Defence Science Journal, Vol. 63, No. 3, May 2013, pp. 298-304, DOI: 10.14429/dsj.63.2737

Automatic Bright Circular Type Oil Tank Detection Using Remote Sensing Images

N.K. Kushwaha, D. Chaudhuri*, and M.P. Singh

Defence Electronics Applications Laboratory, Dehradun–248 001, India
**E-mail: deba_chaudhuri@yahoo.co.in*

ABSTRACT

Automatic target detection like oil tank from satellite based remote sensing imagery is one of the important domains in many civilian and military applications. This could be used for disaster monitoring, oil leakage, etc. We present an automatic approach for detection of circular shaped bright oil tanks with high accuracy. The image is first enhanced to emphasize the bright objects using a morphological approach. Then, the enhanced image is segmented using split-and-merge segmentation technique. Here, we introduce a knowledge base strategy based on the region removal technique and spatial relationship operation for detection of possible oil tanks from the segmented image using minimal spanning tree. Lastly, we introduce a supervised classifier, for identification of oil tanks, based on the knowledge database of large amount data of oil tanks. The uniqueness of the proposed technique is that it is useful for detection bright oil tanks from high as well as low resolution images, but the technique is always better for high-resolution imagery. We have systematically evaluated the algorithm on different satellite images like IRS – 1C, IKONOS, QuickBird, and CARTOSAT – 2A. The proposed technique is detected bright structures but unable to detect the dark structure. If the oil tank structures are bright relative to the background illumination in the image then the detection accuracy by the proposed technique for the high resolution image is more than 95 per cent.

Keywords: Automatic recognition, remote sensed image, resolution, supervised technique, clustering, segmentation, minimal spanning tree

1. INTRODUCTION

Features extraction from satellite/aerial imagery is an important task in many applications that rely on geographic information systems (GIS). At present, remotely sensed images are extensively used in the field of target recognition. In recent years, numerous achievements occurred in the field of object recognition[1-6], such as roads, buildings, planes, ships, oil storage tanks and bridges due to the availability of high resolution data. Various computer assisted recognition and extraction algorithms are presented in field of target recognition and extraction, such as neural networks, wavelet transform, image segmentation, mathematical morphology and genetic algorithm; most of which are based on low-resolution remotely sensed images. In recent years, high-resolution remotely sensed images have become one of the most important products, because they are not as expensive as before and they have some characteristics such as tremendous data, complex feature details and dependence on scale. Thus algorithms based on high resolution remote sensing images are necessary and helpful in extraction. However, few generalized algorithms are available in the literature which aim at recognizing oil storage tanks, especially making use of high-resolution remotely sensed images. Further, high-resolution images still have some disadvantages, such as too many information to find a particular object.

How to detect ground objects by pattern recognition and automatic cartography is worth to be paid attention. Oil tanks are one of the essential elements on the large-scale map. So how to detect them automatically is important for many domains such as disaster monitoring, oil leakage, land environment and mapping. Some automatic oil tank detection algorithms are available in the literature[14]. In these algorithms, template matching[7] and Hough transform[8] are often used to detect oil tanks automatically. But template matching algorithm needs much time. On the other hand, chosen template is affected by many factors such as template scale and rotation. So the technique has low detection measure and it is very hard job to find uniform template. Oil tanks have circular feature in the remote sensing image so Hough transform may be used to detect them[9,10]. But many other factors such as illumination condition, material, structure and types of oil tanks make them undistinguishable in the image. If the features of oil tanks are not achieved fully, they are not detected by Hough transform. So Hough transform doesn't improve oil tanks detection ratio very well.

Zhang[11], *et al*. proposed an automatic oil tank detection algorithm based on image fusion. First, the features of ground objects are improved by fusion. The fused image is then used for detection of oil tank by multiple steps algorithm in their paper, which integrates improved Canny algorithm, improved

Received 10 October 2012, revised 24 December 2012 online published 16 May 2013

ellipsoid Hough transform algorithm and fast matching. Wang[12], *et al*. suggested an automatic circular oil tank detection algorithm using both SAR and optical images. First, the bright areas are extracted from the SAR image to obtain the candidate regions for oil tanks. Second, shape detection is performed in the optical image on those corresponding candidate areas. So for the oil tank detection method proposed by Wang[12], *et al*. both SAR and optical images are required. Thus, an additional step to register both images is necessary. Sometimes, it is difficult to collect the ground control points, resulting in reduced accuracy of the registration process. In addition, the availability of both sensor images for the same time period is questionable. Qiang[13], *et al*. suggested an approach based on image fusion and mathematical morphology for dim target detection from remote sensing images.

This paper presents a method to extract bright oil tanks from low as well as high resolution panchromatic images using a multi-step approach. The main contributions in the proposed method are:

- Morphological based enhancement technique to enhance the possible targets;
- Split-and-merge segmentation technique based on region homogeneity and heterogeneity factors to segment the possible targets;
- Knowledge base strategy for reducing false alarm based on region removal technique and spatial relationship operation and
- Supervised classification for detection of oil tanks based on the analyses of their statistical, texture and other features information by collecting large amount data of oil tanks to customize a knowledge database.

2. OIL TANK DETECTION ALGORITHM

The focus of this paper is the detection of bright oil tank from the high resolution satellite images. Our approach is designed to effectively extract the targets using a six step process as shown in Fig. 1.

- *Image enhancement*: In this step, the target features are enhanced using mathematical morphology.
- *Segmentation*: Split-and-merge clustering technique is used for segmentation of the enhanced image.
- *Region removal* (*area based filtering*): In this step, many regions, which do not correspond to our targets based on area, are removed.
- *Region removal* (*Elongatedness and circularity measure based filtering*): The remaining regions are removed based on elongatedness and circularity measures.
- *Spatial relationship operation*: Unwanted target type regions are removed to obtain actual target using minimal spanning tree (MST)[21] based clustering technique.
- *Supervised classifier*: In this step, a supervised classifier is used for identification of confirmed oil tanks based on the knowledge database of large amount data of oil tanks.

The details of the steps are given below.

2.1 Enhancement technique

The main purpose of enhancement is to improve the contrast of the target features in order to facilitate their downstream recognition. A good enhancement operator will significantly increase the brightness of bright oil tanks in the original image but has no effect on non-target pixels. We propose an enhancement technique based on mathematical morphology[15] that is combined Top-Hat with Bot-Hat algorithms.

This method is a partial preprocess that is output new gray of pixel according to a small neighborhood. Top-Hat transform is difference from original image to opened image which can extract higher gray area considered as object area. Bot-Hat transform is different from original image to closed image which can extract lower gray area considered as background area. We use original image add Top-Hat image, and then minus Bot-Hat image, we get enhanced image at last.

$Top\_Hat = f - (f \circ b)$, $Bot\_Hat\ (f \bullet b) - f$ and

$I = f + Top\_Hat - Bot\_Hat$

where f, b and I are the original image, unit template (structuring element) and enhanced image, respectively.

2.2 Segmentation

Segmentation is the process of partitioning an image into

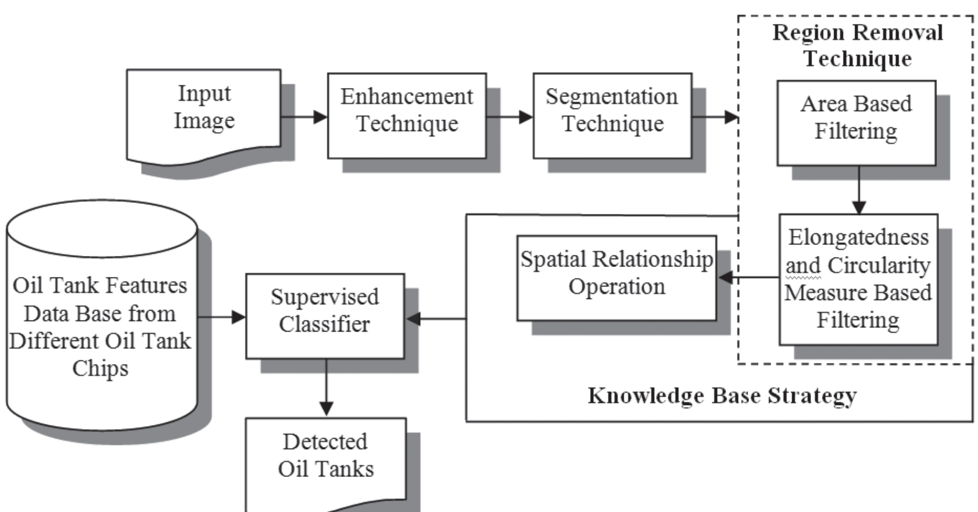


Figure 1. Schematic of the proposed algorithm.

distinct regions such that each region is homogeneous but the union of two adjacent regions is not. In this paper, we have implemented our previous split-and-merge segmentation procedure[16] for segmentation of the enhanced image. The conventional split-and-merge algorithm is lacking in adaptability to the image semantics because of its stiff quad tree based structure. Author in his paper, an automatic thresholding technique based on bimodality detection approach with non-homogeneity criterion is employed in the splitting phase of the split-and-merge segmentation scheme to directly reflect the image semantics to the image segmentation results[16].

The splitting technique is based on bimodality detection approach in recursive way until the homogeneous region is detected. This threshold method can segment the image of two regions well, the chosen optimum threshold k' (*bimodality parameter*) can segment the image into two classes, say I_0 and I_1 effectively, therefore the original image $I = I_0 \cup I_1$. But when there are many classes (more than one) in the image, the above method will fail to segment the image. In this situation multi-level threshold technique is needed to segment the image. Based on this automatic threshold method, we propose a recursive automatic multi-level threshold algorithm for splitting the image.

Let $f_i, i = 0,1,...,L–1$ be the gray level value of the image I and $h_i, i = 0,1,...,L–1$ be the corresponding frequency of $f_i, i = 0,1,...,L–1$ in the image. Here, the measure of homogeneity is defined as the standard deviation (Sd) with respect to mode. If $Sd > T_1$ (where T_1 is the predefined threshold) then the region is a non-homogeneous. Initially, assume that the original image is non-homogeneous. Segment the original image I by above two-level threshold method. The obtained threshold k' of the original image I with gray level [0, L-1] can segment the original image into two regions I_0 with gray level [0, k'] and I_1 with gray level $[k'+1, L-1]$. So, $I = I_0 \cup I_1$. Again we recursively segment both the regions I_0 and I_1 by above two-level bimodality detection threshold approach if they are not satisfies the homogeneity criteria. Let I_0 will be partitioned into I_{00} and I_{01}, and $I_0 = I_{00} \cup I_{01}$. Similarly, I_1 will be partitioned into I_{10} and I_{11}, and $I_1 = I_{10} \cup I_{11}$. In the same way, continue to perform segmentation on I_{00}, I_{01}, I_{11} and I_1, so $I = I_0 \cup I_1 = I_{00} \cup I_{01} \cup I_{10} \cup I_{11} = \dots$. Therefore, the whole segmentation process is to segment gray level image recursively, until no region is left for segmentation.

Since the splitting technique depends upon homogeneity factor, some of the splitted regions may or may not split properly and rechecked through merging technique between the two adjacent regions to overcome the drawback of the splitting technique. In our paper, we have introduced a sequential arrange based or a minimal spanning tree based approach, that depends on data dimensionality of the weighted centroids of all splitted regions for finding the pairwise adjacent regions. Finally, to overcome the problems caused by the splitting technique, a novel merging technique based on the density ratio of the adjacent pair regions have been suggested[16].

2.3 Knowledge Base Strategy

The image is segmented into different regions by the above split-and-merge segmentation technique. After segmentation, we need to get further object recognition according to geometry features of the objects. In this paper, the interesting object is bright oil tank in satellite based remote sensing images. In remote sensing images, oil tanks have obviously different gray value from background. Their sizes (number of pixels) are lies between A_l and A_u, where A_l and A_u are the lower and upper area thresholds. Furthermore, there is no single oil tank and oil tanks are arranged tightly and in order. All these arguments are important criteria for recognition of oil tank.

2.3.1 Region Removal Technique

The result of segmentation is a set of disjoint regions with different clusters that covers the image. Because our segmented image is multi-level clustered image (as the number of clusters), we have implemented a specialized recursive scanning algorithm[17] that is fast and efficient for our application.

In our recursive scanning method, we begin by selecting a pixel with label 1 (say cluster number 1) and label it is 'marked'. The procedure simultaneously looks for all other pixels in its 3×3 neighborhood and marks them if they are also cluster 1. This is a variation of the region growing method, but growing and marking take place in all directions within a 3×3 window simultaneously. Once the pixel is 'marked' it will not be considered in the search procedure. Therefore, this method is very fast. Unlike many other growing methods, this method is independent of a starting point, and there is no requirement to select suitable properties for including points in the various regions during the growing process, except to check for considering cluster number label. The procedure terminates when all regions of all clusters of the segmented image are 'marked'.

After the regions are labeled of each cluster, we compute some shape features. Our goal is to identify oil tank. Three shape parameters, namely, area (A), elongatedness (E) and circularity measure (M) are used to remove unwanted regions, which are not possible oil tanks. Some mathematical formulations, which are used in the next few sub-sections, are described as below.

Let $C_1, C_2, \dots, C_k$ are k number clusters of the segmented image. Let n_j (j=1,2,…,k) be the number of regions of cluster C_j (j=1,2,…,k). Let $R_i(C_j)$ be the i-th region of C_j cluster, where i=1,2,…,n_j and j=1,2,…,k. So the following properties are obviously satisfied.

1. $R_i(C_j) \neq \phi, \ \forall i, j$
2. $R_i(C_j) \bigcap R_m(C_l) = \phi$ if $i \neq m$ and $j \neq l$
3. $R_i(C_j) \bigcap R_i(C_l) = \phi$ if $j \neq l$
4. $R = \bigcup_{j=1}^{k} \bigcup_{i=1}^{n_j} R_i(C_j)$

2.3.1.1 Area based filtering

Now area is computed in straightforward manner i.e. number of pixels of a region. Let $A[R_i(C_j)]$ be the area of i^{th} region and j^{th} cluster. If $A_l \leq A[R_i(C_j)] \leq A_u$ then the corresponding cluster region is considered as possible oil tank. Otherwise the cluster region is not considered as oil tank and this unwanted region is removed. A_l and A_u are the predefined lower and upper area thresholds, respectively. The threshold values A_l and A_u depends on the sensor resolution. Those values for low resolution image are obviously less than the values for high resolution. It is very difficult to say analytically regarding the values of A_l and A_u from an image. Through extensive experimentation we have determined values of A_l and A_u between 10 and 55 for low resolution image and the same in between 15 and 150 for high resolution give the good results.

2.3.1.2 Elongatedness

To compute the elongatedness, we first compute the center of the region $R_i(C_j)$. If the center of the region does not lie inside the region, we choose the nearest point to be the center. We then compute the maximum and minimum distances from the center to the boundary points of $R_i(C_j)$. We define elongatedness as elongatedness(E)=$d_{max} - d_{min}$, where $d_{\max}$ and $d_{\min}$ are the maximum and minimum distances from the center of the boundary of the region $R_i(C_j)$. If $d_{\min}$ is zero, then we take the average of the 5 per cent of the nearest pixels to the region boundary. It is obviously that when $R_i(C_j)$ is more threadlike, then $E[R_i(C_j)]$ is larger and when $R_i(C_j)$ is round, then $E[R_i(C_j)]$ is equal to zero.

2.3.1.3 Circularity measure

The circularity measure is used to describe departure quantity between the object $R_i(C_j)$ and round, which is defined as[19]:

$$M[R_i(C_j)] = \frac{\text{Total non-matching area}}{\text{Matching area}}$$

$$= \frac{\#\left[\left(R_i(C_j)\cup Cir\right)-\left(R_i(C_j)\cap Cir\right)\right]}{\#[R_i(C_j)\cap Cir]}$$

where Cir is the area of the optimal fitted circle[18] i.e. the number of points inside the circle including the boundary points.

Now we have deleted the unwanted regions based on the values elongatedness (E) and circularity measure (M). An object $R_i(C_j)$ will be removed if both $E[R_i(C_j)] > T_E$ and $M[R_i(C_j)] > T_M$, where T_E and T_M are the predefined elongatedness and circularity measure threshold values, respectively. In ideal case for round shape, both the parameters elongatedness and circularity measure are zero. It is obvious that both the values T_E and T_M are very small. The optimal constant values T_E and T_M were determined experimentally to be 0.1 and 0.06, respectively.

We have considered these three parameters area (A), elongatedness (E) and circularity measure (M) as criterion for estimating circular shape object detection. After detecting all circular shape regions from all clusters C_j (j=1,2,…,k), then we have converted the possible oil tanks image into the binary image as targets and non-targets. Next, we have applied minimal spanning tree (MST)[21] based clustering technique in the binary image for formation of clusters of the circular shape objects. This procedure, spatial relationship is also a part of knowledge base strategy.

2.3.2 Spatial Relationship

Generally, oil tanks are arranged tightly and formed clustered. Thus, based on this knowledge, we have developed a MST based clustering algorithm for finding the group of possible oil tanks.

Assume that there are finally PR_j, j=1,2,…,k possible oil tanks regions of the binary image. Let $(x_{j,i}, y_{j,i})$, i=1,2,…,m_j be the m_j points of j-th region PR_j, where j=1,2,…,n. The centroid of j-th region, $(\overline{x}_j, \overline{y}_j)$, is given by

$$\overline{x}_j = \frac{1}{m_j}\sum_{i=1}^{m_j} x_{j,i} \;, \overline{y}_j = \frac{1}{m_j}\sum_{i=1}^{m_j} y_{j,i} \;\; ; j = 1,2,...,n$$

We begin our clustering operation with the computation of the centroids of each region. Using the centroids as nodes in a graph, we compute the MST. The Euclidean distance between two connecting nodes is used as weights for the edges in the graph. MST gives the connectivity of these centroids. If the edge weight of the two connected regions is greater than T_{ED} then those regions are separated; otherwise they are in the same cluster. The threshold value T_{ED} depends on the resolution of the data. When there are less than 2 objects within a cluster then remove those clusters. We have experimentally determined the threshold value T_{ED} to be 10 and give the good arranged cluster.

2.3.3 Supervised classifier

We have already recognized possible oil tanks. These oil tanks might belong to different objects similar to oil tanks, so we should classify these objects. We have developed a supervised classifier for classification of the oil tanks from the possible oil tanks image.

Like most remote sensing applications, we begin our analysis with an initial ground cover classification. Supervised classification is widely used to accomplish this task. One of the critical issues that directly affect the accuracy of classification is the choice of the training data. First we have collected image target chips which are oil tanks from many known images. Then we have extracted 15 features such as minimum gray value, maximum gray value, mean, variance, mode contrast ratio, different texture parameters[20] etc from those known target chips. We set these features as input parameters of our classifier. Let O_F be the set of all target features. The same 15 dimensional features are calculated from each possible oil tanks of the output image after spatial relationship removal technique and computed the minimum distance among all features of the set O_F. If the minimum distance of a possible oil tank is less than the predefined threshold value T_C then the object is a confirm oil tank. Since the classifier is a minimum distance classifier, it is obvious that the corresponding to minimum distance feature is the type of oil tank. But many similar objects like oil tanks in the output image of spatial relationship removal technique frame may be classified as oil tank unless some threshold is introduced. It is true that the minimum distance of similar object like oil tank is much greater than the actual tank but T_C will determined the actual oil tank. We have experimentally determined the threshold value T_C to be 0.3 for low as well as high resolution images.

3. EXPERIMENTAL RESULTS

To test the effectiveness of the approach, we use the panchromatic images obtained using the IRS – 1C, IKONOS,

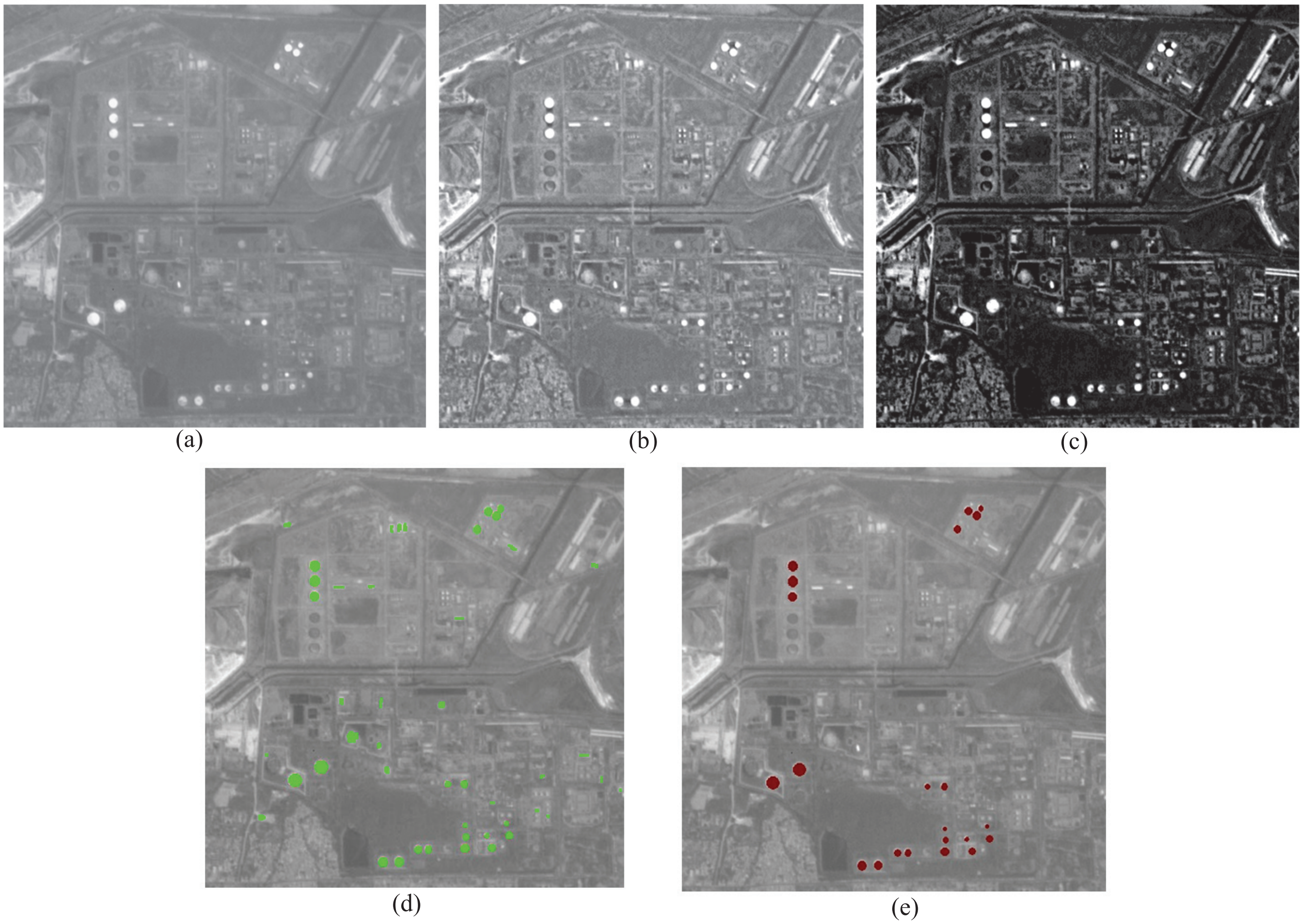


Figure 2. IRS – 1C Panchromatic image (a) original image, (b) enhanced image, (c) segmented image, (d) possible oil tanks and (e) final output.

QucickBird and CARTOSAT – 2A satellites. Fig. 2 (a) shows an original IRS – 1C satellite panchromatic image of size 512 × 512. The enhanced image using the proposed enhancement technique is shown in Fig. 2(b). It is clear that the bright structures in Fig. 2(b) are enhanced in comparison to the original bright structures in Fig. 2(a). Figure 2(c) shows the image after segmentation. The image after removal the unwanted regions using area based, elongatedness and circularity measure filtering is shown in Fig. 2 (d) and the possible oil tanks are highlighted with green color. The result in Fig. 2(d) shows the presence of many other oil tanks like object associated with actual oil tanks. Such oil tanks like objects are removed by the spatial relationship operation and supervised classifier. The final oil tanks are highlighted with pink color and shown in Fig. 2 (e).

Figure 3(a) shows CARTOSAT – 2A satellite panchromatic

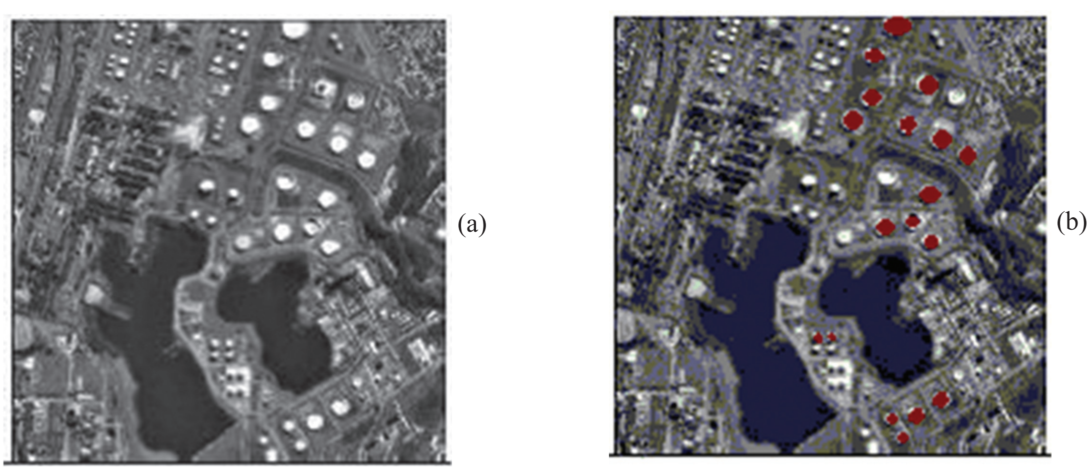
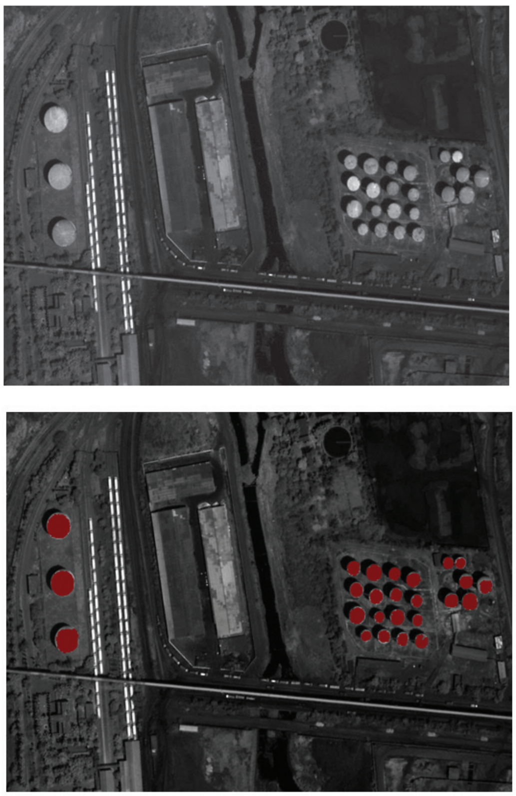


Figure 3. CARTOSAT – 2A panchromatic image (a) original image and (b) final output.

image of size 166×166 and the final oil tanks are highlighted with pink colors and shown in Fig. 3(b). Both the above results show that the precise of oil tank classify in IRS – 1C and CARTOSAT – 2A satellites remote sensing images is between 70 per cent and 86 per cent. The detection capability from IRS – 1C satellite images is poor due to the poor resolution. Though the quality of the image is not good but the proposed technique is detected oil tanks more accurately from CARTOSAT – 2A satellite image because of improved resolution.

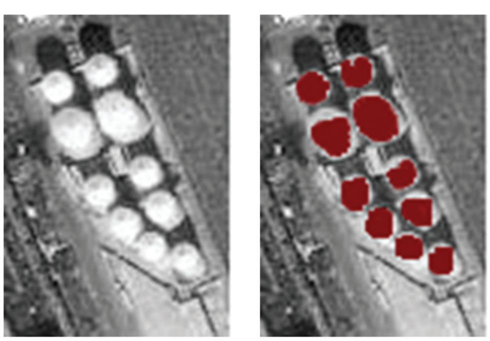
Other high resolution panchromatic images from IKONOS and QuickBird satellites are shown in Fig. 4(a) and Fig. 5(a) of sizes 900×600 and 76×107, respectively. The quality and resolutions for both the images are good. The proposed technique detected oil tanks very correctly from both the images. Both the results show that the precise of oil tank classify in IKONOS and QuickBird satellites remote sensing images is almost 100 per cent. The final results are shown in Fig. 4(b) and 5(b) for IKONOS and QuickBird satellites images.



(a)

(b)

Figure 4. IKONOS Panchromatic image (a) original image and (b) final output.



(a) (b)

Figure 5. QuickBird Panchromatic image (a) original image and (b) final output.

4. CONCLUSIONS

We have presented an automatic approach for circular type bright oil tank detection from high resolution panchromatic remotely sensed imagery. There are many civilian, commercial, and military applications for this problem. The main steps in our algorithm are: image enhancement, segmentation, knowledge base strategy and supervised classifier. The image is first enhanced to highlight the bright objects using a morphological approach. Then the enhanced image is segmented using split-and-merge segmentation technique. We have presented a knowledge base strategy based on the region removal technique and spatial relationship operation for detection of possible oil tanks from the segmented image. Finally, we have introduced a supervised classifier for identification of oil tanks based on the knowledge database of large amount data of oil tanks. The proposed algorithm was evaluated using IRS – 1C, IKONOS, QuickBird and CARTOSAT – 2A satellites panchromatic images. The proposed technique has been correctly and accurately detected oil tanks from good quality and high resolution panchromatic images.

REFERENCES

1. Wang, Y. Extraction of road from remote sensed image based on mathematical morphology. Information Technology University of CPR, 2004.
2. Chaudhuri, D.; Kushwaha, N. K. & Samla, A. Semi-automated road detection from high resolution satellite images by directional morphological enhancement and segmentation technique. *IEEE J. Sel. Topics Appl. Earth Observations Remote Sens.*, 2012, **5**(5), 1538-1544.
3. Chaudhuri. D.; Smala, A.; Agrawal, A.; Sanjay; Mishra, A.; Gohri, V. & Agarwal, R. C. A statistical approach for automatic detection of ocean disturbance features from SAR images. *IEEE J. Sel. Topics Appl. Earth Observations Remote Sens.*, 2012, **5**(4), 1231-1242.
4. Theng, L. B. Automatic building extraction from satellite imagery. *Eng. Letters*, 13:3, EL_13_3_5 (Advance online publication), 4 November, 2006.
5. Xiaoying, J. & Davis, C. H. Automated building extraction from high-resolution satellite imagery in urban areas using structural, contextual and spectral information. *J. Appl. Signal Process.*, 2005, **14**, 2196–2206.
6. Khoshelham, K.; Nardinocchi, C.; Frontoni, E.; Mancini, A. & Zingaretti, P. Performance evaluation of automated approaches to building detection in multi-source aerial data. *ISPRS J. Photogrammetry Remote Sens.*, 2010, **65**, 123–133.
7. Gonzalez, R. C. & Woods, R. E. Digital Image Processing. Pearson Education, Delhi, India, 2008.
8. Illingworth, J. & Kittler, J. A survey of the Hough transform computing. *Vision Graphics Imasge Process.*, 1988, 87-116.
9. Wei, Y. Improved dynamic broad sense Hough transform and its application on round detection. *Surveying Mapping Inf. Eng.*, 1998, **4**, 23–26.

10. Wang, Q. A high speed Hough transform algorithm for circle detection. *Minimicro System-Shenyang,* 2000, **21**(9), 970–974.
11. Zhang, W.; Zhang, H.; Wang, C. & Wu, T. Automatic oil tank detection algorithm based on remote sensing image fusion. *In* the IEEE International Geoscience and Remote Sensing Symposium (*IGARSS*), 2008, **6**, pp. 3956–3958.
12. Wang, Y.; Tang, M.; Tan, T. & Tai, X. Detection of circular oil tanks based on the fusion of SAR and optical images. *In* the Third International Conference on Image and Graphics (*ICIG*), 2004, pp. 524–527.
13. Qiang, Z.; Du, X. & Sun, L. Remote sensing image fusion for dim target detection. *In* the International Conference on Adv. Machatronic Syst. (*ICA Mechs*), 2011, pp. 379 –383.
14. Zhu, C.; Liu, B.; Zhou, Y.; Yu, Q.; Liu, X. & Yu, W. Framework design and implementation for oil tank detection in optical satellite imagery. *In* the IEEE International Geoscience and Remote Sensing Symposium, Munich, Germany. THP.P11, 22–27 July 2012.
15. Serra, J. Image Analysis and Mathematical Morphology, New York: Academic, 1982.
16. Chaudhuri, D. & Agrawal, A. Split-and-merge procedure for image segmentation using bimodality detection approach. *Def. Sci. J.*, 2010, **60**(3), 290– 301.
17. Chaudhuri, D. & Samal, A. An automatic bridge detection technique for multi-spectral images. *IEEE Trans*. *Geosci. Remote Sensing*, 2008, **46**(9), 2720–2727.
18. Chaudhuri, D. A simple least squares method for fitting of ellipses and circles depends on border points of a two-tone image and their 3-D extensions. *Pattern Recognition Letters*, 2010, **31**, 818–829.
19. Chaudhuri, D.; Kushwaha, N. K.; Sharif, I. & Gohri, V. Unique measure of geometrical shape object detection based on area matching. *Def. Sci. J.*, 2012, **62**(1), 58–66.
20. Haralick, R. M.; Shanmugam, K. & Dinstein, I. Texture features for image classification. *IEEE Trans*. *Systems*, *Man Cybern.*, 1973, **3**, 610 – 621.
21. Cormen, T. H.; Leiserson, L. E.; Rivest, R. L. & Stelin, C. Introduction to algorithm, Prentice Hall of India Pvt. Ltd., Eastern Economy Edition, New Delhi, 2002.

Contributors

Mr N.K. Kushwaha received BTech (Computer Sci. Eng.) from Indian Institute of Technology, Kanpur in the year 2009. Presently he is a scientist at Defence Electronics Applications Laboratory (DEAL), Dehradun. His fields of interest include: Image processing, pattern recognition, computer vision and remote sensing.

Dr D. Chaudhuri received MSc (Applied Mathematics) from Jadavpur University, Kolkata, in 1987 and PhD from Indian Statistical Institute, Kolkata in 1994. Currently working as a Scientist at DEAL, Dehradun, India. He has published over 45 papers in international journals and conferences. He is a fellow of IETE. His research interests include: Image processing, pattern recognition, computer vision, remote sensing, and target detection from satellite imagery.

Mr M.P. Singh received BTech (Computer Science and Engineering) from Institute of Engineering andTechnology, Lucknow in the year 2007. Presently working as a scientist at DEAL, DRDO, Dehradun. His fields of interest include: Image processing, pattern recognition, remote sensing and polarimetric SAR image processing.