixels only rather than taking the entire satellite image as input. Jin and Davis (Jin, 2007) restricted to the road layer of a GIS for the context of vehicles, used morphological filtering and finally ANN classifiers for vehicle detection from 1m resolution IKONOS data. In (Zheng, 2006) and (Jin, 2007) both, pixel classification is employed on the candidate pixels. Hence, unlike our method, these methods cannot leverage the characteristics of shapes and objects for classification. Arora et. al. (Arora, 2013a and Arora, 2013b) worked with hyper-spectral images to detect aircraft using fuzzy and sub-pixel classifications. We, however, use less expensive RGB images here. Liu et. al. (Liu, 2013) used orientation and shape in segmentation and then used *k*NN classifier to identify aircrafts. Naturally its accuracy depends on the orientation of the aircraft and view direction. Our method, in contrast, is invariant to pose. Instead of learning from binary sub-images in the segmentation result, we engage a feature space consisting of size, shape, and spectral properties. Banerjee et. al (Banerjee, 2016) used saliency to localise regions of aircraft like objects in satellite image and further leveraged a multi oriented conical pyramid (MOCP) of target templates for matching. This requires generation of MOCP for various types of aircraft.

3. SEGMENTATION

We first carried out several experiments using the existing edge-, clustering-, or region-based algorithms to segment the objects in a satellite image. We try Region-based JSEG (Deng, 2001) algorithm for its ability to segment pattern of pixels in colour images. The popular *K*-means algorithm in the clustering based approach is used for its simplicity. Canny edge detector (Canny, 1986) and Watershed (Meyer, 1990) algorithms are attempted from the edge-based class. Finally, we construct multi-resolution image pyramids by down-sampling the image using Gaussian kernel and then applying watershed segmentation.

From the results we observed that these algorithms do not preserve the shape of an aircraft well and typically result in many fragmented objects (Figure 2). Hence, it gets difficult to reason about the objects. Also these algorithms operate on the whole input image. This is expensive and often unnecessary. Hence we focused on a modified localized approach to segmentation. Naturally, getting local optimum (like threshold) in an image is easier than getting global optimum values. With this we propose the Localized Adaptive Segmentation (LAS) algorithm in the next section. We assume that objects of interest are brighter than their surroundings.

3.1 Localised Adaptive Segmentation (LAS)

We present Localised Adaptive Segmentation (LAS) in Algorithm. 1. Major steps of LAS are -- (1) Generation of seed image, (2) Localised thresholding, and (3) Area-based filtering.

Algorithm. 1 Localised Adaptive Segmentation

1: *Irgb* ← Input RGB Image
2: *Ig* ← Gray scale image of *Irgb*
3: $Ic \leftarrow Ig \bullet b1$
4: $Ith \leftarrow Ic - (Ic \circ b2)$

// Seed image generation
5: *t* ← threshold value obtained by Ostu's method or empirically from *Ith*
6: *It* ← *threshold(Ith, t)*
7: *Is* ← *smooth(It)*

// Localised Thresholding
8: *cntrs* ←Contours of Is
9: *rects* ←Minimum bounding rectangles of *cntrs*

```
for each rect in rects do
    Expand rect by buffer guarding boundary conditions
    Isub ← SubImage(Ith, rect)
    ISubT h ← Isub − (Isub ◦ b3)
    Apply Otsu's thresholding on ISubT h
end for
Io ← Assign all pixels of operating image which does not belong to any expanded rect to 0

// Contour guided area based filtering
tCntrs ← Top level contours of Io
for each cntr in tCntrs do
    if Area(cntr) > tA then
        Select the corresponding object
    end if
end for
```

The input RGB image (*Irgb*) is converted into gray scale (*Ig*) and morphological closing is applied (*Ic*) using rectangular structuring element (*b1*) to remove the shadows of the objects. If the shadows are not removed, it may lead to distortion in the shape of the object obtained by the segmentation. Next the top-hat transformation is applied (*Ith*) to suppress the background and brighter objects larger than the structuring element *b2*. Threshold *t* for the *Ith* is obtained mostly by Otsu's method (Otsu, 1979), though, in some cases empirical values are used. Smoothing (*Is*) is applied to the thresholded image (*It*) to combine small objects in close vicinity.

Top level contour of every object in *Is* is obtained and its bounding rectangle is computed. These bounding rectangles are expanded by a *buffer* distance (guarding the image boundary conditions) which gives background of probable aircraft objects and aids in getting a better threshold value. Top-hat transformation and thresholding are applied on the sub-image defined by the expanded bounding rectangles. This gives a better segmentation of the local sub-image. All the pixels which do not belong to the rectangles are set to *0*. Next, the contour area of the objects in *Io* is computed and only objects having area greater than the threshold *tA* are retained in the output and rest are set to *0*.

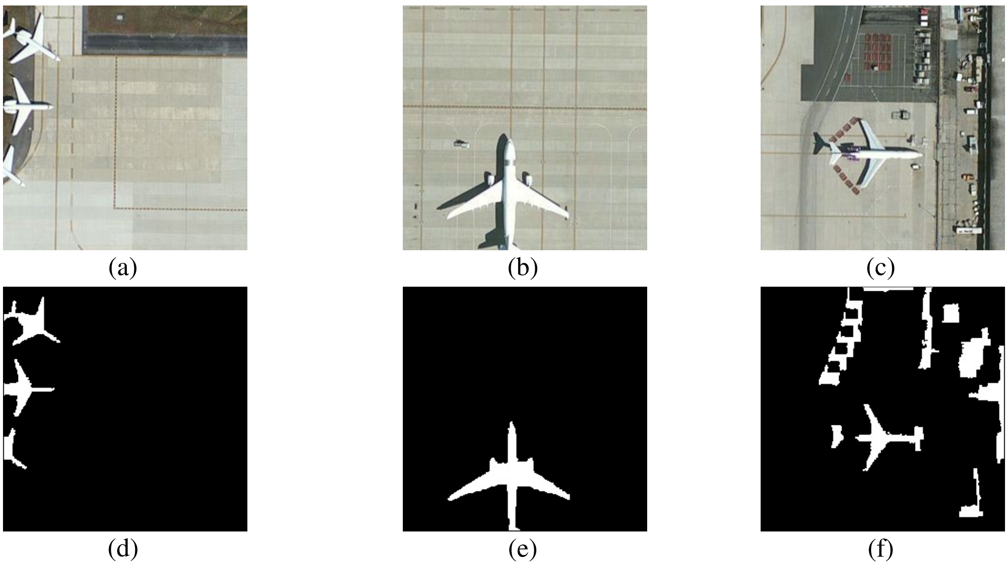
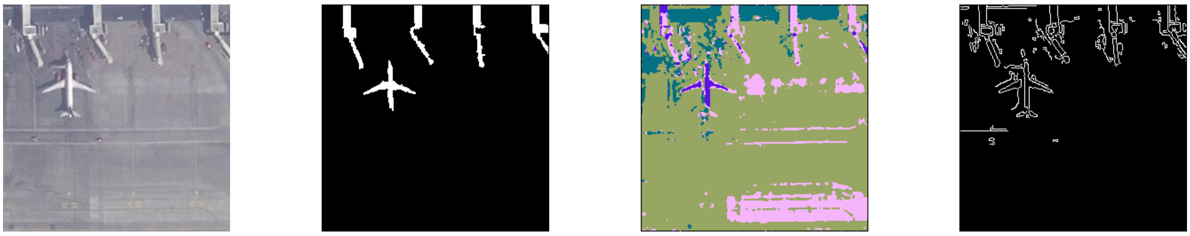


Figure 1. Images with LAS segmentations.

Figure 1 shows the input images and corresponding segmentation results using LAS. For Figure 1(a), even a partially visible aircraft is cleanly segmented in Figure 1(d). The shadow in Figure 1(b) is removed in Figure 1(e). However, the shadow on the body of the aircraft in Figure 1(c) splits the segmented object in two in Figure 1(f). It can be observed from the results that the number of objects in the segmentation output using LAS is less compared to the existing methods. In Figure 2 the results of existing methods are shown for comparison. While LAS preserves the closed shape of the objects, *K*-means and Canny's operator destroy the structures substantially. At times, however, cluttered scenario degrades the result and the parameters like threshold value and size of the rectangular structuring elements are empirical.



(a) RGB Image (b) LAS Result (c) K-means Result After Smoothing (d) Canny Detector Result

Figure 2. Comparison of LAS Segmentation Results

After the segmentation, the top level contours of the objects are computed. OpenCV API for the boundary tracking (Suzuki, 1985) is used for computing contours of objects. Figure 3 shows an example of shape extraction using theis method. These shapes are further used to extract shape parameters of the object and for the mask for computation of spectral (intensity) parameters of the objects. It forms the feature space.

(a) Segmented Image (b) Contour

Figure 3. Shape Extraction

4. CLASSIFICATION

Once the objects have been extracted, we compute six structural and two spectral features for every object. These features are then used in classification. We use *k*NN and SVM algorithms for classification.

4.1 Feature Space Description

The following features are extracted for every object:

1. *Area:* The area of the object
2. *Perimeter:* The arc length of the contour of the object.
3. *Aspect ratio of bounding rectangle: Length / Width* ratio of the minimum bounding rectangle of the object
4. *Solidity*: Ratio of the area of the object to the area of the convex hull of the object
5. *Compactness*: $Perimeter^2 / Area$ of the object.
6. *Circularity*: Area of the object divided by the area of the circle having same perimeter. $\frac{4\pi \times Area}{Perimeter^2}$
7. *Average Pixel Value*: Mean pixel value of the object in the gray scale image
8. *Standard Deviation of Pixel Value:* Standard deviation of pixel values of the object in the gray scale image

Perimeter and area captures the size attributes of the object and features from 3 to 6 capture shape attributes. Features 7 and 8 are intended to capture the spectral attributes of the object.

5. RESULTS AND DISCUSSIONS

Our data set for classification comprises 131 objects extracted from 28 high-resolution satellite images. The segmentation applied on the 28 images produces 131 objects. We manually label them to get 46 aircraft and 85 non-aircraft objects and compute all the 8 features for each object. Out of the 131 objects, 84 objects (31 aircraft and 53 non-aircraft objects) are used for training the classifiers and 47 objects (15 aircraft and 32 non-aircraft objects) are set aside for testing the classifiers. The training objects are from 19 of the 28 images and test objects are from 9 images.

5.1 Classification using *k*NN

For classification we first use *k*NN with equal weights. Experiments are carried out for different values of *k* using Euclidean as well as cosine distances. The response is plotted in Figure 4. Best accuracy of 80.9% is obtained for $k = 3$ with Euclidean distance for test data. So we use *3*NN with Euclidean distance in our experiments. Table 1 shows the confusion matrix of *3*NN corresponding to the training as well as test data sets.

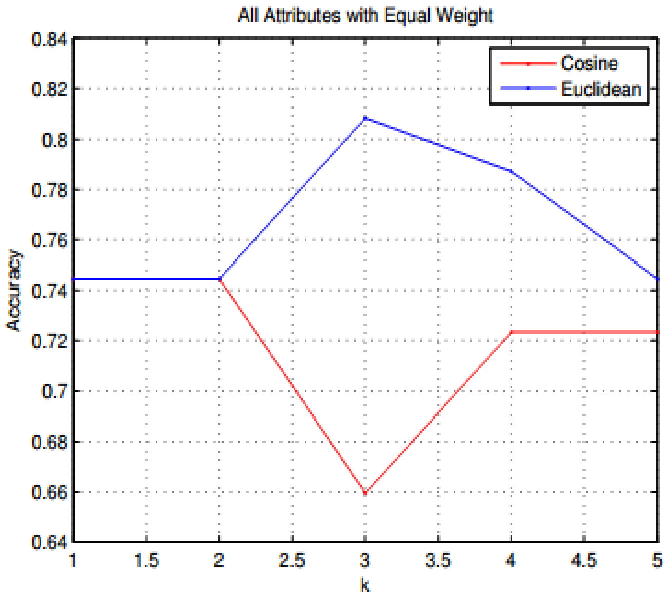


Figure 4. Determination of Optimal *k* Value of kNN

Table 1. Confusion Matrix for 3NN Classifier

	Predicted Class			
	Training Dataset		Test Dataset	
Actual Class	*Aircraft*	*Non- Aircraft*	*Aircraft*	*Non- Aircraft*
Aircraft	26	5	10	5
Non- Aircraft	5	48	4	28

5.2 Classification using SVM

Using SVM, an accuracy of 93.6% is obtained on test data. Linear SVM (Cortes, 1995) is used in the experiment. Table 2 shows the confusion matrix for SVM corresponding to training as well as test data sets.

Table 2. Confusion Matrix for SVM Classifier

	Predicted Class			
	Training Dataset		Test Dataset	
Actual Class	*Aircraft*	*Non- Aircraft*	*Aircraft*	*Non- Aircraft*
Aircraft	27	4	13	2
Non- Aircraft	4	49	1	31

Compared to *k*NN, SVM shows better accuracy. For the test data the number of false positives reduced from 4 in case of *3*NN to 1 for SVM. Also false negatives with *3*NN is 5 whereas it is 2 with SVM. The performance measures for the classifiers are shown in Table 3. Recall is the percentage of aircraft objects correctly recognized out of the total set of aircraft objects. Precision is the percentage of actual aircraft objects out of the total set of objects recognized as aircrafts. Accuracy is the overall percentage of objects (aircraft as well as non-aircraft) correctly recognized.

Table 3: Performance Measures for the Classifiers

	3NN		SVM	
Measures	*Training*	*Test*	*Training*	*Test*
Recall	83.9%	66.7%	87.1%	86.7%
Precision	83.9%	71.4%	87.1%	92.3%
Accuracy	88.1%	**80.9%**	90.1%	**93.6%**

Sample outputs with objects detected using SVM are shown in Figure 5. Green bounding rectangles are the output from our system and red ellipses indicate the error cases. In Figure 5(a), aircraft is detected in a clear image with strong shadows. Figure 5(b) shows detection of aircraft in dark background. In Figure 5(c) one aircraft is detected correctly, however there is a false positive. Figure 5(d), (h), (i) all are true positive cases. In Figure 5(e) one aircraft is missed out in LAS since it is darker. Figure 5(f) indicated false negatives case, as LAS could not segment it right. False negative case due to clutter is shown in Figure 5(f).

Our method gives good result if the objects are not occluded or cluttered. It is orientation independent and works in the presence of shadow. For the LAS segmentation we assumed lighter objects against darker background. So darker aircrafts are not detected (Figure 5(e)). The false positive cases (Figure 5(c)) can be avoided by refining the feature space. In the false negative case (Figure 5(f)) where two aircraft are classified as non-aircraft, segmentation did not produce good result. Cluttered objects with overlapping bounding rectangles also degrade the result (Figure 5(g)). Improving the quality of segmentation and refining the feature space can help get a better recall and precision of the detection of aircrafts.

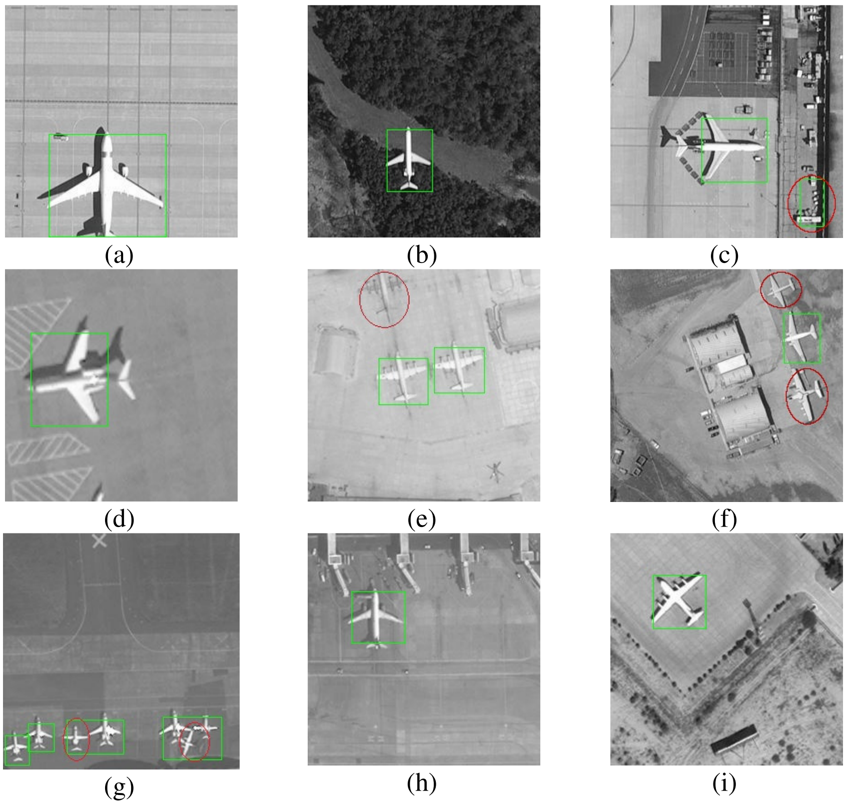


Figure 5. Detection using SVM

Interestingly, the method tries to capture size, shape and spectral properties of the object in the learning and classification process. Hence it will work well for targets other than aircraft too if they have distinctive shapes. The current data set has a limitation of not having mix of civilian, military and cargo aircraft.

6. CONCLUSION

In this paper we present a method for detection of aircraft from high-resolution satellite images using an object-based image classification method. The method segments the image into objects using a novel localized adaptive segmentation algorithm. Six structural and two spectral features are then computed for each object. Finally, suitable classifiers are trained with features from known objects to get the target detection system. Experiments with *k*NN and SVM classifiers show that SVM gives a better accuracy of 93.6% on the test data. From the results we conclude that, common segmentation algorithms do not produce the desired results for high-resolution satellite images. The proposed Localized Adaptive Segmentation algorithm, in comparison, performs well.

The proposed method works well if the aircraft are cleanly separated. If bounding rectangles of the aircraft overlap then the quality of the result degrades. The method can be improved by tuning the three stages - Segmentation, Classification and Enhancement of the feature data base. In future work, we are planning to enhance the feature space by augmenting with additional shape and spectral features such as moment of inertia along axis in XY plane and discrete Fourier transform (DFT) coefficients of 16 bin histogram. Further the proposed method can be extended to compute the orientation and count of each type of aircraft in a satellite image. It can be extended to associate contextual validations in the detection process and for detection of other types of targets.

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