Object Detection from the Satellite Images using Divide and Conquer Model

Lakhwinder Kaur, *Guru Kashi University*
Er.Vinod Kumar Sharma *(Assistant professor), Guru Kashi University*

Abstract - *Object detection is the technique of detection of the object type is sub-type of automatic computer vision. This is a growing research area. Object detection in oceans is called oceanology or oceanological computer vision. In the oceans, the object detection is used to find the information about the ships, Islands and other objects. The ocean imaging is done by the satellites and falls under the SAR or aerial imaging category. In this paper, we are proposing a new method of object detection by using the shape and color analysis, followed by divide and conquer model. The proposed algorithm can be used to detect the crashed aeroplanes, floating containers and many other objects. The proposed system can be used to find any physical object whose colour pattern and shape can be specified (known). Proposed system will be produce accurate results than any existing object detection algorithm. Proposed algorithm will perform more in-depth analysis because it uses the combination three popular approaches: object based analysis, pixel based analysis and shape based analysis.*

Keywords: *object based analysis, pixel based analysis, shape analysis, ship detection, debris detection*

INTRODUCTION

Object recognition refers to the ability of a computer system to locate a specific object in an image or video sequence in order to solve a specified task. While this process may seem trivial to any human, computer vision requires large memory and graphic capabilities in order to function. This paper will review some of the state of the art technologies available (as well as their costs), describe how the underlying technology works, and explain how the systems can be implemented.

Object detection is the technique of detection of the object type is sub-type of automatic computer vision. This is a growing research area. Object detection in oceans is called oceanology or oceanological computer vision. In the oceans, the object detection is used to find the information about the ships, Islands and other objects. The ocean imaging is done by the satellites and falls under the SAR or aerial imaging category. In this paper, we are proposing a new method of object detection by using the shape and color analysis, followed by divide and conquer model. The proposed algorithm can be used to detect the crashed aeroplanes, floating containers and many other objects. The proposed system can be used to find any physical object whose colour pattern and shape can be specified (known). Proposed system will be produce accurate results than any existing object detection algorithm. Proposed algorithm will perform more in-depth analysis because it uses the combination three popular approaches: object based analysis, pixel based analysis and shape based analysis.

There are two main techniques used for object recognition. The first is the model-based approach, and the second method is known as appearance-based object recognition. The model-based approach uses multiple algorithms and has high memory storage requirements. Simply put, the program uses any number of algorithms to perform complex visual pattern recognition, pattern matching, feature matching, and/or boundary detection in order to extract the information from an image shown to the camera so that the information can be stored into a database for future use. One algorithm, in feature matching, can calculate the shape and positioning of a person's facial features then extract the information from the database to match the features with the current image being captured by a camera.

Appearance-based object recognition is a much simpler approach mainly because the program uses a much smaller database that recognizes common shapes and colors in order to match the object with a model. The algorithms calculate the spectral frequency of the object's reflection to determine color since every color corresponds to a specific frequency. Since the appearance modeling used examples to correctly recognize an object according to their shape and color, this approach is also able to cope with many variations due to the image formation/rendering process such as a skewed viewing angle or low lighting in the area.

Edge Detection Methods: The edge detection methods are oriented to the detection of the significant edges in the image. Local edges are detected by edge detectors (e.g. Canny edge detection, see [15]) based on the difference of the pixels' color. Hough transform [16] finds imperfect instances of objects within a certain class of shapes by a voting procedure. The voting procedure uses object candidates that are obtained as local maxima in the so-called accumulator space. This space is explicitly constructed by the algorithm for computing the Hough transform.

Region Growing Methods: In comparison to the edge detection methods, these methods can better handle the noise in the analyzed image. Homogeneity of the regions is the main segmentation criterion for the region detection (gray levels, color, texture, shape, etc.). Split and merge technique [17] uses graph structures to represent the regions or boundaries.

Statistical Methods: The segmentation process starts with a statistical analysis of the image data. The structure of the corresponding information is usually discarded. These methods use thresholding, adaptive thresholding, component labeling, amplitude projection and clustering. Kohonen maps [18], also known as self-organizing maps (SOM), operate in two modes: training and mapping. Training builds the map using input examples, also called vector quantization. Mapping automatically classifies a new input vector.

Knowledge-based Methods: The knowledge related to the segmentation objects properties (shape, color, structure, etc.) is exploited in the detection process. These methods often use templates database. This database is automatically generated from the training data. Alternatively, the related information is inserted manually on the basis of human experience. During the segmentation, the algorithm is trying to transform the well-known objects or templates stored in the database to the objects belonging to the input image. This process is called atlas-warping. The object variability is the most degrading factor of the knowledge based methods. However, if the objects in the structure are similar, these methods are mostly very efficient. A representative method is Active Appearance Models (AAM, see [19]).

Hybrid Methods: This group of methods combines some of the above discussed ideas with other characteristics of the image obtained by means of Watershed transformation [20] or neural networks [21]. The method called fuzzy min-max neural network for image segmentation (FMMIS) grows boxes from a set of pixels called seeds, to find the minimum bounded rectangle.

LITERATURE SURVEY

Yasen Zhang et. al(2014) - presented a new technique to detect inshore ships using shape and context information. In this, a new energy function is proposed based on an model to fragment water and land and minimize it with an iterative global optimization method.

Thomas H et. al(2012) - presents a complicated problem at-sea detection of marine debris, as we know debris items are often relatively small and partially underwater. However, they may accumulate in water parcel boundaries or eddy lines.

Shivani Agarwal, et. al(2013) - assessed the potential of multi-spectral GeoEye imagery for biodiversity assessment in an urban context in Bangalore, India. Twenty one grids of 150 by 150 m were randomly located in the city center and all tree species within these grids mapped in the field.

Nagendra, Harini et. al(2008) – said that high resolution satellite remote sensing has been hailed as a very useful source of data for biodiversity assessment and monitoring, applications have been more developed in temperate areas. This paper examines issues related to hyperspatial and hyperspectral remotely sensed imagery, which constitutes one of the most potentially powerful yet underutilized sources of for tropical research on biodiversity.

Peter Hofmann et. al(2004) – presents that Remote sensing from airborne and spaceborne platforms provides valuable data for mapping, environmental monitoring, disaster management and civil and military intelligence.

Luc Van Gool et. al(2011) - introduces Hough forests which are random forests adapted to perform a generalized Hough transform in an efficient way. Compared to previous Hough-based systems such as implicit shape models, Hough forests improve the performance of the generalized Hough transform for object detection on a categorical level.

Liebelt et. al(2010) - presents a new approach for multi-view object class detection. Appearance and geometry are treated as separate learning tasks with different training data. Our approach uses a part model which discriminatively learns the object appearance with spatial pyramids from a database of real images, and encodes the 3D geometry of the object class with a generative representation built from a database of synthetic models.

PROPOSED MODEL

When an Aero-plane or ship undergoes accidents in the oceans, it is very difficult to spot the debris of those Aero-planes or ships due the size of the oceans. The only effective solution to spot the debris is satellite images. Existing technologies are not capable of differentiating between the debris and other materials when applied to the satellite images. This shows the lack in the technology of spotting the objects and marking the debris from the satellite images.

The objects from the satellite images can be spotted using various technologies like pixel based or object based approaches to detect the objects floating in the oceans. After the detection of objects in the oceans, there is a requirement of high quality object analysis to identify if spotted objects are debris of some missing plane or ship. There are a lot of object floating in the oceans, for example, containers dropped from ships, garbage dropped by ships, objects dragged to the oceans by natural hazards like sunami, twister, etc. The object based and color based approaches can be combined to create a new hybrid approach to spot and analyze the objects floating in the oceans using the high quality satellite images.

RESEARCH METHODOLOGY

We will start our research project by conducting a detailed literature review on oceanography and object detection from SAR images to know the problem in detail. Then, a detailed object analysis mechanism would be also studied to fulfil the requirements for object shape analysis in the debris detection and shape analysis algorithm design. The scenario is based on the object detection based on the object type and colour detection in the SAR images on the basis of divide and conquer algorithm. When an Aero-plane or ship undergoes accidents in the oceans, it is very difficult to spot the debris of those Aero-planes or ships due the size of the oceans. The only effective solution to spot the debris is satellite images. Existing technologies are not capable of differentiating between the debris and other materials when applied to the satellite images. This shows the lack in the technology of spotting the objects and marking the debris from the satellite images. The simulation would be implemented using MATLAB equipped with image processing toolbox. The obtained results would be examined and compared with the existing object detection mechanisms for oceans to address the similar issues.

DESIGN

Object detection is the technique of detection of the object type is sub-type of automatic computer vision. This is a growing research area. Object detection in oceans is called oceanology or oceanological computer vision. In the oceans, the object detection is used to find the information about the ships, Islands and other objects. The ocean imaging is done by the satellites and falls under the SAR or aerial imaging category. In this paper, we are proposing a new method of object detection by using the shape and color analysis, followed by divide and conquer model.

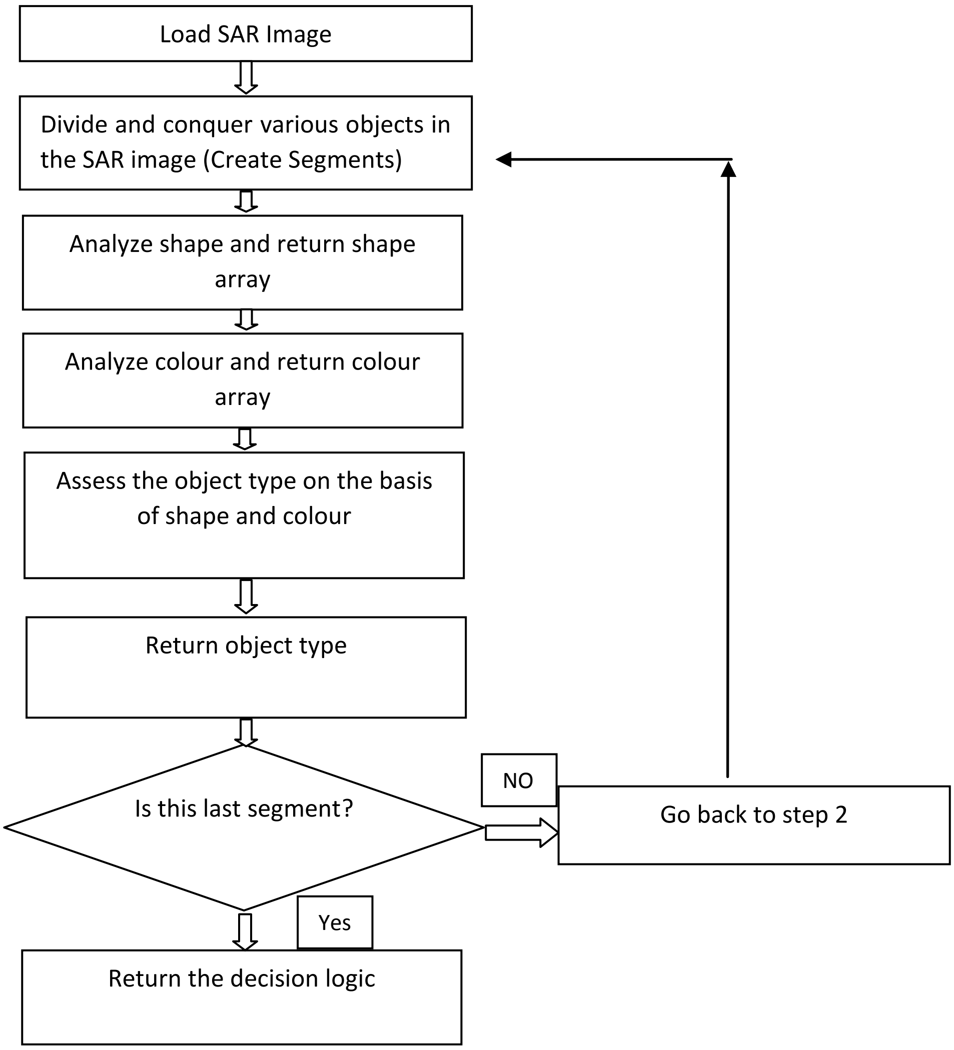

Figure 1.1: The basic working of the system

The proposed algorithm can be used to detect the crashed aeroplanes, floating containers and many other objects. The proposed system can be used to find any physical object whose colour pattern and shape can be specified (known). Proposed system will be produce accurate results than any existing object detection algorithm. Proposed algorithm will perform more in-depth analysis because it uses the combination three popular approaches: object based analysis, pixel based analysis and shape based analysis.

IMPLEMENTATION

The objects from the satellite images can be spotted using various technologies like pixel based or object based approaches to detect the objects floating in the oceans. After the detection of objects in the oceans, there is a requirement of high quality object analysis to identify if spotted objects are debris of some missing plane or ship. There are a lot of object floating in the oceans, for example, containers dropped from ships, garbage dropped by ships, objects dragged to the oceans by natural hazards like sunami, twister, etc. The object based and pixel based approaches can be combined to create a new hybrid approach to spot and analyze the objects floating in the oceans using the high quality satellite images.

The proposed system can be used to find any physical object whose colour pattern and shape can be specified (known). Proposed system will be produce accurate results than any existing object detection algorithm. Proposed algorithm will perform more in-depth analysis because it uses the combination three popular approaches: object based analysis, pixel based analysis and shape based analysis.

Algorithm 1: Proposed object detection algorithm

Assumptions:

1.) *All images are SAR images.*
2.) *All images are high resolution images.*
3.) *All images are of oceans only.*
4.) *Images do not contain any noise like clouds, etc.*
5.) *All images are colored images.*

Algorithm Flow:

1.) Load Image → I
2.) Segment(I) → $\sum_{i=0}^{n} S_I$
3.) For Each Segment
4.) objectShape(S_I{i}) → shapeArray
5.) objectColor(S_I{i}) → colorArray
6.) objectTypeAssessment(shapeArray,colorArray) → objectType
7.) if objectType is valid
    a. selectObject(S_I{i}) → object
    b. Return Object Type
8.) Else
    a. Return False
    b. Return Message → No object found
9.) If this the last segment
    a. Return 0
    b. Exit
10.) Else
    a. Return to step 3

RESULTS AND DISCUSSION

The proposed model has been thoroughly tested and evaluated for the results with various types of image of oceans containing different types and different numbers of objects. The results have been obtained after performing the algorithm on the 20 images of oceans. The ocean images are containing ships, aero planes, other debris, other objects, islands and water streams. The proposed algorithm has proved to be accurate more than 95%. The perfect accuracy is recorded near to 96% for correct object detection in the oceanological images. The images are containing ships, boats, large ships, aero planes, debris and many other objects which have been classified using the proposed algorithm. The 29 objects have been correctly identified out of the total 30 useful objects in all of the 20 images.

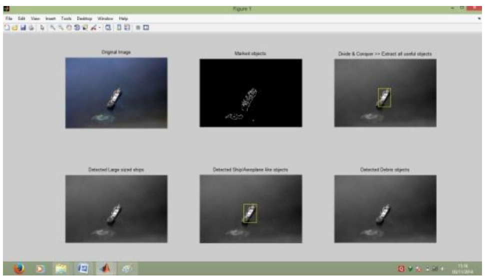

Figure 1.2(a) Ship/Aeroplane like objects are detected

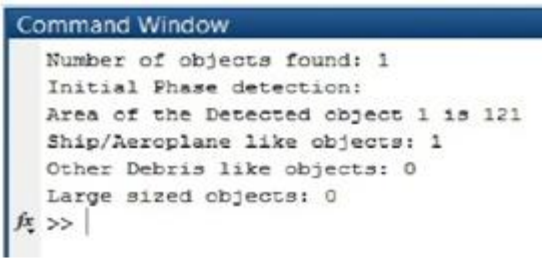

Figure 1.2(b) Performance Calculation

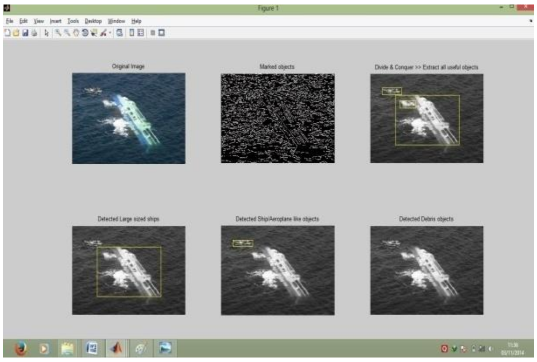

Figure 2.1(a) Large sized ship and Ship/Aeroplane like objects are detected

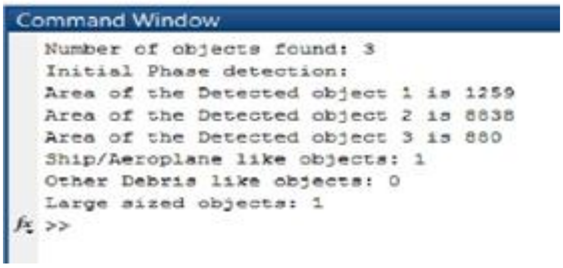

Figure 2.2(b) Performance calculation

The results have been obtained after performing the algorithm on the 20 images of oceans. The images are containing ships, boats, large ships, aero planes, debris and many other objects which have been classified using the proposed algorithm. The 29 objects have been correctly identified out of the total 30 useful objects in all of the 20 images.

INDEX	TOTAL NUMBER OF OBJECTS	TOTAL NUMBER OF USEFUL OBJECTS	TOTAL DETECTED OBJECTS (initial stage)	CORRECTLY DETECTED OBJECTS (final stage)	FALSE DETECTED OBJECTS	NOT DETECTED OBJECTS
1	1	1	1	1	0	0
2	2	2	2	2	0	0
3	2	2	2	2	0	0
4	4	4	4	4	0	0
5	1	1	1	1	0	0
6	1	1	1	1	0	0
7	3	4	3	3	1	0
8	3	3	3	3	0	0
9	2	2	2	2	0	0
10	1	1	1	1	0	0
11	1	1	1	1	0	0
12	1	1	1	1	0	0
13	2	1	1	1	0	0
14	0	0	0	0	0	0
15	1	1	1	1	0	0
16	1	1	1	1	0	0
17	1	1	1	1	0	0
18	1	1	1	1	0	0
19	1	1	1	1	0	0
20	1	1	2	1	1	1
TOTAL	**30**	**30**	**31**	**29**	**2**	**1**

Table 1.1: Result analysis for each object

Accuracy (Percentage) = (Correcly Detected Objects / Total Number Of Useful Objects) * 100
Accuracy = (29/30) * 100
Accuracy = 96.67%

The accuracy has been measured using the following formula of accuracy which has indicated the accuracy percentage of the proposed algorithm to 96 percent. Also the statistical errors have been recorded from the results obtained. The total true positives are 29 and true negative are less and have value of 1. The false positive is 2, whereas only 2 false negative values have been recorded. Here true positive calculate the number of objects which are correctly identified. True negative indicates the number of objects which are correctly rejected. False positive indicates the number of objects which are incorrectly identified and false negative indicates the number of objects which are incorrectly rejected.

Error type	Value
True Positive	29
True Negative	1

False Positive	2
False Negative	2

Table 1.2: Statistical Errors

Method	Recall	Precision
Ship head detection in [8]	75.3	49.8
Ship head detection in [9]	79.5	36.2
Existing ship detection	87.9	90.5
Our proposed ship detection	96.67	93.55

Table 1.3: The Recall and Precision calculations

We have calculated precision and recall on the basis of true positive, true negative, false positive, and false negative.
Precision is the number of true positive divided by the total number of elements labeled as belonging to positive classes (i.e. sum of true positive and true negative)

Precision=TP/TP+FP

Recall is defined as the number of true positives divided by total number of elements that actually belong to the positive classes (i.e. Sum of true positive and false negative)

Recall= TP/TP+FN

CONCLUSION

The proposed algorithm has been developed after evaluating the need of object detection in the oceans. The proposed algorithm has been developed to detect the ships, large ships, large objects, debris and many other objects floating in the ocean waters. The aim of the development is to facilitate the detection, reorganization and classification of floating objects in the remote areas of oceans which are not in human reach or it is very difficult to reach there. The proposed algorithm works with the aerial images and satellite images. The proposed algorithm has been proved successful for detection of ships, large ships, aero planes, debris and other unknown objects. Also, the algorithm is correctly capable of classified the detected objects. The algorithm has detected 96% objects correctly.

FUTURE WORK

- In the future, the algorithm can be enhanced to track the ships in video.
- Also the proposed algorithm can be improved for the higher accuracy than now.
- The proposed algorithm can be tried with other shape and color analysis models to gain the higher accuracy than the existing algorithm.

REFERENCES

1. Liu, Ge, Yasen Zhang, Xinwei Zheng, Xian Sun, Kun Fu, and Hongqi Wang. "*A New Method on Inshore Ship Detection in High-Resolution Satellite Images Using Shape and Context Information.*" Geoscience and Remote Sensing Letters, IEEE 11, no. 3 (2014): 617-621.

2. Mace, Thomas H. "*At-sea detection of marine debris: overview of technologies, processes, issues, and options.*" Marine pollution bulletin 65, no. 1 (2012): 23-27.

3. Iervolino, Pasquale, Martin Cohen, Raffaella Guida, and Philip Whittaker. "*Ship-detection in SAR imagery using Low Pulse Repetition Frequency Radar.*" InEUSAR 2014; 10th European Conference on Synthetic Aperture Radar; Proceedings of, pp. 1-4. VDE, 2014.

4. Agarwal, Shivani, Lionel Sujay Vailshery, Madhumitha Jaganmohan, and Harini Nagendra. "*Mapping urban tree species using very high resolution satellite imagery: comparing pixel-based and object-based approaches.*" ISPRS International Journal of Geo-Information 2, no. 1 (2013): 220-236.

5. Carson, Henry S., Megan R. Lamson, Davis Nakashima, Derek Toloumu, Jan Hafner, Nikolai Maximenko, and Karla J. McDermid. "*Tracking the sources and sinks of local marine debris in Hawai 'i.*" Marine environmental research 84 (2013): 76-83.

6. Rodriguez, Andres, Vishnu Naresh Boddeti, BVK Vijaya Kumar, and Abhijit Mahalanobis. "*Maximum margin correlation filter: A new approach for localization and classification.*" Image Processing, IEEE Transactions on 22, no. 2 (2013): 631-643.

7. Nagendra, Harini, and Duccio Rocchini. "*High resolution satellite imagery for tropical biodiversity studies: the devil is in the detail.*" Biodiversity and Conservation 17, no. 14 (2008): 3431-3442.

8. Benz, Ursula C., Peter Hofmann, Gregor Willhauck, Iris Lingenfelder, and Markus Heynen. "*Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information.*" ISPRS Journal of photogrammetry and remote sensing 58, no. 3 (2004): 239-258.

9. Boyd, Doreen S., and Giles M. Foody. "*An overview of recent remote sensing and GIS based research in ecological informatics.*" Ecological Informatics 6, no. 1 (2011): 25-36.

10. Nagendra, Harini, Richard Lucas, João Pradinho Honrado, Rob HG Jongman, Cristina Tarantino, Maria Adamo, and Paola Mairota. "*Remote sensing for conservation monitoring: Assessing protected areas, habitat extent, habitat condition, species diversity, and threats.*" Ecological Indicators 33 (2013): 45-59.

11. Blaschke, Thomas. "*Object based image analysis for remote sensing.*" ISPRS journal of photogrammetry and remote sensing 65, no. 1 (2010): 2-16.

12. Gibbes, Cerian, Sanchayeeta Adhikari, Luke Rostant, Jane Southworth, and Youliang Qiu. "*Application of object based classification and high resolution satellite imagery for savanna ecosystem analysis.*" Remote Sensing 2, no. 12 (2010): 2748-2772.

13. Wang, Kai, Steven E. Franklin, Xulin Guo, and Marc Cattet. "*Remote sensing of ecology, biodiversity and conservation: a review from the perspective of remote sensing specialists.*" Sensors 10, no. 11 (2010): 9647-9667.

14. Viola, Paul, and Michael Jones. "*Rapid object detection using a boosted cascade of simple features.*" In Computer Vision and Pattern Recognition, 2001. CVPR 2001. Proceedings of the 2001 IEEE Computer Society Conference on, vol. 1, pp. I-511. IEEE, 2001.

15. Lienhart, Rainer, and Jochen Maydt. "*An extended set of haar-like features for rapid object detection.*" In Image Processing. 2002. Proceedings. 2002 International Conference on, vol. 1, pp. I-900. IEEE, 2002.

16. Schneiderman, Henry, and Takeo Kanade. "*A statistical method for 3D object detection applied to faces and cars.*" In Computer Vision and Pattern R ecognition, 2000.

Proceedings. IEEE Conference on, vol. 1, pp. 746-751. IEEE, 2000.

17. Felzenszwalb, Pedro F., Ross B. Girshick, David McAllester, and Deva Ramanan. "*Object detection with discriminatively trained part-based models.*"Pattern Analysis and Machine Intelligence, IEEE Transactions on 32, no. 9 (2010): 1627-1645.

18. Lienhart, Rainer, Alexander Kuranov, and Vadim Pisarevsky. "*Empirical analysis of detection cascades of boosted classifiers for rapid object detection.*" In Pattern Recognition, pp. 297-304. Springer Berlin Heidelberg, 2003.

19. Gall, Juergen, and Victor Lempitsky. "*Class-specific hough forests for object detection.*" In Decision Forests for Computer Vision and Medical Image Analysis, pp. 143-157. Springer London, 2013.

20. Gall, Juergen, Angela Yao, Nima Razavi, Luc Van Gool, and Victor Lempitsky. "*Hough forests for object detection, tracking, and action recognition.*" Pattern Analysis and Machine Intelligence, IEEE Transactions on 33, no. 11 (2011): 2188-2202.

21. Liebelt, Joerg, and Cordelia Schmid. "*Multi-view object class detection with a 3d geometric model.*" In Computer Vision and Pattern Recognition (CVPR), 2010 IEEE Conference on, pp. 1688-1695. IEEE, 2010.

22. Felzenszwalb, Pedro F., Ross B. Girshick, and David McAllester. "*Cascade object detection with deformable part models.*" In Computer vision and pattern recognition (CVPR), 2010 IEEE conference on, pp. 2241-2248. IEEE, 2010.

23. Ferrari, Vittorio, Frederic Jurie, and Cordelia Schmid. "*From images to shape models for object detection.*" International Journal of Computer Vision 87, no. 3 (2010): 284-303.