# Maritime Situation Awareness Capabilities from Satellite and Terrestrial Sensor Systems

Rob Dekker, Henri Bouma, Eric den Breejen, Bert van den Broek, Patrick Hanckmann, Maarten Hogervorst, Ali Mohamoud, Robin Schoemaker, Joris Sijs, Reinier Tan, Alexander Toet, Arthur Smith

TNO, PO Box 96864, 2509 JG The Hague, The Netherlands
e-mail: rob.dekker@tno.nl

**Abstract**
Maritime situation awareness is supported by a combination of satellite, airborne, and terrestrial sensor systems. This paper presents several solutions to process that sensor data into information that supports operator decisions. Examples are vessel detection algorithms based on multispectral image techniques in combination with background subtraction, feature extraction techniques that estimate the vessel length to support vessel classification, and data fusion techniques to combine image based information, detections from coastal radar, and reports from cooperative systems such as (satellite) AIS. Other processing solutions include persistent tracking techniques that go beyond kinematic tracking, and include environmental information from navigation charts, and if available, ELINT reports. And finally rule-based and statistical solutions for the behavioural analysis of anomalous vessels. With that, trends and future work will be presented.

## 1. Introduction

Maritime situation awareness is an important issue in border surveillance, counter piracy, traffic monitoring, and fisheries control. Actually, it is the basis in many operations. Maritime situation awareness is supported by the maritime situational picture: a combination of information from land, airborne, and satellite sensor systems, augmented with heterogeneous information from Geographical Information Systems (GIS) and vessel information repositories. Relevant sensor systems can be divided into cooperative and non-cooperative systems. Examples of cooperative systems are Automatic Identification Systems (AIS) from terrestrial bound or satellite receivers, Vessel Monitoring Systems (VMS) that are used in fisheries, and Long Range Identification and Tracking (LRIT). Many of these systems are global, using satellite receivers or satcom. Non-cooperative systems are coastal radar, ground- or vessel-based cameras, and satellite and airborne Earth Observation (EO) systems. EO systems can be divided into optical (generally visual and near-infrared) and Synthetic Aperture Radar (SAR) systems. Most satellite EO systems are sun-synchronous, implying that they come over at the same local solar-time. Advantage of SAR systems is that they are less sensitive to cloud cover.

Extraction of the relevant information from these sensors to support the maritime security operator takes a lot of processing: vessel detection, vessel classification, data fusion, persistent tracking, and behavioural analysis (Figure 1). Data fusion can in fact take place at any point in the processing flow, but here is chosen for the most logical step, prior to persistent tracking. Behavioural analysis is sometimes referred to as anomaly detection based on behavioural patterns. The Netherlands Organisation for Applied Scientific Research TNO is working on all of these processing steps in different national and international programmes, including EU FP7 Space and Security. In these

Paper presented at MAST (Maritime Systems and Technology) Europe Conference 2013

programmes the task of TNO is to come up with new concepts and innovative solutions, beyond the current state of art. In the following sections different solutions and trends will be presented, including representative results. Some solutions have the status of proof of concept, while others are ready for operational implementation. This paper will end with conclusions.

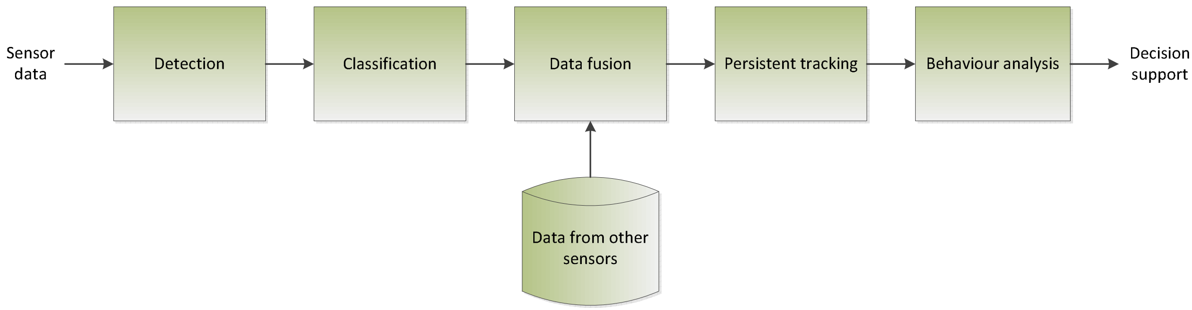


Figure 1. General maritime situation awareness processing chain.

## 2. Vessel detection

Detection of vessels and other maritime objects as applied to EO images, aims at the discrimination between vessels and their background. A common detector for optical and SAR images is the Constant False Alarm Rate (CFAR) detector [1], [2]. The detector compares the pixel under test with its local background statistics to decide whether this pixel is a potential vessel and not a background pixel. An important issue in vessel detection is the suppression of background clutter, such as surface wave patterns, that lowers the probability of detection and causes false detections. The intensity of clutter is generally proportional to wind speed and sea state, which means that for high wind speeds and sea states it is more difficult to reliably detect all vessels in your area of interest, while keeping the number of false alarms sufficiently small [3], [4]. Figure 2 shows an example of vessel detection including clutter removal applied to a high-resolution optical GeoEye-1 satellite image (panchromatic resolution 0.5 m; multi-spectral resolution 2.0 m).

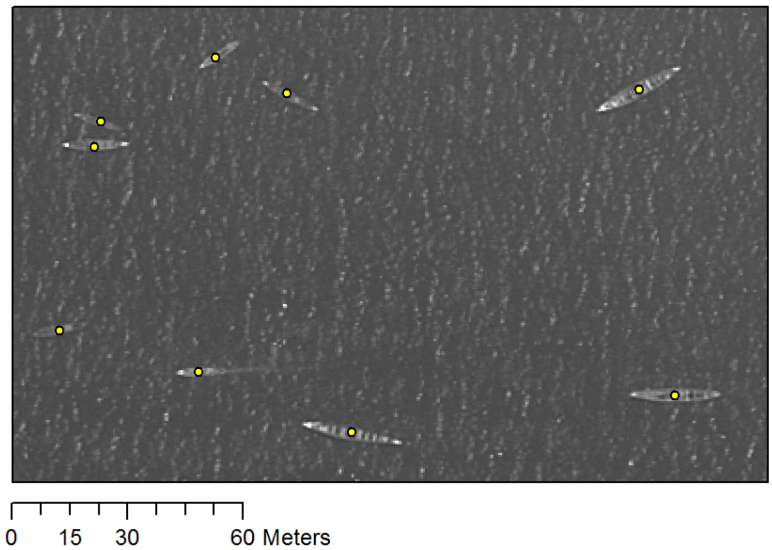


Figure 2. Example of small vessel detection off the coast of Mbour, Senegal. The yellow dots represent the detected vessel centres-of-gravity. Satellite image: © GeoEye, Inc. (2012), provided by e-GEOS S.p.A. under GSC-DA.

## 3. Vessel classification

After detection, a vessel will be classified in for instance the type of vessel. Therefore, all EO image pixels that belong to one vessel will be grouped, a process that is also referred to as segmentation. Subsequently characteristics will be extracted from that group of pixels (also referred to as feature extraction), and are compared with a database. Among these features are geometric, statistical, and spectral characteristics. In maritime situation awareness, vessel length is an important parameter to classify a vessel. Which means that in segmentation of a moving vessel, it has to be separated from its wake to estimate the proper vessel length. For this purpose a more robust segmentation scheme had to be developed, that includes wake detection, ship-wake separation based on profile clustering, and a special module for small vessel segmentation [5]. Applying this scheme (in combination with vessel length estimation) to high-resolution optical GeoEye-1 images of the North Sea, showed an improvement of the Root Mean Square Error (RMSE) of 73 %, compared to baseline segmentation (Figure 3).

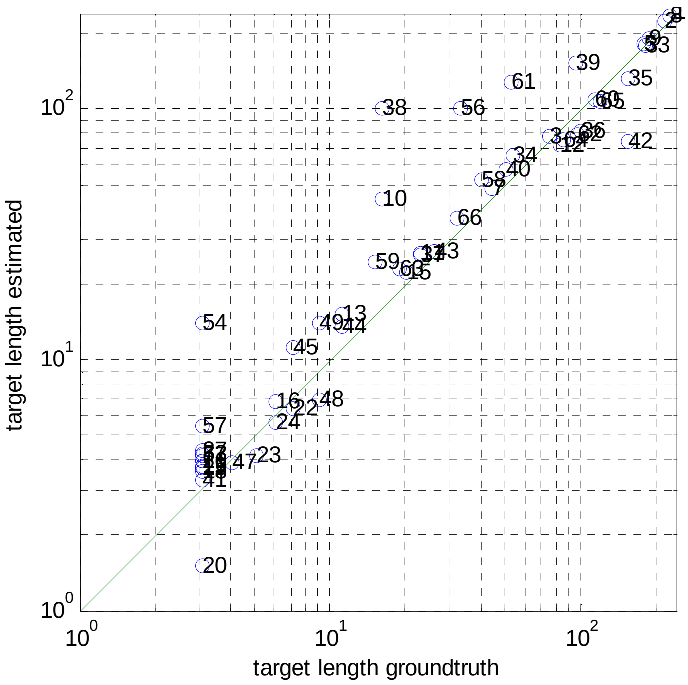


Figure 3. Estimated target vessel length against true target vessel length, based on robust segmentation, ship-wake separation, and length estimation; applied to optical images of the North Sea off the coast of Rotterdam, The Netherlands. Produced using products © GeoEye, Inc. (2011), provided by e-GEOS S.p.A. under GSC-DA.

## 4. Data fusion and persistent tracking

When multiple sensors are available it is beneficial to combine their output in a single operational picture. For instance to confirm or exclude vessel detections, or in case of a confirmation to obtain more information on a vessel. With that we would like to persistently track the operational picture in time. Tracking is generally based on kinematic information (i.e. position and velocity), but when time intervals become larger, vessel attributes such as derived for vessel classification become more important. Basic processing steps in sensor data fusion and persistent tracking are:

- Spatial alignment of sensor information, also referred to as co-registration. This includes correction for Doppler shifts in SAR images [3], [6].

- Temporal alignment of sensor information by means of interpolation or extrapolation (in tracking also referred to as prediction).
- Association of sensor information given alignment errors [7].

Data fusion can be applied to cooperative and non-cooperative sensors. However, we must take into account that cooperative sensors generally deliver tracks (i.e. series of detections or plots that are already associated), while non-cooperative EO systems generally deliver single plots from single images. Well known examples are fusion of coastal radar and AIS, and fusion of SAR EO systems and AIS, e.g. [6]. Persistent tracking using non-cooperative systems is more difficult than with cooperative systems because less information on the vessel is available to associate detections. With that, kinematic information becomes less reliable over time and other prediction strategies have to be found. One possibility is to include geographical information such as navigation charts, vessel traffic lanes, and coastline [8]. Figure 4 shows an example of prediction over larger time intervals based on a sample of Vessel Traffic Services (VTS) Rotterdam, The Netherlands. A trend in persistent tracking is to apply additional information from for instance Electronic Intelligence (ELINT) sensors that provide signatures of the vessel's radar systems. Our focus at this moment is to determine efficient tracking strategies for sparse information, for instance from ELINT sensors.

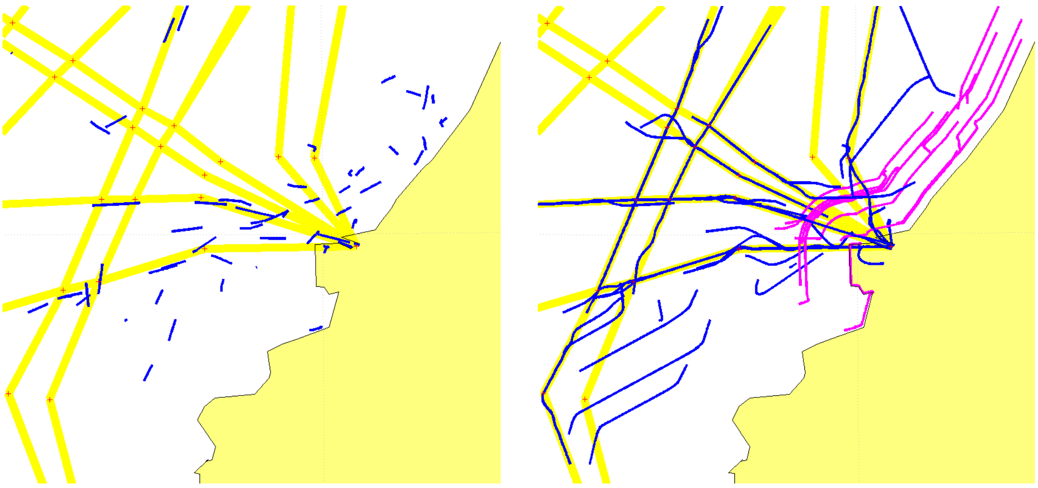

Figure 4. Prediction of vessel tracks over 2 hours (right) based on 10 minutes of data (left) of VTS Rotterdam, The Netherlands. The smaller vessels (magenta tracks) follow the coastline, whereas the larger vessels (blue tracks) follow the shipping lanes.

## 5. Behaviour analysis

Analysis of vessel behaviour is done to narrow the potential number of ships of interest in the different maritime domains. Here we make a distinction between logical methods and statistical methods. Logical methods are generally based on rules that are obtained from expert knowledge, e.g. [9]. Examples are Structured Query Language (SQL), Case Based Reasoning, and Complex Event Processing (CEP), e.g. [10]. Statistical methods are based on statistical rules such as Mahalanobis distance, Local Outlier Factor, and Support Vector Machines (SVM), e.g. [11]. Statistical methods include machine learning strategies, where vessel traffic data is used to train a classifier. Which method to use is dependent on the sensor and the information that is available (expert knowledge, geographical information, training data, etc.), and whether the behaviour is distinctive and stable enough to allow statistical description. Important to note is that the behavioural analysis capabilities of EO systems are limited, compared with for instance coastal radar or AIS, because EO systems generate single plots. Unless the data can be correlated to vessel tracks in data fusion. EO systems alone can only determine behaviour based on vessel position, length, and possibly type, in combination with geographical information or other vessels (e.g. vessel in restricted area, distance between vessels is small). At TNO several behavioural analysis strategies were evaluated, mainly in well-known marine environments such as the North Sea and English Channel, e.g. [12], where geographical information is available. Examples are SQL, CEP, and Mahalanobis distance (Figure 5). In expeditionary areas such as the Indian Ocean, historical vessel trajectories can be used to obtain vessel traffic patterns. Trend in behaviour analysis is to combine multiple rules and methods (including statistical analysis). Our focus at this moment is to develop methods based on statistical information that support rule-based systems.

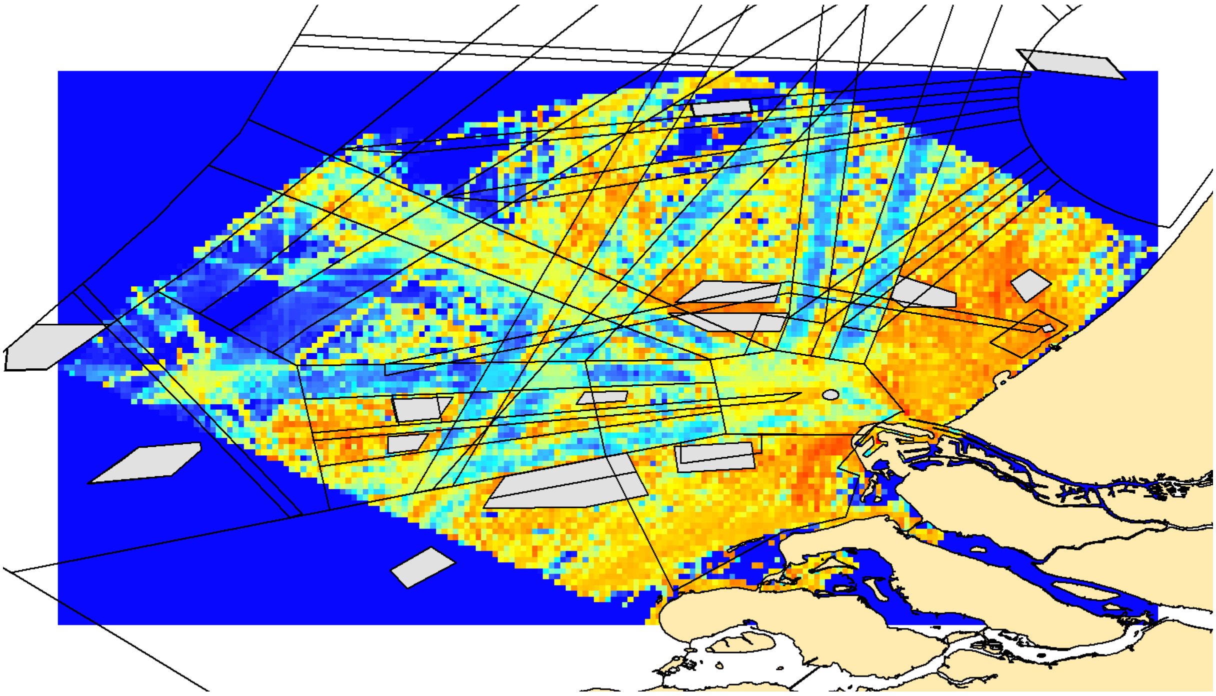

Figure 5. Example of statistical information (standard deviation of course over ground, based on coastal radar and AIS) near VTS Rotterdam, The Netherlands. Here we see that the course over ground in the shipping lanes is much more homogeneous than for instance in areas directly off the coast. Geographical information: Rijkswaterstaat Noordzee.

## 6. Conclusions

This paper gives an overview of different solutions that make a maritime situation awareness processing chain. Among the solutions are algorithms for vessel detection, vessel classification, data fusion, persistent tracking , and behaviour analysis. The first two generally apply to EO sensors. Data fusion goes beyond EO sensors and includes information from cooperative sensors and other non-cooperative sensors such as coastal radar. The fused information is input to persistent tracking and behaviour analysis. Trend in persistent tracking is to apply additional information from for instance Electronic Intelligence (ELINT) sensors that provide signatures of the vessel's radar systems. Trend in behaviour analysis is to combine multiple rules and methods (including statistical analysis). Our focus at this moment is to determine efficient tracking strategies for sparse information, for instance from ELINT sensors, and statistical methods that support rule-based behaviour analysis.

**Acknowledgement**

The research leading to these results has received funding from the European Union Seventh Framework Programme *(FP7/2007-2013)* under *grant agreement* n° 241598, 263079, and 263468.

**References**

[1] I.S. Reed and X. Yu, 1990, Adaptive Multiple-Band CFAR Detection of an Optical Pattern with Unknown Spectral Distribution, *IEEE Trans. Acoustics, Speech, Signal Processing, Vol. 38, No. 10*, pp. 1760-1770.

[2] L.M. Novak and S.R. Hesse, 1991, On the performance of order-statistics CFAR detectors, *IEEE Conference Record of the 25$^{th}$ Asilomar Conference on Signals, Systems and Computers, Vol.2*, pp. 835-840.

[3] K. Eldhuset, 1996, An Automatic Ship and Ship Wake Detection System for Spaceborne SAR Images in Coastal Regions, *IEEE Trans. Geoscience Remote Sensing, Vol. 34, No. 4*, pp. 1010-1019.

[4] C. C. Wackerman, P. Clemente-Colon, W. G. Pichel and X. Li, 2002, A two-scale model to predict C-band VV and HH normalized radar cross section values over the ocean, *Can. J. Remote Sensing, Vol. 28, No. 3*, pp. 367-384.

[5] H. Bouma, R.J. Dekker, R.M. Schoemaker and A.A. Mohamoud, 2013, Segmentation and wake removal of seafaring vessels in optical satellite images, *submitted to SPIE Security and Defence, Dresden, Germany, 23-26 September 2013*.

[6] C. Brekke, D.J. Weydahl, Ø. Helleren and R. Olsen, 2008, Ship traffic monitoring using multi-polarisation satellite SAR images combined with AIS reports, *Proc. 7$^{th}$ European Conference on Synthetic Aperture Radar (EUSAR), Friedrichshafen, Germany, 2-5 June 2008*.

[7] S. Blackman and R. Popoli, *Design and Analysis of Modern Tracking Systems*, Artech House, Norwood, MA, 1999.

[8] M. Vespe, M. Sciotti, F. Burro, G. Battistello, and S. Sorge, 2008, Maritime multi-sensor data association based on geographic and navigational knowledge, *Proc. IEEE Radar Conference, Rome, Italy, 26-30 May 2008*.

[9] M. Nilsson, J. van Laere, T. Ziemke and J. Edlund, 2008, Extracting rules from expert operators to support situation awareness in maritime surveillance, Proc. 11$^{th}$ Int. Conf. Information Fusion, Cologne, Germany, 30 June-3 July 2008.

[10] F. Terroso-Sáenz, M. Valdés-Vela, C. Sotomayor-Martínez, R. Toledo-Moreo and A.F. Gómez-Skarmeta, 2012, A Cooperative Approach to Traffic Congestion Detection With Complex Event Processing and VANET, *IEEE Trans. Intelligent Transportation Systems, Vol. 13, No. 2*, pp. 914-929.

[11] G.K.D. de Vries and M. van Someren, 2012, Machine learning for vessel trajectories using compression, alignments and domain knowledge, *Expert Systems with Applications, Vol. 39*, pp. 13426–13439.

[12] A.J.E. Smith, 2006, Pro-active methods for maritime border control, *Proc. Maritime Systems and Technologies Conference (MAST), Nice, France, 4-6 September 2006*.