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A combined use of multispectral and SAR images for ship detection and characterization through object based image analysis

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ABSTRACT

Marine routes represent a huge portion of commercial and human trades, therefore surveillance, security and environmental protection themes are gaining increasing importance. Being able to overcome the limits imposed by terrestrial means of monitoring, ship detection from satellite has recently prompted a renewed interest for a continuous monitoring of illegal activities.
This paper describes an automatic Object Based Image Analysis (OBIA) approach to detect vessels made of different materials in various sea environments. The combined use of multispectral and SAR images allows for a regular observation unrestricted by lighting and atmospheric conditions and complementarity in terms of geographic coverage and geometric detail. The method developed adopts a region growing algorithm to segment the image in homogeneous objects, which are then classified through a decision tree algorithm based on spectral and geometrical properties. Then, a spatial analysis retrieves the vessels' position, length and heading parameters and a speed range is associated. Optimization of the image processing chain is performed by selecting image tiles through a statistical index. Vessel candidates are detected over amplitude SAR images using an adaptive threshold Constant False Alarm Rate (CFAR) algorithm prior the object based analysis.
Validation is carried out by comparing the retrieved parameters with the information provided by the Automatic Identification System (AIS), when available, or with manual measurement when AIS data are not available. The estimation of length shows R^2=0.85 and estimation of heading R^2=0.92, computed as the average of R^2 values obtained for both optical and radar images.

Keywords: Copernicus, ship detection, clandestine immigration, Object Based Image Analysis, multispectral images, SAR images, European Union

1. INTRODUCTION

1.1 Background

Seas and oceans have been place of commercial trades throughout human history. With oceans covering nearly 70% of world surface, maritime transport is essential to world's economy and international trade. According to the United Nations Conference on Trade and Development (UNCTAD), around 80% of global trade by volume are carried by sea and are handled by ports worldwide [1]. Throughout the last century, the shipping industry has seen a general trend of growth in total trade volume. Increasing industrialization and the liberalization of national economies have fueled free trade and a growing demand for consumer products [2]. Since seaborne trade volumes have generally moved parallel with economic and industrial activity growth, the volume of maritime trade is expected to increase as the world's economy and population continue to expand [3].
Besides legal commercial trades, seas of the world are theatre of illegal activities, as piracy, drug trafficking, illegal fishing, cross-border crime, marine pollution, human smuggling and clandestine immigration. In particular, the magnitude of migration flows towards Europe has induced in the last years a rapidly growing attention in government and citizens. Therefore, surveillance, security and environmental protection themes are gaining increasing importance and efficient monitoring methods are required.

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1.2 Ship detection from satellite

Ship detection from satellite imagery is a well-known application. However, in the last years it has prompted a renewed interest as support for a continuous monitoring of illegal activities. Existing commercial satellites for earth observation provide a robust platform for observing maritime activities beyond shore-based sensors and traditional tracking systems, offering a variety of data types, imaging opportunities and repeating coverage [4]. The combined use of high and medium resolution optical and SAR (Synthetic Aperture Radar) images allows for a regular observation unrestricted by lighting and atmospheric conditions and complementarity in terms of geographic coverage and geometric detail. Moreover, the necessity to detect vessels made of different materials (e.g. wooden, rubber or metallic) makes the mutual use of the two acquisition systems particularly significant in terms of detection results, as the use of a single technology may lead to missed identification or misclassification.

Being an active microwave sensor, SAR is ideally able to operate in all-weather and lighting conditions. Moreover, the trade-off between resolution and coverage that SAR offers [5] with different imaging modes (i.e., stripmap, spotlight or wide-swath) is particularly useful for ship detection, since high resolution surveys over small areas or low resolution surveys over wide areas can be scheduled according to specific needs. However, SAR images can be characterized by a high level of noise and are sensitive to sea surface state due to environmental conditions that occur during the observation time (winds and waves). As shorter wavelengths interact with smaller objects, intense signal can come from ocean background together with the strong return provided by ship targets, thus producing high clutter, which tends to obscure smaller ships and create false alarm [4, 6]. Besides incidence angle, polarization and orientation of the ship respect to the sensor can play a role in vessel detection rates [7]. All these factors, summed up with lower spatial resolution and the less regular ships appearance in radar images than in optical images, make SAR images visual interpretation difficult [7, 8].

Electro-Optical sensors have some shortcomings, too: clouds can obscure the field of view, sunlight is required to make observations and high-resolution optical systems have limited swaths. Different reflectivity of sea waves, sea surface roughness, weather, solar angle and imaging sensors, bring great variations in image intensity and contrast between foreground and background [9]. Nevertheless, current spatial resolutions allows the detection of very small targets [8], granting a more accurate features estimation [10], and the improved temporal resolution produced by the growth in the number of small optical satellite missions, enables frequent monitoring of the same areas [11].

Although less research has been carried out on the use of optical sensors for ship detection respect to radar, it has become a topic of recent interest [4] and several methods have been presented in literature. Existing ship detection techniques for optical data can be roughly divided into three categories: sea state analysis combined with threshold based methods [8, 12, 13], genetic algorithms and neural networks [14, 15] and textural and geometrical descriptors [16-17].

On the other hand, many techniques have been proposed in literature for ship detection through SAR data. The most popular category is that of adaptive thresholding (Constant False Alarm Rate) detectors [18], due to their simple implementation and reliable statistical approach. Other more sophisticated methods rely on multi-channel information, such as polarimetric detectors [19] or along-track interferometry [20].

2. METHODS

2.1 Data

The dataset used within this work comprises images acquired in different weather and sea conditions, and include ships of different shape, size and speed. Table 1 summarizes data and their main specifications.

Vessels' length and heading retrieved through the developed ship detection algorithm are validated with data acquired by the Automatic Identification System (AIS), an automatic tracking system made of a radio device operating in the maritime VHF band, which continuously receives and transmits information with other nearby ships and ground-based stations for identifying and locating vessels. The information exchanged between AIS devices can be grouped in static data (ship name and type, length, MMSI and IMO numbers, load and type of cargo) and dynamic data (ship position, speed, heading, estimated time of arrival, departure harbor, next port of call), which are of particular interest to large-area sea surveillance. The AIS system turns out to be a useful instrument to retrieve known ship routes at the time of the reference optical or radar image acquisition, and helps in the identification of unknown possible illegal vessels by crosschecking estimates with real data [21, 22, 23].

Within this work, AIS data were only available for the COSMO-SkyMed and Sentinel-2 images. For this application, AIS data have been acquired in a time span comprised between two minutes before and two minutes after the image acquisition time; consequently, records are characterized by a temporal shift between the time of the last received ship's position and the image acquisition time. Thus, in order to match AIS data with detected vessels, each ship's position was shifted backward or forward to the image acquisition time, based on the ships' speed and heading data provided by AIS and assuming they were moving with a uniform rectilinear motion (i.e. with no speed and heading changes). AIS positions corresponding to SAR images were also corrected to account for the boat-off-the-wake effect. This shows as a displacement of the vessel from its wake in the sensor along-track direction and is due to a velocity component in the radar line-of-sight (LOS) direction [18]. This correction was done based on AIS velocity records, scene acquisition geometry and sensor trajectory.

Table 1. Dataset and specifications.

			Spatial resolution (pixel size) [m]	
Sensor	**Acquisition Data**	**Location**	**Multispectral band**	**Panchromatic Band**
WorldView-2	31/12/2010 03/04/2011	Xiapu (China) Sydney (Australia)	2	0.5
QuickBird-2	16/05/2001	Venice (Italy)	2.4	0.6
GeoEye-1	12/02/2009	Venice (Italy)	1.6	0.4
Sentinel-2	Various	Various	10	n/a
COSMO-SkyMed	07/01/2012 19/09/2012	Hong Kong area	~3	n/a

2.2 Vessel detection

Optical images are first pre-processed through radiometric calibration and atmospheric correction. A Minimum Noise Fraction (MNF) transform is applied to multispectral images in order to select the component, which, through noise segregation, allows discriminating between ships, wakes and background [24, 25]. An Object Based Image Analysis (OBIA) is then adopted to detect vessels over optical and radar images, exploiting both spectral and geometric properties of the targets. This approach is chosen for its adaptability to analyze images acquired by different sensors in various atmospheric and sea conditions and even characterized by different spatial resolution. Object-based image analysis consists in a two-step process composed by segmentation and classification, where textural and contextual/relational characteristics among objects are exploited. A region growing algorithm segments the image in homogeneous objects, which are then classified through a decision tree algorithm based on spectral (i.e. intensity) and geometrical properties (i.e. area, length to width ratio). OBIA parameters are selected through a trial-and-error procedure.

For the optical component, the image processing chain is optimized to reduce computational time. The input image (the selected MNF component) is tiled through a chessboard segmentation and only tiles including potential vessels are retained for further processing. This selection is made according to the skewness (i.e. symmetry) of the pixels' reflectance distribution. Tiles with a Gaussian distribution (i.e. symmetrical) are expected to include only sea, while tiles with a skewed distribution are candidates for containing vessels and are thus retained for further processing (Figure 1a, left panel).

Processing of SAR images requires an additional step before OBIA: vessels candidates are detected using a Constant False Alarm Rate (CFAR) algorithm applied on amplitude data. This method is based on an adaptive threshold, which selects brighter pixels over a darker background, defined according to a Gaussian modelling of the sea statistics. Figure 1a (right panel) shows a comparison between image tiles including a ship and image tiles including sea, where cells with intensities greater than a threshold (determined from the background statistics in order to ensure a given probability of false alarm) and with a non-Gaussian distribution are labelled as belonging to a vessel. More details of the CFAR algorithm are described in [24-25]. The output of this phase is a binary image, which is then processed through the OBIA pipeline described for optical images. Examples of object extraction with optical and radar images are shown in figure 1b.

2.3 Parameters extraction

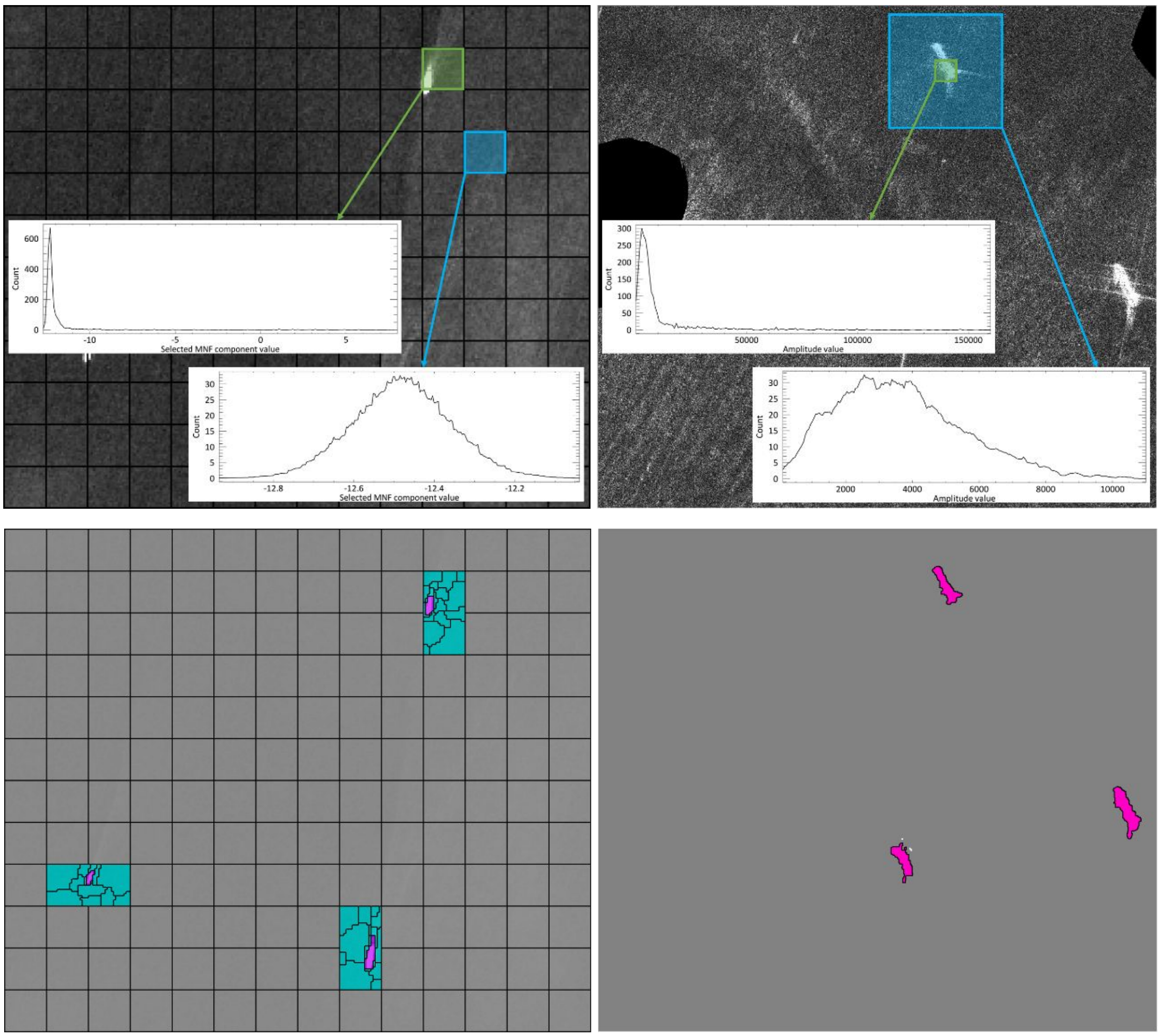
Vessels' position, length and heading are estimated through the spatial analysis of the features extracted. Each feature is fitted to an ellipse, whose major and minor axes are defined by the standard deviation of the x- and y- coordinates from the mean centre of the points cluster which constitutes each object. These two measures define the axes of an ellipse encompassing the distribution of features. Ships object are also enclosed with a rectangle of the smallest width, as lengths estimated from the ellipse have shown a systematic underestimate respect to the referring measured one. Thus, vessels' parameters are extracted as follows:

i) Position is estimated through the geographic coordinates of the centroid of the ship's ellipse;

ii) Length is estimated as the mean value of ellipse major axis and rectangle length;

iii) Heading (clockwise respect to the North) is estimated from the orientation of the wake's ellipse. For vessels detected with SAR (single frequency), heading is retrieved from the geometry of the object "ship".

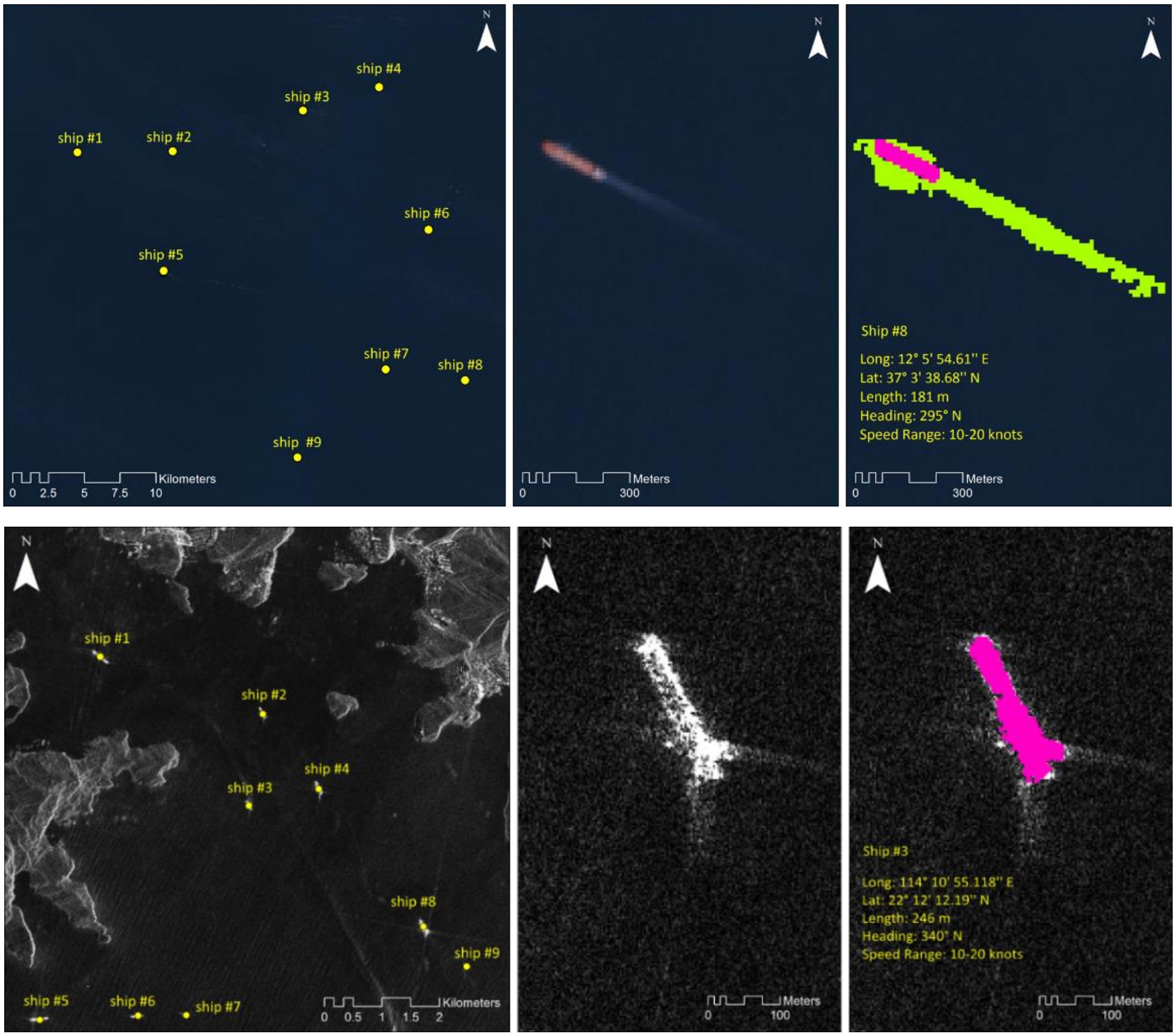
Vessel's speed complements its parametric characterization. While the speed of small vessels could be somehow estimated from high-resolution satellite images (both SAR and multispectral), however this is not possible using existing medium resolution Earth observation systems. Thus, this work did not accounted for the computation of speed. On the other hand, each vessel was assigned a predetermined speed class based on its size. Speed classes have been determined subdividing a sample of real ships provided with AIS data into length classes and by assigning them their speed mean value.
Figure 2 shows an example of ship detection and parameters estimation applied to Sentinel-2 and COSMO-SkyMed.



a)

b)

Figure 1. a) Image pre-processing prior to feature extraction: comparison between tiles including a ship and tiles with only sea. Sentinel-2 (left panel) and COSMO-SkyMed (right panel). b) Feature extraction: for optical images, OBIA is applied only over tiles with a skewed distribution of reflectance values (left panel). For SAR images, OBIA is applied on the binary image generated with CFAR. Detected vessels are in pink.



a)
b)

Figure 2. Results for ship detection and parameters estimation. a) Sentinel-2 image acquired over Mediterranean Sea; b) COSMO-SkyMed image acquired over Hong Kong. Ship object is in dark pink and wake object in green (detected only on with optical image).

3. RESULTS

Figure 3a shows results for high-resolution optical images (WorldView-2, GeoEye-1 and QuickBird-2). Due to the lack of AIS data, validation was performed through manual measurement of 50 ships. The vessels' length has a high coefficient of determination ($R^2 = 0.87$). Although linear regression shows a higher dispersion of the estimates for ships smaller than 20 meters respect to estimates of bigger ships, the proposed approach is able to detect ships less than 10 meters long. Besides, headings are estimated with a near perfect correlation with the measured ones ($R^2 = 0.99$).
For medium resolution optical images, vessels' length shows R^2=0.70, while heading shows R^2=0.73. These statistics were computed from a larger a sample of 337 vessels (Figure 3b). The dataset available for the Sentinel images comprises vessels of various size (from 10 to 400 m in length), detected with a unique set of parameters, and worse results compared to high resolution are probably due to the presence of outliers.

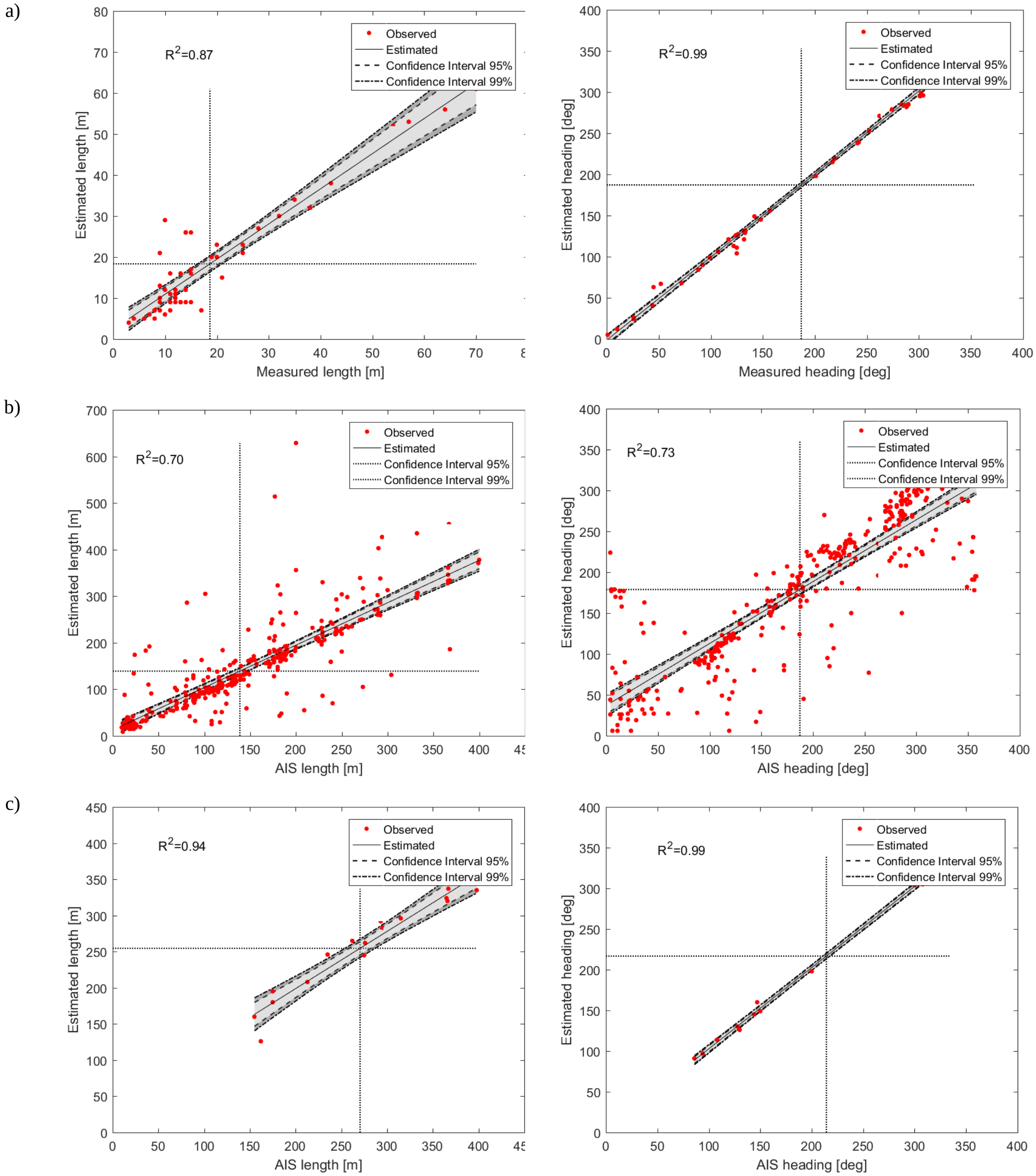


Figure 3. Validation of results. Regression graphs for length (left panel graphs) and heading (right panel graphs) estimates for a) high resolution optical images (WorldView-2, GeoEye-1 and QuickBird-2), b) medium resolution optical images (Sentinel-2), c) high resolution SAR images (COSMO-SkyMed). Estimates are represented within upper and lower 95% and 99% confidence bounds for the regression line.

Moreover, despite the high detail and accuracy achievable with high-resolution images, some errors in the estimate of ships' length and heading can occur when using optical data. Fast moving vessels are often followed by extremely bright wakes. Being similar in reflectivity to the vessels themselves, wakes can be partially misclassified thus overestimating the ships' length. On the other hand, very slow moving vessels can be followed by weak wakes. Being sometimes hardly distinguishable from the background, their misclassification could compromise an accurate estimate of heading. Besides, small bright clouds and sea waves and crests that usually occurring in open sea could be misclassified as vessels, thus generating some false positive detections.
Figure 3c shows results using SAR images. Both length and heading are estimated with very high accuracy, resulting in R^2 values respectively of 0.94 and 0.99, exceeding those retrieved for optical images. However, the dataset available for SAR images include all big ships, resulting in an easier detection than for optical images. Some errors of vessel size and heading estimates can be due to the use of a Gaussian model of the sea statistics, which is not suited to properly deal with sea clutter respect to other more traditional distributions (i.e. K-distribution).

4. CONCLUSIONS

In this work, a ship detection algorithm based on OBIA has been applied in parallel over optical and radar image. The proposed approach allows identifying with a satisfying accuracy even small/medium size vessels in complex sea environments. Length and heading estimates show respectively R^2=0.85 and R^2=0.92, computed as the average of R^2 values obtained for both optical and radar images, denoting a better estimate of heading respect to length common for all the experiments. Although requiring different pre-processing operations and filtering techniques, optical and radar data could be properly combined in order to assure a continuous and reliable vessel detection, thanks to their technological peculiarity and specific acquisition characteristics. High and medium resolution images can be conveniently adopted to reach high detail or cover wide areas according to specific needs.
Findings confirm that the proposed approach based on a combined use of optical and radar data could be significant for monitoring purposes of small and large areas and could prompt effective actions towards a sustainable management of world seas and oceans and fostering maritime security and surveillance.

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