



Survey on Detection and Tracking of Vessels in Coastline Areas

Vishal Gupta and Monish Gupta

EasyChair preprints are intended for rapid dissemination of research results and are integrated with the rest of EasyChair.

December 12, 2019

Survey on Detection and Tracking of Vessels in Coastline Areas

Vishal gupta¹, Dr. Monish Gupta²

Kurukshetra university kurukshetra¹, Kurukshetra University Kurukshetra²
v.vishu22@gmail.com¹, monish_gupta1976@kuk.ac.in²

Abstract- Video surveillance system in capable conditions is a defender among the most unique research topics in computer vision getting much thought in the latest decade. Piracy attacks are the most concern topic in the coastline areas. There have much work been done on detection and tracking of vessels to curb the suspicious activities but there are lot of challenges in the traditional methods. In this paper we have summarized the different work done and techniques proposed by different authors. The problem of dynamic nature of coastline area needs to be defined clearly in a statistical manner.

Index Terms— coastal surveillance, ship detection, tracking, vessels etc

I. Introduction

Video surveillance system in capable conditions is a defender among the most unique research topics in computer vision, getting much thought in the latest decade. Maritime observation can be portrayed as the compelling affirmation of all maritime activities that impact the security, the economy or nature. Object distinguishing proof and tracking are vital and testing assignments in various computer vision applications; for instance surveillance, vehicle course and self-sufficient robot course. Small boats and people on jet skis can attack maritime vessels and warships. Small and agile boats are difficult to detect and track correctly with a radar sensor. The development of an autonomous video surveillance system is essential to improve port security, coastal defense, support other sensor types and curb unwanted event occurrences such as illegal fishing, immigration, pirate, terrorist attacks, ship collisions and drug trafficking. A part of the difficulties in the coastline area are listed below:

- A. Extraction of background from foreground
 - The trouble in demonstrating the flow of water (counting waves, wakes and froths) for background subtraction and detection of frontal area objects.
 - Variations in object appearances because of separation and edge of review, and
 - Changes in light and climate conditions, for example, because of mists, daylight, rain, glimmer, and so on.
- B. Piracy Attack

Piracy Sea is an old issue that holds on to current circumstances in various problem areas over the world. A breakdown of attacks is appeared in Fig1. We separated how the decrease of piracy attacks is affecting vessel movement along the North–South transport courses crossing the Indian Ocean, dynamically reconstructing the route to conditions that boundary fuel utilization and Time Sea.

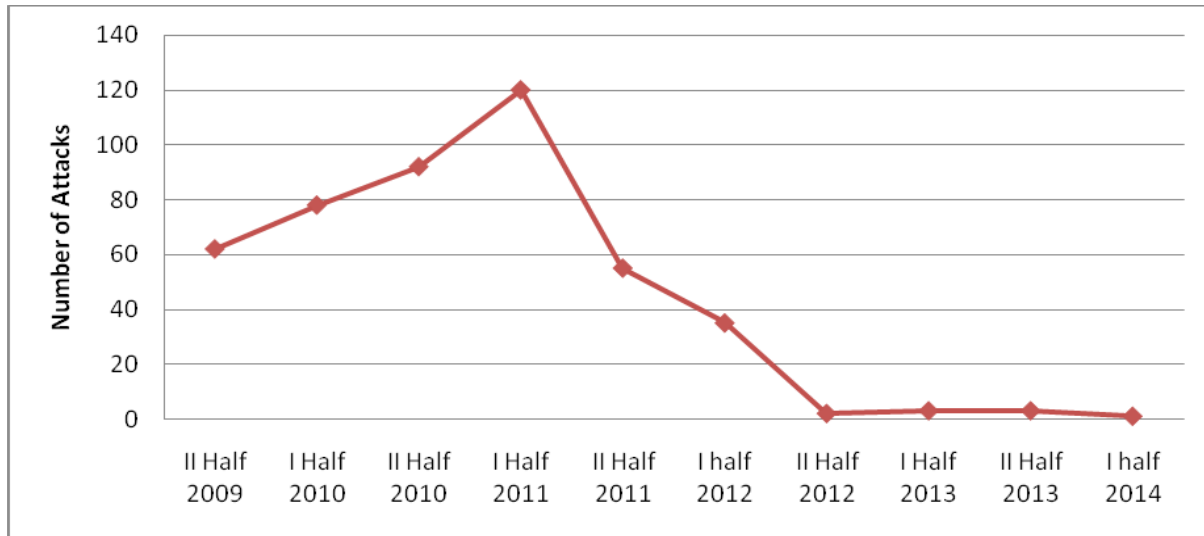


Fig 1: Number of piracy attacks during the time period covered by the ship tracking historical data. Source: EU Naval Force—Somalia [25].

Measurements of suspicious occasions, piracy attacks and interruptions source: EU NAVAL FORCE SOMALIA - OPERATION ATALANTA [25] [Table 1]. With regards to piracy, the information of what is going on sea joined with met-oceanographic information and insight on potential Piracy Action Groups (PAGs) can be utilized to perform dynamic hazard investigation [26]. Keeping in mind the end goal to assemble the supposed Maritime Situational Image (MSP) in wide territories, information from numerous perception and self-detailing system can be mixed to track Vessels Sea [27, 28]. In the robbery setting, the outside maritime powers working in the territory have utilized information from AIS and LRIT and bring in reports from the boats and their own perception system to accomplish the vital MSA. AIS and LRIT are likewise being utilized as a part of boundary building ventures for sea experts in the region, e.g. under the EU-financed Piracy, Maritime Awareness and Risks (PMAR) extend.

Table 1: The rise and decline of piracy activities around Somalia in the last 9 years

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
SUSPICIOUS EVENTS	8	59	99	166	74	20	5	1	2	2
TOTAL ATTACKS	24	163	174	176	34	7	2	0	1	6
OF WHICH PIRATED	14	46	47	25	4	0	0	0	0	2
DISRUPTIONS	0	14	65	28	16	10	1	0	0	3

II. Literature Review

The paper by [Rodrigo da Silva Moreira, (2015)][1] proposes a maritime vessel tracker named EWRN (Ensemble Wizard's Rodrigo Nelson), composed of an ensemble of WiSARD weightless neural network classifiers. A failure detector analyzes vessel movement with a Kalman filter and corrects the tracking, if necessary, using FFT matching.

Traffic monitoring in nautical environment is broadly covered in the literature, but most of the maritime monitoring systems are based on RF radars. Much less work has been done on using visual information for detection, identification, and tracking of marine vessels. Visual monitoring in maritime domain is complicated because of the moving background such as flickering water, moving surfaces and clouds, changing lighting conditions. Due to this complex set of conditions the previous research in the field has mostly been focused on visual surveillance of harbors and took scene-related assumptions.

The paper by [Sergiy Fefilyatyev (2014)][2] proposed to take video and imagery of the surrounding ocean surface and analyze it for the presence of ships, thus, potentially enabling automatic detection and tracking of marine vehicles as they transit in the vicinity of the platform. The system transmits the data to the ground control via bi-directional RF satellite link and can have its mission parameters reprogrammed during the deployment. The described unit is low cost, easy to deploy, recover and does not reveal itself to the potential targets.

The paper by [Dilip K. Prasad (2016)][3] discusses the technical challenges in maritime image processing and machine vision problems for video streams generated by cameras. Even well documented problems of horizon detection and registration of frames in a video are very challenging in maritime scenarios.

III. Scope of Marine detection and Tracking

Situation awareness is understood as a key requirement for safe and secure shipping at sea. The primary sensor for maritime situation assessment is still the radar, with the AIS being introduced as supplemental service only.

In the process of Motion detection and tracking, every image generated needs to pass through a two-stage process for the filtering and clarification so that usable data can be extracted from the image. Firstly, each image is pre-processed to minimize marine snow, remove background artifacts and convert to a single channel. The second pre-processing step is reducing marine snow through filtering. Since most of the optical snow moves quickly relative to the targets, the proper selection of time, t causes the snow to be filtered out while the targets are retained. Too low value of t results in the optical snow not being filtered out. Too high a value results in slower-moving objects being filtered out, or the location of the edges being misidentified (in particular, the pixels along the leading edge being replaced by background pixels). Finally, background subtraction is performed to remove lighting and lens artifacts. This requires a few seconds of video in which there are no objects of interest. For each pixel, the temporal median is calculated and the resulting image is called the "background". In the final preprocessing step, the background is subtracted from the image.

In the paper by [Siegert, G., et al. (2010)], [4] they presented a framework to assess the current situation picture based on marine radar image processing. Essentially, the framework comprises a centralized IMM-JPDA multi-

target tracker in combination with a fully automated scheme for track management, i.e., target acquisition and track depletion.

[S. Fefilyat'ev and D. Goldgof, (2008)] [5] proposed a technique for marine detection based on detection of marine vehicles in individual video frames and tracking the detected targets through the video sequence with the help of a tracking algorithm. Several performance metrics are utilized for performance evaluation of the proposed approach. Accuracy of detection in 90% range is shown on a dataset of 30 short video sequences taken by a prototype of the system.

IV. Problems associated with Marine detection and Tracking

The dynamic nature of the sea caused by waves, boat wakes, and weather conditions poses huge challenges for the development of a stable background model. Moreover camera motion, reflections, lightning and illumination changes may contribute to false detections. Dynamic background subtraction (DBGS) is widely considered as a solution to tackle this issue in the scope of vessel detection for maritime traffic analysis [R. Kalman, (1960)][6].

This section addresses the problems of automatic detection and tracking of man-made objects in subsea environment with poor visibility and marine snow. The major problems associated with the detection and tracking in Marine environment are:

- The term marine snow refers to underwater debris including sediment and planktonic organisms (e.g., algae and krill). Marine snow creates high-contrast visual clutter that interferes with the detection of lower-contrast objects of interest.
- Background Subtraction
- Optical Snow and Edge Detection
- Motion Estimation and optimal estimation error
- Modification to stationary, non stationary statistics, to growing-memory and infinite-memory filters.

The paper by [Roeland T'Jampens (2016)], [7] focuses on the DBGS techniques suggested for ships are investigated and optimized for the monitoring and tracking of birds in marine video content. In addition to background subtraction, foreground candidates are filtered by a classifier based on their feature descriptors in order to remove non-bird objects. Different types of classifiers have been evaluated and results on a ground truth labeled dataset of challenging video fragments show similar levels of precision and recall of about 95% for the best performing classifier. The remaining foreground items are counted and birds are tracked along the video sequence using spatio-temporal motion prediction.

The paper by [Stateczny, A. and Kazimierski, W., (2008)], [8] presents the results of simulation research aimed at determining the manoeuvre detection threshold of a neuron filter, based on GRNN artificial neural network. The structure of a filter has been presented, from which the necessity of manoeuvre detection results and a detector has been described able to be used in this case; it is based on an analysis of course and speed increase in particular estimation steps.

The increased threat of piracy, surveillance is an absolute must on cargo ships travelling in these dangerous areas. While radar systems have been extensively used in maritime environments, these generally require large, metallic targets. Modern pirates favors small, fast rigid inflatable boats that are mainly non-metallic and thus difficult to detect while the solution to this would seem to be the use of manual detection using dedicated crew members on board, the small number present at any given time makes this unfeasible. Unlike humans that grow tired, automated video surveillance systems are able to constantly monitor camera feeds and keep track of a number of objects of interest around the ship.

The paper by [Duncan Frost (2013)] [9] discusses such technique is level set segmentation which evolves a contour to objects of interest in a given image. This method works well but gives incorrect segmentation results when a target object is corrupted in the image. This paper also focuses on the possibility of factoring in prior knowledge of a ship's shape into level set segmentation to improve results, a concept that is unaddressed in maritime surveillance problem. It is shown that the developed video tracking system outperforms level set-based systems that do not use prior shape knowledge, working well even where these systems fail.

V. Application of Marine detection and Tracking

Maritime surveillance can be defined as the effective recognition of all maritime activities that impact the security, the economy or the environment [S. Kazemi, et al. (2013)][10]. About 80% of all world trade is carried by sea transport. With the growing use of maritime transport, an increase of pirate attacks, activities such as traffic of prohibited substances, illegal immigration and fishing, terrorist attacks at port areas and collisions between marine vehicles primarily at channels and near the ports and coasts is occurring.

The manual operation of surveillance systems is not efficient due to fatigue, stress and the limited ability of human beings to perform certain tasks, the development of automated systems for maritime surveillance is essential to reduce the occurrence of unwanted events [K. M. Gupta, et al. (2009)][11]. The use of cameras in maritime surveillance systems has increased [D. Bloisi, et al. (2011)][12]. Cameras are essential to assist and supplement the radars and other sensors. They are cheap, flexible [W. Kruger and Z. Orlov, (2010)][13] and can be installed on almost every platform type.

Low and high frequency radars are expensive, hampered by clutter [S. Fefilyayev, (2008)][14], have blind zones close to the transmitting antenna [H. Wei, et al. (2009)][15] and detect with low efficiency the vehicles built with non-conductive materials [Z. L. Szpak and J. R. Tapamo, (2011)][16].

Efforts have been made worldwide for the development of maritime surveillance systems. The European project AMASS - Autonomous Maritime Surveillance System - was created to develop a surveillance system with FLIR cameras installed on advanced platforms. The AVITRACK system and MAAW - Maritime Activity Analysis Workbench are surveillance systems based on cameras. The ARGOS system has been active since 2007 and is used to monitor the maritime traffic at Gran waterway in Venice, Italy.

[Burkle et al. (2010)][17] proposed a surveillance system based on cameras installed on different platforms and land bases to increase the system coverage area. New technologies have been emerged allowing the data fusion extracted from different systems and sensors. The cameras are one of the main system components.

VI. Methods of Marine detection and Tracking

- Vision Detection Using Sky Segmentation Techniques

A vision-based obstacle detection system for small unmanned aerial vehicles (UAVs) is presented by [T.G. McGee, R. Sengupta et al., (2005)][18]. Obstacles are detected by segmenting the image into sky and non-sky regions and treating the non-sky regions as obstacles. The feasibility of this approach is demonstrated by using the vision output to steer a small unmanned aircraft to fly towards an obstacle. The experiment was first verified in hardware in the loop (HIL) simulation and then successfully implemented on a small modified remote control plane using a large inflatable balloon as the obstacle.

- Vision Detection Using Image Processing Techniques

The paper by [[A.A. Smith](#) and [M.K. Teal](#) (1999)] [19] describes the continuing development of an image processing system for use on high-speed passenger ferries. The system automatically identifies objects in a maritime scene and uses the detected motion to alert a human observer to potential collision situations. Three integrated image-processing algorithms, namely an image preprocessor, a motion cue generator, and a target tracker, perform the identification and tracking of maritime objects.

The paper by [[Paul Westall](#), (2009)][20] investigates a machine vision system that addresses the human lost in problem by exploiting the useful properties of alternate colour spaces. In particular, the paper investigates the fusion of colour information from HSV, RGB, YCbCr and YIQ colour spaces within the emission matrix of a Hidden Markov Model tracker to enhance video based maritime target detection. The system has shown promising results.

- Vision Detection Using Machine Learning Techniques

This paper by [S. Fefilatyeve, V. Smarodzinava, L. O. Hall and D. B. Goldgof, (2006)] [21] investigates how to detect the horizon line in a set of images using a machine learning approach. The performance of the SVM, J48, and naive Bayes classifiers, used for the problem, has been compared. Accuracy of 90-99% in identifying horizon was achieved on image data set of 20 images.

In this paper, [[Timo Ahonen](#), [Matti Pietikäinen](#) et al., (2012)][22] proposes a novel approach to compute rotation-invariant features from histograms of local non invariant patterns. They apply this approach to both static and dynamic local binary pattern (LBP) descriptors. LBP-HF is a novel rotation-invariant image descriptor computed from discrete Fourier transforms of LBP histograms. The approach can also be generalized to embed any uniform features into this framework, and combining the supplementary information.

- Vision Detection Using Linear Filtering and Prediction Techniques

The classical filtering and prediction problem is re-examined by [[R. E. Kalman](#) (1960)][6] using the Bode-Shannon representation of random processes and the “state-transition” method of analysis of dynamic systems. New results are: (1) The formulation and methods of solution of the problem apply without modification to stationary and non stationary statistics and to growing-memory and infinite-memory filters. (2) A nonlinear difference (or differential)

equation is derived for the covariance matrix of the optimal estimation error. From the solution of this equation the coefficients of the difference (or differential) equation of the optimal linear filter are obtained without further calculations. (3) The filtering problem is shown to be the dual of the noise-free regulator problem. The new method developed here is applied to two well-known problems, confirming and extending earlier results.

In this work [MDR Sullivan and M. Shah, (2008)][23] proposed a method for securing port facilities which uses a set of video cameras to automatically detect various vessel classes moving within buffer zones and off-limit areas. Vessels are detected by an edge-enhanced spatiotemporal optimal trade-off maximum average correlation height filter which is capable of discriminating between vessel classes while allowing for intra-class variability. Vessel detections are cross-referenced with e-NOAD data in order to verify the vessel's access to the port. This approach does not require foreground/background modeling in order to detect vessels, and therefore it is effective in the presence of the class of dynamic backgrounds, such as moving water, which are prevalent in port facilities.

- Vision Detection Using Automated Intelligence Techniques

The paper by [Duncan Frost and Jules-Raymond Tapamo, (2013)][9] explores the possibility of factoring in prior knowledge of a ship's shape into level set segmentation to improve results, a concept that is unaddressed in maritime surveillance problem. It is shown that the developed video tracking system outperforms level set-based systems that do not use prior shape knowledge, working well even where these systems fail.

REFERENCES

1. da Silva Moreira, R. and Ebecken, N.F.F., Maritime Vessel Tracking with an Ensemble of WiSARD Classifiers in Video.
2. Shreve, M., Brizzi, J., Fefilyayev, S., Laguev, T., Goldgof, D. and Sarkar, S., 2014. Automatic expression spotting in videos. *Image and Vision Computing*, 32(8), pp.476-486.
3. Prasad, D.K., Prasath, C.K., Rajan, D., Rachmawati, L., Rajabaly, E. and Quek, C., 2016. Challenges in video based object detection in maritime scenario using computer vision. *arXiv preprint arXiv:1608.01079*.
4. Kovacs, K.F., Haight, R.G., McCullough, D.G., Mercader, R.J., Siegert, N.W. and Liebhold, A.M., 2010. Cost of potential emerald ash borer damage in US communities, 2009–2019. *Ecological Economics*, 69(3), pp.569-578.
5. S. Fefilyayev and D. Goldgof, "Detection and tracking of marine vehicles in video," *2008 19th International Conference on Pattern Recognition*, Tampa, FL, 2008, pp. 1-4.
6. Kalman, R.E., 1960. A new approach to linear filtering and prediction problems. *Journal of Basic Engineering*, 82(1), pp.35-45.
7. T'Jampens, R., Hernandez, F., Vandecasteele, F. and Verstockt, S., 2016, December. Automatic detection, tracking and counting of birds in marine video content. In *2016 Sixth International Conference on Image Processing Theory, Tools and Applications (IPTA)* (pp. 1-6). IEEE.

8. Stateczny, A. and Kazimierski, W., 2008, May. Determining manoeuvre detection threshold of GRNN filter in the process of tracking in marine navigational radars. In 2008 International Radar Symposium (pp. 1-4). IEEE.
9. Frost, D. and Tapamo, J.R., 2013. Detection and tracking of moving objects in a maritime environment using level set with shape priors. *EURASIP Journal on Image and Video Processing*, 2013(1), p.42.
10. Kazemi, S., Abghari, S., Lavesson, N., Johnson, H. and Ryman, P., 2013. Open data for anomaly detection in maritime surveillance. *Expert Systems with Applications*, 40(14), pp.5719-5729.
11. Gupta, K.M., Aha, D.W., Hartley, R. and Moore, P.G., 2009, April. Adaptive maritime video surveillance. In *Visual Analytics for Homeland Defense and Security* (Vol. 7346, p. 734609). International Society for Optics and Photonics.
12. Bloisi, D., Iocchi, L., Fiorini, M. and Graziano, G., 2011, September. Automatic maritime surveillance with visual target detection. In *Proc. of the International Defense and Homeland Security Simulation Workshop (DHSS)* (pp. 141-145).
13. Krüger, W. and Orlov, Z., 2010, November. Robust layer-based boat detection and multi-target-tracking in maritime environments. In *2010 International WaterSide Security Conference* (pp. 1-7). IEEE.
14. Fefilatye, S. and Goldgof, D., 2008, December. Detection and tracking of marine vehicles in video. In *2008 19th International Conference on Pattern Recognition* (pp. 1-4). IEEE.
15. Wei, H., Nguyen, H., Ramu, P., Raju, C., Liu, X. and Yadegar, J., 2009, May. Automated intelligent video surveillance system for ships. In *Optics and Photonics in Global Homeland Security V and Biometric Technology for Human Identification VI* (Vol. 7306, p. 73061N). International Society for Optics and Photonics.
16. Szpak, Z.L. and Tapamo, J.R., 2011. Maritime surveillance: Tracking ships inside a dynamic background using a fast level-set. *Expert systems with applications*, 38(6), pp.6669-6680.
17. Bürkle, A. and Essendorfer, B., 2010, November. Maritime surveillance with integrated systems. In *2010 International WaterSide Security Conference* (pp. 1-8). IEEE.
18. McGee, T.G., Sengupta, R. and Hedrick, K., 2005, April. Obstacle detection for small autonomous aircraft using sky segmentation. In *Proceedings of the 2005 IEEE International Conference on Robotics and Automation* (pp. 4679-4684). IEEE.
19. Smith, A.A. and Teal, M.K., 1999. Identification and tracking of maritime objects in near-infrared image sequences for collision avoidance.

20. Westall, P., O'Shea, P., Ford, J.J. and Hrabar, S., 2009, June. Improved maritime target tracker using colour fusion. In *2009 International Conference on High Performance Computing & Simulation* (pp. 230-236). IEEE.
21. Fefilatyeve, S., Smarodzinava, V., Hall, L.O. and Goldgof, D.B., 2006, December. Horizon detection using machine learning techniques. In *2006 5th International Conference on Machine Learning and Applications (ICMLA'06)* (pp. 17-21). IEEE.
22. Linder, N., Konsti, J., Turkki, R., Rahtu, E., Lundin, M., Nordling, S., Haglund, C., Ahonen, T., Pietikäinen, M. and Lundin, J., 2012. Identification of tumor epithelium and stroma in tissue microarrays using texture analysis. *Diagnostic pathology*, 7(1), p.22.
23. Sullivan, M.D.R. and Shah, M., 2008, March. Visual surveillance in maritime port facilities. In *Visual Information Processing XVII* (Vol. 6978, p. 697811). International Society for Optics and Photonics.
24. Comaniciu, D., Ramesh, V. and Meer, P., 2003. Kernel-based object tracking. *IEEE Transactions on Pattern Analysis & Machine Intelligence*, (5), pp.564-575.
25. EU Naval Force—Somalia, Key Facts and Figures. Retrieved from: <http://eunavfor.eu/key-facts-and-figures> (accessed 11.05.2015).
26. Hansen, J., et al. Information domination: Dynamically coupling METOC and INTEL for improved guidance for piracy interdiction. NAVAL RESEARCH LAB WASHINGTON DC, 2011.
27. Posada, Monica, et al. "Maritime awareness for counter-piracy in the Gulf of Aden." Geoscience and Remote Sensing Symposium (IGARSS), 2011 IEEE International. IEEE, 2011.
28. Mazzarella, Fabio, et al. "Data fusion for wide-area maritime surveillance." Workshop on Moving objects at Sea. 2013.